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# AN INTEGRATED MULTI-SOURCE INFORMATION FUSION APPROACH FOR ENTERPRISE USER PORTRAIT CONSTRUCTION IN TECHNOLOGICAL DEMAND IDENTIFICATION

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**Abstract:** In the context of the innovation-driven development paradigm, the accurate identification of enterprise technological demands has become a core theoretical and practical issue in the field of technology transfer. Traditional demand identification paradigms are constrained by single-dimensional text analysis, leading to the lack of a systematic understanding of technological demands. To address this gap, this study proposes an integrated multi-source information fusion approach for enterprise user portrait construction oriented to technological demand identification. This approach systematically clarifies the connotation of enterprise technological demand portraits, defines the multi-dimensional information sources of portrait construction based on methodological logic, establishes a feature extraction system based on the dual dimensions of explicit and potential demands, and explores the mechanism of technological demand reconstruction through multi-source information fusion. This study enriches the methodological system of user portrait and technological demand identification, and provides technical guidance for breaking the information asymmetry in technology transfer.
**Keywords:** Technological demand; Enterprise user portrait; Multi-source information fusion approach; Demand identification; Feature extraction

## 1 INTRODUCTION

### 1.1 Research Background

With the in-depth advancement of the innovation-driven development strategy, enterprises, as the main body of technological innovation, their technological demands have become the core link connecting technological supply and industrial application[1]. However, the current technology transfer field is plagued by information asymmetry, which essentially stems from the lack of a systematic and in-depth methodological support for technological demand identification[2]. Traditional demand identification paradigms rely excessively on explicit text expression, ignoring the potential demand connotation contained in multi-dimensional information, and failing to form a holistic and in-depth understanding of enterprise technological demands[3].

The fundamental limitation of traditional paradigms lies in the one-sidedness of information sources and the shallowness of demand mining[4]. From the methodological perspective, technological demand is a multi-dimensional concept integrating explicit expression, potential implication and constraint conditions, which cannot be fully captured by a single information source[5]. Multi-source information, including explicit demand expression, behavioral implication and attribute constraints, has inherent complementary and verifiable characteristics, which provides a methodological possibility for breaking through the limitations of traditional paradigms[6]. Therefore, developing an integrated multi-source information fusion approach for enterprise user portrait construction oriented to technological demand identification has become an important technical path to solve the problem of information asymmetry in technology transfer.

### 1.2 Research Significance

The theoretical significance of this study lies in three aspects: first, it clarifies the connotation and multi-dimensional structure of enterprise technological demand portraits, which helps to enrich the methodological system of user portrait research in the specific field of technology transfer; second, it proposes an integrated multi-source information fusion approach for demand identification, breaking through the methodological limitations of single-dimensional text-driven demand identification, and providing a new technical perspective for in-depth demand mining; third, it explores the mechanism of technological demand reconstruction based on multi-source information fusion, which helps to clarify the logical relationship between multi-source information integration and accurate demand identification, and lay a methodological foundation for the improvement of technology transfer practice.

From the perspective of practical application, this study provides systematic technical guidance for the practice of enterprise technological demand identification. The proposed integrated approach can help technology transfer institutions establish a scientific demand cognition system, avoid the one-sidedness of demand understanding caused by single information sources; at the same time, it can guide enterprises to clarify their own technological demand connotation, and promote the accurate matching between technological supply and demand at the operational level, which has important guiding significance for optimizing the efficiency of technology transfer.

### 1.3 Research Framework

This study follows the methodological research logic of "concept definition - problem analysis - approach development - mechanism exploration". Firstly, it clarifies the core connotation and boundary of enterprise technological demand portraits; secondly, it analyzes the methodological limitations of traditional demand identification paradigms and the necessity of multi-source information integration; thirdly, it develops the overall integrated multi-source information fusion approach for portrait construction, including information source dimension definition, feature extraction system and demand reconstruction mechanism; finally, it discusses the theoretical contribution and application extension of the approach. The full text focuses on methodological derivation and logical construction, forming a complete technical research chain.

## 2 CONNOTATION AND RESEARCH OBJECTIVES

### 2.1 Connotation of Enterprise Technological Demand Portraits

Enterprise technological demand portrait, in the methodological sense, refers to a systematic and structured abstraction of enterprise technological demand connotation, which is constructed through the integration and induction of multi-source information. Its core characteristics are as follows: first, systematicness, which integrates the multi-dimensional connotation of technological demand, including explicit demand, potential demand and constraint conditions, and avoids one-sided understanding of demand; second, operability, which provides clear technical indicators for demand identification rather than abstract theoretical description; third, guiding nature, which provides technical guidance for the identification and matching of technological demands, and is the core bridge connecting technological supply and demand.

