A Review of Technology Fusion Research Based on Patent Data (Postprint)

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Abstract

[Purpose/Significance] Conducting technology convergence research based on patent data represents the primary approach and a prominent direction in technology convergence studies. Aiming to provide references and inspiration for subsequent research endeavors in technology convergence, this paper presents a relatively comprehensive review of the current state of domestic and international technology convergence research based on patent data. [Method/Process] Existing research is categorized into six types according to research content: studies on technology convergence measurement and prediction methods, measurement and trend prediction of technology convergence patterns in specific fields, between multiple fields, and across all fields, research on measurement indicators for technology convergence, studies on characteristic factors influencing technology convergence, technology opportunity discovery from the perspective of technology convergence, and research on the relationship between technology convergence and innovation. The research achievements of each category are reviewed and evaluated. [Results/Conclusions] Technology convergence research based on patent data has achieved certain accomplishments; however, issues persist, including unreasonable measurement bases, lack of validation for prediction methods, and insufficient attention to all-field research. These problems can be addressed by introducing semantic relationships to optimize technology convergence networks, employing graph neural network techniques to improve technology convergence prediction methods, and perfecting measurement and prediction methods for all-field technology convergence.

Full Text

A Review of Technology Convergence Research Based on Patent Data

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Abstract:
[**Purpose/Significance**] Research on technology convergence based on patent data represents the primary approach and a hot direction in this field. This paper provides a comprehensive review of domestic and international research on technology convergence using patent data, aiming to offer references and insights for future work in this area. [**Method/Process**] Existing studies are categorized into six types according to their research content: (1) measurement and prediction methods for technology convergence; (2) measurement and trend prediction of technology convergence in specific fields, across multiple fields, and across all fields; (3) measurement indicators for technology convergence; (4) characteristic factors influencing technology convergence; (5) technology opportunity discovery from the perspective of technology convergence; and (6) the relationship between technology convergence and innovation. The research achievements in each category are reviewed and discussed. [**Result/Conclusion**] While certain results have been achieved in technology convergence research based on patent data, several problems remain, including unreasonable measurement bases, lack of validation for prediction methods, and insufficient attention to whole-field research. These issues can be addressed by introducing semantic relationships to optimize technology convergence networks, employing graph neural network techniques to improve prediction methods, and refining measurement and prediction approaches for whole-field technology convergence.

Keywords: technology convergence; technology fusion; patent data; technological innovation; convergence measurement indicator
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1 Introduction

In today' s world, increasingly complex socioeconomic and technological problems require integrating technical knowledge from different disciplines to solve. Against the backdrop of continuous cross-disciplinary knowledge spillovers and integration, technology convergence has become increasingly normalized, continuously driving the emergence and breakthrough of new technologies.

The concept of technology convergence is generally believed to have been first proposed by N. Rosenberg in 1963, who identified a social phenomenon of "Technological Convergence" in his study of changes in the U.S. machinery equipment industry [1]. After years of development, this concept has evolved into a series of related concepts, such as technological convergence, technological cross-fertilization, and technological integration [2-5]. However, the academic community does not strictly distinguish among these concepts in actual research, so this paper treats all of them as "technology convergence."

Studying technology convergence is significant for several reasons. At the macro-level decision-making support level, it helps: (1) understand the innovation process from a convergence perspective and guide breakthroughs in existing technologies and multi-technology integration to promote technological innovation; (2) solve complex problems, as new complex socioeconomic and technological issues require fusing multiple technologies despite the diversity and specialization of existing knowledge and technology; (3) provide guidance for national/regional/industrial parks in technology layout and rational matching of supporting technologies; and (4) support technology forecasting, as understanding the technology convergence process provides a basis for early prediction of emerging technologies, generic technologies, and disruptive technologies [6]. At the micro-level innovation guidance level, it helps: (1) enterprises with forward-looking layout by enabling early detection of convergence signs, allowing them to form strategic alliances or acquire new technologies early on, particularly providing references for giant enterprises to introduce new technologies and achieve technological transformation to overcome the "innovator' s dilemma" [7]; (2) enhance enterprise competitiveness by prompting them to adopt knowledge and technologies beyond traditional frameworks; and (3) discover technology opportunities through cooperation for win-win outcomes. Given this context, academic research on technology convergence continues to expand, making a review of existing studies valuable for inspiring further research.

