Research Advances in Emerging Technology Identification from a Network Perspective (Postprint)

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Abstract

[Purpose/Significance] Emerging technology identification assists nations, enterprises, and other organizations in grasping technology frontiers, discovering technological opportunities, seizing market first-mover advantages, and creating social value. This study reviews the research progress on emerging technology identification to provide references for related research. [Method/Process] Based on clarifying the concepts and characteristics of emerging technology, this paper elaborates on relational network-based methods for emerging technology identification, and summarizes from the perspectives of network nodes, network relationships, and measurement metrics, while proposing recommendations for future research. [Results/Conclusions] Relational network-based emerging technology identification methods include approaches based on citation relationships, co-occurrence relationships, and similarity relationships. Network nodes for emerging technology identification primarily derive from paper and patent data. The existing indicator system encompasses bibliometric indicators and network structural feature indicators. Future research on emerging technology identification can be enhanced through enriching data sources, fusing network relationships, and refining measurement metrics; concurrently, it should focus on strengthening the exploration of fused networks integrating multi-source data and multi-type relationships in emerging technology identification.

Full Text

Research Progress on Emerging Technology Identification from the Perspective of Relational Networks

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Abstract

[**Purpose/Significance**] Emerging technology identification helps nations and enterprises grasp technological frontiers, discover technological opportunities, seize market opportunities, and create social value. This paper reviews the research progress on emerging technology identification to provide references for future studies. [**Method/Process**] Based on clarifying the concepts and characteristics of emerging technologies, this paper introduces emerging technology identification methods based on relational networks in detail, summarizes network nodes, network relationships, and measurement indicators, and proposes recommendations for future research. [**Result/Conclusion**] Relational network-based emerging technology identification methods include citation-based, co-occurrence-based, and similarity-based approaches. Network nodes primarily derive from paper and patent data, while existing indicator systems include bibliometric indicators and network structure characteristic indicators. Future research can be improved by enriching data sources, integrating network relationships, and refining measurement indicators, with particular emphasis on exploring fusion networks that integrate multi-source data and multiple relationships in emerging technology identification.

Keywords: emerging technology; relational network; technology identification

1 Introduction

The current technological revolution and industrial transformation are in full swing amid complex and changing international circumstances, making the accurate identification of emerging technologies crucial for China's future security and scientific innovation development. In 2011, the U.S. Intelligence Advanced Research Projects Activity funded the "Foresight and Understanding from Scientific Exposition (FUSE)" program [1], aiming to develop automated methods for systematic, continuous, and comprehensive assessment of emerging technologies using information from published scientific, technical, and patent literature. The EU's PromTech project [2] focused on locating emerging technologies through analysis of scientific literature. In March 2020, NATO's Science and Technology Organization released *Science & Technology Trends: 2020-2040* [3], which identified emerging and disruptive technologies for the next two decades by integrating measurement tools from multiple international organizations.

Previous scholars have reviewed emerging technology research from various perspectives. Hou Jianhua et al. [4], Zhou Meng et al. [5], Wang Le et al. [6], and Liu Xiaoling et al. [7] summarized concepts and management practices or categorized identification methods from qualitative and quantitative perspectives, but few conducted systematic and in-depth analysis from a relational network perspective. Xu Jianguo et al. [8] examined emerging technology identification methods from temporal and data association dimensions, highlighting the emergence of more studies based on fused relational networks but without detailed elaboration. Lu Xiaobin et al. [9] reviewed emerging technology identification from bibliometric and evolutionary perspectives, emphasizing network science and technology mapping methods, but only described the meanings of different networks. While relational networks represent one important approach among broader emerging technology identification methods, this paper focuses specifically on relational network-based methods. We first systematically review the concept of emerging technologies by searching relevant domestic and international literature. Second, we summarize and compare existing relational network-based methods, analyzing their advantages, disadvantages, and application scenarios. Finally, we propose future development directions for multi-source data nodes, multiple relationship networks, and multi-dimensional indicator systems to provide references for scholars.

Under the wave of technological change, the formation process and dependency relationships of emerging technologies are complex, making identification difficult. Therefore, accurately identifying emerging technologies represents a key challenge in scientific and technological innovation.

2 Concept and Characteristics of Emerging Technologies

2.1 Literature Retrieval Strategy

In Web of Science, we adopted D. Rotolo et al.'s [10] retrieval strategy: TS=(”emerg* technolog” *or ”technolog* emerg” *or ”emerg* of* technolog” *or ”emerg* scienc* technolog” *or ”emerg* topic” *or ”emerg* of* topic*“), index=(SCI-EXPANDED, SSCI), time span=all years, limited to social science journals, yielding 449 documents. In CNKI, we searched for the theme”emerging technology identification + emerging topic identification” in core journals and CSSCI sources without time limitation, retrieving 64 documents. After manual screening, we obtained 56 documents and supplemented them through reference tracking. Since some scholars did not strictly distinguish between emerging technologies and emerging topics, and their identification methods are similar, we included relevant emerging topic identification studies in our review.

