Postprint: Directed Technical Interaction Analysis Based on Patent Co-classification

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Abstract

[Purpose/Significance] Unlike existing literature that primarily focuses on technological correlation relationships within specific technical fields, this paper analyzes and predicts directed interactive influence relationships among multiple technologies, providing strategic support for promoting target technology advancement and predicting technological progress. [Method/Process] Based on patent co-classification data from 35 technical fields in China, and building upon the patent interactive influence analysis method by Choi et al., we calculate directed interactive influence values among the 35 technical fields, group technology pairs according to the magnitude of influence values, construct a technology interactive influence network, and analyze the changing trends of interactive influences. [Results/Conclusion] There exists a high proportion of biased and unidirectional influencing technology pairs across the entire technical domain. Food chemistry (FOC) is the technology field that exerts the greatest influence. Measurement (MEA) in the instrumentation field, electrical machinery, apparatus, energy (EAE) and COM (computer technology) in the electrical engineering field, and basic materials chemistry (BMC), materials, metallurgy (MAM) in the chemistry field are core fields in the interactive influence network, positioned at the core of the interactive influence network.

Full Text

Preamble

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Analysis of Directed Technological Cross Impact Based on Patent Co-classification

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Abstract

[**Purpose/Significance**] Unlike existing literature that primarily focuses on technical relationships within specific technology fields, this paper analyzes and predicts directed cross-impact relationships among multiple technologies, providing strategic support for promoting target technology development and forecasting technological progress. [**Method/Process**] Based on patent co-classification data from 35 technology fields in China, this study calculates directed cross-impact values among 35 technology fields by extending the patent cross-impact analysis method proposed by Choi et al. The technology pairs are then grouped according to impact magnitude, and a technological cross-impact network is constructed to analyze evolving interaction patterns. [**Result/Conclusion**] The findings reveal a high proportion of biased and one-way impacting technology pairs across the entire technological domain. Food Chemistry (FOC) emerges as the most influential technology field. Measurement (MEA) in the instrument field, Electrical Machinery, Equipment, Energy (EAE) and Computer Technology (COM) in electrical engineering, as well as Basic Materials Chemistry (BMC) and Materials, Metallurgy (MAM) in the chemistry field constitute core domains within the cross-impact network, occupying central positions in the interaction structure.

Keywords: patent co-classification, technology field, directed cross-impact

Classification Number: G250

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1 Introduction

As the pace of technological innovation accelerates, relationships among technologies have become increasingly complex and dynamic. These inter-technological relationships influence technology diffusion, and the continuous integration and interaction among multiple technologies have elevated the importance of using cross-impact analysis for technology forecasting and analysis. Traditional cross-impact analysis relies on expert qualitative evaluation or intuition [1-3], making it difficult to maintain consistency in results. C. Choi et al. proposed a quantitative cross-impact analysis method based on patent data [4], which overcomes the subjective arbitrariness of probability estimation in qualitative approaches and establishes a foundation for subsequent technological cross-impact research. D. Thorleuchter et al. [5] compared differences between internal and external R&D technology cross-impacts to analyze characteristics, networks, complex relationships, and changing trends in interactions. C. Kim et al. employed association rule mining and analytic network process methods to identify core technologies in information and communication fields based on technological cross-impact [6]. Ma Rongkang and Liu Fengchao constructed an analytical framework using patent co-classification to identify cross-impact patterns across different nanotechnology fields, comparing nanotechnology development models in the United States, Japan, Germany, and South Korea, and discussed China' s nanotechnology development status and policy implications for achieving leapfrog development [7]. Qin Lifang calculated cross-impact values between any two technologies based on the number of patents jointly contained in nanotechnology, biotechnology, and information technology hotspots from 2000-2011, and analyzed influence relationships among technologies by setting impact thresholds [8]. S. Gauch et al. proposed criteria for identifying technology convergence trends and measuring technological convergence, using exploratory methods to identify technology clusters, distinguishing convergence trends through breadth of technology fields, and employing cross-impact assessment for in-depth analysis to measure convergence levels and trends [9].