Currently, research approaches to technology convergence can be divided based on data sources into: paper data [8], patent data, standard data [9], and Wikipedia data [10]. In terms of research output volume, patent data-based research is the mainstream direction. This paper therefore tracks the progress of technology convergence research based on patent data. We retrieved Chinese and English papers from CNKI and Web of Science (search strategies shown in Table 1), and after removing irrelevant articles such as those simply analyzing "fusion technology" noise (e.g., "Research on Data Fusion Technology for Fatigue Driving State" and "Analysis of Multi-Sensor Fusion Technology Patents for Smart Cars"), we conducted a comprehensive review.

2 Review of Existing Research

After manually reviewing the retrieved literature, we categorized the remaining 100 papers (excluding one review article) into six types based on research content: (1) research on measurement and prediction methods for technology convergence; (2) measurement and trend prediction of technology convergence in specific fields, across multiple fields, and across all fields; (3) research on measurement indicators for technology convergence; (4) research on characteristic factors influencing technology convergence; (5) technology opportunity discovery (identifying emerging or frontier technologies) from the perspective of technology convergence; and (6) research on the relationship between technology convergence and innovation. The distribution of Chinese and English studies across these categories is shown in Figure 1 [Figure 1: see original paper]. Research on measurement and prediction methods constitutes the main type, with 30 papers. Studies on convergence measurement and trend prediction in specific/multiple/all fields and research on the relationship between convergence and innovation follow, with 19 and 17 papers respectively. The number of Chinese and English studies is similar. Research on technology opportunity discovery from a convergence perspective is relatively scarce, with only 8 papers. The following sections discuss each category in detail.

2.1 Research on Measurement and Prediction Methods for Technology Convergence

Research on measurement and prediction methods represents the primary focus of existing studies. Our analysis reveals that current patent-based technology convergence research mainly addresses: (1) technology representation, (2) construction of technology convergence relationships, (3) measurement of convergence degree and identification of important convergence relationships, (4) dynamic analysis of technology convergence, and (5) prediction of future convergence trends.

2.1.1 Technology Representation Methods Technology, as a method and principle for solving problems, is relatively abstract. To quantify and calculate technology, effective representation is essential. Current research employs four main representation methods: keyword clusters, technology topics, semantic anchor points, and technology classifications (see Table 2).

Keyword clusters represent technology using sets of keywords that characterize technical connotations. Luan Chunjuan [11] argued that citing patents with coupling relationships represent converging technologies, identifying converging technologies by analyzing keyword clusters in citing patents. This approach is easy to implement but noisy, and the technical representation requires manual interpretation.

Technology topics use topics identified through LDA (Latent Dirichlet Allocation) models, with experts naming the technologies. B. Song [12] employed LDA to identify technology topics in the safety field and then analyzed convergence trends through keyword co-occurrence clustering. This method depends on expert naming.

Semantic anchor points define semantic anchors for specific technology fields and calculate semantic similarity between patents and these anchors to judge convergence. K. Eilers [13] proposed this approach to study one-way and two-way technology convergence in UV-LED technology. This method also essentially uses keyword clusters but requires multiple validations for similarity threshold selection.

Technology classification uses categories from manual classification systems (such as IPC, MC, USPC) to represent technologies, which is the most common approach. Examples include Y. J. Geum [14] using USPC, P. R. Kim [15] using IPC, and Wang Xianwen [16] using MC. Since technology fields better explain convergence processes, mapping existing classification systems to technology domain classifications is also common. For instance, J. Y. Choi [17] used WIPO's IPC-to-technology field mapping table to establish relationships between IPC and ISI-OST-INPI technology field classifications (hereafter ISI classification). For more fine-grained, customized revelation of converging technologies, Dong Fang [19] predefined a robotics technology classification system, constructed a training dataset, and used LDA-DNN automatic classification to categorize patents.