2.2 Conceptual Definitions

Since the concept of emerging technology was proposed, scholars and institutions have defined it from different perspectives: (1) emphasizing technological innovation in terms of “newness” in time and content; (2) focusing on the “emerging” aspect—technologies that are rising, continuously emerging, or transforming and may significantly impact future industries and markets; (3) comprehensively considering both technological attributes and effects based on G. S. Day et al.'s theory.

G. S. Day et al. [11] defined "emerging technology" in *Wharton on Managing Emerging Technologies* as science-based innovations with the potential to create new industries or transform existing ones. Domestic scholar Hua Hongming et al. [12] defined it from a commercialization perspective as technologies not yet commercialized but likely to be commercialized within 3-5 years, or currently applied technologies that will undergo significant changes.

Table 1 summarizes representative definitions, showing that while no unified concept exists, definitions focus on "new" and "emerging," reflecting essential characteristics: novelty, growth, continuity, community, impact, and uncertainty [10]. Novelty, rapid growth, and impact are key features for identification, with scholars increasingly incorporating additional characteristics for comprehensive judgment.

3 Relational Network-Based Emerging Technology Identification Methods

Broadly speaking, emerging technology identification is a research problem within technology forecasting—the systematic process of describing a technology's future emergence, performance, characteristics, or impacts [22]. Emerging technology identification specifically detects which technologies are emerging to support technological innovation decisions [23].

Emerging technologies are influenced by technology, market, economy, talent, and other factors, possibly arising from major breakthroughs (0-to-1 innovations) or recombination of existing technologies. During development, dynamic scientific or technological associations form as entities become connected through co-occurrence, citation, similarity, or other relationships over time. These association networks dynamically expand, representing knowledge flow and diffusion and giving rise to emerging technologies. Therefore, emerging technologies often manifest as complex networks, and introducing network analysis can help identify them by integrating path weights and node characteristics.

Researchers build networks for emerging technology identification and prediction by combining emerging technology features, data external features, and network structural features to establish indicator systems, conducting empirical studies in specific domains to validate effectiveness. This framework has been widely applied internationally and domestically, as shown in Figure 1 [Figure 1: see original paper].

A key challenge is representing the technology relational network with appropriate entities and relationships [9]. Network nodes can be documents, topics, keywords, or classification codes at different granularities, or different entity types like inventors/authors or institutions. Edges represent association methods, with weights reflecting relationship strength. Since node granularity/types are rich and manipulable, this paper classifies technology relational networks by relationship type: citation networks (including direct citation, co-citation, bibliographic coupling), co-occurrence networks, and similarity networks.

3.1 Citation Relationship Network-Based Methods

Citation relationships intuitively show knowledge associations between scientific documents. Analyzing citation networks with temporal analysis can identify and predict emerging technologies [24] (see Table 2). Citation relationships include direct citation, bibliographic coupling, and co-citation.

A common approach assumes citing and cited papers share similar research topics. Clustering citation networks yields research topics, and evaluation indicators identify emerging themes. Co-citation analysis originated with H. Small et al. [25], who used co-citation network clustering to reveal "highly active" areas in science. C. Chen [26] integrated burst detection into CiteSpace to identify emerging topic trends in heterogeneous networks of terms and co-cited paper clusters. H. Small [27] performed multiple clusterings on paper co-citation networks across three time slices to measure field emergence and development.

For direct citation network clustering, Y. Kajikawa et al. [28] topologically clustered the largest connected component in paper citation networks, calculating each cluster's average publication year to track emerging technologies in energy research. The same team [29] improved this method by analyzing each cluster's average age and parent-child relationships, using topological measures (cluster degree and participation coefficient) to detect emerging trends, with empirical studies in gallium nitride, complex networks [30], and regenerative medicine [31]. H. Small et al. [13] combined direct citation clustering and co-citation threading to detect emerging topics at scale. Y. Zhou et al. [32] constructed inter-domain citation networks between biotechnology and information technology, used Newman's topological clustering algorithm to partition the network, and applied LDA for fusion cluster theme analysis.

O. Kuusi and M. Meyer [33] argued patent coupling analysis has stronger timeliness than co-citation for predicting technological breakthroughs. Li Bei and Chen Xiangdong [34] proposed patent citation coupling clustering for emerging technology identification, using USPTO data to calculate coupling strength among nano patents and identify emerging technologies through comprehensive analysis of grant time, growth rate, and claim counts.