Existing literature primarily focuses on technical relationships within specific technology domains, without comprehensively examining association impact values across multiple technology fields. Moreover, previous studies have overlooked the directionality of technology flows. Technology knowledge flow represents a process of knowledge transfer with both knowledge exporters and recipients, and this limitation affects the exploration of technology knowledge flow activity patterns [10]. Huang Bin et al. [11] recognized this issue and improved upon C. Choi' s patent cross-impact analysis method by examining five technologies in the solar concentrator field from three aspects: impact type classification, impact direction, and influence of specific technologies. In studies analyzing technological cross-impact, patent co-classification serves as a common data source. When a patent involves product combinations with two or more uses, examiners assign multiple classification codes corresponding to those uses. The primary classification represents the patent' s main use and most fully reflects its technical subject, having the highest relevance to the patent' s technological innovation, while secondary classifications represent subsidiary uses. From an information science perspective, patent classification provides knowledge organization for patents. Although classification codes are manually assigned by patent examiners, the OECD manual (1994) explicitly states that patents are categorized according to technical characteristics, making these classifications potential indicators of technological relationships. Furthermore, co-classification analysis assumes that the frequency of classification codes assigned to a patent can represent knowledge connections and spillover intensity [12], offering the advantage of analyzing multiple technology levels through multi-level classification while overcoming time lags in patent co-citation and inconsistencies in co-word qualitative judgments [6]. H. Lim and Y. Park [13] and H. Park and J. Yoon [14] note that in a patent, proprietary knowledge of the invention is assigned to the primary classification code, which has the highest relevance to the patent' s technological innovation, while other related knowledge is assigned to multiple secondary classification codes. The relationship between primary and secondary classifications can be viewed as the direction of knowledge flow. Zhou Lei and Yang Wei argue that the essence of patent co-classification is that the primary classification produces knowledge while secondary classifications receive knowledge, and their relationship should be regarded as technological knowledge flowing from the source to the application end [10].

Building on existing literature, this study combines patent co-classification information and technology flow directionality. Based on C. Choi' s patent cross-impact analysis method and referencing Huang Bin et al.' s research, we examine directed cross-impact values among different technology fields using patent co-classification data, calculating association impact values to provide strategic support for enhancing target technology competitiveness and forecasting technological progress. First, we calculate directed cross-impact values between technology fields. Second, we classify technology pairs based on these values. Third, we construct a cross-impact network to identify complex relationships among technologies. Finally, we analyze temporal changes in cross-impact values. The results help decision-makers predict future trends and formulate better R&D strategies.

2 Patent Data Collection and Processing

To comprehensively cover cross-impacts among different technology domains, we selected 35 sub-fields across five major technology domains from WIPO' s "IPC-Technology Concordance Table" published in May 2008 (see Table 1). Although the distinction among these 35 technology fields is not sufficiently clear, making some technologies appear similar literally, similar technologies have different emphases and application domains. Moreover, this table provides the initial classification standard and serves as a reference for other classification systems, making research based on it meaningful. Data were collected from the CNIPR patent information service platform, covering authorized Chinese invention patents from 1996-2016. Patent authorization represents an important indicator of patent quality [15], and invalid patents due to expiration or non-payment of annual fees were excluded to improve data accuracy.

Using the primary and secondary International Patent Classification (IPC) codes assigned to each authorized invention patent, we constructed a 35$×$35 asymmetric technology association co-classification matrix. Rows represent primary classification technology fields, columns represent secondary classification fields, and element values represent the count of patents with co-classifications corresponding to the primary (row) and secondary (column) fields, indicating the frequency of technology knowledge flow from row field i to column field j. Since we focus on relationships among the 35 fields and consider data availability, relationships between each technology field and itself are not considered.

The search expression used was: primary classification = (field i) AND classification = (field j) AND province code = (Beijing or Tianjin or Hebei or Shanxi or Inner Mongolia or Liaoning or Jilin or Heilongjiang or Shanghai or Jiangsu or Zhejiang or Anhui or Fujian or Jiangxi or Shandong or Hubei or Hunan or Guangdong or Guangxi or Sichuan or Guizhou or Yunnan or Tibet or Shaanxi or Gansu or Qinghai or Ningxia or Xinjiang or Hainan or Chongqing). Through co-classification retrieval, we extracted valid authorized patents across 35 technology fields from 1996-2016 as our sample data.