From the theoretical structure, enterprise technological demand portrait is composed of three core dimensions: core demand dimension, potential demand dimension and constraint dimension. The core demand dimension reflects the explicit technological needs of enterprises, which is the direct embodiment of enterprise technology upgrading and development needs; the potential demand dimension reflects the implicit technological needs contained in enterprise behavior and development strategy, which has the characteristics of concealment and derivation; the constraint dimension reflects the objective conditions that restrict the satisfaction of technological demands, which is an important basis for the feasibility of technological demand matching.

### 2.2 Research Objectives

The core objective of this study is to develop a systematic and operable integrated multi-source information fusion approach for enterprise user portrait construction oriented to technological demand identification. The specific objectives include: first, clarifying the connotation, boundary and structural system of enterprise technological demand portraits, laying a solid foundation for subsequent methodological development; second, defining the multi-source information source system for portrait construction based on methodological logic, clarifying the basis and scope of each information dimension; third, establishing a feature extraction system based on the dual dimensions of explicit and potential demands, specifying the technical path and logical process of feature extraction; fourth, exploring the mechanism of technological demand reconstruction based on multi-source information fusion, and clarifying the logical relationship between multi-source information integration and accurate demand identification.

## 3 THEORETICAL BASIS AND LITERATURE REVIEW

### 3.1 Theoretical Basis

#### *3.1.1 User portrait theory*

User portrait theory is the core theoretical basis of this study. It originated from the field of marketing, and its core idea is to abstract the characteristics of users through the integration of multi-dimensional information, so as to realize the accurate understanding of users. In the field of technology transfer, the application of user portrait theory needs to be combined with the characteristics of technological demand[7]. Different from the consumer demand in the marketing field, enterprise technological demand has the characteristics of professionalism, complexity and long-term, which requires the portrait construction to focus on the professional connotation of technology and the strategic development needs of enterprises[8]. The application of this theory in this study focuses on the extension of user portrait theory to the specific field of technological demand, and develops a portrait system that conforms to the characteristics of enterprise technological demand and has strong operability.

#### *3.1.2 Multi-source information fusion theory*

Multi-source information fusion theory provides the core methodological support for this study. The core idea of this theory is to integrate information from different sources through specific technical methods to realize the complementary advantages of information and improve the accuracy and comprehensiveness of information understanding[9]. In the process of enterprise technological demand portrait construction, multi-source information has the characteristics of heterogeneity and complementarity. Multi-source information fusion theory provides a methodological basis for solving the problems of information redundancy and conflict in the integration process, and is the key technical support for realizing in-depth demand mining[10].

#### *3.1.3 Technological demand identification theory*

Technological demand identification theory clarifies the core connotation and identification logic of technological demand. This theory holds that technological demand is the product of the interaction between enterprise development strategy and external environment, and its identification needs to take into account both explicit demand expression and implicit demand implication[11]. The theoretical basis of this study focuses on the integration of technological demand identification theory and multi-source information fusion theory, and develops a portrait-based demand identification approach, which helps to improve the systematicness and accuracy of demand identification.

### 3.2 Literature Review

Existing research on enterprise technological demand identification mainly focuses on two directions: single-dimensional text analysis and multi-source data-driven analysis. In the field of single-dimensional text analysis, scholars have carried out a lot of research on demand extraction based on text mining technology, and developed a variety of text-driven demand identification methods. However, these studies are limited by the one-sidedness of information sources, and it is difficult to fully capture the potential connotation of technological demand[12].

In the field of multi-source data-driven analysis, some scholars have begun to explore the integration of multi-dimensional data to identify technological demands, and initially developed a multi-source data integration framework. However, existing research still has obvious methodological limitations: first, the connotation and structural system of technological demand portraits are not clearly defined, and the methodological basis of portrait construction is insufficient; second, the selection of multi-source information sources lacks systematic methodological guidance, and the logical relationship between information sources and demand dimensions is not clear; third, the mechanism of multi-source information fusion and demand reconstruction is not deeply explored, and the technical logic of demand identification is not complete[13].

In the field of user portrait research, existing studies are mostly concentrated in the field of marketing and e-commerce, and there are few studies on user portrait construction in the specific field of technology transfer. The existing related research lacks the integration with technological demand characteristics, and cannot meet the methodological needs of enterprise technological demand identification. Therefore, there is an urgent need to develop a systematic integrated multi-source information fusion approach for enterprise user portrait construction oriented to technological demand identification, which is also the core methodological gap that this study aims to fill[14].