Recent applications have integrated complex network analysis, main path analysis, and genetic models. T. S. Cho and H. Y. Shih [35] analyzed patent citation networks (1997-2008) using structural holes to identify emerging technologies. J. C. Ho et al. [36] used main path analysis in paper citation networks to determine fuel cell technology trends and breakthrough solutions, predicting lifecycle stages through growth curve analysis. S. Zhang and F. Han [37] identified novelty through patent direct citation clustering and calculated patent influence using genetic models, selecting clusters meeting both criteria as emerging themes in solar photovoltaics. H. Xu et al. [38] measured uncertainty and ambiguity by analyzing topic position changes in citation networks across time periods, though this approach only used topological structure and ignored factors like policy, ethics, and social impact.

Despite widespread use, citation-based methods have limitations. First, temporal lag exists since citation counts correlate with publication age. Results tend to identify "emerged" hot topics rather than "emerging" technologies, which have fewer, newer documents with lower citations. Second, most analyses consider only citation relationships or frequencies, neglecting textual relationships and failing to fully utilize document features.

3.2 Co-occurrence Relationship Network-Based Methods

Co-occurrence networks treat entities as nodes and co-occurrences as edges, using clustering, social network analysis, and neural networks for identification (see Table 3). From a textual perspective, analyzing co-occurrence networks of technical terms or keywords can reveal emerging technologies.

R. L. Ohniwa et al. [40] identified emerging topics in life sciences by screening keywords based on MeSH term growth rates in PubMed, clustering them through co-word analysis, and measuring clustering coefficient differences across periods. W. H. Lee [41] argued understanding data characteristics is the first step, using centrality measures (degree, betweenness, closeness) on co-word networks to infer new technologies. Y. G. Kim et al. [42] built semantic hierarchical networks from patent keywords, reordering nodes by earliest filing date and frequency to create patent maps for emerging technology prediction. Fang Shu et al. [43] noted this method's simplicity and clarity but criticized its circular reasoning, limited keyword selection, simplistic matrix assignment, and K-means' requirement for predetermined cluster numbers.

Improvements have broken single keyword clustering methods. M. Katsurai and S. Ono [44] proposed TrendNets to find rapidly growing (not just popular) topics by converting temporal co-word networks into matrices decomposed into smooth (static) and sparse (bursty) components, clustering bursty terms with Louvain method. J. Yoon et al. [45] extracted adjective/verb-described attributes and functions using Stanford dependency parser, interpreting IPFN metrics through social network analysis. N. Choudhury et al. [46] used dynamic recurrent neural networks on keyword co-occurrence networks to predict emerging trends rather than just implicit relationships. L. Huang et al. [47] built dynamic co-word networks with term frequency weights.

Domestic scholars have also contributed. Huang Lucheng et al. [48], Wang Lingyan et al. [15], and Zhang Weichong et al. [49] built keyword co-occurrence networks to identify emerging themes. Liu Junwan et al. [50] constructed undirected weighted co-occurrence networks, using AUC and coefficient of variation to test link prediction algorithms, selecting AA index to predict future emerging topic associations. Different co-occurrence strength calculation methods exist, from simple frequency counts to processed measures like cosine index [51] and "document-topic" probability distributions [50].

However, co-occurrence methods have limitations. Most studies ignore relationship strength or use simple frequency, lacking semantic relationship revelation. Clustering analysis often selects high-frequency words to represent clusters, neglecting non-high-frequency or bursty terms that may indicate emerging technologies, resulting in superficial analysis.

3.3 Similarity Relationship Network-Based Methods

Similarity networks use node similarity as edges, with nodes at different granularities (topics, documents, sentences, keywords) (see Table 4). Text similarity is commonly used: converting node texts to vectors and calculating similarity, sometimes based on existing relationships like citations.

Text feature construction methods include TF, TF-IDF, word/sentence vectors. Similarity measures include Euclidean and cosine distance. B. Yoon and Y. Park [53] used k high-frequency keyword counts as patent vectors, calculated Euclidean distances with thresholds for clear network structure, and analyzed high-tech trends using technology center index, cycle index, and keyword cluster metrics. T. Furukawa et al. [54] used TF-IDF vectors to build temporal conference paper networks based on cosine similarity. J. Yoon and K. Kim [55] extracted Subject-Action-Object (SAO) structures from patents, calculated semantic sentence similarity for patent similarity matrices, and detected latest technology clusters through node degree, cluster density, and impact index.

With NLP development, vectorization methods have diversified. Kong Dejing et al. [56] used BERT to vectorize patent texts, built semantic similarity networks to identify outlier patents as candidate emerging technologies, used DNN to learn relationships between outlier patent indicators and technology impact, and predicted future impact of current outliers. K. Song et al. [57] clustered patent coupling networks by similarity, selecting outlier patents as candidates and identifying promising technologies through technical and market feature indicators. Y. Zhou et al. [58] calculated similarity from patent coupling matrices, combined technical impact and social impact assessments to develop a deep learning framework. P. Erdős et al. [59] defined patent similarity as Euclidean distance of citation vectors, using clustering to identify patent clusters and track temporal cluster structure changes.

