Review of Research Methods for Technology Topic Evolution (Postprint)

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Abstract

[Purpose/Significance] Technical topic evolution analysis holds significant importance for understanding the developmental trajectory of technology and predicting future technology trends. Systematically reviewing the methods for technical topic evolution analysis contributes to understanding the current research status and lays a foundation for further research. [Method/Process] The methods for technical topic evolution analysis in existing research are categorized into three major types: qualitative, quantitative, and combined qualitative-quantitative approaches, with representative methods in each category being elaborated. [Results/Conclusion] Based on a systematic review of existing methods for technical topic evolution analysis, the limitations of current research and prospects for future research are proposed.

Full Text

Preamble

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A Review of Research Methods for Technological Topic Evolution
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Abstract

[Purpose/Significance] The analysis of technological topic evolution is of great significance for understanding the trajectory of technological development and predicting future technology trends. Reviewing the methods for analyzing technological topic evolution helps to understand the current research landscape and lays a foundation for further studies. **[Method/Process]** This paper categorizes existing research methods for technological topic evolution analysis into three major types: qualitative methods, quantitative methods, and hybrid methods combining qualitative and quantitative approaches, and elaborates on representative methods within each category. [**Results/Conclusion**] Based on a systematic review of existing methods for technological topic evolution analysis, this paper identifies current research limitations and proposes future research directions.

Keywords: technological topic evolution; patent analysis; text mining; literature review
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1 Introduction

Modern technological development is advancing at a rapid pace, with increasing technology flows, cooperation, and convergence across industries. Technological interconnections are becoming tighter, and technological progress in one industry is closely related to technological changes in others [1-2]. As the main drivers of social innovation, enterprises face the challenge of continuously innovating to develop new products. Consequently, technological complexity and diversity are growing daily, the pace of technological innovation is accelerating, its intensity is increasing, and uncertainty in technological development continues to rise [3]. The prevailing view holds that technological development is continuous and cumulative, exhibiting distinct stages, and can reflect the current state of technological activities. This provides reliable assistance for researchers to investigate and trace the origins and development of technologies, and is significant for identifying priority areas in science and technology and allocating resources rationally. With rapid scientific and technological progress, technological advancement and innovation have become important drivers of economic development. Meanwhile, scholars have conducted research on technological topic evolution from different perspectives, gradually improving the theories and methods of technological evolution studies.

2 Research Methods for Technological Topic Evolution

In today's fiercely competitive market environment, decision-makers need to identify potential directions for technological emergence to choose the right path for further research planning and activities. Analyzing and tracking the history and current development of a specific technology is therefore crucial for gaining competitive advantages and seizing important development opportunities [4]. Understanding the evolution of technological topics can provide decision support for the management of scientific research, such as planning science and technology development, optimizing R&D project management and investment, predicting technology development trends, and identifying key technical talents in a particular field. To reveal the evolution process of a specific technology, different researchers have proposed numerous methods from various perspectives.

From a qualitative research perspective, representative analytical methods include: Morphology Analysis proposed in the 1940s [5], TRIZ (Theory of Inventive Problem Solving) [6], and the Delphi Survey used by RAND Corporation in the 1950s for studying technological topic evolution and technology forecasting [7]. Qualitative methods for technological topic evolution analysis heavily rely on experts' domain knowledge, making them highly subjective and costly. Therefore, many scholars have proposed quantitative research-based analytical methods that rely more on statistical or machine learning algorithms rather than expert knowledge. For example, J. M. Utterback et al. [8] modeled the technology life cycle using mathematical models, while R. Haupt et al. [9] proposed using quantitative patent indicators such as backward citations, citation immediacy, forward citations, and dependent claims to determine a technology's development stage in its life cycle. With the development of information technology and the construction of specialized patent databases, an increasing number of scholars have proposed technology topic evolution analysis methods based on patent classification, patent citations, and patent text [10-13]. Additionally, some scholars have proposed methods combining qualitative and quantitative research [14-17]. In summary, current technology topic evolution analysis methods mainly fall into three categories: qualitative methods, quantitative methods, and hybrid methods.

2.1 Qualitative Research Methods

Qualitative research methods for technological topic evolution analysis primarily depend on experts' domain knowledge and experience. Representative qualitative analysis methods include Morphology Analysis, Delphi Survey, and TRIZ.

