A Study on Patent-Based Recommendation Methods for Potential Enterprise R&D Partners (Postprint)

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Abstract

【Objective】To address the challenge of accurately identifying potential R&D partners, this paper proposes a patent-based recommendation method for potential enterprise R&D partners.

【Method】Based on TRIZ theory, semantic features such as function, scientific effect, and efficacy are extracted from relevant patents to construct a domain patent technology tree. Key information from enterprise technology requirements is extracted and matched to the technology tree. Potential R&D partners are then identified based on patent holders and evaluated using the Analytic Hierarchy Process (AHP).

【Results】The study obtains Derwent patent data in the water heater anti-scale technology domain, identifies and evaluates potential R&D partners, thereby demonstrating the feasibility of the proposed method.

【Limitations】Regarding semantic feature extraction, the extraction accuracy needs to be improved due to the considerable flexibility of Chinese grammatical structures.

【Conclusion】The proposed method can identify and evaluate potential R&D partners and recommend R&D partners capable of addressing enterprise technological needs.

Full Text

Preamble

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Abstract

Objective: To address the challenge of accurately identifying potential R&D partners, this paper proposes a recommendation method for enterprise potential R&D partners based on patents. **Methods**: Grounded in TRIZ theory, we extracted semantic features such as functions, scientific effects, and efficacy from relevant patents to construct a domain patent technology tree. Key information from enterprise technology requirements was extracted and matched within this technology tree, enabling the identification of potential R&D partners through patentees and their evaluation using the Analytic Hierarchy Process. **Results**: We retrieved Derwent patent data in the water heater anti-scale technology domain to identify and evaluate potential R&D partners, thereby demonstrating the feasibility of the proposed method. **Limitations**: Regarding semantic feature extraction, the accuracy needs improvement due to the considerable flexibility of Chinese grammatical structures. **Conclusions**: This method can discover and evaluate potential R&D partners, providing enterprises with recommendations for R&D partners capable of addressing their technical needs.

Keywords: Patent; Technology Tree; TRIZ; R&D Partners

In today' s competitive market, it has become increasingly impossible for enterprises to provide products and services relying solely on their own capabilities. Consequently, collaborative R&D has grown increasingly important for enterprises. The selection of R&D partners affects the success or failure of joint development efforts and has become one of the critical strategic issues for enterprises. On the other hand, patent literature serves as humanity' s primary technical carrier and a highly innovative product that embodies collective wisdom and contains cutting-edge technical information. Patents also represent rights; a company' s patent portfolio fully reflects its technical level, making patents an important standard for measuring a company' s technological innovation and R&D capabilities [1]. Moreover, patents provide detailed technical descriptions that reveal the essential nature of many inventions and offer high operability [2].

Based on this research background, this paper proposes a patent data-driven recommendation method for enterprise potential R&D partners. The method involves using domain patents as data sources to extract relevant semantic features and construct a domain patent technology tree. Using enterprise-specific technical requirement documents as a basis, we extract key information including technical fields, technical problems, technical means, and technical effects. By matching this key information within the domain technology tree, we achieve precise positioning of relevant patents. We then construct an evaluation index system applicable to assessing patent-based enterprise potential R&D partners, evaluate patent holders of relevant patents, and ultimately identify potential R&D partners for specific enterprise technical needs.

2.1 Research on Technology Tree Construction Methods

A technology tree is a hierarchical diagram representing relationships among product components, technologies, and technical functions within a specific technical domain. Currently, two primary methods exist for constructing domain technology trees.

The first method centers on the technology evolution tree theory in TRIZ (Theory of Inventive Problem Solving). This approach begins by analyzing the current state of domain technology development and selecting the most appropriate evolution route from the evolution paths as a template. According to system optimization requirements, core technical features of existing technologies are then added to the tree structure as branches. By matching domain technology development characteristics on the main evolution route template and following the direction of technology route development, this method enables mastery and prediction of the domain' s technology development direction.

