Review of Emerging Technology Identification Methods: Postprint

Authors: Wang Le, Wu Xinnian

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Abstract

[Purpose/Significance] This study systematically reviews emerging technology identification methods from both domestic and international contexts, summarizes the current research status, analyzes existing problems, and provides references for future research on emerging technology identification methods. [Method/Process] Based on literature review and bibliometric analysis, this paper inductively summarizes current mainstream emerging technology identification methods, analyzes the characteristics, advantages, and disadvantages of various methods in the emerging technology identification process through typical cases, and proposes recommendations for future research on emerging technology identification methods. [Results/Conclusions] Current emerging technology identification methods include both quantitative and qualitative approaches. Common methods include those based on measurement models, bibliometrics, and text mining, with an increasing tendency toward multi-method fusion applications. However, existing research still has some deficiencies. Future research on emerging technology identification methods should strengthen the exploration of the essential characteristics of emerging technologies, enhance the explanatory significance of specific identification methods for emerging technologies, and jointly improve the timeliness of emerging technology identification from both data sources and identification methods. Simultaneously, exploration of effective fusion and application methods for multi-source data in emerging technology identification should also be strengthened.

Full Text

Research on Identification Methods of Emerging Technologies: A Review

Wang Le[1],[2],[3], **Wu Xinnian**[1],[2],[3]

[1]Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000
[2]Lanzhou Library, Chinese Academy of Sciences, Lanzhou 730000
[3]Department of Library, Information and Archives Management, School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049

Abstract:
[**Purpose/Significance**] This paper systematically reviews identification methods for emerging technologies both domestically and internationally, summarizes current research status, analyzes existing problems, and provides references for future research on emerging technology identification methods. [**Method/Process**] Based on literature research and bibliometric analysis, we summarize mainstream emerging technology identification methods, analyze the characteristics of each method and their advantages and disadvantages in the identification process through typical cases, and propose suggestions for future research. [**Result/Conclusion**] Current emerging technology identification methods include both quantitative and qualitative approaches, with common methods including measurement model-based, bibliometric, and text mining methods, which increasingly tend toward multi-method fusion applications. However, existing research still has some deficiencies. Future research should strengthen exploration of the essential characteristics of emerging technologies, enhance the interpretive significance of specific identification methods for emerging technologies, and improve the timeliness of identification from both data sources and methods. Additionally, research should strengthen the exploration of effective fusion and application methods for multi-source data in emerging technology identification.

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With the accelerating pace and increasing complexity of technological evolution, along with enhanced cross-disciplinary interdependence among technologies, the difficulty of rapidly identifying emerging technologies with significant development potential from numerous new technologies continues to grow. Consequently, the identification and forecasting of emerging technologies have become increasingly prominent research topics in recent years.

No consensus has been reached in academia regarding the definition and characteristics of emerging technologies. The most widely accepted definition comes from the Wharton School of the University of Pennsylvania's 2000 publication *Wharton on Managing Emerging Technologies*, which defines emerging technologies as innovative technologies based on science that may create a new industry or transform an old one [1]. Regarding characteristics, the most recognized framework was proposed by D. Rotolo et al. [2], emphasizing novelty, relatively rapid growth, coherence, prominent impact, and uncertainty. For identification

purposes, scholars typically focus on the "new" and "emerging" aspects—namely novelty and relatively rapid development. At the national level, strengthening emerging technology identification helps optimize overall scientific research layout and long-term planning. At the enterprise level, it aids in determining R&D priorities, investment directions, and reducing investment risks. Moreover, emerging technology identification forms the foundation for studying frontier, breakthrough, and disruptive technologies, as some emerging technologies may evolve into these categories. Enhancing research on identification and forecasting methods to continuously improve accuracy and efficiency holds significant strategic and practical importance. Based on this understanding, we conducted systematic research on currently used emerging technology identification methods to classify and analyze these approaches, providing references for subsequent research.