## 4 INTEGRATED MULTI-SOURCE INFORMATION FUSION APPROACH FOR ENTERPRISE USER PORTRAIT CONSTRUCTION

### 4.1 Overall Architecture of the Integrated Approach

Based on the theoretical basis of user portrait theory, multi-source information fusion theory and technological demand identification theory, this study develops an overall architecture of the integrated multi-source information fusion approach for enterprise user portrait construction, which is composed of four core modules: multi-source information source definition, demand feature extraction, multi-source information fusion and technological demand reconstruction. The logical relationship between each module is as follows: multi-source information source definition is the foundation of the approach, which clarifies the scope and connotation of information required for portrait construction; demand feature extraction is the core module of the approach, which abstracts demand features from multi-source information through specific technical methods; multi-source information fusion is the key technical means to realize in-depth demand understanding, which integrates multi-dimensional feature information to avoid information redundancy and conflict; technological demand reconstruction is the ultimate goal of the approach, which forms a systematic and structured demand understanding through the integration of multi-dimensional features.

The core technical logic of the approach is: taking the accurate identification of enterprise technological demand as the core goal, taking multi-source information integration as the technical means, through the systematic extraction and fusion of multi-dimensional information features, to realize the structured abstraction of enterprise technological demand, and construct a systematic and operable user portrait, so as to provide technical support for breaking the information asymmetry in technology transfer.

### 4.2 Definition of Multi-source Information Source Dimension

Based on the connotation of enterprise technological demand and the operational requirements of portrait construction, this study divides the multi-source information sources of enterprise user portrait construction into four core dimensions from a methodological perspective: explicit demand expression information, behavioral implication information, attribute constraint information and strategic guidance information. Each dimension has its unique connotation and demand reflection function, and provides targeted data support for the subsequent feature extraction module.

#### *4.2.1 Explicit demand expression information*

Explicit demand expression information refers to the direct expression of enterprise technological demand, which is the most direct data basis for understanding explicit demand. From the methodological perspective, this type of information reflects the core technological needs of enterprises for technology upgrading and development, and its core connotation includes the direction of technological demand, the core technical problems to be solved, and the expected goals of technology application. The technical significance of this dimension lies in providing a direct data basis for the extraction of core demand features.

***4.2.2 Behavioral implication information***

Behavioral implication information refers to the implicit information related to technological demand contained in enterprise behavior. From the methodological perspective, enterprise behavior is the external manifestation of its internal demand, and the behavioral information related to technology has inherent implication for potential technological demand. The core connotation of this dimension includes the attention behavior to technological information, the search behavior for technical solutions, and the interactive behavior with technology suppliers. The technical significance of this dimension lies in supplementing the limitations of explicit demand expression and providing a data basis for the extraction of potential demand features.

***4.2.3 Attribute constraint information***

Attribute constraint information refers to the objective attribute information of enterprises that restricts the satisfaction of technological demand. From the methodological perspective, the satisfaction of technological demand cannot be separated from the objective conditions of enterprises. Attribute constraint information determines the feasibility of technological demand matching. Its core connotation includes enterprise industry attributes, resource capacity attributes, and operation status attributes. The technical significance of this dimension lies in providing a data basis for the extraction of demand constraint features and ensuring the feasibility of demand identification.

***4.2.4 Strategic guidance information***

Strategic guidance information refers to the information related to technological development strategy contained in enterprise development planning. From the methodological perspective, enterprise technological demand is closely related to its long-term development strategy, and strategic guidance information can reflect the long-term and directional characteristics of technological demand. Its core connotation includes enterprise R&D planning, industrial upgrading strategy, and market expansion strategy. The technical significance of this dimension lies in improving the depth and long-term of demand understanding, and providing a data basis for the extraction of long-term demand features.

### 4.3 Construction of Demand Feature Extraction Module

Based on the multi-source information source dimension and the structural system of enterprise technological demand portraits, this study constructs a demand feature extraction module based on the dual dimensions of explicit and potential demands, which includes three core feature categories: core demand features, potential demand features and constraint features. The extraction of each category of features follows the technical logic of "information dimension - feature connotation - extraction method".

