

Identification of Technology Convergence Growth Points from a Dynamic Evolutionary Process Perspective: Postprint

Authors: Li Chang, Zhou Jinjin, Yang Zhongkai

Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] This paper proposes a novel method for identifying technology fusion growth points from the perspective of technological dynamic evolution, aiming to identify technology fusion domains with growth potential. [Method/Process] First, two stages of evolution paths are proposed, and the evolution paths of technology fusion growth points are summarized. Then, based on the characteristics of technology fusion growth points, significant attribute features are summarized to construct an identification indicator system. Finally, changes in attributes along the evolution paths are calculated to achieve identification of technology fusion growth points. [Results/Conclusions] Through experiments and comparison with existing studies, the results demonstrate that the proposed method can effectively identify technology fusion growth points and trace the origins and evolutionary processes of technologies.

Full Text

Research on the Identification of Technology Fusion Growth Points from the Perspective of Dynamic Evolution Process

Li Chang¹, Zhou Jinjin², Yang Zhongkai¹

¹Faculty of Humanities and Social Sciences, Dalian University of Technology, Dalian 116024

²College of Economics and Management, Northeast Agricultural University, Harbin 150006

Abstract:

[Purpose/Significance] This paper proposes a novel method for identifying

technology fusion growth points from the perspective of dynamic technological evolution, aiming to identify technology fusion fields with growth potential. **[Method/Process]** First, the study proposes two stages in the evolution path, summarizes the evolution path of technology fusion growth points, and constructs an identification index system based on their significant attribute characteristics. Finally, by calculating attribute changes along the evolution path, the identification of technology fusion growth points is realized. **[Result/Conclusion]** Through experiments and comparison with existing research, the method effectively identifies technology fusion growth points and can trace the origin and process of technology.

Keywords: technology fusion growth point; dynamic evolution process; attribute characteristics; nanomedicine

Classification Number: G306

DOI: 10.13266/j.issn.0252-3116.2022.07.010

As technological transformation and problem complexity intensify, relying on a single knowledge domain is insufficient to address complex and dynamic technical challenges [?, ?]. Technology fusion forms new technologies through cross-penetration between different domains [?], providing rich technological solutions [?] and becoming a primary source of industry innovation [?, ?], gradually emerging as a crucial force in modern scientific and technological development [?]. Technology fusion growth points represent fields where knowledge with combinatorial potential from multiple technological domains permeates, absorbs, and reorganizes to form technology fusion areas with growth potential. These points reflect future evolutionary directions of fusion technologies and provide references for science and technology policy formulation as well as for researchers to grasp technological innovation opportunities and conduct effective innovation. Therefore, identifying technology fusion growth points among complex, numerous, and intertwined technologies is particularly important.

Early research on technology fusion identification focused on measuring the degree of technology fusion [?]. Over time, increasing attention has been paid to forecasting future technology fusion degrees [?], with identification processes primarily comprising two steps: link relationship calculation and fusion relationship identification. The former uses citation and patent IPC co-occurrence relationships as links between technologies. The latter includes three categories: first, threshold-based identification of link relationships, such as using anchor technologies and patent-anchor similarity thresholds to identify technology fusion [?]; second, machine learning identification, training optimal models for technology fusion recognition [?]; and third, indicator-based methods, including network metrics like betweenness centrality and degree centrality [?], as well as composite indicators like convergence index [?], convergence strength [?], and entropy-gravity concepts [?]. Some scholars have also studied technology fusion evolution paths [?].

Current research is insightful but has limitations: (1) It lacks research on technology fusion growth points, ignoring identification of technology fusion fields with growth potential; (2) The origin and process of technology fusion are difficult to trace, with some studies comparing technological ecological networks between fixed periods [?], failing to clearly show the entire fusion process; (3) The essence of technological evolution is knowledge evolution [?], and technology fusion begins with micro-level knowledge cross-fusion [?], but lacks identification research from the micro-level; (4) It ignores influences and interactions between different domains, focusing on identifying fusion relationships between IPC pairs while neglecting fusion relationships among three or more technologies. Moreover, technology has hierarchical structures [?], and IPC codes, with their fixed meanings, may not classify emerging technologies [?] and cannot flexibly adjust technology hierarchies according to specific needs.