To understand the overall landscape and conduct classification analysis based on core papers, we selected Web of Science and CNKI as data sources. The Web of Science search strategy was: TS=((identif* or forecast* or discover* or detect* or predict* or assess* or evaluat* or anticipat* or demystif* or measur*) AND ("emerg* technolog*" *or "technolog* emerg*" *or "emerg* topic*" *or "technolog* potential")), with indexes=(SCI-EXPANDED, SSCI, CPCI-S) and all years, yielding 9,608 relevant documents. The CNKI search strategy was: SU=('emerging technology'+'emerging topic'+'technology potential') AND SU=('identification'+'forecasting'+'measurement'+'discovery'+'evaluation'+'assessment'+'detection'), with source category=all journals and publication time=unlimited, yielding 203 papers (retrieved July 16, 2019). Through bibliometric analysis of basic indicators, we understood the current state of research in this field. Based on analysis of impact indicators and manual review, supplemented by citation tracking of important literature, we selected 55 core papers (38 English and 17 Chinese) that characterize the research trajectory and have high impact, as well as reflect the latest research progress. Our classification analysis of emerging technology identification methods primarily focuses on these core documents.

1 Overall Trends in Emerging Technology Identification Methods Research

Research on emerging technology identification and forecasting methods began in the 1980s, with annual paper output, participating institutions, and researchers gradually increasing after 1995 and entering a rapid growth phase after 2010. In terms of disciplinary distribution, domestic papers are concentrated in business administration, quantitative economics, library and information science, and science and technology management, while foreign literature spans computer science, management science, business, and some natural sciences. Major journals include *Technological Forecasting and Social Change*, *Scientometrics*, *Journal of Intelligence*, *Information Studies: Theory & Application*, and *Journal of the China Society for Scientific and Technical Information*. Notable scholars include A.L. Porter, P. Shapira, J. Youtie, Huang Lucheng,

Wu Feifei, and Zhou Yuan. [Figure 1: see original paper] shows the research development trends.

Core keywords in this field include bibliometrics, patent analysis, machine learning, data mining, text mining, big data, citation networks, social network analysis, content analysis, topic detection, models, technology roadmaps, clustering, and classification. [Figure 2: see original paper] illustrates the keyword clustering results. The annual distribution of keywords is shown in . Bibliometric methods have the highest application proportion, while machine learning has developed most rapidly in recent years, with deep learning increasingly applied in the past five years. Emerging technology identification is the most critical component of the broader field, as only through early identification can subsequent forecasting of development goals, potential pathways, and resource requirements be conducted.

2 Analysis of Common Emerging Technology Identification Methods

Broadly speaking, emerging technology identification is a subcategory of technology forecasting. Technology forecasting involves predicting the emergence, characteristics, and impacts of specific technologies at future time points [3], while "identification" involves classification or qualification based on existing facts. Emerging technology identification determines which technologies are emerging based on signals in existing data. Technology foresight is a systematic process for depicting the long-term future of technology development and its interaction with society and the environment [3].

From literature review, Delphi method, scenario analysis, technology roadmapping, bibliometrics, and measurement models are commonly used in technology forecasting. Delphi, scenario analysis, and roadmapping appear more frequently in technology foresight activities (e.g., Japan's large-scale foresight exercises every five years since the 1970s). When applied to emerging technology identification, these methods often need to be combined with quantitative approaches like bibliometrics and text mining.

2.1 Measurement Model-Based Emerging Technology Identification Methods

Many scholars consider identification criteria for emerging technologies and construct corresponding measurement models. These methods have significantly impacted the methodology system, showing that identification approaches are increasingly considering the core characteristics of emerging technologies and standardizing processes for more convenient application. Essentially, model-based methods represent substantial scientific improvements, and refining indicator assignment and calculation methods can enhance identification accuracy.

For example, Huang Lucheng et al. [4] proposed an attribute comprehensive

evaluation and decision system based on emerging technology characteristics, constructing an indicator system including technical indicators (advancement, uniqueness, complexity, R&D input/output, standardization reliability) and market indicators (market size-prospect, growth rate, market structure change potential, value creation). Applied to ten new material technologies, this method identified one emerging, four new, and five general technologies, overcoming subjective expert scoring limitations and ensuring scientific objectivity, though some indicator computability and assignment methods need improvement.