Overall, keyword clusters, technology topics, and semantic anchors can represent technologies at a fine granularity but suffer from ambiguous meanings (requiring manual interpretation), difficulties in temporal analysis, noise, and excessive manual intervention. They are suitable for analyzing sub-fields and identifying new technologies from a convergence perspective. Patent classification numbers, as the intellectual product of domain and patent examination experts, offer advantages such as complete data, relatively clear conceptual scope, easy quantification, and support for temporal analysis, but suffer from coarse granularity. They are suitable for macro-field analysis and tracking historical convergence trajectories.

2.1.2 Construction of Technology Convergence Relationships Building technology networks based on inter-technology relationships is fundamental to convergence research. Three main approaches exist: co-occurrence relationships, citation relationships, and semantic relationships.

Co-occurrence-based construction is clear and straightforward, making it extremely common in current research (e.g., Y. J. Geum [14], P. R. Kim [15]). **Citation-based** construction facilitates dynamic analysis, as demonstrated by E. Kim [20] who built convergence networks for printed electronics patents and dynamically analyzed field convergence trends through network centrality indicators. **Semantic relationship-based** construction is not limited by coarse classification granularity or citation delays. F. Passing [21] built convergence relationships in smart grids by calculating semantic similarity between grid infrastructure technology and three other technologies.

Due to citation delays and incomplete patent citation data, citation-based research is relatively limited. Patent classification numbers offer complete metadata and high data quality, making co-occurrence-based research the mainstream approach. However, since classification numbers also suffer from coarse granularity and inability to reflect new technologies [22], and semantic mining can compensate for these deficiencies, semantic relationship-based research is expected to receive more attention.

2.1.3 Measurement of Convergence Degree and Identification of Important Relationships After building technology convergence networks, measuring convergence degree and identifying important relationships in large-scale complex networks becomes a key concern. Table 3 summarizes the relevant methods.

These methods include: Herfindahl index for measuring convergence in specific fields; patent coefficient method and patent cross-impact method for measuring pairwise technology convergence; clustering analysis and association rule mining for identifying important convergence technologies (clusters) or typical relationships; and social network analysis for identifying key nodes, links, or overall network characteristics. Specific indicators are discussed in Section 2.3.

2.1.4 Dynamic Analysis of Technology Convergence Technology convergence is a long-term dynamic process with different characteristics at each stage. Dynamic analysis helps clearly demonstrate convergence paths and trajectories.

Time-window analysis is the most common method, presenting convergence trends through time slices and using citation relationships (coupling, co-citation) to represent technology flow directions. For example, E. Kim [20] analyzed dynamic convergence trends in printed electronics; Zhang Xinqi [40] used citation relationships to represent time series and analyzed the trend of specific IPC classifications shifting from technology absorption to diffusion positions; C. Lee [41] analyzed convergence trajectories in communication technology using patent citation information. Some scholars further divide time windows into stages: Li Shugang [42] divided the time window for perceptual artificial intelligence into introduction, growth, maturity, and decline phases, creating a "convergence trend quadrant" for more intuitive visualization.

2.1.5 Prediction of Future Technology Convergence Trends Predicting future convergence trends effectively realizes the value of convergence research and has attracted increasing attention. Current methods include link prediction, neural networks, and time series forecasting (see Table 4).

Link prediction methods forecast convergence trends based on technology convergence networks. Y. Park [44] built knowledge flow networks from patent citations and used link prediction to forecast potential citation relationships for convergence prediction and opportunity discovery. **Neural network** methods predict trends based on convergence relationship matrices. J. Kim [43] used DSM (Dependency Structure Matrix) to identify key converging technologies and neural networks to predict trends, validated through biotechnology-IT convergence. **Time series forecasting** uses models like ARIMA on convergence relationship time series, as demonstrated by Li Shugang [42] predicting convergence dispersion trends.

Existing studies have explored convergence prediction, but most use only one machine learning model, making effectiveness difficult to judge. Features rely on manual specification, primarily network structural features like CN, LP, SimRan, Jaccard similarity, AA, RA, and betweenness centrality. These indicators depend on node similarity without considering temporal dimensions or node features, requiring improvement in future research.