To address these limitations, this study proposes a method for identifying technology fusion growth points from an evolution process perspective. First, from a knowledge flow perspective, it summarizes the evolution path of technology fusion growth points and distinguishes their significant attribute characteristics, laying a theoretical foundation for identification. Second, it uses topic models to identify technology domains, constructs technology evolution networks to identify technology fusion fields and evolution paths, and identifies growth points based on attribute changes along these paths. Finally, it conducts an empirical study using nanomedicine as an example to verify the method's feasibility and effectiveness.

2 Theoretical Foundation

2.1 Evolution Path of Technology Fusion Growth Points

M.C. Roco's "NBIC (Nanotechnology, Biotechnology, Information Technology, Cognitive Science)" framework proposes a "fusion-differentiation" model [?, ?], explaining technology fusion processes from a knowledge perspective and arguing that technology fusion begins with knowledge collisions between different domains. Additionally, Popper's "World Three Theory" [?] and Zhao Hongzhou et al.'s view that knowledge continuously detaches from original technology domains, with compatible knowledge colliding and reorganizing on new thinking to generate new knowledge [?, ?], provide theoretical foundations for constructing evolution paths and identification at the knowledge level.

Therefore, based on the "fusion-differentiation" model framework, this study discusses the evolution path of technology fusion fields from a knowledge flow perspective, dividing it into three parts: fusion starting point, fusion process, and fusion outcome, as shown in [Figure 1: see original paper].

(1) Fusion Starting Point. Technology fusion involves relationships between at least two technology domains in relatively discrete, identifiable states.

(2) Fusion Mid-Process. Relationships between relevant technology domains gradually strengthen. Knowledge continuously inherits and mutates through cross-fusion, with relative distances between technology domains decreasing and new knowledge accumulating, expanding technology fusion fields. However, at this stage, technology fusion fields lack sufficient patents, scientific literature, and other carriers to form a clear technology domain, remaining in an implicit stage that is difficult to observe directly.

(3) Fusion Outcome. When new knowledge accumulates to a certain degree, it either forms a new technology domain or enriches the connotation of existing technologies. As fusion carriers continuously increase, a clearly observable, explicit technology fusion field gradually forms. The first observed technology fusion field can be called a Technology Convergence Generation Point (TCGP). Technology fusion fields remain in a state of deepening development with growth potential and experience new technological development patterns.

2.2 Attribute Induction

Technology fusion is the process of transforming knowledge fusion into innovation potential [?]. Combining knowledge evolution characteristics and technology evolution theory [?], this study induces four aspects—fusion direction, fusion process, fusion stage, and fusion trend—to clarify the significant attribute characteristics of technology fusion growth points relative to other technologies.

(1) Fusion Direction. Due to the non-exclusivity of knowledge, knowledge evolution has “genetic” inheritance and “developmental” mutation characteristics. Inheritance involves knowledge flow from one generation to the next, while mutation generates new knowledge based on original knowledge. In the inheritance and mutation of technology fusion, different technology domains fuse to generate new knowledge, providing new methods for solving new problems. This new knowledge is either methodologically advanced and technologically sophisticated, or theoretically strong and high-level, generally being at the forefront of development. Therefore, technology fusion growth points have the attribute of being frontier.

(2) Fusion Process. Knowledge continuously detaches from original technology domains for cross-fusion into new knowledge [?]. Thus, cross-cutting is a prerequisite for fusion, giving technology fusion growth points the attribute of cross-cutting nature.

