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RESEARCH ARTICLE

Lingling ZHANG, Siting HUANG

New technology foresight method based on intelligent knowledge management

Abstract The increasing importance of technology foresight has simultaneously raised the significance of methods that determine crucial areas and technologies. However, qualitative and quantitative methods have shortcomings. The former involve high costs and many limitations, while the latter lack expert experience. Intelligent knowledge management emphasizes human–machine integration, which combines the advantages of expert experience and data mining. Thus, we proposed a new technology foresight method based on intelligent knowledge management. This method constructs a technological online platform to increase the number of participating experts. A secondary mining is performed on the results of patent analysis and bibliometrics. Thus, forward-looking, innovative, and disruptive areas and relevant experts must be discovered through the following comprehensive process: Topic acquisition → topic delivery → topic monitoring → topic guidance → topic reclamation → topic sorting → topic evolution → topic conforming → expert recommendation.

Keywords technology foresight, intelligent knowledge management, technological online platform

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Lingling ZHANG (✉)
School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China; Research Center on Fictitious Economy & Data Science, Key Laboratory of Big Data Mining and Knowledge Management, Chinese Academy of Sciences, Beijing 100190, China
E-mail: Zhangll@ucas.ac.cn

Siting HUANG
School of Economics and Management, University of Chinese Academy

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1 Introduction

The current world economy and society are more dependent on the capability and efficiency of technological innovation than before (Pietrobelli and Puppato, 2016; Liang and Li, 2017). Science and technology has become the measure of a country's national competitiveness. This important indicator has attracted governments' attention worldwide.

Technology foresight is based on the long-term "integrated forecasting" of science, technology, economy, and society. Such foresight also selects strategic research fields and general technology. Therefore, countries and governments can use the market's "optimal configuration" to maximize economic and social benefits (Martin and Johnston, 1999; Ren et al., 2016). Optimal configuration aims to grasp the development trends and frontier areas of future science and technology and to support decision-makers regarding scientific and technological development plans and strategic policies in any region. Suitable technology development policies aim to optimize resource allocation and strive for the future high point of technological development and competitive advantage (Liang et al., 2015).

Many countries, such as the United Kingdom, Japan, the United States, Germany, France, South Korea, and India, have successively performed technical foresight activities. Technology foresight is slowly forming a global wave (Liu et al., 2016; Fang et al., 2017). It largely depends on the selection and use of technology foresight methods whether technology foresight activities could be successfully implemented and obtain accurate and credible foresight results (Ren et al., 2016).

Qualitative methods are the main tools in technology foresight. Delphi survey has gradually become the core method in traditional technology foresight activities (Georghiou and Halfpenny, 1996). The Japanese government has implemented 10 technology foresight activities since 1971. Delphi survey is the main method of these 10 science and technology foresights, and reports lay a solid basis for the decision-making of science and technology strategies (Zhang and Kuang, 2016). Qualitative methods fully consider the frontier crossover, destructiveness, permeability, cross-border, uncertainty, and non-reproducibility of innovative technologies. These methods also take advantage of experts with rich experience and innovation. In addition, qualitative methods can be applied to medium- or long-term technology foresight. However, these methods are frequently time consuming and costly.

With the development of Internet technology, data- and technology-driven quantitative technology foresight methods play increasingly important roles in technology foresight. Quantitative methods focus on extracting science and technology trend from massive data on the Internet. The disadvantage is the lack of expert experience, which may lead to erroneous foresight results.

The current technology foresight method system cannot completely meet the need of policy makers. To overcome the shortcomings of experts, Spinosa pioneered the "Democracy Commitment", stating that technology foresight is inseparable from the broad decentralization and full participation of people (Spinosa et al., 2002). Intelligent knowledge management highlights the importance of human–machine combination. Thus, this study proposes a technology foresight method based on intelligent knowledge management. Through human–machine combination, technology foresight can attain objectivity. The research addresses the following problems:

(1) Qualitative and quantitative methods have their own advantages and disadvantages. Is a low-cost consultancy with a wide range of general experts possible through the use of results from data analysis?