Ren Zhijun et al. [5] constructed feature vectors combining content indicators (frequency, duration, attribution) and trend indicators (growth rate, relative growth rate, author share), using LDA topic models to identify technical themes and calculating similarity with Gartner's emerging technology themes to identify 25 emerging technologies from 1,000 themes. Similarly, M.N. Kyebambe et al. [6] argued that emerging technology traces can be found in patent databases years before full emergence, studying characteristics of patents that later generated emerging technologies (claims, citations, non-patent literature citations, technology lifecycle, cited technology similarity, assignee similarity) to create patent feature vectors and build classification models. However, using only seven features limited cluster granularity and sensitivity.

K. Song et al. [7] identified outlier patents through patent coupling networks based on content similarity, selecting recent patents with minimal similarity to existing ones as candidates, then using technical and market feature indicators to identify truly promising emerging technologies. However, market feature indicators based on customer evaluation data only work in domains with sufficient review accumulation. Q. Wang et al. [8] proposed identification criteria closely aligned with the definition of emerging technologies—novelty, relatively rapid growth, scientific impact, and coherence—quantifying these through bibliometric indicators.

Overall, measurement model-based methods have developed rapidly in recent years and are widely applied. Main challenges include difficulty in scientifically defining indicator selection and representation, weight determination, and model construction. Some indicator assignment methods remain problematic. Moreover, without a unified definition of emerging technologies, model construction based on core characteristics remains controversial.

2.2 Bibliometrics-Based Emerging Technology Identification Methods

With the rapid development of bibliometric software, bibliometric methods are increasingly applied in emerging technology identification. Basic research is the source of innovation, and scientific literature contains rich technological innovation information that can reveal innovation trajectories. This approach has gained growing attention.

2.2.1 Scientific Paper Data-Based Methods Scientific papers can capture early-stage technology development signals, but because they represent basic research, they primarily identify emerging topics and research fields rather than full-fledged emerging technologies. They serve as analysis of basic research stage development and can support assessment of continuous innovation potential.

Traditional bibliometric indicators are commonly applied. For instance, C. Mund et al. [9] selected five domains and used indicators like journal size, age, reference age, author count, and collaboration to identify emerging topics, finding significant domain-specific differences. "Research team size" worked better in medicine, while "journal size and age" were more effective in engineering.

Some scholars have developed innovative indicators. E. Schiebel et al. [10] built a diffusion model for domain term evolution using literature filtering indicators (high/low diffusion, relative frequency) and diachronic cluster analysis to identify emerging topics in optoelectronic devices.

Citation networks (direct citation, co-citation, bibliographic coupling) are frequently used for clustering analysis. K. Fujita et al. [11] compared three weighted citation networks, finding weighted networks more effective than unweighted ones for detecting emerging research fronts, with citation frequency as weight being more effective than publication year difference or keyword similarity. H. Small [12] used direct citation and co-citation networks with differential functions to select emerging topics, assessing them through recent major achievements.

To reduce publication delays, some scholars use conference papers, particularly important in computer science. T. Furukawa et al. [14] and Wang Yanpeng [15] used conference proceedings. Wang Yanpeng et al. [15] categorized key technologies into hot, generic, and emerging, using Sci2tool's BurstDetection algorithm on AI conference papers to identify 15 emerging technologies. J. Kleinberg's [16] BurstDetection algorithm is widely embedded in tools like CiteSpace and Sci2, though relying solely on burst detection may lack accuracy.

Overall, paper-based bibliometric methods are widely applied but typically identify "emerging technology topics" rather than full technologies, as they don't consider technology-market fit or application prospects. Traditional bibliometrics involves limited indicators and requires combination with other methods and personalized innovations, such as Schiebel et al.'s [10] diffusion indicators.