(3) Fusion Stage. According to the “law of uneven evolution of subsystems,” some technologies have formed clear technology fusion fields, while others, due to time, practical conditions, and other reasons, have fewer effective record carriers and cannot or are difficult to observe [?]. However, technologies continue to grow and may form clearly observable technology domains at some point in the future. Therefore, the complete fusion stage is a sequential superposition of “implicit stage” and “explicit stage.”

(4) **Fusion Trend.** According to the “S-curve evolution law of technology systems,” technology fusion growth points require time to grow and will continue to develop and deepen in the future without experiencing technological decline, thus possessing the attribute of sustainable development.

Technology fusion growth points have five attributes: cross-cutting nature, high attention, frontier nature, key nature, and sustainable development. These attributes are relative concepts, meaning they are more pronounced compared to other technologies within a certain time period. Moreover, technology fusion growth points should possess all these attributes simultaneously across different time segments.

3 Method Framework

This study identifies technology fusion growth points by measuring unique attribute changes along evolution paths. The proposed identification process is shown in [Figure 2: see original paper]. The process involves: (1) data collection, preprocessing, and time window division; (2) identifying technologies in different time windows, calculating inheritance and differentiation relationships between adjacent windows, and constructing technology evolution networks; (3) building rules to identify TCGP, identifying technology fusion evolution paths and fields based on TCGP locations; and (4) identifying growth points based on attribute change trends of technology fusion fields along evolution paths. Key components are detailed below.

3.1 Technology Evolution Network Construction

The WI-LDA topic model effectively reduces difficulty in identifying assimilation topics and enhances topic readability and interpretability [?]. This study uses the WI-LDA topic model to identify technologies in different time windows and proposes a new enhanced semantic similarity model and technology differentiation identification model to measure inheritance and differentiation relationships between adjacent time windows, constructing technology evolution networks.

3.1.1 Enhanced Semantic Similarity Model Technology similarity calculation primarily uses “bibliographic information” [?] and “lexical” [?] approaches. The former relies on citations and patent IPC co-occurrence, but IPC co-occurrence cannot fully reflect technology fusion [?], citations have lag [?], and cannot describe content-based associations [?]. The latter uses word flow volumes between technologies [?], but words alone lack semantic context [?].

Therefore, this study combines patent IPC and text semantics to propose an enhanced semantic similarity model. It uses WI-structured words for cosine

similarity calculation, considering both technical terms and their semantic context (IPC). Only words in the same context share meaning, enabling precise technology similarity measurement:

$$sim(v_{w_{ix}}, v_{w_{iy}}) = \frac{\sum_{i=1} (w_{ix_i} \times w_{iy_i})}{\sqrt{\sum_{i=1} w_{ix_i}^2} \times \sqrt{\sum_{i=1} w_{iy_i}^2}}$$

where $v_x = (w_{ix_1}, w_{ix_2} \dots w_{ix_i})$ and $v_y = (w_{iy_1}, w_{iy_2} \dots w_{iy_i})$ are technology word vectors, and w_{ix} and w_{iy} are word-IPC context combinations.

3.1.2 Technology Differentiation Identification Model Technology differentiation involves partial knowledge from previous-period technologies diffusing into next-period technologies, while inheritance is knowledge flow of the same technology across time periods. As shown in [Figure 3: see original paper], A_i are inheritance and differentiation technologies of A and B , sharing knowledge elements “1,2,4” and “4,5”. Since element “4” in A_i is inherited from A (already existing at time t in A), the knowledge element diffused from B to A_i is “5”. Therefore, inherited knowledge must be excluded when calculating differentiation, leading to the technology differentiation identification model:

$$D_v = \begin{cases} sim(A_i, B) \text{ without } \alpha, & \text{if } (\alpha = P(A \cap B)) \geq 0 \\ sim(A_i, B), & \text{otherwise} \end{cases}$$

where D_v is the degree of technology differentiation, and the similarity model is the enhanced semantic similarity model from Section 3.1.1.