(2) Is conducting "deep" or "secondary" mining, discussion, screening, and even new and innovative topics possible after the quantitative analysis process?

(3) Existing technology foresight methods place strong emphasis on gaining strategically important research areas and common technologies, but can the most appropriate researchers for these technologies be found through further research?

This paper proceeds as follows. Section 2 provides a literature review of qualitative and quantitative methods and intelligent knowledge management. Section 3 explores the theoretical foundation, basic concepts, and theoretical frameworks of technology foresight method based on technology platform. Section 4 outlines certain key research problems for future research. Section 5 concludes the paper.

2 Literature review

From the knowledge management view, technology foresight is a process that constantly refines, filters, and creates knowledge and systematically identifies strategic areas and technologies based on mining data, information and expert experience, and wisdom. Technology foresight methods are divided into qualitative and quantitative methods (Magruk, 2011). Qualitative methods are driven by expert experience and wisdom, whereas quantitative methods are driven by data and technology. Intelligent knowledge management is a process of extracting, storing, sharing, transforming, and utilizing derived original knowledge to support decision-making (Zhang et al., 2009a; Zhao et al., 2018). Intelligent knowledge management also combines the advantages of qualitative and quantitative technology foresight methods. The following is a literature review of these three aspects.

2.1 Qualitative methods of technology foresight

Qualitative methods, including Delphi method, road mapping, expert conference method, scenario analysis, and brainstorming, are extensively used in technology foresight activities worldwide.

Delphi method is the core method for technology foresight (Grupp and Linstone, 1999). Delphi survey relies on experts' tacit knowledge and wisdom that is broadly applied as a foresight tool nowadays (Czaplicka-Kolarz et al., 2009). Focusing on the management of tacit expert knowledge, Delphi method is a process of consulting and investigating multi-expert interviews on a large scale and reaching a consensus through experts on technology predictions or foresights (Bai et al., 2017). Scenario analysis is designed to correlate certain areas of relevance by indicating interactions between trends and key events in each area, thereby visualizing future technological developments. Scenario analysis is often used as an analytical framework in conjunction with other methods (Wack, 2017). As a tool for predicting and depicting technological development paths, technology roadmap has been widely used in different enterprises, industries, and national technology development planning to reduce uncertainty in innovation and planning (Willyard and McClees, 1987).

Applying each foresight method reveals their limitations in practice, consequently compelling a few researchers to combine two or more of these methods. For example, Kanama (2013) integrated the Delphi method with road mapping as a new technology foresight process. Drew (2006) combined scenario methods with technology road mapping to identify disruptive innovations at the early stage. Hussain et al. (2017) proposed scenario-driven road mapping and used scenario planning first to identify plausible images of the general environment.

With the development of technology, large-scale expert surveys have been realized, and the traditional qualitative Delphi survey method has slowly developed in the direction of combining qualitative and quantitative methods. Certain scholars employ the quantitative Delphi method to collect expert opinions by using questionnaires in multiple rounds of expert surveys (Celiktas and Kocar, 2012). Halal (2013) used online surveys and statistical methods to improve the efficiency and scientific results of the Delphi method (Halal, 2013). Jun et al. (2015) provided patent analysis results to expert-assisted decision-making.

Qualitative methods allow a rich generation of original ideas, full participation of all members among a small group, and a rank-ordered set of decisions based on a mathematical voting method (Karlsen, 2014). The disadvantages of qualitative methods are evident. Expert group work is often laborious, frustrating, and inefficient (Karlsen, 2014). The number of experts is also limited owing to high cost (Murry Jr and Hammons, 1995). Moreover, the limitations of qualitative methods are increasingly imposed (Shin and Han, 2001; Tichy, 2004).

2.2 Quantitative methods of technology foresight

Quantitative analysis remains comparatively rare in technology foresight, but related studies abound. Quantitative methods include growth curve, bibliometrics, patent analysis, data mining, social network analysis, and technology forecasting using data envelopment analysis. The application of data mining methods follows an evident growth trend (Zhou et al., 2017).