The second method involves extracting relevant information about technology and function, then building the overall structure of the technology tree based on the logical structure of the original information. Yoon et al. [3] proposed a systematic technology roadmapping method based on quantitative data, using text mining to extract core information from product design and patents for identifying existing products and technologies, thereby generating a complete set of detailed product and technology configurations to support innovation. Lee et al. [4] proposed a technology roadmap construction method based on literature and qualitative analysis, using broadband network technology as a case study to construct a technology tree from a technical perspective. Cascini et al. [5] utilized a computer-aided patent portfolio analysis system to extract function-related semantic information from patents, calculated patent similarity by comparing invention function trees, and constructed a technology tree for the circuit interruption device domain from a functional perspective. Fantoni et al. [6] adopted the Function-Behavior-Structure (F-B-S) framework, using text mining techniques combined with keywords, concepts, relationships, and regular expressions to extract functions, behaviors, and structures from patents, then constructed a technology tree. Choi et al. [7] proposed a technology tree construction method based on SAO (Subject-Action-Object) extraction technology from the perspective of product, technology, and function display. After SAO structure extraction, K-means clustering was applied to cluster SAO structures. By identifying word characteristics, the clustered word phrase types were classified into product, technology, material, and technical attribute categories, while AO types were divided into inclusion, influence, and attribute types. Finally, the domain technology tree was constructed by combining these three dimensions of the technology tree. Russo et al. [8] proposed a new functional search method based on the Function-Behavior-Scientific Effect-Structure ontology in

TRIZ, defining function as the purpose of a technical system' s existence. By extracting key information such as functions, behaviors, and structures from patents, they constructed a local knowledge base to form a domain technology tree. Wang Chaoxia et al. [9] argued that a Patent Solution (PS) consists of SC (Technical Solution Components) and SR (Technical Relationships in the Solution). Technical solution components were further subdivided into TS (Technical System), FL (System Flow), and TA (Attributes), while technical relationships were subdivided into RS (Composition Relationships), RA (Attribute Relationships), and RF (Functional Relationships). Finally, information extraction was achieved through pattern matching, and hierarchical relationships were used to form connections among elements in each model.

In summary, the first technology tree construction method relies heavily on the builder' s knowledge background and experience, making it difficult to expand and imposing significant limitations. Existing research on the second method primarily focuses on product, technology, and functional perspectives of technology trees, without considering the perspective of functional effects. Therefore, based on the second method and using the Derwent patent database as a data source, this paper extracts semantic information including functions, scientific effects, and functional effects contained in patents from patent titles and abstracts. Combined with syntactic structures and using patents as indexes, we achieve domain technology tree construction.

2.2 Research on R&D Partner Selection

When selecting R&D partners, enterprises must determine the criteria and index system to be adopted, as different criteria reflect different enterprise needs. Foreign scholars have established a research foundation on factors affecting R&D partner selection. Cantner et al. [10] reviewed research on factors influencing R&D partner selection, grounded in the resource-based view of the firm and combined with German patent data to verify the positive effects of technological overlap, potential knowledge flow, future cooperation value, and previous cooperation on R&D partner selection. Lhuillery et al. [11] used French Innovation Survey (CIS) data to explore factors influencing failure in collaborative R&D projects from four aspects: enterprise type, previous cooperation experience, knowledge spillovers, and intellectual property rights and enterprise characteristics. Chun et al. [12] applied a probit model for sample selection to explore factors influencing R&D cooperation in small and medium-sized enterprises. Results indicated that internal knowledge spillovers have a significant positive impact on SMEs' participation in R&D cooperation, suggesting that SMEs may have particular characteristics when establishing external R&D cooperation connections if the importance of external knowledge is not considered.

Domestic scholars have also established a foundation in research on factors influencing R&D cooperation. Wang Jinfu et al. [13] grounded in 3C theory, considered factors affecting R&D partners from four aspects: capability, compatibility, commitment, and cooperation intention, further subdividing them into 9 aspects and 35 influencing factors, designing questionnaires based on these factors for statistical analysis and verification. Ji Huisheng et al. [14] argued that knowledge characteristics are the main factors influencing enterprise R&D partner selection, with mismatched knowledge between cooperating enterprises and inefficient knowledge sharing being important causes of collaborative R&D failure, and constructed a knowledge characteristic index system for R&D partner selection using the Analytic Hierarchy Process. Yuan Xiaodong et al. [15] proposed a patent information analysis method for selecting enterprise R&D partners using patent data. This method divided the patent analysis process into technical and subject perspectives, completing technical analysis from three aspects: patent technology development trends, patent technology maturity, and core patent analysis, while completing subject analysis from three aspects: R&D qualification comparison, relative patent position analysis, and relative patent advantage comparison. Su Huishuang et al. [16] reviewed relevant literature on R&D partner selection and concluded that important factors influencing enterprise R&D partner selection include organizational size, R&D intensity, complementary resources, organizational openness to the external environment, mutual trust, compatible culture, and cooperation experience.