***4.3.1 Extraction of core demand features***

Core demand features are extracted based on explicit demand expression information and strategic guidance information, reflecting the explicit and directional connotation of enterprise technological demand. From the methodological perspective, the extraction of core demand features follows the technical path of "demand expression abstraction - strategic alignment - feature definition", with detailed technical details as follows:

First, in the stage of demand expression abstraction, a two-step text preprocessing process is adopted for explicit demand expression information (such as technical demand declarations and R&D planning texts). First, noise reduction is implemented through stop-word removal (using domain-specific stop-word lists, e.g., common functional words in technical documents) and part-of-speech filtering (retaining nouns, verbs, and adjectives related to technical concepts). Then, keyword extraction is performed using the TF-IDF algorithm combined with domain thesaurus weighting—specifically, the weight of terms included in the industry technological thesaurus is increased by 1.5 times to enhance the recognition accuracy of professional technical terms. The top 30 terms with the highest composite weights are selected as preliminary demand feature candidates.

Second, in the strategic alignment stage, a semantic similarity matching model based on BERT is constructed to align the preliminary feature candidates with the enterprise's strategic guidance information. The model is pre-trained on a large-scale corpus of enterprise technological strategy texts, and fine-tuned using domain-specific data to optimize the semantic representation of technical concepts. The alignment threshold is set to 0.7 (based on cosine similarity), and only candidates with similarity scores exceeding the threshold are retained to ensure that the extracted core demand features are consistent with the enterprise's long-term development strategy.

Finally, in the feature definition stage, semantic clustering is implemented using the K-means algorithm to eliminate redundant features. The number of clusters K is determined by the elbow method, and each cluster is labeled with a core technical concept (e.g., "intelligent manufacturing equipment" "green energy-saving technology") to form structured core demand features, including technological field features (clustered core concepts), technical goal features (derived from semantic analysis of demand goals, e.g., "efficiency improvement" "cost reduction"), and development stage matching features (aligned with strategic planning cycles, e.g., "short-term R&D" "long-term industrialization").

***4.3.2 Extraction of potential demand features***

Potential demand features are extracted based on behavioral implication information and strategic guidance information, reflecting the implicit and derivative connotation of enterprise technological demand. The technical path of "behavioral implication analysis - demand derivation - feature abstraction" is refined with specific technical details as follows:

In the behavioral implication analysis stage, behavioral sequence analysis is implemented using the Hidden Markov Model (HMM). Enterprise behavioral data (browsing, search, interaction) is converted into a sequence of behavioral states (e.g., "browsing technical achievements" "searching for technical solutions" "consulting experts"), and the transition probability between states is calculated. States with transition probabilities exceeding 0.6 are identified as high-correlation behavioral chains, which are considered to reflect potential demand tendencies. For example, the chain "searching for photovoltaic technology - browsing photovoltaic module test cases - consulting photovoltaic energy storage experts" indicates a potential demand for photovoltaic energy storage technology.

In the demand derivation stage, a preference inference model based on collaborative filtering is constructed. The model takes the high-correlation behavioral chains as input, and infers the enterprise's preference intensity for different technical directions by comparing the behavioral similarity with benchmark enterprises (with clear technological demand orientations). The preference intensity is quantified using a 5-point scale, where scores ≥4 indicate high-potential demand directions. Meanwhile, combined with strategic guidance information, the long-term derivation of potential demands is realized—for example, if the enterprise's strategic planning emphasizes "carbon neutrality", the potential demand for photovoltaic technology is further derived as "low-cost photovoltaic energy storage integration technology".

In the feature abstraction stage, the inferred potential demand directions are encoded into structured features using one-hot encoding combined with weight assignment. The weight of each potential demand feature is determined by the product of behavioral chain correlation coefficient and strategic alignment score, forming features such as technological attention preference features (e.g., "photovoltaic energy storage: weight 0.85"), demand derivative features (e.g., "low-cost integration: weight 0.72"), and long-term development potential demand features (e.g., "carbon-neutral oriented photovoltaic technology: weight 0.91").

#### *4.3.3 Extraction of constraint features*

Constraint features are extracted based on attribute constraint information, reflecting the objective constraint conditions of enterprise technological demand satisfaction. The technical path of "attribute analysis - constraint identification - feature definition" is supplemented with detailed technical operations as follows:

In the attribute analysis stage, attribute dimension reduction is implemented using the Principal Component Analysis (PCA) algorithm to eliminate redundant attribute information. The input attributes include enterprise industry category, registered capital, R&D investment ratio, number of R&D personnel, qualification certification level, etc. The PCA algorithm retains the principal components with cumulative variance contribution rate ≥85%, which are identified as core attribute dimensions affecting technological demand satisfaction.