2.1.1 Morphology Analysis Morphology Analysis is a representative qualitative approach commonly used in technology forecasting and technology topic evolution analysis. Its basic idea is to divide the analysis object into different dimensions to describe it as comprehensively and completely as possible [5]. Typically, a system consists of several subsystems, each comprising multiple different elements. Morphology Analysis identifies the elements of each dimension (subsystem), combines these elements, and examines possible system combinations to determine the optimal solution. The key to Morphology Analysis lies in modeling complex problems in a non-quantitative manner [18]. Therefore, it is more a method for structured problem modeling than problem-solving, and the modeling process relies heavily on domain experts. However, traditional Morphology Analysis has limitations in constructing technology morphology scientifically and systematically. To address this, B. Yoon and Y. Park [19] proposed a keyword-based Morphology Analysis method that first uses text mining to extract keywords from patent texts, then performs factor analysis on these keywords to obtain a technology dictionary, which is subsequently used to construct technology morphology for analyzing technology opportunities, technology forecasting, and technology topic evolution [20-21]. Morphology Analysis has been applied in fields such as LED lighting technology [22] and 3D printing [23]. Current development trends involve combining it with quantitative methods like bibliometrics, conjoint analysis, or text mining to reduce manual intervention and achieve scientific and efficient identification of technology opportunities.

2.1.2 Delphi Method In technology topic evolution analysis and technology forecasting, simple statistical information often fails to meet analytical needs, making it necessary to incorporate expert opinions. The Delphi Method relies fully on experts' knowledge and experience, enabling them to make judgments, assessments, and predictions through investigation and research, making it an effective means of tapping into expert insights [24]. C. Y. Hung et al. [25] used a modified Delphi method to predict the impact of iPad on Taiwan's PC ecosystem, summarizing survey results using frequency tables and graphical analysis. C. Markmann et al. [26] conducted risk analysis for supply chain security technology through the Delphi method to identify and assess future technological challenges. Additionally, J. Keller et al. [27] performed technology forecasting for Information and Communication Technology (ICT) using the Delphi method. Since the Delphi method completely depends on experts' experience and knowledge, its analytical results can be unstable with changes in experts. Its effectiveness also relies on methods for collecting, using, and planning expert opinions, such as scenario analysis and technology roadmapping. The key to improving the accuracy and reliability of the Delphi method lies in enhancing expert knowledge, such as incorporating patent information sources and quantitative patent analysis methods in the early survey stages to provide experts with reliable information sources and reference points. The Delphi method remains a commonly used approach in technology forecasting and technology topic evolution analysis.

2.1.3 TRIZ Method TRIZ is an innovation problem-solving theory developed by Soviet inventor H. Altshuller and his colleagues between 1946-1985 based on the analysis of patents from various countries [28]. It consists of methods, tools, and algorithms for solving technical problems and achieving innovation, with the core idea that resolving technical contradictions and conflicts drives the evolution of technical systems. TRIZ can predict technology development directions at both macro and micro levels [29]. The macro level involves the evolution trends of entire technical systems (e.g., technology life cycles), while the micro level involves specific evolution routes for different technology branches. TRIZ's "Problem-Solution (P-S)" heuristic analysis mode is an important method for technology paradigm evolution analysis, helping to understand technology evolution rules, with better effects in small technology branch fields, as demonstrated in empirical studies on unmanned aerial vehicles [30], dispensing machines [31], and distribution transformers [32].

Since TRIZ was developed from mechanical and engineering patents, using it alone cannot well reflect patent characteristics in other fields. Moreover, although the "problem-solution" approach is an important component, the semantic relationship between problems and solutions is not well revealed. To address these issues, recent trends involve combining TRIZ with natural language processing, text mining, data mining, and semantic analysis [33-35] to expand TRIZ's applicable fields and reveal semantic relationships between problems and solutions. Examples include integrating data mining technology with multidimensional analysis and TRIZ knowledge bases into knowledge maps [36], using structural equation methods to identify coupling relationships between TRIZ and patent texts [37], and using modern semantic technologies to build personalized semantic TRIZ models [38].

2.2 Quantitative Research Methods

Qualitative methods are overly dependent on domain experts' knowledge and experience, making them subjective, unstable, and costly. To overcome these limitations, many scholars have proposed quantitative research methods for technology topic evolution analysis [39-41]. Patent data, as carriers of technical, legal, and business information, are highly structured and easily accessible. Due to legal requirements and commercial importance, patent information is rigorously compiled and comprehensive, making it the primary data source for technology convergence research. Patent data contain rich information, including structured metadata (e.g., patent citations, classifications) and unstructured patent texts, facilitating technology topic evolution analysis. This paper divides quantitative research methods into six categories: technology life cycle methods, patent classification-based methods, patent citation-based methods, patent text-based methods, patent network analysis methods, and methods combining multiple patent elements.