Patent analysis refers to the use of textual information, including patent holders, inventors, claims, abstracts, and legal status for index and citation analysis; thus, the development status of technology fields is explored, and the future development of technology is predicted from multiple dimensions (Brockhoff, 2002). Abraham and Moitra (2001) analyzed Indian patent data to provide firms with information that can aid the Indian government with their strategic planning efforts (Abraham and Moitra, 2001). Qiao (2013) combined patent bibliometrics with technology foresight to identify trends in the field of metallurgy through frequency and co-classification analyses. Liang et al. (2015) applied patent scientometrics methods in technology foresight and considered the new energy automobile an example.

Bibliometric analysis aims to use the titles, abstracts, keywords, authors, and institutions included in the scientific literature data to perform statistical descriptions and citation analysis. From the perspectives of research trends, hotspots, and frontiers, researchers help grasp the hidden development of technology (Schaeffer and Uyterlinde, 1998). Wang et al. (2015) used bibliometric theories and methods to analyze technology foresight papers.

Valuable information and knowledge prediction technology are extracted from the aspects of topic identification, gap analysis, and trend prediction by classifying, clustering, correlating, predicting, and visualizing data, such as literature, patents, news, reports, and economic trends (Cascini et al., 2009; Thorleuchter and Van den Poel, 2013). Using quantitative methods can avoid selectivity bias through multiple evaluation indicators. These methods are more objective, fair, reasonable, and efficient than “self-assessment” or peer reviews.

However, traditional Delphi method and the technology-driven quantitative method have certain disadvantages.

(1) Traditional technology foresight methods are time consuming and costly; the number of experts is also limited (Murry Jr and Hammons, 1995). Delphi method often takes two to three years and requires a large number of staff apart from the consulting experts.

(2) Experts have a strong subjective color and biases (Takahashi et al., 2014). Technology foresight results reveal subjective factors, such as expert knowledge, evaluation scale, and physiological state. Experts’ problem evaluation is typically intuition-based and lacks rigorous research and statistical evidence. Judging a clear future of the entire technology, economy, and environment is difficult for them (Courtney, 2001). Moreover, experts often overestimate the future of their own research field.

(3) Qualitative methods cannot easily determine the criteria and conditions of expert selection, the number of experts, and the knowledge structure of experts. Different structures or different experts may lead to different results.

(4) Data and technology-driven quantitative methods focus on the perfection of quantitative analysis and technology and the lack of domain knowledge and expert experience (Zhang et al., 2019a). The results often have low applicability and support for decision-making. After mining rough data rules for massive data, the methods stop abruptly; in addition, the “deep” or “secondary” mining results, such as classification and evaluation, are neglected (McGarry, 2005). Moreover, quantitative methods are generally applicable to short-term forecasts.

Therefore, a new technology foresight method that can accurately predict future technology is necessary.

3 Theoretical foundation, definitions, and framework

3.1 Theoretical foundation

Technology foresight is a systematic long-term study of science, technology, economics, and social development. Relying on individual abilities to solve this problem is insufficient. Given the limitations of individual knowledge structures, skills and experiences, and the differences in perspectives, different people have different breadth and depth of thinking when they solve the same problem (Hong and Page, 2004). Groups can compensate for the limitations of personal thinking problems and provide the best answer. Delphi and brainstorming methods are the collective wisdom of authoritative experts in various fields. Collective intelligence generates comprehensive and accurate technology foresight results. Such methods have reached a good conclusion. However, these methods generally involve high-level experts, and the number of experts is limited due to factors, such as cost and time. To illustrate, over 5000 experts were invited by Japan's 10th technology foresight with large costs and complicated processes.