3 Technical Interaction Impact Types

3.1 Direction of Technical Interaction Impact

The direction of technology association impact determines technology development trends and provides a decision-making foundation for R&D investment support. This paper analyzes direct association impacts between technology pairs. If the number of patents with i as primary classification and j as secondary classification exceeds those with j as primary and i as secondary, the association impact is defined as i' s biased impact on j. Conversely, it is defined as j' s biased impact on i. If only patents with i as primary and j as secondary exist (or only j as primary and i as secondary), field i is said to have a one-way association impact on field j (or vice versa). If the counts are equal and non-zero, fields i and j have equal association impact. If neither exists, fields i and j have no association impact.

3.2 Types of Technical Interaction Impact

Referencing Huang Bin et al.' s research, we classify direct technical interaction impacts as follows:

(1) **Association impact of technology field i on j**: The conditional probability that field j appears as a secondary classification among all patents with field i as primary classification, as shown in Equation (1):

Let $N_{i主 \to j副}$ represent the number of patents with primary classification i and secondary classification j before time T (i≠j), and $N(i_{主})$ represent the total number of valid authorized patents with primary classification i.

(2) **Impact value of technology field j on i**: The probability that field i appears as a secondary classification among all patents with field j as primary classification, as shown in Equation (2):

Let $N_{j主 \to i副}$ represent the number of patents with primary classification j and secondary classification i, and $N(j_{主})$ represent the total number of valid authorized invention patents with primary classification j.

From a technology knowledge flow perspective, if technology fields i and j have biased or equal impact, development in either can promote the other. If field i has one-way impact on field j, i' s development can promote j' s development, but not vice versa. If fields i and j have no impact, neither' s development promotes the other.

4 Results

4.1 Cross-Impact Values Between Technology Fields

As shown in Table 2 , by summing row totals and column totals, we obtain the total impact emitted and received by 35 technology fields. In Table 2, technology i represents the impacting technology, and technology j represents the impacted technology. The table also lists the maximum impact values and corresponding technology fields for each of the 35 fields. Electrical engineering technologies are indicated in bold italics with underlining, instrument technologies in bold italics, chemistry technologies in bold, mechanical engineering technologies in italics, and other fields in regular font.

Overall, electrical engineering and chemistry fields exhibit the greatest impact on themselves and receive the most impact from themselves. The instrument field receives and exerts the most impact on electrical engineering and chemistry fields. Mechanical engineering is heavily influenced by its own technologies while also significantly impacting electrical engineering and chemistry. Other fields receive and exert substantial impact on instrument and mechanical engineering fields. The most influential technology is Food Chemistry (FOC), with a cumulative impact value of 0.996, indicating that 99.6% of patents in the food chemistry field also appear in patents of other technology fields.