2.2.1 Technology Life Cycle Method The technology life cycle represents a cyclical pattern of technological topic evolution, generally divided into four stages: embryonic, growth, maturity, and decline [42]. H. Ernst [43] combined the four stages of the technology life cycle with TRIZ theory to form an S-curve model and proposed using quantitative patent indicators to represent technology performance metrics. Technology life cycle analysis typically uses mathematical models to fit S-curves, with common models including Logistic and Gompertz models, using patent application volumes to fit and predict the technology life cycle model and further analyze the stage of technology development. Additionally, some studies analyze technology life cycles through multiple technical indicators [44], representative ones including forward/backward citation counts, citation median, technology growth rate, technology maturity coefficient, and technology aging coefficient [9]. Compared with using S-curves alone, some scholars argue that technology trajectory theory is more suitable for technology topic evolution analysis and better meets the needs of technology life cycle prediction [45]. Other scholars have improved traditional technology life cycle models, such as M. Li [46], who proposed a technology life cycle analysis framework combining bibliometrics and technology life cycle methods to analyze the evolution process and development stages of graphene technology. C. Lee et al. [47] proposed a stochastic technology life cycle method, defining seven time-series patent indicators and using Hidden Markov Models to estimate technology probabilities. M. Rezaeian et al. [48] created a three-step technology forecasting approach—life cycle analysis, text mining, and automatic clustering—to discover and evaluate potential opportunities for new R&D activities in specific research fields. In empirical research, the development trend of technology life cycle methods is to combine them with various patent metrics or measurement methods to improve accuracy and reliability.

2.2.2 Patent Classification-Based Methods Patent classification reflects the technical content of patents. Analyzing patent classification information along the time dimension using statistical methods can reveal the evolution process of a specific technology over time. Scholars have used structured information in patent documents to analyze technology topic evolution and predict future technology development trends [49]. Patent co-classification analysis is a commonly used method for technology topic evolution analysis based on patent classification. If patent classification numbers representing different technology directions (e.g., IPC, USPC) co-occur (e.g., appear together in the same patent document), it indicates a relationship between these two technology directions. Analyzing these relationships enables technology topic analysis. K. Suzuki et al. [50] conducted technology analysis based on the co-occurrence of patent IPC classification numbers. Patent co-classification can also be viewed as a network relationship, allowing analysis through social network analysis methods. S. Jeong et al. [51] built an IPC co-occurrence network based on the co-occurrence relationships of IPC classification numbers in patent documents, where each node represents a technology direction. The more patents containing two technology directions, the stronger the relationship between them. Analyzing network characteristics (e.g., network density, average node degree) can reveal the evolution of different technology topics over time.

Clustering analysis is often combined with patent classification information for technology analysis and forecasting. G. Kim et al. [52] used k-means clustering based on patent CPC classification to identify and define newly formed technology clusters and evaluated their prospects using patent indicators such as independent claims. Association rule analysis is also frequently used to mine co-occurrence information of patent classifications. For example, W. S. Lee et al. [53] mined strong association rules from IPC co-occurrence relationships, built an IPC co-occurrence network based on these rules, and performed link prediction on the IPC co-occurrence network to forecast future technology development trends, combining topic analysis to extract keywords for identifying potential emerging fields.

2.2.3 Patent Citation-Based Methods Due to standardized and easily accessible data, patent citation analysis has become an important research tool for technology topic evolution analysis and technology forecasting [54]. Citation relationships reflect the technical and scientific foundations of a patent. Patent citation analysis involves analyzing citation relationships between patent documents [55]. Patent citation relationships mainly include direct citation, co-citation, and bibliographic coupling, each with different emphases: direct citation reflects technical specialization, co-citation reflects interconnections in different technology developments, and bibliographic coupling reflects technical commonality [56-58].

Based on patent citation relationships, patent citation networks can be constructed. Current methods for analyzing patent citation networks mainly fall into three categories [44]: methods combining patent citation networks with clustering analysis, methods identifying main knowledge flow paths in patent citation networks, and methods based on social network analysis. Patent citation relationships can reflect technology flow and similarity. Combining patent citation networks with clustering analysis can group similar patent technologies into clusters based on citation relationships. Analyzing the relationships between different technology topics and their changes over time can further identify technology evolution and judge development trends [4, 56-57, 59-60]. Some studies [54, 61-62] have proposed metrics for measuring citation weights to identify main knowledge flow paths in patent citation networks and map technology evolution trajectories. Main path analysis, a key method in technology topic evolution analysis that aims to reflect knowledge flow by identifying important paths based on citation weights, has been used to identify technological topics. V. Batagelj [63] improved the main path algorithm to handle large-scale networks with millions of nodes and applied it to patent citation networks to extract technology topics. B. Verspagen [61] and A. Martinelli [54] used this algorithm to analyze patent citation networks in the fuel cell and telecommunications switching industries, obtaining clear technology topic evolution trajectories.