Many studies have indicated that the judgment of a large group may be more accurate than the judgment of a few experts. Certain researchers have reviewed the literature and stressed that group decision-making may overcome personal biases. They also claim that increasing group diversity can decrease group biases (Bang and Frith, 2017). Individuals reconsider their position and judgement because of identity diversity (Antonio et al., 2004; Loyd et al., 2013). Group diversity also reduces the risk of exclusively relying on a local solution when a good solution exists (Østergaard et al., 2011). Wells et al. (2008) argued that a large group of people generally offer a clearer illustration of future events than experts or a small group of experts. In addition, Katsikopoulos and King (2010) suggested that the level of group and individual intelligence is influenced by the form of decision-making. When deciding for the first operation, group wisdom is often less convincing than expert wisdom. By contrast, when deciding for the second operation, group aggregation information is always better than expert opinion.

With the development of the Internet in the 21st century, users can easily and quickly obtain rich and wide-ranging information from the Internet. Indeed, this accessibility provides great convenience for knowledge sharing. Such development also possibly enables the comprehensive utilization of group intellectual resources. In the information era, massive data become available for analysis in support of decision-making (Elgendy and Elragal, 2014). Big data analysis is based on large samples, which far exceed the sample size of previous surveys. Therefore, hidden patterns can be discovered from large samples, which are rarely gained by experts (Zhang et al., 2009b). Many scholars argue that network environment likely generates and exerts group wisdom. Davenport and Cronin (2000) indicated that network environment expands communication tools and contents through three scenarios, which also likely generate group wisdom. Stiles and Cui (2010) investigated the dynamics and roles of developers in open source software. The Facebook 2017 Hot Topics and Trends Report under the Open Network both collated the hot conversations in 2017 and predicted topics that would dominate the trend in 2018. These results are based on real and reliable data and insights from two billion Facebook users.

Technology foresight is a complex problem requiring integration into the analysis of data, such as literature and patent, based on authoritative experts' wisdom. Mining a large amount of small wisdom can compensate for the limitations of authoritative experts. However, the conclusions based on large sample analysis are usually rough. Owing to the ambiguity, uncertainty, and high risk of technology topics, the current artificial intelligence cannot convincingly distinguish whether the foresight results are prospective. Thus, combining experience and wisdom is necessary for deep mining and research.

Integrating many experts with data mining results also requires consideration, thus assisting technology foresight in determining practical and forward-looking technologies and fields. Intelligent knowledge management focuses on human–machine interaction and emphasizes that knowledge discovery is a dynamic process. This method can be applied to technology foresight when solving problems.

Intelligent knowledge management is the cross-field between data mining and knowledge management. Before the proposal of intelligent knowledge management, cross-field research is scarce. Anand et al. (1996) mentioned that "user's prior knowledge and previously discovered knowledge can be combined into the discovery process" in the Evidence-Based Data Mining (EDM), a general framework for data mining based on evidence theory. Yoon and Kerschberg (1993) proposed the concept of knowledge discovery and evolution in a database. Certain scholars have proposed domain-driven data mining methods (Cao, 2010; Zhang et al., 2019b). Luan (2002) demonstrated the importance of using knowledge management and data mining to support marketing decisions.

Zhang et al. (2009b) first proposed the concept of intelligent knowledge management. She applied knowledge management theory to the data mining results and claimed that data mining is strongly related to knowledge and knowledge management. They analyzed the process of intelligent knowledge management with four transformations among original data and rough, intelligent, and actionable knowledge.

By adding intelligent knowledge management to the technology foresight process, the advantages of qualitative and quantitative methods can be combined.

3.2 Technological online platform, a "Ba" to create new knowledge

The technology foresight process can be regarded as the knowledge management process that extracts, selects, and creates knowledge from data, information and expert experience, and wisdom. A model distinguishes the knowledge creating process into four parts—socialization, externalization, combination, and internalization, which together form the acronym "SECI" (Nonaka et al., 2001). During this process, dynamic interactions exist between tacit and explicit knowledge. In technology foresight, tacit knowledge refers to expert experience and knowledge, whereas knowledge from Internet data and information is explicit (Zhang et al., 2016). SECI model also suggests that knowledge is created through interactions among individuals. However, experts using the Delphi method are anonymous and cannot communicate with one another. No interaction is observed in bibliometrics or patent analysis. Moreover, the number of experts in the brainstorming method is limited owing to costs. Therefore, interaction in the current technology foresight method is limited. However, interaction among people plays a key role in the comprehensiveness and accuracy of technology foresight.