Specifically, technology pairs in groups 2, 3, 11, 16, 17, 18, 25, 33, and 34 are mutual impacting and impacted technologies. Within the electrical engineering domain, communication technology (TEL) and audiovisual technology (AVT) show $I_{\mathrm{TEL}\to\mathrm{AVT}}(0.2416) < I_{\mathrm{AVT}\to\mathrm{TEL}}(0.3620)$, with a biased impact $I_{\mathrm{AVT}\to\mathrm{TEL}} = 0.1204$, indicating AVT' s greater influence on TEL. Digital communication technology (DIG) has the highest impact on TEL ($I_{\mathrm{DIG}\to\mathrm{TEL}} = 0.5359$ versus $I_{\mathrm{TEL}\to\mathrm{DIG}} = 0.3843$), with DIG' s greater influence showing $I_{\mathrm{DIG}\to\mathrm{TEL}} = 0.1516$. Across domains, Food Chemistry (FOC) most strongly impacts pharmaceuticals (PHA) in the chemistry field, with $I_{\mathrm{FOC}\to\mathrm{PHA}}(0.4175) > I_{\mathrm{PHA}\to\mathrm{FOC}}(0.3949)$, yielding FOC' s biased impact $I_{\mathrm{FOC}\to\mathrm{PHA}}(0.2226)$. In mechanical engineering, machine tool technology (MAT) most strongly impacts handling technology (HAN), with $I_{\mathrm{MAT}\to\mathrm{HAN}}(0.0701) > I_{\mathrm{PHA}\to\mathrm{FOC}}(0.1122)$, showing MAT' s biased impact on HAN. Cross-domain impacts reveal that Macromolecular Chemistry/Polymers (MCP) in chemistry has greater biased impact on Other Special Purpose Machinery (OPM) in mechanical engineering. Furniture and Games technology (FUG) from other fields more strongly impacts Medical Technology (MED) in instruments, with $I_{\mathrm{MED}\to\mathrm{FUG}}(0.0642) > I_{\mathrm{FUG}\to\mathrm{MED}}(0.107)$. For Textile and Paper Machines (TPM) in mechanical engineering, $I_{\mathrm{TPM}\to\mathrm{OCG}}(0.0827) > I_{\mathrm{OCG}\to\mathrm{TPM}}(0.1345)$, indicating Other Consumer Goods (OCG) from other fields has greater impact on TPM. Biomaterials Analysis (ABM) in instruments is most impacted by Biotechnology (BIO) in chemistry, with $I_{\mathrm{BIO}\to\mathrm{ABM}}(0.0958) > I_{\mathrm{ABM}\to\mathrm{BIO}}(0.3059)$, showing ABM' s greater influence with biased impact $I_{\mathrm{ABM}>\mathrm{BIO}} = 0.2101$.

Among non-mutually-maximum-impact technology pairs, within-domain impacts show IT Management Methods (ITM) most strongly impacts Digital Communication (DIG), with $I_{\mathrm{ITM}\to\mathrm{DIG}}(0.0537) < I_{\mathrm{DIG}\to\mathrm{ITM}}(0.3999)$, demonstrating ITM' s biased impact $I_{\mathrm{ITM}\to\mathrm{DIG}} = 0.4638$. Basic Communication Processes (BCP) is most impacted by DIG, with $I_{\mathrm{DIG}\to\mathrm{BCP}}(0.0277) < I_{\mathrm{BCP}\to\mathrm{DIG}}(0.1680)$, showing BCP' s biased impact on DIG ($I_{\mathrm{DIG}>\mathrm{BCP}} = 0.1403$). Computer Technology (COM) is most impacted by DIG, with $I_{\mathrm{DIG}\to\mathrm{COM}}(0.3063) < I_{\mathrm{COM}\to\mathrm{DIG}}(0.2301)$, indicating DIG' s biased impact on COM ($I_{\mathrm{DIG}\to\mathrm{COM}} = 0.1403$). In chemistry, Organic Fine Chemistry (OFC) is most impacted by Chemical Engineering (CHE), with $I_{\mathrm{CHE}\to\mathrm{OFC}}(0.2074) < I_{\mathrm{OFC}\to\mathrm{CHE}}(0.1899)$, showing CHE' s greater influence ($I_{\mathrm{CHE}>\mathrm{OFC}} = 0.0175$).

