Identifying University Patent Transfer Targets through Multi-level Demand Analysis: A Case Study of Graphene (Postprint)

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Abstract

[Purpose/Significance] The identification of technology transfer targets for university patents is of positive significance for improving the conversion rate of patent transfers, effectively promoting the close integration of science and technology with the economy, and achieving innovation-driven development. [Method/Process] This study uses enterprise technology demands to represent market demands. First, a domain-specific multi-dimensional information technology tree is constructed based on an improved technology tree method. Then, on the basis of classifying technology demands, the textual features and content characteristics of technology demand documents are analyzed to determine demand extraction rules and demand types. Finally, a demand-technology matching model for different scenarios is constructed. [Results/Conclusion] The effectiveness of the proposed model is empirically analyzed using patent data from the graphene domain. The results demonstrate that matching university patents that meet the conditions based on technology demands, thereby identifying potential clients for university patent operations, constitutes an effective approach for the targeted promotion of university patents and the facilitation of patent transfer and commercialization.

Full Text

Identifying University Patent Transfer Targets from a Multi-Level Demand Analysis Perspective: A Case Study of Graphene

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Abstract

[**Purpose/Significance**] Identifying university patent transfer targets is crucial for improving patent transfer and conversion rates, effectively promoting the close integration of science and technology with the economy, and achieving innovation-driven development. [**Method/Process**] This study uses enterprise technology requirements to represent market demand. First, an improved technology tree method is employed to construct a domain multi-dimensional information technology tree. Based on the classification of technical requirements, the textual and content characteristics of requirement documents are analyzed to determine extraction rules and requirement types. Finally, demand-technology matching models for different scenarios are constructed. [**Result/Conclusion**] An empirical analysis using graphene patent data demonstrates the model's effectiveness. The results show that matching university patents based on technical requirements to identify potential patent operation clients is an effective means of strategically marketing university patents and promoting their conversion.

Keywords: demand analysis; patent transfer target; multi-dimensional technology tree; university patent
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Scientific and technological innovation extends far beyond laboratory research—it must be transformed into real drivers of economic and social development. As key actors in the national innovation system, Chinese universities possess the country's richest scientific and technological resources, producing substantial scientific achievements annually, with patents being a major component. By the end of 2018, universities nationwide held 298,000 valid invention patents, with 75,000 invention patents authorized that year, accounting for 17.9% and 21.6% of China's total respectively. However, despite this vast patent portfolio, less than 5% have been truly industrialized, raising serious concerns about transfer and conversion rates. This not only wastes significant scientific resources but also hinders technological progress. Since patent operation ultimately aims to maximize market benefits, accelerating patent transfer and conversion is critical for enhancing technology's contribution to economic development and leveraging innovation's leading role.

2. Literature Review

Patent transfer and conversion typically involves three parties: patent suppliers (primarily universities and research institutes), patent recipients (mainly enterprises), and support/auxiliary parties. This study focuses on enterprises as market competition entities that serve as patent recipients. Existing research on identifying patent conversion targets includes: Thomson Reuters' use of global data resources and integrated tools like ThemeScape, patent citation maps, and TDA to provide universities with patent portfolio analysis, technology landscape analysis, and R&D conversion opportunity analysis to identify potential partners or licensees. I. Park et al. used network analysis to identify technological similarity among patent holders, recommending highly similar entities for industry-academia-research collaboration. X. Wang et al. mined institution groups with similar R&D goals through SAO (Subject-Action-Object) semantic analysis of patent titles and abstracts. I. Ji et al. identified potential technology users through patent citation analysis. Xu Haiyun et al. identified potential industry-academia-research partners by analyzing network cores and institutional competitiveness in the innovation chain using multi-source data and qualitative-quantitative methods. Luo Jian et al. proposed a three-stage intelligence analysis process for technology transfer target identification: technology decomposition, technology search, and collaboration feasibility assessment. However, due to the complexity of patent transfer processes and influencing factors, traditional identification methods remain prevalent, including questionnaires, promotional activities, email advertising, and telephone interviews. The Stanford OTL model involves finding internal champions through conferences and industry events, while order-based R&D addresses enterprise-specific needs but fails to fully reflect market demand and technology trends.