2.2 Measurement and Trend Prediction in Specific/Multiple/All Fields

Research on domain-specific technology convergence is valuable for revealing development trends and identifying opportunities. Studies have examined specific fields, multiple fields, and all fields.

Specific field studies: Liu Xin [47] analyzed 3D printing industry convergence using IPC-ISI co-classification analysis. Su Hua [37] analyzed nuclear science and technology diversification using co-classification and social network analysis. Miao Hong [48-49] examined elderly wearable technology convergence from overall development and internal change perspectives, using Louvain algorithm to detect key nodes and communities. Li Shugang [42] analyzed perceptual AI technology convergence using ISI co-occurrence relationships. J. Choi [50] analyzed automotive industry convergence using ISI-SPRU-OST mapping.

Multiple field studies: Y. J. Geum [14] used citation and co-classification analysis to prove IT-biotechnology convergence and studied its breadth and intensity. Liang Weijun [23] used Herfindahl index to study agriculture-biotechnology convergence in China, finding low-level integration. Luan Chunjuan [30] measured and visualized nano-bio convergence. Huang Lucheng [33] extracted converging technology pairs from IT-biotechnology networks using association rule mining. Lü Yibo [51] examined IoT-AI convergence through patent applications, technology distance, and convergence degree. Feng Ke [31] compared dynamic evolution paths across electronic information, automotive, and equipment manufacturing industries.

All-field studies: S. Jeong [52] analyzed convergence stages and scope using Korean patent data (1996-2010). W. S. Lee [45] used triadic patents from US-Japan-Europe (1955-2011) with "association rule mining + link prediction + topic modeling" to identify important convergence themes. O. Kwon [46] built a convergence network from all 2014 USPTO patents, identifying special nodes through centrality and broker analysis and predicting trends through link prediction.

Overall, specific and multiple field studies exist both domestically and internationally, but all-field studies are only conducted by foreign scholars. With increasing availability of domestic patent data, all-field convergence research deserves attention from Chinese scholars.

2.3 Research on Measurement Indicators for Technology Convergence

Measurement indicators are essential tools for convergence research. Some studies directly design indicators, such as Luan Chunjuan' s intra-technology convergence index [53] and inter-technology convergence index [54] for micro- and meso-level analysis, and J. Yun' s volatility and continuity indicators [55] for dynamic trends. Most studies propose indicators within specific convergence research contexts. We summarize these from three perspectives: overall network indicators, node importance indicators, and technology cohesion/diversity indicators.

2.3.1 Overall Network Measurement Indicators Technology convergence networks are complex networks, so most complex network indicators apply. Table 5 lists these indicators, which analyze overall network characteristics such as network size, number of relationships, and average degree centrality.

2.3.2 Node Importance Measurement Indicators Identifying key technologies in convergence networks is crucial. Table 6 summarizes node importance indicators, which primarily measure centrality and burstiness to identify important nodes.

2.3.3 Technology Cohesion and Diversity Indicators The core feature of convergence networks is "convergence." Table 7 lists indicators measuring convergence strength (cohesion) and breadth (diversity). Cohesion indicators measure the volume of patents covering multiple technologies (e.g., "convergence intensity," "technology binding force"). Diversity indicators measure the variety of technologies in converging patents (e.g., "convergence breadth," "technology difference index"). Scholars have also introduced indicators from other disciplines, such as the Herfindahl index from market competition analysis [23] for technology concentration, and Shannon-Wiener index and Simpson diversity index from biology [18] for technology diversity.

These indicators require accurate identification of multiple technologies in patents, analyzing convergence relationships through quantitative statistics.

2.4 Research on Characteristic Factors Influencing Technology Convergence

This research aims to analyze what causes technology convergence or correlates with it. Factors can be categorized as macro-environmental and micro-quantitative indicators.

Macro-environmental factors: C. S. Curran [2] summarized drivers as scientific discoveries and technological development (supply side), user demand changes (demand side), and political, legal, and regulatory reasons (intermediate). C. H. Song [66] further summarized these as technology development, regulatory measures, customer preferences, and social change.