Cross-domain pairs show Engines, Pumps, Turbines (EPT) in mechanical engineering most strongly impacts Electrical Machinery, Equipment, Energy (EAE), with impact value $I_{\mathrm{EPT}\to\mathrm{EAE}} = 0.1650$ versus EAE' s impact on EPT of 0.0265. Despite mutual promotion, EAE more strongly influences EPT, with biased impact value $I_{\mathrm{EAE}\to\mathrm{EPT}} = 0.1385$. IT Management Methods (ITM) in electrical engineering is most impacted by Thermal Processing Equipment (TPA) in mechanical engineering, with $I_{\mathrm{TPA}\to\mathrm{ITM}}(0.2253) < I_{\mathrm{ITM}\to\mathrm{TPA}}(0)$, showing TPA' s one-way impact on ITM ($I_{\mathrm{TPA}\to\mathrm{ITM}} = 0.2253$). Semiconductors (SEM) in electrical engineering is most impacted by Optical Technology (OPT) in instruments, but $I_{\mathrm{OPT}\to\mathrm{SEM}}(0.1540) < I_{\mathrm{SEM}\to\mathrm{OPT}}(0.1711)$, indicating SEM' s greater influence on OPT ($I_{\mathrm{SEM}>\mathrm{OPT}} = 0.1711$). Measurement Technology (MEA) in instruments is most impacted by Microstructure and Nanotechnology (MSN) in chemistry, with $I_{\mathrm{MSN}\to\mathrm{MEA}}(0.3300) < I_{\mathrm{MEA}\to\mathrm{MSN}}(0.0533)$, showing MSN' s greater influence ($I_{\mathrm{MSN}>\mathrm{MEA}} = 0.2767$). Control Technology (CON) in instruments is most impacted by IT Management Methods (ITM), with $I_{\mathrm{ITM}\to\mathrm{CON}}(0.1971) < I_{\mathrm{CON}\to\mathrm{ITM}}(0.0376)$, demonstrating ITM' s greater influence. Medical Technology (MED) in instruments is most impacted by Pharmaceuticals (PHA) in chemistry, with $I_{\mathrm{PHA}\to\mathrm{MED}}(0.1471) < I_{\mathrm{MED}\to\mathrm{PHA}}(0.0951)$, showing PHA' s greater influence ($I_{\mathrm{PHA}>\mathrm{MED}} = 0.052$). Biotechnology (BIO) in chemistry is most impacted by Biomaterials Analysis (ABM) in instruments, with $I_{\mathrm{ABM}\to\mathrm{BIO}}(0.3059) > I_{\mathrm{BIO}\to\mathrm{ABM}}(0.0958)$, indicating ABM' s greater biased impact ($I_{\mathrm{ABM}>\mathrm{BIO}} = 0.2101$).

4.2 Technology Grouping

Grouping technology pairs based on association impact helps understand their characteristics. Using the reference line Y=X, we divide technology pair regions into biased, one-way, equal, and no-impact zones. Simultaneously, using average impact values (Y=0.0326, X=0.0262) as boundary values, we divide the entire impact region into four quadrants: high-high, high-low, low-high, and low-low impact zones. Figure 1 [Figure 1: see original paper] shows these classifications, where the X-axis $I_{j \to i}$ represents impact from primary classification technology j on secondary classification technology i, and the Y-axis $I_{i \to j}$ represents impact from primary classification technology i on secondary classification technology j. For example, point (ITM,DIG) projects onto the Y-axis as $I_{\mathrm{ITM} \to \mathrm{DIG}}$ (ITM' s impact on DIG) and onto the X-axis as $I_{\mathrm{DIG} \to \mathrm{ITM}}$ (DIG' s impact on ITM). Point (FOC,PHA) shows Y > X with both values in the high-high range.

Overall, all 110 points in the high-high impact zone represent biased impact relationships, indicating that high-high technology pairs can mutually promote each other, with one technology exerting greater influence. Among 56 technology pairs in the high-low zone, all except TPA's one-way impact on ITM show biased impacts. In the low-high zone' s 49 points, except for two one-way impacts, all show bidirectional or biased impacts. Among 380 points in the low-low zone, 40 represent one-way impacts and 31 show no impact. We should prioritize and manage technology fields showing biased and one-way impacts in the first three zones to inform technology development strategies.

4.3 Cross-Impact Network Graph

After calculating impact values between technology fields, complex relationships among two or more technologies (e.g., one technology may impact multiple technologies, and multiple technologies may impact one technology) require network graphs for identification. Nodes and edges represent technologies with bidirectional or one-way impacts and their association strengths. Arrows indicate directions of biased and one-way impacts. Lower edge thresholds produce denser networks. Figure 2 [Figure 2: see original paper] shows the overall complex network based on impact values among 35 technology fields from 1996-2016. Biased impact pairs are white points, one-way impacts are gray points. The dense network reveals highly correlated connections, though the numerous nodes and complex relationships make core domain impacts difficult to discern clearly.