Additionally, methods for selecting R&D partners have been extensively studied by numerous scholars, with successful applications of the Analytic Hierarchy Process, goal programming techniques, and other methods in R&D partner selection. Song et al. [17] proposed a patent portfolio-based approach for evaluating potential R&D partners, overcoming the weakness of focusing on individual enterprise capability assessment when selecting potential R&D partners. Lee et al. [18] proposed a method for large companies to select small companies as R&D partners. This method first considered technology roadmaps as essential elements for selecting R&D partners, then used semantic analysis to generate a series of suitable potential SME R&D partners, and finally used a Bayesian network model based on patent information to identify potential SME R&D partners for large companies.

Comprehensive analysis reveals that foreign scholars have begun using patent data to identify and evaluate R&D partners, while domestic research in this area remains limited. Therefore, this paper adopts Derwent patent data as a data source, matching domain patent technology trees with enterprise requirement documents to better assist enterprises in selecting R&D partners.

3 Design of Patent-Based Potential R&D Partner Recommendation Method

This study utilizes TRIZ theoretical knowledge and text mining methods to extract semantic features such as functions, scientific effects, technical attributes, and functional effects from relevant patents. Technical attribute extraction assists in scientific effect extraction. We construct a domain patent technology tree through the co-occurrence relationships of these semantic features in patents. We then extract technical fields, technical problems, technical means, and technical effects from enterprise-specific requirement documents. By positioning the target patents for enterprise needs within the domain technology tree using the above key information, we select patents most relevant to enterprise requirement documents to form a local requirement patent database. The enterprise requirement patent acquisition scheme is shown in Figure 1 [Figure 1: see original paper].

3.1 Patent Semantic Feature Extraction Scheme

We extracted three types of semantic features from patent text information (titles and abstracts): patent functions, applied scientific effects, and achieved functional effects. Derwent patent database patents are rewritten by professionals, making their titles and abstracts more standardized. The abstracts are formatted into several relatively independent sections: the NOV section primarily describes the core innovation points of the patent, including the most prominent innovations compared to previous patents and the technologies (scientific effects) applied to achieve these innovations. The ADV section mainly introduces the functional effects achieved when implementing the technology, such as being more environmentally friendly, safer, or more convenient. The ADV description sometimes also includes functional descriptions and should therefore serve as source data for patent functional semantic feature extraction. The USE section of the abstract primarily introduces the technical fields where the patent may be applied in the future and which other technologies it may be used by.

Therefore, according to the research purpose and based on the above description of Derwent patent characteristics, we designed the following semantic feature extraction scheme: primarily extracting functions from titles and using the ADV description section of abstracts to assist in patent function extraction; extracting applied scientific effects from the NOV description section of abstracts; and extracting achieved functions and their effects from the ADV description section of abstracts. The extraction scheme is shown in Figure 2 [Figure 2: see original paper].

3.2 Semantic Feature Annotation and Extraction

Before text semantic feature extraction, patent text features must undergo preprocessing. This includes dividing document text content into paragraphs, then into sentences, and finally segmenting words within each sentence. We calculate word frequencies in sentences, combine word features, context, and text structure to annotate word parts of speech, and use stop word lists to eliminate irrelevant words. After text preprocessing, semantic feature extraction proceeds in three parts.

(1) Function Extraction Function is an abstract description of input and output management used to achieve design intent in a certain environment. In simple terms, function is the value of an object’ s existence and the spe-

cific role it can achieve. Function expression methods are mainly divided into three types: Verb+noun combinations, such as increase temperature, reduce space; Input-output transformations, where inputs and outputs can be energy, material, or information, such as input energy as kinetic energy, output energy as electrical energy; Input-output transformations between behaviors and states, such as converting liquid water into gaseous steam.