3.2 Technology Fusion Evolution Path and Domain Identification

This section measures fusion relationship strength between technologies in the same period, identifies TCGD based on generation patterns, and identifies evolution paths and fusion domains. Semantic similarity is key evidence for determining fusion [?], and increasing semantic similarity between different technologies can be considered an indicator of the fusion process [?]. This study uses enhanced semantic similarity to judge technology fusion relationship strength.

3.2.1 TCGP Identification Identifying TCGP requires two conditions: (1) before TCGP formation, similarity between two or more technologies continuously increases over time; (2) it conforms to TCGP generation patterns and continues to be inherited to the present. Only technologies meeting both conditions are identified as TCGP.

3.2.2 Technology Fusion Domain Identification On the same technology fusion evolution path, TCGP serves as a boundary line: before is the implicit

technology fusion domain, after is the explicit technology fusion domain. Explicit domains are represented by technology topics, while implicit domains, lacking sufficient carriers to form clear technology domains, are represented by technical terms. These terms are new knowledge formed through knowledge fusion during the transition from previous to next periods—words that didn't exist previously or have different technical backgrounds. The specific identification method is shown in .

3.3 Technology Fusion Growth Point Identification

This study identifies growth points by measuring changes in cross-cutting nature, high attention, frontier nature, and key nature along evolution paths, and uses sustainable development to identify future-potential fields. For comparison, attribute indices are created by comparing technology attribute values with mean values of all technologies in the time period. Regression models fit and predict comprehensive attribute values based on sustainable development; an upward trend indicates increasingly prominent attributes and higher likelihood of being a growth point.

3.3.1 Cross-cutting Nature Index The probability of text belonging to a technology indicates the likelihood that the text's topic is that technology. Larger probability values for all texts in a specific time window suggest the technology involves more topics, broader research scope, and potentially greater cross-fusion degree:

$$B_k = \frac{\sum_{d=1}^n (k/n)}{k}$$

where B_k is the cross-cutting index (larger values indicate stronger cross-cutting nature), and k and n represent the probability of text d belonging to technology domain k and total text count, respectively.

3.3.2 Key Nature Index Calculated primarily using betweenness centrality and degree centrality. The former measures a technology's intermediary role in the entire technology system (higher values indicate stronger control over information exchange), while latter measures a technology's importance in the network (higher values indicate greater significance):

$$C_{r_k} = \frac{bc_k}{k}$$

where C_{r_k} is the key nature index (larger values indicate stronger key nature), and bc_k and dc_k represent betweenness centrality and degree centrality of technology domain k , respectively.

3.3.3 High Attention Index High attention reflects research intensity. More patents [?], IPC categories, and quantities indicate greater research effort and potential attention:

$$D_k = \frac{\sum_{i=1}^n (k/n)}{k}$$

where D_k is the high attention index (larger values indicate greater attention), and k and cl_i represent patent count and IPC category/quantity growth rate under technology domain k , respectively.

3.3.4 Frontier Nature Index Frontier nature focuses on knowledge level of research outcomes. Higher citations indicate more references and borrowing, suggesting higher knowledge level:

$$C_{e_k} = \frac{\sum_{i=1}^n (c_i/n)}{k}$$

where C_{e_k} is the frontier nature index (larger values indicate stronger frontier nature), c_i represents citation count of text i in technology point k , and n is text count.

3.3.5 Sustainable Development Index Using time series data, regression models fit and predict the four attributes. Technologies meeting attribute requirements and showing overall growth trends are identified as growth points. Before fitting, comprehensive attribute values are formed using weights determined by the coefficient of variation method to reduce manual intervention.

4 Empirical Analysis

4.1 Data Acquisition and Preprocessing

This study validates the method using technology fusion relationships in nanomedicine. Using the Derwent database, the search query was determined based on literature review and expert knowledge: “TS=(nano* and (medicine* or drug*)) “, retrieved on April 8, 2021, spanning before 2021. After removing duplicates and non-standard patents, 33,217 patents were obtained.