To filter nodes with strong connections and identify core technology fields, we increased the edge threshold to 0.1, displaying only impacts exceeding this value in Figure 3 [Figure 3: see original paper]. Node size reflects degree centrality based on impact values, and edge thickness represents association strength. After filtering, fields with high centrality—MEA (Measurement) in instruments, EAE (Electrical Machinery, Equipment, Energy) and COM (Computer Technology) in electrical engineering, BMC (Basic Materials Chemistry) and MAM (Materials, Metallurgy) in chemistry—emerge as core domains that both receive impact from and significantly influence other nodes. Among impacts >0.1, instrument MEA receives one-way impacts from electrical EAE, mechanical engineering TRA (Transport), instrument CON (Control), ABM (Biomaterials Analysis), electrical engineering BCP (Basic Communication), chemical MSN (Microstructure and Nanotechnology), and PHA (Pharmaceuticals), while exerting one-way impact on COM. These core domains have bidirectional (biased) impacts with mechanical engineering MCP (Macromolecular Chemistry/Polymers), OPM (Other Special Purpose Machinery), BMC (Basic Materials Chemistry), and others.

4.4 Changes in Cross-Impact

Technology association impacts change with evolving demands and emerging technologies. Analyzing these changes helps determine which technologies should receive investment and development to achieve desired outcomes, informing public and private R&D strategic decisions. Considering data completeness for specific years, this section examines changes in cross-impacts among 35 technology fields from 2004-2014. Figure 4 [Figure 4: see original paper] shows changes in bidirectional impacts $I_{i\to j}$ and $I_{j\to i}$ for the 10 most changing technology pairs. For example, pair (TEL, AVT) shows an upward trend: in 2004, Y-axis (F1) and X-axis (F2) values were 0.0774 and 0.4500 respectively, but by 2014 became 0.4108 and 0.4454, indicating increasingly closer relationships. Technology pairs showing decreasing trends include (OPT, TEL), (BIO, PHA), (CIE, OPM), (MSN, MEA), and (FUG, CON). Pairs decreasing in both directions include (ABM, BIO), (ABM, PHA), (TEL, DIG), and (COM, TEL).

5 Conclusions and Recommendations

Based on valid authorized invention patent data from 1996-2016 across 35 Chinese technology fields, this study constructed an asymmetric technology association matrix and analyzed direct association impacts. The results provide methods for analyzing technology development and forecasting future trends, offering new references for promoting technology integration through technological cross-impacts. Specific conclusions are:

(1) Direct interaction relationships among technologies are classified as biased, one-way, equal, and no-impact. Electrical engineering and chemistry fields have the greatest impact on and receive the most impact from themselves. The instrument field receives and exerts the most impact on electrical engineering and chemistry fields. Mechanical engineering is heavily influenced by its own technologies while significantly impacting electrical engineering and chemistry. Other fields receive and exert substantial impact on instrument and mechanical engineering fields. These domain impacts are determined by the knowledge and resource elements required for technology R&D. In addition to within-domain biased impacts, cross-domain biased impacts occur between some electrical engineering and mechanical engineering technologies, electrical engineering on instruments, chemistry on instruments, chemistry on mechanical engineering, and other fields on instrument and mechanical engineering technologies. No clear patterns govern inter-technology impacts.

(2) Grouping technology pairs reveals that high-high impact points all repre-

sent biased impacts, indicating mutual promotion where one technology exerts greater influence. High-low and low-high zone pairs show biased impacts except for a few one-way impacts. Low-low zone pairs show limited influence, exhibiting only one-way or no impacts. We should prioritize technology fields with biased and one-way impacts.

(3) Networks built from biased and one-way impact pairs can identify complex relationships among multiple technologies. MEA (Measurement) in instruments, EAE (Electrical Machinery, Equipment, Energy) and COM (Computer Technology) in electrical engineering, and BMC (Basic Materials Chemistry) and MAM (Materials, Metallurgy) in chemistry are core domains in the cross-impact network. These core domains are strategic emerging and foundational support fields that both receive impact from and significantly influence other nodes.