When enterprises seek competitive advantages or encounter bottlenecks in R&D, they generate specific needs for external solutions, making them potential patent transfer targets. Humboldt University emphasizes that patent conversion requires industrial participation and close, trust-based university-industry partnerships. Zhao Ziyi et al. proposed that domestic patent operations should focus on identifying potential technology suppliers and seekers. Pu Xuelian and Li Chang et al. recognized demand's guiding and driving role in university patent conversion. Tang Heng et al. proposed a market demand-oriented, customer value-driven patent operation model for universities. Zhai Dongsheng et al. mined potential R&D partners from enterprises through technology tree construction and technical requirement document analysis. These studies demonstrate growing recognition of demand-oriented technology matching, which enhances the precision and relevance of patent transfer.

While existing research provides valuable references, current methods mostly focus on technological similarity and resource complementarity between supply and demand sides. Studies addressing enterprise demand remain conceptual, lacking practical implementation and deconstruction of complex requirements. Demand represents the best entry point, and identifying patent transfer targets based on requirements can significantly enhance precision. Therefore, this study improves technology tree construction methods, analyzes multi-level demand characteristics from enterprise technology requirements, and proposes demand-technology matching methods applicable to various scenarios to accurately identify patent transfer targets and promote market-research alignment.

3. Methodology for Identifying Patent Transfer Targets

The core of this study's identification method lies in constructing a demand-technology matching model using patents as the data source and enterprise technical requirements as the matching dimension. The process involves: (1) constructing a domain multi-dimensional technology tree, (2) analyzing and classifying enterprise technical requirements, and (3) building a demand-technology matching model.

3.1 Domain Technology Tree Construction

A technology tree is a hierarchical representation of technical features and their relationships, typically comprising products, technologies, and functions in a specific domain. It serves as an important analytical tool for identifying key technologies and dissecting existing technical architectures. By extracting technical element features and following logical structures, domain technology tree construction can significantly alleviate manual construction limitations. Current Chinese multi-dimensional technology trees are limited and often based on SAO structures, which, while enhancing semantic information, result in low co-occurrence rates in document clustering. This study adopts a hybrid approach combining coarse-grained and fine-grained extraction rules to construct a domain multi-dimensional technology tree.

Patent literature has standardized text structures: titles describe core functional events, while abstracts articulate core technologies and advantages, including technical solutions, functional effects, problems solved, and applicable fields. However, Chinese patent abstracts lack deep hierarchical division, with sections like "function + technical solution + effect + field" or "function + technical solution + field" intermingled. This complicates targeted extraction, necessitating multi-dimensional information location before extraction, topic modeling, and multi-dimensional linking. The detailed steps are shown in .

Multi-dimensional information extraction focuses on analyzing and extracting technical functions, effects, and application domains from invention titles and abstracts, excluding specific technical solutions from patent specifications for two reasons: (1) each patent is creative with low technical repetition points, and (2) technical solution descriptions are complex and obscure, offering limited analytical value. The final multi-dimensional technology tree structure is shown in [Figure 1: see original paper].

3.2 Technical Demand Analysis

Demand is the starting point of technological innovation and its ultimate realization venue. Analyzing requirement documents can better align with market needs. This section uses requirement documents as data sources to analyze their textual characteristics for improved semantic extraction. Technical requirement documents typically include fields such as demand name (DN), technical field

(TF), expected aims (EA), background (BD), contact details (CD), and other information (OI). A sample is shown in .

Influenced by demand subjects' cognition, requirement documents vary in clarity and professionalism. Some provide detailed solutions, while others remain vague or implicit. Therefore, different requirement types must be clearly classified to understand true technical intentions before matching. Enterprise technology demands generally fall into three categories (see):

1. **Broad Requirements (Type I):** Concise expressions with weak specificity, only indicating general directions without specific problems, technical details, or constraints.
2. **Singular Requirements (Type II):** Clear statements of specific technical problems, typically bottlenecks encountered in enterprise R&D, with relatively simple technical issues and single expected targets.
3. **Comprehensive Requirements (Type III):** Complex expressions with strong specificity, involving multiple technical problems and targets.

Semantic extraction of requirement documents yields more concise and effective information. The DN field represents urgent technical problems (future functions), typically expressed as noun phrases or noun-verb combinations with possible adverb/adjective modifiers. The EA field includes technical solutions, targets, effects, and application domains, requiring rule-based extraction combined with manual judgment.