For time window division, due to limited data before 2000, that period was designated as a single window; remaining periods were divided into two-year windows based on patent counts combined with fixed window methods. This yielded 10 time windows with patent counts: 584, 1945, 2067, 2159, 2740, 3229, 3773, 4846, 6224, and 5131.

The dataset was preprocessed by merging invention titles and abstracts, performing word segmentation, noun extraction, and stopword removal. IPC subgroups were selected as semantic context through experimental testing.

4.2 Technology Fusion Growth Point Identification Process

4.2.1 Technology Evolution Network Construction First, the elbow method determined optimal topic numbers (k) by calculating the sum of squared errors (SSE) between all data points and cluster centers in the algorithm, generally selecting the point of maximum distortion. The optimal topic numbers for 10 time windows were: 3, 5, 8, 11, 12, 13, 15, 17, 23, and 25. WI-LDA parameters were set as: alpha (document-topic associations) = $50/K$, beta (topic-term associations) = 0.1, with 2000 iterations.

Enhanced semantic similarity and technology differentiation identification models calculated inheritance and differentiation relationships between adjacent technologies. After discussion and testing, a minimum similarity threshold of 0.5 for inheritance determination proved effective. The resulting technology evolution network is shown in [Figure 4: see original paper].

4.2.2 Technology Fusion Evolution Path and Domain Identification

Based on semantic similarity calculations between two or more technologies in the same time window, 3T3 and 6T9 showed continuously increasing similarity over time, conforming to TCGP formation patterns and continuous inheritance, identifying them as TCGP. Technologies on the evolution paths of 3T3 and 6T9 showed explicit technology fusion characteristics, designated as Technology A and Technology B, respectively, as shown in [Figure 5: see original paper].

Technology A and Technology B showed increasing similarity over time, cross-fusing without forming a clear technology domain—characteristic of implicit technology fusion. This fusion field was designated as Technology AB, with its evolution path as the implicit technology fusion evolution path. The identified technology fusion evolution paths are shown in .

4.2.3 Technology Fusion Growth Point Identification

Cross-cutting nature, key nature, high attention, and frontier nature of Technologies A, B, and AB along evolution paths were measured. The coefficient of variation method weighted the four attribute indices into a comprehensive attribute value, with results shown in .

For sustainable development calculation, the first nine periods (T1-T9) were used for regression fitting to validate the method, with 2017-2018 (T9) onward as prediction. As shown in [Figure 6: see original paper], Technologies B and AB achieved R^2 values above 0.95, while Technology A' s minimum was 0.7699, indicating good overall fit. The regression prediction results showed small gaps with actual 2019-2020 values, demonstrating scientifically valid fitting results.

Based on trend analysis, Technology B shows clear growth trends, predicted to maintain sustained growth for a long period. Technology AB's trend is more moderate, likely experiencing slow growth in coming years. According to the sustainable development characteristic of technology fusion growth points, Technology B and Technology AB are identified as technology fusion growth points.

4.3 Results Analysis

Based on evolution paths and representative technical terms at different times, Technology B is stem cell nanotechnology—using nanoparticles to label and promote stem cell production. During 2004-2010, it was in a potential stage mainly involving nanomaterial imaging. In 2011-2012, it first formed a clear technology domain 6T9, focusing on using signals to track stem cells. During 2015-2018, it had close relationships with Technology A but few intersections with others, focusing on inducing stem cell production and improving efficiency. In 2019-2020, research shifted toward cancer prevention, treatment effect evaluation, and safety.

Technology AB is multifunctional nanomaterials—nanoparticles containing diagnostic, delivery, therapeutic, and safety functions. Overall, since 2009-2010, Technology B has maintained close relationships with Technology A (nanocancer therapy technology), with increasingly high content similarity and deepening integration, making nanoparticles more cancer-treatment oriented. This strengthened relationship formed Technology AB. In content evolution: 2004-2010 mainly involved nanomaterial imaging functions; 2011-2012 involved particle development such as gold and silver nanoparticles; 2013-2016 strengthened therapeutic functions with increasing nanoparticle categories like carbon nanoparticles and gold nanoclusters; 2017-2020 emphasized safety functions with preparation-related research emerging.