Based on these conclusions, we propose the following policy recommendations:

(1) Decision-makers should prioritize technology fields with biased and one-way impacts based on direct impact values. They can predict technological progress by examining how one technology' s development affects another and formulate public policies and technology strategies to accelerate target technology development.

(2) Analyzing temporal changes in technology pair impacts can reveal development patterns and overall directions. By identifying increasing and decreasing impact trends from annual patent information, decision-makers can select optimal R&D investment timing, formulate development strategies, and determine which technologies should receive investment to achieve desired outcomes.

(3) Investment in the most influential technology, Food Chemistry (FOC), and core technologies MEA, EAE, COM, BMC, and MAM should be increased to fully exploit development potential in chemistry, mechanical engineering, and electrical engineering fields. This leverages the influence of the most impactful technology and utilizes core domains' network control capabilities to achieve technological renewal and breakthroughs while fostering related emerging technology fields.

References

[1] SCHULER A, THOMPSON WA, VERTINSKY I, et al. Cross impact analysis of technological innovation and development in the softwood lumber industry in Canada: a structural modeling approach[J]. IEEE transactions on engineering management, 1991, 38(3): 224–236.

[2] BLANNING R W, REINIG B A. Cross-impact analysis using group decision support systems: an application to the future of Hong Kong[J]. Futures, 1999, 31(1): 39-56.

[3] VILLACORTA P J, MASEGOSA A D, CASTELLANOS D, et al. A new fuzzy linguistic approach to qualitative cross impact analysis[J]. Applied soft computing, 2014, 24(11): 19-30.

[4] CHOI C, KIM S, PARK Y. A patent-based cross impact analysis for quantitative estimation of technological impact: the case of information and communication technology[J]. Technological forecasting and social change, 2007, 74(8): 1296-1314.

[5] THORLEUCHTER D, VAN DEN POEL D, NZIE A. A compared R&D-based and patent-based cross impact analysis for identifying relationships between technologies[J]. Technological forecasting & social change, 2010, 77(7): 1037-1050.

[6] KIM C, LEE H, SEOL H, et al. Identifying core technologies based on technological cross-impacts: an association rule mining (ARM) and analytic network process (ANP) approach[J]. Expert systems with applications, 2011, 38(10): 12559-12564.

[7] MA Rongkang, LIU Fengchao. International comparison of nanotechnology development models based on patent cross-impact analysis[J]. China Soft Science, 2012(12): 49-58.

[8] QIN Lifang. Research on NBI convergence trends based on patent cross-impact method[D]. Beijing: Beijing University of Technology, 2013.

[9] GAUCH S, BLIND K. Technological convergence and the absorptive capacity of standardization[J]. Technological forecasting and social change, 2015, 91(2): 236-249.

[10] ZHOU Lei, YANG Wei. Mining technology knowledge flow networks based on patent IPC[J]. Modern Intelligence, 2016, 36(1): 45-50.

[11] HUANG Bin, HUANG Lucheng, WU Feifei, et al. Research on technology impact relationships based on patent cross-impact analysis[J]. Science and Technology Management Research, 2015, 35(15): 147-151.

[12] BRESCHI S, LISSONI F, MALERABA F. Knowledge-relatedness in firm technological diversification[J]. Research policy, 2003, 32(1): 69–87.

[13] LIM H, PARK Y. Identification of technological knowledge intermediaries[J]. Scientometrics, 2010, 84(3): 885-916.

[14] PARK H, YOON J. Assessing coreness and intermediarity of technology sectors using patent co-classification and citation analysis[J]. Scientometrics, 2014, 98(2): 853-890.

[15] LI Bei, CHEN Xiangdong. Research on cooperative innovation in Chinese traditional medicine based on patent collaboration networks[J]. Chinese Journal of Traditional Chinese Medicine, 2015, 40(6): 1212-1218.

Author Contributions

Li Ruixi: Conceptualized the study, processed data, and wrote the manuscript;
Chen Xiangdong: Provided valuable revision suggestions;
Cui Yunxia: Collected patent data;
Cui Caixia: Collected patent data.

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