With the development of social network analysis methods, an increasing number of scholars are using these methods to analyze technology evolution stages in patent citation relationship networks [64-65]. M. S. Mariani et al. [66] proposed using basic citation counts, PageRank scores of citation networks, and adjusted PageRank scores incorporating network topology and temporal information to identify important patents early and track recent trends in technology improvement.

2.2.4 Patent Text-Based Methods Text mining primarily involves organizing, analyzing, and mining text information to discover potential data patterns, internal relationships, and extract valuable information and knowledge from large amounts of unstructured text, making it an important tool for technology topic evolution analysis. Early representative methods include word frequency analysis, which extracts technical keywords from patent texts and reflects research status in technology fields based on keyword frequency. Subsequently, more studies have applied methods such as topic feature identification, term mapping, co-word analysis, association analysis, network analysis, and semantic analysis to technology topic evolution research. B. Yoon et al. [11] converted patent documents into keyword vectors based on technical keyword frequency and established patent networks by calculating distances between patent documents to analyze technology trends.

In recent years, emerging methods include SAO (Subject-Action-Object) structure extraction [71-73] and improved topic models [74], which mine patent texts from a semantic analysis perspective to study technology topic evolution. SAO structure extraction represents technical information such as problems, solutions, functions, and effects, often using SAO structures instead of keywords. Compared with traditional keyword extraction methods, SAO structures contain richer and more hierarchical semantic information. The Latent Dirichlet Allocation (LDA) model is a popular method in topic analysis. The key challenge in applying it to technology topic evolution analysis is how to use topic models to represent the dynamic evolution process of topics. An increasing number of scholars are using improved topic models to address this issue, including extensions of basic topic models and combinations of topic models with other machine learning algorithms. For example, topic modeling can be performed separately on text data for each time window to calculate topic similarity between adjacent periods, or Dynamic Topic Models (DTM) can be used directly to characterize topic evolution through state space. Chen Wei et al. [75] proposed an LDA-HMM hybrid method that uses LDA to model patent documents and generate technology topics, and Hidden Markov Models (HMM) to determine the evolution history and future trends of technology topics.

2.2.5 Patent Network Analysis Methods Patent network analysis methods extend social network analysis methods to the patent domain. Social network analysis, originating from sociology research, is a popular method for systematically analyzing social structures. It attempts to establish mapping relationships among participants such as individuals, groups, organizations, or other entities, using quantitative techniques to generate relevant metrics to measure network characteristics and visualize network nodes [76]. Based on social network analysis theory, patent network analysis methods are used to study the structural characteristics of interaction relationships in patent datasets, using a set of keywords as input to generate a network that characterizes patents and their relationships [77-78].

Patent network analysis methods are more useful than traditional methods as they reveal the overall relationships between patents and the relative positions of individual patents or patent portfolios. Combined with various network metrics, they help discover evolution trends in technology fields and research topics. For more precise or fine-grained analysis of topic evolution trends, it is often necessary to incorporate the semantic context of technology topics into patent networks. C. C. Wu [79] proposed a weighted keyword-based patent network method (WKPN) that uses the Delphi method to extract appropriate patent keywords and the Analytic Hierarchy Process to assign weights to keywords. Based on this, a patent similarity matrix is constructed to build patent networks for analyzing biofuel technology development trends and identifying the evolution of emerging fields in energy technology.

2.2.6 Methods Combining Multiple Patent Elements In addition to methods considering patent classification, patent citations, or patent text separately, recent scholars have proposed combining multiple patent elements to consider technology topic evolution from multiple dimensions. Patent elements used for technology topic evolution analysis include patent citations, classification numbers, patent texts, inventors, and patentees. Common approaches involve selecting two or more patent elements and establishing models to comprehensively consider different patent elements, or integrating the processing results of one patent element into the analysis of another to achieve technology topic evolution analysis. For example, J. Tang et al. [80] proposed the Dynamic Inventor-Company-Topic (DICT) model, which combines three elements—patent inventors, patentees, and patent text—with temporal factors to obtain technology topics and their temporal changes. This research also developed the Patent-Miner tool specifically for technology topic evolution analysis. L. Feng et al. [81] used patent text and patent IPC classification numbers to propose a similarity measurement model combining two types of patent elements, performing patent clustering for technology topic analysis. Chen Liang [82] applied patent text mining results to patent citation network analysis, combining dynamic programming ideas to propose a main-multiple path method. Empirical results in the hard disk drive head field demonstrated that this method can effectively extract the evolution trajectories of main technology topics.