The first expression method is most common in patents. Therefore, using patent titles and ADV sections of abstracts as primary data sources for patent function extraction, we employ the first expression method as the basic extraction rule, combined with the second function expression method. By determining whether the noun following the verb corresponds to specific expressions of energy, material, or information, we complete patent function extraction.

(2) Scientific Effect Extraction Scientific effects describe the transformation process between system inputs and outputs, governed by scientific principles and system attributes and accompanied by phenomena. Based on 100 commonly used scientific effects, we enumerate as many nouns, verbs, adverbs, and adjectives involved in these scientific effects as possible. We classify these scientific effects into categories such as mechanical, thermal, acoustic, electromagnetic, chemical, and biological, then identify subcategories through the content of specific scientific effects to build a local foundational scientific effect database.

Using the NOV description text sections of DII patent abstracts as source data, we identify corresponding feature words from the above scientific effect database to recognize scientific effects applied in patents and classify patents by scientific effects. A single patent may correspond to multiple scientific effects.

(3) Functional Effect Extraction Functional effects are characteristic descriptions of functions, representing a modification of functions. When patents achieve specific functions through scientific effects, they inevitably bring about related functional effects, such as improved safety, improved reliability, or speed. Functional effects describe additional effects achieved when implementing specific functions. They have two expression forms in patent text: first, as adverbs modifying functional verbs, such as quickly sterilizing, safely disinfecting; second, expressed through verb+noun forms, such as improving safety, improving efficiency. The second expression is most common in patents.

The only difference between the second functional effect expression and the first function expression is that the noun following the functional verb in functions represents words like energy, material, or information, while the noun following functional effect verbs are mostly words like safety, efficiency, stability, etc. Therefore, when extracting functional effects from ADV sections of abstracts, we use both patterns to complete the extraction.

3.3 Technology Tree Construction Based on Patent Semantic Features

(1) Determine the internal hierarchical structure of extracted semantic features from patents. Through synonym merging of feature concepts, achieve clustering of concept-related information to form relatively independent foundational semantic feature knowledge blocks within each semantic feature.

(2) Using the co-occurrence relationships between "patent functions" and "patent scientific effects," and between "patent scientific effects" and "patent functional effects" within the same patent as criteria, respectively achieve connections between "function" concepts and "scientific effect" concepts, and between "scientific effect" concepts and "functional effect" concepts in the domain technology tree to build the overall framework of the domain technology tree.

(3) Add bibliographic items from patent data, such as patent numbers, patentees, citation counts, and other features to leaf nodes of the domain technology tree, achieving comprehensive representation from patent bibliographic features to patent semantic features and comprehensively displaying knowledge and associations within the domain technology from multiple dimensions. The final technology tree structure is shown in Figure 3 [Figure 3: see original paper].

3.4 Semantic Information Extraction from Enterprise Specific Requirements

Requirements are formatted as structured tables for enterprises to complete, including entries such as title, requirement description, requirement background, possible technical directions, and excluded technical solutions. This study primarily extracts information from these entries. Among them, titles, requirement descriptions, and background descriptions mainly match technical effects and technical problems through verb-object structures. Possible technical directions and excluded technical solutions, being relatively concise fields, can be directly extracted as technical means fields.

Technical problems are issues that the requiring party urgently needs to resolve, i.e., functions that future technical solutions should achieve. Therefore, extracting technical problems is equivalent to extracting functional features from requirement descriptions. In Chinese, functional descriptions are mostly verb-noun combinations, with possible adverbs before verbs and adjectives before nouns, such as: (adverb)+verb+(adjective)+noun. Adverbs and adjectives in parentheses may be omitted, as in quickly eliminating scale, safely providing oxygen. This paper summarizes functional verbs in text information provided by the requiring party, as shown in Table 1 .

Technical effects are effects inevitably brought about when achieving specific functions. In functional expression patterns, adverbs primarily represent technical effects, such as safely and quickly mentioned above. Therefore, technical effects in requirement documents can be extracted by identifying adverbs that modify functional verbs.

3.5 Matching Algorithm for Requirement Patents in Domain Patent Technology Tree

The domain patent technology tree comprehensively and intuitively displays all functions achieved by scientific effects and their functional effects in the domain, and has annotated which patents apply which scientific effects, achieve which functions, and reach which functional effects through patent number indexing. Therefore, the most direct matching method at this stage is to first match technical problems extracted from enterprise specific requirements with function fields in the technology tree to meet the requiring party' s basic functional needs, then match technical means and technical effects extracted from requirement documents with scientific effects and functional effects in the domain patent technology tree. The matching method is shown in Figure 4 [Figure 4: see original paper].