2.2.2 Patent Data-Based Methods A. Pilkington [19] pioneered using patents for emerging technology identification in 2004. Patent data better reflects technological innovation than papers, making it the most widely used data source, though its time lag is more severe due to examination periods.

Patent citation counts are commonly used as value indicators, but their ability to reflect future value is questioned [20]. A RAND report noted the non-linear relationship between citations and value. Liu Tong et al. [21] used USPTO clas-

sification data to analyze relationships between patent application numbers and classification counts over time, identifying quantum dot technology as emerging via S-curve analysis.

Patent direct and co-citation networks are often combined with social network analysis. P.C. Lee et al. [22] used social network analysis in patent citation networks to calculate centrality metrics, identifying five emerging technologies bridging different patent subclasses in Taiwan's innovation system. Li Ruixi [24] used patent co-classification data to build asymmetric technology knowledge flow networks, identifying core, intermediary, and emerging technologies through centrality and structural hole analysis. Huang Lu et al. [25] used weighted co-word networks with link prediction to identify emerging technologies based on novelty and influence, validating the method in perovskite materials.

Visualization extends beyond citation networks to patent maps. S. Lee et al. [26] created keyword-based patent maps, identifying "gaps" (low-density but large-scale blank areas) and testing them through application growth rates to distinguish emerging from declining technologies. However, two-dimensional mapping remains limited.

Scholars continuously refine patent indicators. G. De Rassenfosse et al. [27] proposed counting all priority patent applications by a country's inventors regardless of filing office to improve coverage. P. Erdi et al. [28] defined citation vectors to measure patent similarity, clustering in co-citation networks to identify emerging clusters, though network simplification and weighting need validation. Li Bei et al. [29] used patent coupling clustering with grant time, growth rate, and claims count to identify two emerging nanotechnologies, but risked overlooking nascent technologies with few connections. G. Kim et al. [30] proposed similar indicator-based methods.

To address time lag, G. De Rassenfosse et al. [27] counted priority applications rather than granted patents. A. Breitzman et al. [13] proposed the Emerging Clusters model for near-real-time identification by finding next-generation patents citing hot patents, scoring clusters on public sector ratio, science index, originality index, and reference index.

H.M. Jarvenpaa et al. [31] criticized single-database approaches. C. Lee et al. [20] used 18 immediately available technical feature indicators as inputs and three latent impact indicators (citations in 3, 5, and 10 years) as outputs, capturing non-linear relationships through neural networks to predict patent value and identify emerging technologies. However, using only citations as output seems limited, and the neural network's non-linear relationship lacks interpretability.

Overall, patents better reflect technological innovation but suffer from severe time lags. How to minimize this impact remains a key concern.

2.2.3 Fusion of Paper and Patent Data Increasingly, studies combine paper and patent data to reduce single-source bias, though this increases workload.

Wang Lingyan et al. [32] established an evaluation system with three bibliometric indicators (term frequency changes, strategic coordinate metrics, co-word network metrics) and four patent indicators (application growth rate, technology growth rate, patent family size changes, citation rate), using text clustering and network analysis to identify emerging industrial biotechnologies, validated through expert consultation and policy comparison. T. Ogawa et al. [33] identified sub-research fields through paper citation clustering, then measured patent relevance and temporal changes to identify emerging technologies in polymer electrolyte fuel cells.

Multi-source data fusion is challenging due to data heterogeneity and lack of standards for source proportions [34, 35]. Xu Lulu et al. [36] proposed correlation analysis as a prerequisite for fusion, assuming textual features, development trends, topics, and scenarios should be correlated. Using paper, funding, and patent data with PLDA topic models, they identified four emerging graphene technology themes, though fusion depth was limited.

2.3 Text Mining-Based Emerging Technology Identification Methods

Text mining methods, primarily analyzing semantic information in papers and patents, mainly include topic model-based and structural semantic analysis-based approaches. These represent significant improvements in processing large-scale literature efficiently.