3.3 Demand-Technology Multi-Dimensional Matching

Type I (Broad Requirements) Matching: Uses fuzzy matching to find patents with generally consistent directions. Characteristics include broad technical solutions, weak specificity, easy satisfaction, low search costs, and numerous potential clients.

Type II (Singular Requirements) Matching: Addresses specific problem contexts by finding targeted solutions. Characteristics include moderate specificity, requiring technical evaluation, and limited matching results.

Type III (Comprehensive Requirements) Matching: Employs multi-objective matching to find solutions maximizing client needs. Results are relatively fewer in number. Specific matching rules for the three types are shown in .

4. Empirical Study

4.1 Data Sources

The empirical study uses graphene as a case. Graphene's high specific surface area, ultra-thin properties, and superior strength and conductivity offer excellent market prospects. China leads global graphene R&D and industrialization, with patent applications exceeding half of the world's total. However, most related technologies remain in universities, with relatively few enterprise patents and low market activation. Therefore, this study uses Chinese university graphene patents as the dataset, sourced from the PatSnap database.

Based on literature review and expert knowledge, the search query used "graphene" as the keyword, with authorization dates through 2017, and university/research institute applicants. The search formula: TTL:(graphene*) AND ISD:[* TO 20171231] AND ANS_{TYPE}:(*ACADEMY), executed on July 22, 2018, yielded 3,659 initial patents. After filtering, 3,048 patents remained. Technical requirement documents were obtained from public platforms like JiE Network and Xianji Network, totaling 58 documents classified into: 15 Type I, 25 Type II, and 18 Type III requirements. Sample data are shown in .

4.2 Information Extraction and Technology Tree Construction

First, classified requirement documents underwent semantic extraction. Function information was extracted from the DN field, while expected targets were extracted from the EA field using manual judgment and extraction rules. Partial results are shown in .

Second, multi-dimensional information was located and extracted from university graphene patents using Baidu's semantic tools and Python NLP techniques for functions, effects, application domains, and technical solutions. Results are shown in .

Third, the LDA model was applied for topic modeling with parameters: alpha = 50/k, beta = 0.01, and 5,000 iterations. Partial results are shown in . Based on clustering, patents were indexed to connect semantic features, constructing the university graphene patent technology tree (partial view in [Figure 2: see original paper]).

4.3 Technology Matching and Client Identification

Using the proposed matching method, enterprise requirements were matched against patents at multiple levels. To objectively evaluate accuracy, domain experts assessed matching results based on "demand satisfaction degree" and "technology usefulness" on a 0-10 scale. Partial results are shown in .

The study identified 23 matched demand subjects, including companies like Jiangsu Huifeng Lubrication Materials and Tangshan Baichuan Group, as well as individuals from Xianji Network. The distribution was: 10 Type I, 9 Type II, and 4 Type III. Expert evaluation confirmed 16 successful identifications (7 Type I, 7 Type II, 2 Type III), achieving nearly 70% accuracy and demonstrating method feasibility.

The analysis reveals: (1) **Type I requirements** match most easily, with the highest evaluation scores. For example, requirements for "graphene application technology" were extended to downstream applications like batteries, composites, and semiconductors before topic matching. (2) **Type II requirements** require more precise matching. For instance, graphene metal composite needs were first matched to the graphene composites theme (Topic-F1), then refined using the "metal" keyword for secondary matching. (3) **Type III requirements** are most complex, requiring multi-objective matching across function, technical solution, and effect dimensions. For example, electrochemical graphene preparation requirements needed to satisfy multiple conditions including yield, layer control, and process parameters. While some similar patents were found (e.g., CN106676562B), technical details differed, resulting in lower match quality.

These results show that demand-based patent matching aligns closely with market needs, with multi-level demand analysis capturing user characteristics more precisely. However, the limited sample size and complex technology tree construction process present challenges. The persistent gap between university patents and enterprise demand indicates that university R&D still lacks market orientation.

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Author Contributions

Yi Huifang: Designed the research framework, collected and processed data, and drafted the manuscript.
Wu Hong: Conceived the research topic and design, supervised writing, and revised and finalized the manuscript.

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