4.4 Results Validation

Validation examines “identification result correctness” and “proposed method advantages.”

4.4.1 Identification Result Correctness This assesses whether “development status and trends” and “research content” align with reality. Using the WoS Core Collection database, scientific literature on stem cell nanotechnology and multifunctional nanomaterials was retrieved with queries “TS=(“stem cell” and “nano”)” and “TS=(Nano-particle* AND (therapy* OR treatment) AND (carrier OR delivery) AND (secure OR safe) AND (signal OR labeled* OR track*))” for “before 2021,” retrieved on April 31, 2021, yielding 3,500 and 938 records, respectively. Literature quantity trends are shown in [Figure 7: see original paper].

Stem cell nanotechnology literature first appeared in 2001, continuously emerg-

ing after 2004, indicating a gestation period that aligns with the identified TCGP emergence. After 2008, it maintained relatively rapid growth, with future trends matching identified trends. Multifunctional nanomaterial literature first appeared in 2003, roughly matching Technology AB' s 2004-2006 emergence, entering slow growth after 2006 with predicted continued slow growth. The identified technologies' emergence times, overall changes, and trends basically match reality.

Reviewed literature shows stem cell nanotechnology, as an emerging cross-cutting technology, has potential in disease treatment and regenerative medicine. In drug delivery, antibiotic resistance, imaging, diagnostics, and cancer therapy, new multifunctional nanoparticles are emerging [?], with specific content matching reality.

4.4.2 Proposed Method Advantages Comparisons with existing literature [?] on identification objects, methods, and results are shown in .

Analysis indicates the proposed method performs well in both “identification result correctness” and “method advantages,” demonstrating feasibility and validity.

5 Conclusion and Outlook

This study proposes a method for identifying technology fusion growth points from a dynamic evolution perspective. First, it summarizes evolution paths and attribute characteristics of technology fusion growth points. Second, it constructs technology evolution networks using topic models combined with enhanced semantic similarity and technology differentiation identification models. Third, it identifies technology fusion domains and their evolution paths within networks, predicting comprehensive attribute values along paths to identify growth points. Finally, nanomedicine patents validate the method, with comparisons showing accurate identification of growth points and ability to trace origins and processes.

Contributions: First, to our knowledge, this is among the earliest research on technology fusion growth points, focusing on identifying fields with growth potential. Second, theoretically, it summarizes significant attributes and evolution paths from a knowledge flow perspective, dividing paths into implicit and explicit stages, providing theoretical foundations for future research. Third, methodologically: (1) it provides an identification framework for future research; (2) it proposes new semantic similarity and differentiation models for patent data, enriching technology evolution research; (3) the evolution path identification method can trace origins and processes, clearly showing “implicit” and “explicit” stages.

Limitations: Specific attribute calculation indices are derived from existing

literature but may have biases. Optimal index selection through simple, effective methods is important for technology fusion and other indicator-based research. Evolution relationship thresholds relate to “time window length” and “different domains,” requiring analyst subjectivity and reliability. Technology development is also driven by policies and external environments, and technology fusion may experience sudden leaps. Future research can address leapfrog-type fusion technologies.