4 Evaluation of Enterprise Potential R&D Partners Based on Patents

In the process of searching for R&D partners, enterprises need to consider information including: technical characteristics of potential R&D partners, such as technical strength and R&D capability; openness characteristics of potential R&D partners, such as R&D openness and cooperation degree with the requiring enterprise; and collaborative R&D effect characteristics of potential R&D partners, including evaluation of historical collaborative R&D effects.

The criteria for effective collaborative R&D evaluation primarily involve assessing potential R&D partners through patent analysis. The patent-based enterprise potential R&D partner analysis proposed in this paper consists of three major categories: technical strength, R&D openness, and collaborative R&D effects, as shown in Figure 5 [Figure 5: see original paper].

Technical strength and R&D openness focus on the characteristics of R&D partners. Technical strength represents the technical capabilities of potential R&D partners in the cooperation domain, including technical and operational knowledge and experience. Potential R&D partner technical strength is evaluated according to four sub-criteria: technology share, technology leadership, technology impact index, and family patent impact index. R&D openness is measured through two sub-indicators: organizational openness and joint ownership. Expected collaborative R&D effects include two sub-criteria: collaborative patent citation index and collaborative patent family index. Calculation methods for each sub-indicator are shown in Table 2 .

5.1 Data Collection

This study uses the water heater anti-scale technology domain as the research object. This technology domain primarily involves keywords such as water heater, scale, anti-scale, and scale removal. Based on these keywords, the search formula for the technology domain was determined as TS=(((scale* and (prevention* or prevent* or inhibit* or control* or avoid* or removal* or reduc*)) or antiscal* or scaleinhibition or anti-scal*) and water and heater*), with the search period from January 1, 1963 to [date not specified].

5.2 Patent Semantic Feature Extraction

(1) We annotated and extracted three types of semantic features from patents: patent functions, applied scientific effects, and achieved functional effects. Patent functions were extracted from titles and ADV sections of abstracts, scientific effects from NOV sections of abstracts, and functional effects from ADV sections of abstracts. Patent semantic feature extraction examples are shown in Table 3 .

(2) Extracted functions from patents primarily involve preventing/inhibiting scale formation, as shown in Figure 6 [Figure 6: see original paper]. A minority of patents can achieve scale removal functions. Extracted scientific effects applied in patents were merged into 11 categories: Magnetic field, Ultrasound, Electric field, Vibration, Gas/steam, Phase change, Circulation flow, Control temperature, Control pressure, Functional ceramics, and Scale inhibitor. Among these, only Scale inhibitor belongs to chemical scientific effects, while the others are physical scientific effects.

As shown in Figure 6, functions in the water heater anti-scale technology domain can be divided into scale inhibition and scale removal. The vibration scientific effect can be applied to both scale inhibition and scale removal. Scale inhibition can also be achieved through magnetic, ceramic, temperature control, and scale inhibitor (chemical) methods, reaching functional effects such as increased safety, speed, convenience, and high performance.

5.3 Domain Patent Technology Tree Construction

Using patents as indexes, we established connection relationships among various semantic features based on their co-occurrence relationships and contextual relationships within patents. We aggregated semantic features extracted from patents in the water heater anti-scale domain, performed synonym merging of these semantic features, and constructed the technology tree for this domain. Since semantic features of patents originate from patent text information, and each patent has its own index—patent number—and patents also contain bibliographic items such as patent owners (patentees), patent application/publication dates, and countries/regions where patents are valid, after constructing the domain technology tree, we also need to add these bibliographic items to the technology tree to form a complete patent dimension that comprehensively portrays each patent. The partial technology tree after adding bibliographic items is shown in Figure 7 [Figure 7: see original paper].

Figure 7 can comprehensively display both semantic information and temporal/geographic information of patents. For example, patent JP2015021723-A applies magnetic scientific effects to achieve scale inhibition while reaching the effect of improved safety, and also shows that it is a patent applied for in Japan with publication year 2015. Therefore, the technology tree with added bibliographic items displays more comprehensive information.