Another important concept is mentioned in Nonaka's paper—"Ba" (Nonaka et al., 2001). "Ba" offers a context to create knowledge. "Ba" enables participants to share their time and opinions, accelerating the spiral cycle of knowledge creation. To enhance the comprehensiveness and accuracy of technology foresight, "Ba" is necessary as it can promote communication among experts. The development of the Internet enables people to communicate online. Therefore, technological online platform is suitable for technology foresight. The online platform breaks the limitations of the traditional technology foresight method. The current study uses SECI model and intelligent knowledge management to explain data and knowledge transformation on the platform (Fig. 1).

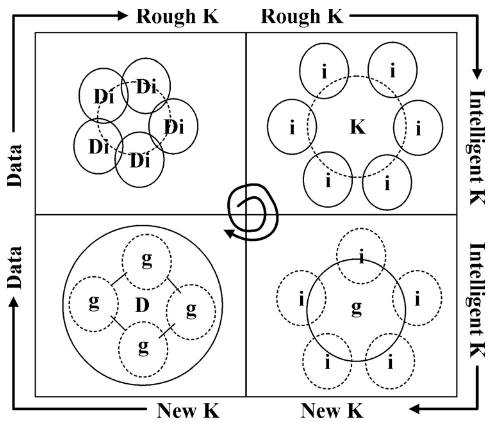

Fig. 1 Transformation process: Data → Rough Knowledge → Intelligent Knowledge → New Knowledge (D: data; i: individual; g: group; K: knowledge).

Rough knowledge is mined from big data, such as patents and papers. In the first step, several technologies are raised. In the second step, rough knowledge is placed on the platform, and individuals reconsider their opinion on prospective technology based on the results in the first step. These individuals indicate that rough knowledge becomes intelligent knowledge. In the third step, individuals discuss with one another on the same topic group and form new ideas. In the fourth step, different groups form their own opinions, and the interaction among them on the platform can be regarded as data for analysis. This technology foresight process is also a cycle to form comprehensive foresight results.

Technological online platform encourages the transformation process. The platform has the following characteristics:

First, results of bibliometrics and patent analysis are placed on the platform, allowing experts to discuss online, which is the process of intelligent knowledge management. Subsequently, the interactive data about the topics are analyzed, and the most popular topic is determined. This human–machine combination can generate reliable results.

Second, technological online platform can enhance experts' enthusiasm to participate, reduce organizational cost and difficulty, and improve information exchange effectiveness. The traditional technology foresight method, including Delphi, brainstorming, and scenario analysis, requires many complex steps. These methods are both costly and difficult to implement. However, in online platforms, direct online communication reduces organizational cost while increasing experts' convenience.

Third, by overcoming time and space limitations, the number of participating experts is not limited. They can read relevant information, expound their opinions and comments, and discuss with others anytime and anywhere. They can also promptly express relevant needs and real-time problems. This interactive participation method ensures that experts have sufficient time to judge whether a technology has potential. The number of people is also not limited, and everyone expresses his or her own views. Therefore, the diversification of opinions can enhance the depth and breadth of understanding a problem.

3.3 Definitions and framework

To further understand the technology foresight method based on intelligent knowledge management, basic concepts and definitions are introduced first.

Definition 1: Technology foresight is a process involved in systematically evaluating the long-term future of science, technology, economy, and society to identify strategic research areas; emerging generic technologies likely yield the greatest economic and social benefits (Martin and Johnston, 1999).

According to this definition, technology foresight aims to select promising technologies and areas. All methods applied to technology foresight find certain technologies or areas.

Definition 2: Topics concern technologies or areas evaluated during the technology foresight process.

As previously mentioned, technological online platform is the most crucial part in our new method, which combines the advantages of qualitative and quantitative methods.

Definition 3: Technological online platform is a place in which experts can communicate with one another and discuss about topics during the technology foresight process.