References

- [1] HACKLIN F, BATTISTINI B, KROGH G. Strategic choices in converging industries[J]. MIT Sloan Management Review, 2013, 55(1): 65-73.
- [2] JEONG S, LEE S. What drives technology convergence? Exploring the influence of technological and resource allocation contexts[J]. Journal of Engineering and Technology Management, 2015, 36(2): 78-96.
- [3] CURRAN C. The anticipation of converging industries[M]. London: Springer, 2013.
- [4] ROCO M C, BAINBRIDGE W S. The new world of discovery, invention, and innovation: convergence of knowledge, technology, and society[J]. Journal of Nanoparticle Research, 2013, 15(9): 1946-1963.
- [5] CURRAN C, LEKER J. Patent indicators for monitoring convergence—examples from NFF and ICT[J]. Technological Forecasting and Social Change, 2011, 78(2): 256-273.
- [6] KARVONEN M, KÄSSI T. Patent citations as a tool for analyzing the early stages of convergence[J]. Technological Forecasting and Social Change, 2013, 80(6): 1094-1107.
- [7] GATES A J, KE Q, VAROL O, et al. Nature’ s reach: narrow work has broad impact[J]. Nature, 2019, 575(7781): 32-34.
- [8] MOON S, KIM S. On patent analysis method for technological convergence[J]. Procedia Social & Behavioral Sciences, 2012, 40(40): 657-663.
- [9] SONG C H, ELVERS D, LEKER J. Anticipation of converging technology areas—a refined approach for the identification of attractive fields of innovation[J]. Technological Forecasting and Social Change, 2017, 116(3): 98-115.
- [10] EILERS K, FRISCHKORN J, EPPINGER E, et al. Patent-based semantic measurement of one-way and two-way technology convergence: the case of ultraviolet light emitting diodes (UV-LEDs)[J]. Technological Forecasting and Social Change, 2019, 140(3): 341-353.
- [11] KIM T S, SOHN S Y. Machine-learning-based deep semantic analysis approach for forecasting new technology convergence[J]. Technological Forecasting

and Social Change, 2020, 157: 120095.

[12] PARK H, YOON J. Assessing coreness and intermediarity of technology sectors using patent co-classification analysis: the case of Korean national R&D[J]. *Scientometrics*, 2014, 98(2): 853-890.

[13] LUAN C J, QIN X, HUANG F. Theory and method for measuring convergence index between technology categories[J]. *Science and Technology Management Research*, 2016, 36(8): 188-193.

[14] LI S Y, FANG S. Research progress on data analysis methods for measuring technology fusion and trends[J]. *Data Analysis and Knowledge Discovery*, 2017, 1(7): 2-12.

[15] YONGRAE C, MINSUNG K, WOLFGANG G. Entropy and gravity concepts as new methodological indexes to investigate technological convergence: patent network-based approach[J]. *PLoS One*, 2014, 9(6): e98009.

[16] FENG K, ZENG D M, ZHOU X. Dynamic evolution path of technology fusion[J]. *Science Research*, 2019, 37(6): 986-995.

[17] LEE C, HONG S, KIM J. Anticipating multi-technology convergence: a machine learning approach using patent information[J]. *Scientometrics*, 2021, 126(3): 1867-1896.

[18] XU H, WINNINK J, YUE Z, et al. Topic-linked innovation paths in science and technology[J]. *Journal of Informetrics*, 2020, 14(2): 101014.

[19] DAHLIN K B, BEHRENS D M. When is an invention really radical?[J]. *Research Policy*, 2005, 34(5): 717-737.

[20] ARTHUR W B. The nature of technology: what it is and how it evolves[M]. Translated by CAO D M, JIANG G H. Hangzhou: Zhejiang People's Publishing House, 2014: 329-344.

[21] CAVIGGIOLI F. Technology fusion: identification and analysis of drivers of convergence for the case of nano- and biotechnologies[J]. *Technological Forecasting and Social Change*, 2016, 55/56: 22-32.

[22] ROCO M C. Coherence and divergence of megatrends in science and engineering[J]. *Journal of Nanoparticle Research*, 2002, 4(4): 9-19.

[23] BAINBRIDGE W S, ROCO M C. Science and technology convergence: with emphasis for nanotechnology-inspired convergence[J]. *Journal of Nanoparticle Research*, 2016, 18(7): 211-230.

[24] HACKLIN F. Management of convergence in innovation[J]. *Contributions to Management Science*, 2007, 2010(42): 1014-1021.

[25] ZHAO H Z, JIANG G H. Knowledge units and exponential laws[J]. *Science of Science and Technology Management*, 1984(9): 39-41.