Similarity-based methods use SAO structures, TF-IDF, LDA, BERT for text representation, and cosine similarity for semantic distance measurement, combined with indicators, machine learning, and deep learning. While more precise semantically, they suffer from low computational efficiency, weak interpretability, and cannot fully prove emerging status through low similarity alone.

4 Review of Network-Based Emerging Technology Identification

The three relational network-based methods share key components: network node determination, relationship construction, and analysis methods/indicators. We summarize existing research from multi-source nodes, multiple relationships, and multi-dimensional indicators, proposing improvements.

4.1 Multi-Source Data Nodes

Current research primarily uses paper and patent data, mostly single-source. While papers and patents cover emerging technology characteristics (timeliness, comprehensiveness, continuity, novelty, innovativeness) [15], emerging technologies' high uncertainty and ambiguity require multi-source heterogeneous data for comprehensive analysis and cross-validation. For example, Zhang Hao [60] fused academic papers, patents, and business data for better forecasting. Zhang Weichong et al. [49] used seven document types (patents, journal papers, dissertations, conference papers, books, fund projects, industry reports) with abstract-based topic parsing for blockchain technology verification (see Table 5).

Although multi-source attempts exist, research lacks network analysis across different data types for emerging technology identification. Data timeliness remains critical, as delays between knowledge generation and publication pose concerns.

4.2 Multiple Network Relationships

Entities have different association methods, with edge weights reflecting relationship strength (see Table 6). Citation-based methods are most common, intuitively showing knowledge flow and technological paths but suffering from temporal lag and coarse granularity without semantic features.

Co-occurrence networks, as horizontal associations, compensate for citation lag and textual neglect, using finer-grained nodes (keywords, terms) to emphasize semantic relationships. However, they are sensitive to node selection and co-occurrence strength calculation, with ambiguous clustering affecting results.

Similarity networks use text vectors as nodes, analyzing semantic information at different granularities to compensate for citation/keyword analysis limitations and describe evolutionary relationships temporally. They better address forecasting by transforming identification into dimension-based modeling problems [9]. However, low similarity alone doesn't prove emerging status, requiring deeper semantic research.

Current research primarily uses single relationships with similar clustering-based analysis approaches. Complex networks may not provide intuitive technological insights, requiring expert interpretation. Building multiple relationship networks, mining them effectively, and improving interpretability are future priorities.

4.3 Multi-Dimensional Indicator Systems

Existing indicator systems include bibliometric and network structure features (see Table 7). Bibliometric indicators focus on development status and trends, measuring innovation, novelty, growth, impact, and continuity through paper/patent counts, citations, growth rates, etc. Multi-indicator fusion approaches include topic evolution deviation (combining publication volume, citations, and lifecycle) [70] and EScore (integrating persistence, novelty, growth, community, and scope) [71]. Special indicators capture unique features like IPC categories and patent family sizes.

Network structure indicators use node, edge, or overall features (degree, centrality, clustering coefficient, density) [15, 41, 45]. For example, PageRank measures topic influence [51], while structural holes identify potential emerging technologies in IPC categories [35].

Current systems are primarily bibliometric, with fewer network structure studies that lack interpretability. Most rely on single-dimensional analysis and expert judgment, with domain-specific, non-uniform indicators lacking validation.

4.4 Future Outlook

Despite achievements, emerging technology identification faces challenges with increasing relationship complexity. Future improvements should:

1. **Enrich data sources**: Integrate papers, patents, fund projects, policies, business reports, and media/public opinion data. Use Node2vec, BERT for homogenization, converting heterogeneous data into document/topic-level nodes.

2. **Integrate multiple relationships**: Build dynamic multi-relationship networks using citation, co-occurrence, and similarity relationships. Fuse separate networks using alignment methods from knowledge networks, incorporating data features into node/edge weights.

3. **Develop comprehensive indicators**: Integrate data, technical, and network structural features through data-layer, relationship-layer, and network-layer fusion to improve accuracy (see Figure 2 [Figure 2: see original paper]).

Notably, fund, paper, and patent data represent different research stages with varying lags and contributions. Different terminologies across data types require careful handling. Method scalability across domains also needs further validation through international and industry comparisons.

This review categorizes relational network-based emerging technology identification into citation, co-occurrence, and similarity-based methods, analyzing characteristics and issues from network nodes, relationships, and indicator perspectives. Future breakthroughs can leverage deep learning and NLP to fuse multi-source heterogeneous texts, building dynamic multi-relationship fusion networks for more effective identification.

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