5.5 Identification and Evaluation of Potential R&D Partners

This study uses Company A as the requiring enterprise for the empirical research. The company' s partial requirement description for water heater anti-scale technology is shown in Table 4 .

Through the matching algorithm, combining the domain patent technology tree constructed in this empirical study with semantic features extracted from the enterprise requirement document, we achieved matching of requirement patents in the water heater anti-scale technology domain.

Table 4 shows partial content of the water heater anti-scale technology requirement document. Using the specific content of relevant items in the enterprise requirement document as source data, we extracted relevant semantic information. The technical field was directly located from the "domain" entry in the enterprise requirement document combined with tags. Therefore, the technical fields for this requirement document are water heater, personal health, and purification. Technical problems were identified by recognizing verb-object structures in the requirement document and selecting meaningful verb-object structures that represent functional requirements, such as scale formation, bacteria breeding, and self-processing. Technical means were identified primarily by recognizing nouns combined with a technical means corpus to identify limitations on technical means in the requirement document, such as ultrasound and magnetic methods. Technical effects were identified by recognizing adverbs modifying verb structures or identifying verb-object structures representing effects, such as convenient scale cleaning and rapid cleaning. In summary, semantic features from the enterprise requirement document are summarized in Table 5 .

First, we refined the patent set by matching technical problems extracted from the enterprise requirement document with function items in the domain patent technology tree to meet the requiring party' s basic functional needs. Technical problems described in the requirement document, such as reducing scale formation, cleaning scale, and bacteria breeding, were matched with patent functions, screening 1,219 relevant patents capable of solving corresponding technical problems. We then further refined the relevant patent set by matching technical effects extracted from the requirement document, such as convenience, performance, speed, and cost, with functional effect items in the domain patent technology tree. Among patents that could solve the above technical problems, 932 patents also achieved corresponding technical effects. Analysis of scientific effects applied in these 932 relevant patents still included all 11 extracted scientific effects.

By analyzing the eight evolution laws proposed in TRIZ and combining them with scientific effects extracted from the water heater anti-scale technology domain, we selected appropriate evolution laws as the basis for screening advanced technology patents. This example selected the seventh evolution law, namely the law of evolution toward micro-level and field application. According to the requirements of this evolution law and combining the temporal distribution of patents applying various scientific effects in the water heater anti-scale technology domain, we selected scientific effects such as Magnetic field, Ultrasound, Electric field, and Control temperature as advanced technologies. Patents applying these scientific effects were regarded as advanced patents, comprising 612 relevant patents. Patentees of this patent set were considered potential R&D partners.

According to the evaluation index system for enterprise potential R&D partners, we scored each main patentee on various indicators to obtain total scores for each patentee. Panasonic' s scores for each indicator are shown in Table 6 .

Based on calculations of each indicator value in the potential R&D partner evaluation index system, we calculated indicator values for the top 5 patentees (potential R&D partners) by patent count, normalized the results as shown in Table 7 .

We summed the normalized indicator values for each potential R&D partner to calculate comprehensive evaluation values, then ranked potential R&D partners according to these comprehensive evaluation values, with results shown in Table 8 .

In summary, this paper extracts semantic features such as functions, scientific effects, and functional effects from patents in specific technology domains to construct domain patent technology trees. For enterprise specific requirements, we extract key information including technical fields, technical problems, technical means, and technical effects. By matching scientific effects to TRIZ evolution laws, we position advanced scientific effects and combine them with technical problems and effects described in requirements to precisely locate relevant patents of advanced technologies, thereby identifying potential cooperation partners. Furthermore, we design evaluation indicators from three aspects—potential R&D partners' technical strength, R&D openness, and collaborative R&D effects—to construct a patent-based enterprise potential R&D partner evaluation index system for assessing R&D partners.

However, this paper also has aspects requiring improvement. During semantic feature extraction, due to the considerable flexibility and diverse expression forms of the Chinese language, the accuracy of extraction patterns needs further improvement. Future research could define more accurate patterns based on in-depth analysis of large Chinese document corpora to enhance the accuracy of key information extraction.

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Zhai Dongsheng, Guo Cheng, Zhang Jie: Designed research scheme;
Guo Cheng, Xia Jun: Processed data, implemented recommendation method, completed experiments, drafted the paper.

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