2.3.1 Topic Model-Based Methods Topic models cluster documents' latent semantic structures unsupervised [37]. LDA is most common, representing each document as a probability distribution of topics, and each topic as a distribution of words, enabling technology theme identification and classification.

Ren Zhijun et al. [5] used LDA to extract technology themes, calculating similarity with Gartner's themes to reduce expert workload. Dong Fang et al. [38] combined LDA with SVM classification and ARIMA forecasting to predict development trends. D. Choi et al. [39] identified four technology themes (dominant, emerging, saturated, declining) in logistics by calculating patent share and change rates.

However, LDA is unsupervised with low controllability [38]. Zhou Yuan et al. [40] proposed a supervised machine learning approach incorporating expert knowledge to improve accuracy. Later, Zhou Yuan et al. [41] enhanced this with semi-supervised clustering, elevating from word-level to sentence-level theme descriptions to strengthen semantic interpretation.

Liu Yufei et al. [42] introduced deep transfer learning for technology term identification, using Bi-LSTM models with expert-labeled patent abstracts to automatically identify and classify technical terms, effectively filtering high-frequency non-technical terms.

Overall, topic model-based methods primarily preprocess themes and terms

rather than directly "identifying" emerging technologies, significantly reducing manual costs. However, complete algorithmic reliance lacks persuasiveness due to emerging technologies' novelty and ambiguity, requiring combination with expert judgment.

2.3.2 Structural Semantic Analysis-Based Methods Defining and extracting keywords in emerging technology domains is challenging due to inconsistency and lack of standardization [20, 43]. Structural semantic analysis automatically extracts attributes, functions, and relationships, mitigating these issues.

The SAO (Subject-Action-Object) structure is commonly used. Li Xin et al. [44] extracted SAO structures from patent claims, clustered patents using improved semantic similarity algorithms, and identified emerging technologies through time-sliced patent maps, validated in perovskite solar cells. C. Yang et al. [45] improved SAO networks to calculate relationship strength, combining with social network analysis based on structural holes and centrality changes to identify and forecast graphene technology trends.

Some combine SAO with TRIZ theory. Zhai Dongsheng et al. [46] used SAO-C structure to extract functional and effect signals, locking onto weak signals through "function + effect" combinations, then identifying emerging weak signals through applicants, timing, and effects, demonstrated in contact lens disinfection.

Current research lacks interpretation of relationships between technological development drivers and trends [47]. Development drivers involve market needs, problem-solving, and function realization, obtainable through expert opinion or structural semantic analysis from patents and reviews, reducing subjectivity and resource consumption. Structural semantic analysis shows significant research potential.

Conclusion

Since *Wharton on Managing Emerging Technologies* [1], emerging technology identification has remained a research hotspot. Current research shows several characteristics:

1. Emerging technology identification receives increasing attention from institutions at all levels for strategic planning, R&D prioritization, and investment direction, playing an important supporting role in technology decision-making.
2. Different research entities have different purposes, leading to different methods and application scenarios.
3. Research 热度 continues to rise, with bibliometrics and patent analysis being most widely applied, while machine learning and text mining are developing rapidly, and deep learning is emerging.

However, deficiencies remain:

1. **Insufficient research on essential characteristics** leads to inadequate methodological targeting.
2. **Weak interpretability** of identification methods, with many indicators lacking clear connections to emerging technology identification.
3. **Data timeliness constraints** remain unresolved, with most research being retrospective due to time lags in papers and patents.
4. **Lack of exploration into multi-source data fusion** methods, which is difficult and lacks theoretical guidance.

Future research should:

1. Strengthen exploration of essential characteristics to build more comprehensive identification standard systems.
2. Enhance interpretability to better bridge methods and results.
3. Overcome timeliness constraints by exploring additional data sources and optimizing indicators to reduce time lag effects.
4. Deepen theoretical and methodological exploration of multi-source data fusion to open new avenues for technology identification and forecasting.

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Author Contributions:
Wang Le: Proposed the framework, responsible for literature collection, analysis, and paper writing.
Wu Xinnian: Proposed the topic, responsible for paper revision and improvement.

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