The proposed technology foresight method based on intelligent knowledge management involves nine processes to make use of Internet data and ensure experts' active participation (Fig. 2). These nine processes include topic acquisition → topic delivery → topic monitoring → topic guidance → topic reclamation → topic sorting → topic evolution → topic conforming → expert recommendation.

Process 1: Topic acquisition. Based on big data analysis, quantitative technology foresight methods, such as bibliometrics and patent analysis, are used to obtain preliminary topics.

Process 2: Topic delivery. Topics generated from Process 1 are placed in the corresponding areas on the technological online platform to invite experts for discussion.

Process 3: Topic monitoring. The quality of expert mining results depends on the quality of topic discussions. Therefore, effectively monitoring topic comments or responses after delivering the topic is necessary. Problems in the topic discussion are timely and effectively observed during the topic monitoring process. Topic discussion provides answers to obtain complete technical foresight results.

Process 4: Topic guidance. Based on big data (papers, patents, projects, and standards), recommending relevant knowledge and information material to experts on a technological online platform is necessary to guide the topic discussion during the interaction process.

Process 5: Topic reclamation. After delivering topics to the relevant technological online platform, expert discussion can generate interaction data that represent their opinion. Mining interaction data can result in useful information, which can help identify potential topics. Topic reclamation is a process of periodically recycling interaction data and information about the topics.

Process 6: Topic sorting. Topic sorting is a key process of identifying which topics are crucial in the future and are important to improve national innovation ability. The process of identifying important topics can be transferred into topic sorting. The more important the topic is, the higher rank it has. To obtain ranking results, realizing topic re-generation based on machine learning and short text mining is necessary. These topics are sorted via computer algorithms and techniques, considering the weight of expert authority. Top ranking is the result of technical foresight based on intelligent knowledge management.

Process 7: Topic evolution. During expert discussion, topics may be derived, migrated, and cross-examined.

Process 8: Topic conforming. Results of topic sorting and evolution are handed over to the authoritative expert for the final judgments. Delphi method can be added in this process.

Process 9: Expert recommendation. After the process, key technologies and areas are finally conformed. The results reveal a high-level team of experts who can undertake relevant research.

Figure 3 illustrates that technological online platform encourages the transformation process. The platform provides a place for people to discuss topics. The spiral cycle of creating new knowledge should be managed by the moderators. The process that includes topic delivery, topic monitoring, and so on, is necessary during the spiral cycle. Interaction data from the transformation process are analyzed, and the results are placed in the platform again as