Compared with other quantitative methods, methods combining multiple patent elements provide more systematic and comprehensive exploration of technology forecasting and topic evolution. B. Yoon [83] integrated patent text information and citation information, using Generative Topographic Mapping (GTM) and link prediction to develop patent maps and identify promising technology opportunities, achieving systematic identification of technology opportunities and detailed technology characteristics display for important references in technology planning.

2.3 Hybrid Qualitative and Quantitative Methods

Qualitative research methods for technology topic evolution analysis are overly dependent on domain experts' knowledge and experience, making them subjective and unstable. Quantitative research methods often ignore domain experts' knowledge, and their results typically require domain knowledge for interpretation. Due to the respective limitations of quantitative and qualitative methods, some scholars have proposed hybrid methods that combine qualitative and quantitative approaches to fully leverage the characteristics of both types of methods. L. Huang et al. [14] proposed a method combining patent analysis (quantitative) with technology roadmapping (qualitative) for technology analysis, mapping science and technology planning to future development trends. Y. Jeong et al. [15] proposed a new technology roadmapping method (qualitative) based on patent keyword analysis (quantitative) and technology ontologies (qualitative). Hu Zhengyin [38] proposed a personalized semantic TRIZ architecture based on multidimensional indexing and analyzed the evolution of graphene technology by combining the proposed personalized semantic TRIZ with technology roadmapping. In hybrid methods, the key is how to organically combine qualitative and quantitative methods.

3 Summary and Outlook

Technology topic evolution analysis is significant for tracing the trajectory of technological development and the history of internal technology activities, reflecting the current state of technological activities, identifying priority areas in science and technology, and optimizing the allocation of scientific and technological resources. Based on a review of current technology topic evolution analysis methods, this paper identifies the following limitations: (1) Qualitative analysis methods are overly dependent on domain experts' knowledge and experience, making them subjective, unstable, and costly; (2) Technology life cycle methods and patent classification/citation-based methods tend to be macro-level, lack intuitiveness, cannot delve into patent documents to obtain technical details, and often fail to meet diverse analytical needs; (3) Patent text-based methods, while intuitive and detailed, still have room for improvement, such as further reducing manual interpretation of analysis results and providing more reasonable and diverse analytical means by combining patent citations and classification information; (4) Patent network analysis methods, though capable of discovering relationships between patents or technology topics, are mostly based on static networks that do not capture dynamic network changes, requiring further strengthening in discovering topic evolution processes; (5) Methods combining multiple patent elements integrate structured and unstructured patent information, enabling multi-angle and full exploitation of patent information, representing a future development trend.

Overall, traditional qualitative research consumes substantial human and material resources and is difficult to transfer. Technology life cycle methods and patent classification/citation-based methods remain at the macro level and cannot finely analyze technology topic evolution processes. If technology topic evolution analysis is to be applied to enterprise or national technology management decision-making, it must first achieve efficiency, low cost, precision, and portability. Therefore, using machine learning or data mining methods based on patent text or combining patent text with other elements to reduce manual intervention and achieve automation and precision in technology topic evolution analysis will be the future development trend. However, current research of this type remains at the academic exploration stage and has not yet formed standardized methods for application and promotion. Moreover, current technology topic evolution analysis still focuses more on current and historical trends, with less than ideal effectiveness in discovering new technology topics and predicting new development trends.

Based on this, the author believes that future research on technology topic evolution should, on the one hand, strengthen theoretical research to better understand and grasp the patterns and mechanisms of technology topic evolution, thereby further promoting the development of analysis methods. For example, technology topic evolution results from the combined effects of internal dynamics within technology fields, environmental development push, and demand pull, requiring systematic consideration and study. On the other hand, the rapid development of data mining, machine learning, and social computing has enriched the analytical methods for technology topic evolution, providing new ideas for its analysis. How to apply these methods to technology topic evolution analysis or how to combine them for such analysis deserves further in-depth research.

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Note: Figure translations are in progress. See original paper for figures.