Micro-quantitative indicators examine relationships between patent metrics (backward citations, non-patent references, inventor count, IPC subclass count, institutional collaboration, organization type, patent filing countries, technology field size, inventor team size) and convergence. For example, F. Caviggioli [67] proved that patents with lower technical complexity (measured by backward citations, non-patent references, and inventor count) are more likely to converge. K. Kim [68] demonstrated positive effects of inter-firm collaboration on convergence in ICT. J. Y. Choi [69] studied impacts of institution type (public research institutes, universities, enterprises). Song Yuxiao [70] found that fewer filing countries, faster technology absorption/diffusion, larger field size, more cited patentees, and stronger government-enterprise collaboration lead to complementary technology convergence. Feng Ke [71] examined impacts of applicant team size, inventor team size, university-industry collaboration, and government S&T program investment.

Overall, macro-environmental factors are widely accepted, while recent research focuses more on relationships between specific quantitative indicators and convergence to inform decision-making.

2.5 Technology Opportunity Discovery from a Convergence Perspective

Technology convergence can spawn new technologies, making early opportunity discovery valuable. P. R. Kim [15] defined "convergence index," "emergence index," and "impact index" to identify frontier ICT technologies. Z. N. Wang [72] identified emerging 3D printing topics by measuring term persistence, growth, and community involvement, comparing converging vs. non-converging patents. S. Lee [73] forecasted promising healthcare-IoT convergence technologies using "co-word analysis + Girvan-Newman clustering + expert interpretation." Zhou Lei [74] identified emerging technologies in fiber optic communications by treating patents involving different fields as emerging technology carriers. Du Jian et al. [75-77] proposed identifying innovation frontiers at the science-technology intersection by clustering networks built from high-quality patent-paper citations. Shen Jinhua [39] identified high-value weak ties through "community convergence potential" and "technology convergence value" indicators to build prediction networks and discover opportunities.

These results provide new approaches for identifying emerging and frontier technologies and can be applied to more fields.

2.6 Research on the Relationship Between Technology Convergence and Innovation

Technology convergence aims to stimulate innovation and meet new demands, while also being a result of innovation. Measuring this relationship is another important research direction. C. Lee [78] used zero-inflated negative binomial regression to prove the positive impact of convergence on innovation in the U.S. pharmaceutical industry. K. Kim [79] studied the impact of convergence capability on innovation activities in semiconductor, automotive, telecommunications, and medical device industries. Liao Lei [80] analyzed IT enterprise innovation dynamics and convergence drivers, proposing optimal patent breadth to incentivize convergence-based innovation. Mao Jianqi et al. [81,82] found an inverted U-shaped relationship between organizational convergence degree and innovation performance. Liu Na [83] proved that convergence degree significantly positively impacts patent value (high citations).

These studies preliminarily prove convergence' s positive impact on innovation, but the underlying mechanisms require further detailed investigation through case studies in specific convergence scenarios.

3 Summary and Outlook

Our review reveals that patent-based technology convergence research is feasible, with scholars developing methods, indicators, and applications that provide important references. However, three main problems require future improvement:

1. **Measurement basis needs refinement**: Current studies use classification co-occurrence frequency as the convergence measurement basis without considering that different co-occurrences (e.g., within vs. across IPC sections) may reflect different convergence degrees. Future research should consider using semantic relationships between classification numbers to weight co-occurrences and build semantic-weighted convergence networks with improved indicators.

2. **Prediction methods need optimization**: Existing prediction relies on manually constructed features, lacks validation, and ignores temporal dimensions. Since 2018, graph neural networks (GNN) have achieved good results in complex network analysis [84], offering capabilities for automatic feature identification and temporal consideration. Future work should introduce GNN to automatically identify network features and integrate temporal information for improved prediction methods, with comparative validation against existing models.

3. **Whole-field research deserves attention**: Domestic research focuses on specific and multiple fields, with no whole-field studies found. Given the clear trend of multi-point breakthroughs and cross-disciplinary convergence in global S&T development [85], macro-level measurement and prediction methodologies are needed for China' s decision-making and innovation guidance.

In future work, we will address these issues through: (1) introducing semantic relationships to optimize convergence networks, (2) employing GNN to improve prediction methods, and (3) refining whole-field measurement and prediction methods, providing methodological and theoretical support for practical technology convergence work in China.

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