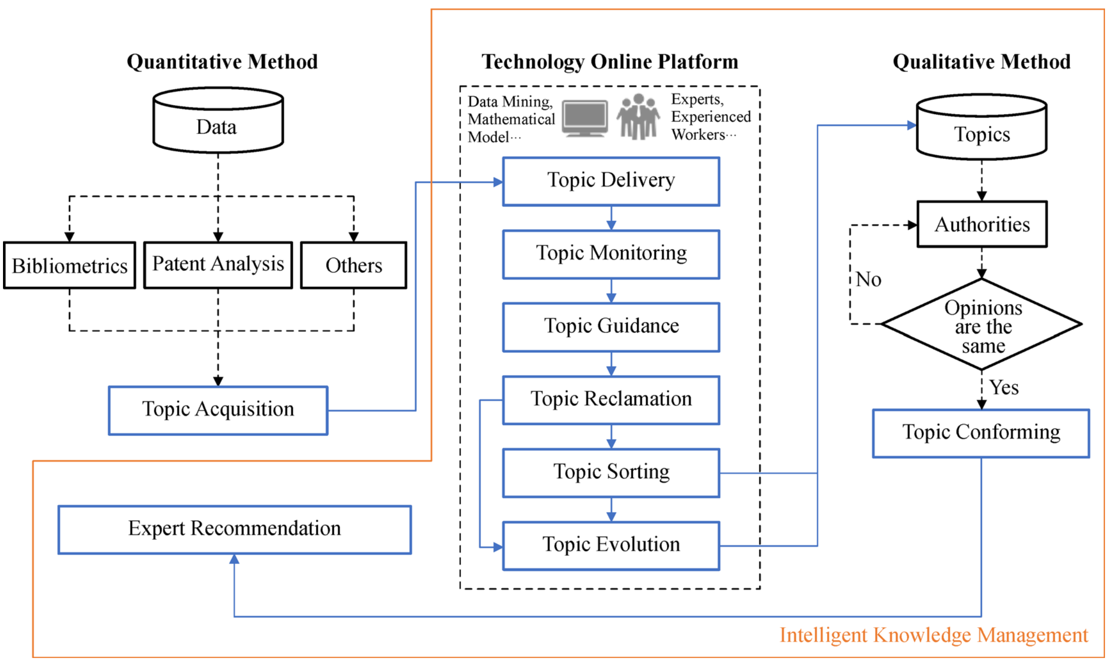

Fig. 2 Technology foresight frame based on intelligent knowledge management.

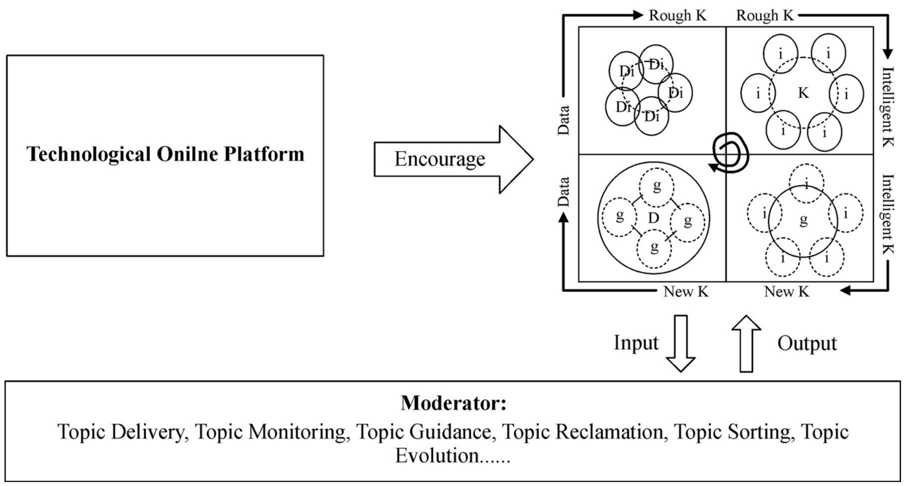

Fig. 3 Relationship among technological online platform, transformation process, and moderators.

rough knowledge. Technology foresight results based on this method become comprehensive and accurate because many experts and discussions have been involved in the process.

The research has the following innovations:

(1) A new method of technology foresight framework based on intelligent knowledge management is proposed. The framework illustrates the following process: Topic acquisition → topic delivery → topic monitoring → topic guidance → topic reclamation → topic sorting → topic evolution → topic conforming → expert recommendation.

(2) Intelligent knowledge management is used to combine quantitative and qualitative methods and tacit and explicit knowledge.

(3) Technological online platform, which is a "Ba" to create new knowledge, is added to the technology foresight process. This platform encourages many experts and experienced workers to participate in the technology foresight process and contribute their wisdom. Such factors allow a wide coverage, high participation, and high feasibility of the technology foresight process.

(4) Mining interactive data in the platform enhances intelligence and automation during the technology foresight process.

(5) Expert recommendation is forwarded to recommending experts and teams engaged in relevant research.

4 Research directions

The new technology foresight method based on intelligent knowledge management can be a promising research area that involves cross fields of computer science, knowledge management, collective intelligence, and behavioral science. However, many research directions remain unexplored.

4.1 Key technologies of topic delivery, guidance, and monitoring

Understanding topic delivery, guidance, and monitoring on the technological online platform is a complex problem to solve.

Topic delivery has two problems. The first problem is how to expand semantic meanings of topics. Such topics are typically in the form of a sentence or a descriptive text message, and their language is concise. Although further highlighting the subject is the goal, little contextual information leads to insufficient semantic description. Therefore, enriching the semantic relationship implied among words is necessary. The second problem is how to place topics on a technology-related community or section with a strong topic relevance.