- [26] LIU Z Y. Reflections on several issues of knowledge mapping[R]. Dalian: Dalian University of Technology WISE Laboratory, 2010.
- [27] HACKLIN F, MARX T C, FAHNRI F. Coevolutionary cycles of convergence: an extrapolation from the ICT industry[J]. *Technological Forecasting & Social Change*, 2009, 76(6): 723-736.
- [28] PORTER M E, STERN S. Measuring the “Ideas” production function: evidence from international patent output[J]. *NBER Working Papers Series*, 2000, 9(3): 47-57.
- [29] ZHOU Y, DONG F, KONG D, et al. Unfolding the convergence process of scientific knowledge for the early identification of emerging technologies[J]. *Technological Forecasting and Social Change*, 2019, 144(7): 205-220.
- [30] LI C L, GAO F, PAI Y X. On interdisciplinary potential knowledge growth points and their identification methods[J]. *Science Research*, 2021, 39(6): 1007-1014.
- [31] WU H, YI H F, MA Y X, et al. Research on WI-LDA model for patent technology topic analysis[J]. *Library and Information Service*, 2018, 62(17): 68-74.
- [32] RODRIGUEZ A, KIM B, TURKOZ M, et al. New multi-stage similarity measure for calculation of pairwise patent similarity in a patent citation network[J]. *Scientometrics*, 2015, 103(2): 565-578.
- [33] MOEHRLE M G, PASSING F. Applying an anchor-based patent mapping approach: basic conception and the case of carbon fiber reinforcements[J]. *World Patent Information*, 2016, 45(1): 1-9.
- [34] PASSING F, MOEHRLE M G. Measuring technological convergence in the field of smart grids: a semantic patent analysis approach using textual corpora of technologies[C]//2015 Portland International Conference on Management of Engineering and Technology. Portland: IEEE, 2015.
- [35] RODRIGUEZ A, KIM B, TURKOZ M, et al. New multi-stage similarity measure for calculation of pairwise patent similarity in a patent citation network[J]. *Scientometrics*, 2015, 103(2): 565-578.
- [36] MILANEZ D H, FARIA L I L, AMARAL R M D, et al. Claim-based patent indicators: a novel approach to analyze patent content and monitor technological advances[J]. *World Patent Information*, 2017, 50(9): 64-72.
- [37] KIM J, LEE S. Forecasting and identifying multi-technology convergence based on patent data: the case of IT and BT industries in 2020[J]. *Scientometrics*, 2017, 111(1): 47-65.
- [38] AN J, KIM K, MORTARA L, et al. Deriving technology intelligence from patents: preposition-based semantic analysis[J]. *Journal of Informetrics*, 2018, 12(1): 217-236.

- [39] AN X, LI J, XU S, et al. An improved patent similarity measurement based on entities and semantic relations[J]. *Journal of Informetrics*, 2021, 15(2): 1-16.
- [40] SMALL H, BOYACK K W, KLAVANS R. Identifying emerging topics in science and technology[J]. *Research Policy*, 2014, 43(8): 1450-1467.
- [41] BREITZMAN A, THOMAS P. The emerging clusters model: a tool for identifying emerging technologies across multiple patent systems[J]. *Research Policy*, 2015, 44(1): 195-205.
- [42] PELAZ B, ALEXIOU C, ALVAREZ-PUEBLA R A, et al. Diverse applications of nanomedicine[J]. *ACS Nano*, 2017, 11(3): 2313-2382.

Author Contributions: Li Chang: research design, data analysis, paper writing; Zhou Jinjin: partial paper writing, revision and proofreading; Yang Zhongkai: research design and improvement.

Citation: Li C, Zhou J J, Yang Z K. Research on the identification of technology fusion growth points from the perspective of dynamic evolution process[J]. *Library and Information Service*, 2022, 66(7): 99-109.

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

Source: ChinaXiv – Machine translation. Verify with original.