In the process of topic guidance and monitoring, several key points are noted as follows: 1) Track and monitor comment information and interaction generated in the topic interaction; 2) monitor the login and interaction data of the topic discussed by the participating users in the technology community; and 3) identify the interactions affecting problem solving. Analyzing background knowledge related to topic views and interactive information is analyzed. Moreover, relevant knowledge and information materials are recommended to continuously guide the topic.

4.2 Promote the accuracy of topic sorting

Topic sorting contains two steps, namely, interactive data mining and topic score calculation.

After placing topics to the technological online platform, expert groups can produce massive interactive data, which are mostly short texts. Technology topics are generated from such text data by using deep learning, parallel/distributed computing methods, and short text clustering.

During the mining process, the interactive information on the platform considers the characteristics of the experts to conduct a good sentiment analysis of comments. The topics are sorted according to the interactive data on the technology platform. Experts have different cultural and professional backgrounds, which can influence the quality of results in determining how to provide scientific weight to experts' professional level and reasonable evaluation to their interaction behavior. Relevant details, such as expert attributes, research areas, institutions, academic level, commitment projects, international influences, and other important factors, are recorded to obtain expert knowledge and level evaluation.

Topic sorting involves the analysis of short-sentence sentiments, scientific and technical personnel characteristics, and construction of sorting models.

4.3 Recommended topics of relevant experts or research teams

A high-level expert team is discovered to conduct research on related scientific and technological innovation topics through the complete portrayal of scientific community experts, the establishment of scientific research social network, and the use of graph mining, expert mining, intelligent knowledge management, and other methods.

Investigating relevant methods and key technologies of intelligently discovered relevant experts or teams is important. Expert background information mining is also crucial. Experts' background information from different data sources is obtained, and a report on the wisdom of scientific and technological talents is generated. Academic super graphs and entity association models are established, and related experts whose background is relevant to the topics are discovered. The key is the accuracy of experts' background information. Thus, integrating the expert background information of multi-source discoveries, such as knowledge maps, web data, literature data sources, and associated data sources, is necessary.

5 Conclusions

The new technology foresight method based on intelligent knowledge management integrates theories of expert mining, data mining, intelligent knowledge management, and meta-synthesis. The method aims to conduct a secondary mining on the results from big data, such as patents and papers. Subsequently, the wisdom of expert groups is excavated, converged, and condensed on the technological online platform to explore real-world, forward-looking, innovative, and disruptive innovation areas. The new method also inspires expert wisdom to emerge on the human–human and human–machine environment. Relevant results and experts are gained and found, respectively, during the following comprehensive process: Topic acquisition → topic delivery → topic monitoring → topic guidance → topic reclamation → topic sorting → topic evolution → topic conforming → expert recommendation. Compared with other technology foresight methods, this new method has the following advantages:

(1) Improving the accuracy of technology foresight. The second mining of patent and document results can improve their reliability and accuracy. The initial selection field and related technologies are adjusted on the basis of the secondary mining results. The possibility of missing important areas and technologies during the technology foresight process is also substantially reduced.

(2) Reducing cost and breaking through space and quantity constraints. A technological online platform that adopts an online communication discussion mode without restrictions on the number of experts, is established. Experts can communicate with one another anytime and anywhere. Such an interaction can lead to new ideas and directions.

(3) Extending the scope of technology foresight. Technology foresight can predict applied technology, but predicting basic science and "disruptive technology" is difficult. Research on basic science and disruptive technology is more valuable than simple frontier tracking and should be the focus of technology foresight. The technology platform brings together many domain-related workers on the network. Continuous discussions and interactions on the online platform generate many innovative topics.

(4) Matching technical results to appropriate experts. High-level expert teams that can conduct research on related scientific and technological innovation topics by using certain technical methods, must be discovered.

This method improves technical foresight comprehensiveness and accuracy by combining human cognition and experience with information extracted from massive data with the participation of expert groups, data, and various information and computer technologies.

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