In the constraint identification stage, a fuzzy clustering-based constraint classification method is adopted. The core attribute dimensions are clustered using the FCM (Fuzzy C-Means) algorithm, and each cluster is labeled with a constraint type based on domain knowledge. For example, clusters with low R&D investment ratio (≤3%) and few R&D personnel (≤10) are labeled as "resource capacity constraints"; clusters in traditional industries with no high-tech certification are labeled as "industry attribute constraints".

In the feature definition stage, feature coding is performed for each constraint type. For quantitative constraint indicators (e.g., R&D investment ratio), a 3-level coding is adopted (low: 0, medium: 1, high: 2) based on industry average values; for qualitative constraint indicators (e.g., qualification certification), binary coding is adopted (yes: 1, no: 0). Finally, structured constraint features are formed, including resource capacity constraint features (e.g., "R&D investment: low (0)"), industry attribute constraint features (e.g., "traditional industry (1)"), and operation status constraint features (e.g., "stable operation (1)"). These features provide an important technical basis for the feasibility judgment of subsequent technological demand matching.

### 4.4 Multi-source Information Fusion and Technological Demand Reconstruction Mechanism

Multi-source information fusion and technological demand reconstruction are the core technical links to realize the accurate identification of enterprise technological demand. This study develops a multi-source information fusion mechanism based on "layered fusion - semantic alignment - conflict resolution", and realizes the reconstruction of enterprise technological demand through this mechanism.

#### *4.4.1 Layered fusion mechanism*

Layered fusion mechanism refers to the step-by-step fusion of multi-source information according to the level of information abstraction, which includes three core layers with detailed technical implementation details:

First, information level fusion (data preprocessing layer). This layer adopts a unified data standardization method for multi-source original information: for text-type information (explicit demand expression, strategic guidance), it is converted into a 768-dimensional vector using the BERT pre-trained model; for behavioral sequence information, it is converted into a state transition matrix (dimension: number of behavioral types × number of behavioral types); for attribute constraint information, it is normalized to [0,1] using the min-max scaling method. After standardization, the multi-source information is integrated into a unified data pool, and duplicate data is removed using the SimHash algorithm (similarity threshold: 0.95) to complete preliminary data cleaning.

Second, feature level fusion (core fusion layer). This layer adopts a weighted feature concatenation method to integrate core demand features, potential demand features, and constraint features. The weight of each feature type is determined by the information gain ratio: core demand features (information gain ratio ≥0.6) are assigned a weight of 0.5, potential demand features (information gain ratio 0.3-0.6) are assigned a weight of 0.3, and constraint features (information gain ratio ≥0.4) are assigned a weight of 0.2. The weighted features are concatenated to form a multi-dimensional feature vector (dimension: sum of dimensions of each feature type), and the L2 normalization is performed to eliminate the influence of feature scale differences.

Third, decision level fusion (result integration layer). This layer adopts the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) multi-criteria decision-making method. The ideal solution and negative ideal solution are constructed based on the multi-dimensional feature vector, and the Euclidean distance between each feature vector and the ideal/negative ideal solution is calculated. The relative closeness degree of each feature vector to the ideal solution is used as the demand confidence score (range: [0,1]). Feature vectors with confidence scores ≥0.7 are selected to form a valid demand feature set, which provides a basis for subsequent technological demand reconstruction.

#### *4.4.2 Semantic alignment mechanism*

Semantic alignment mechanism is the key to solving the heterogeneity of multi-source information, with the following detailed technical logic:

First, a domain-specific semantic framework for technological demand is constructed. The framework includes three core semantic dictionaries: technical concept dictionary (collecting 5000+ professional technical terms in the field of technology transfer), demand type dictionary (classifying demands into "product upgrading", "process optimization", "core technology breakthrough", etc.), and constraint condition dictionary (defining 20+ common constraint terms). Each term in the dictionary is assigned a unique semantic ID and hierarchical category (e.g., "photovoltaic energy storage" belongs to "new energy technology" category, semantic ID: T00123).

Second, semantic mapping of multi-source information is implemented. For text-type information, semantic annotation is performed using the CRF (Conditional Random Field) model trained on domain corpus, mapping text terms to the semantic framework; for behavioral information, semantic inference is performed based on the correlation between behavioral states and technical concepts (e.g., "browsing photovoltaic module test cases" is mapped to "photovoltaic energy storage" (T00123)); for attribute information, semantic matching is performed based on the constraint condition dictionary.

Finally, semantic consistency verification is carried out. The cosine similarity between the semantic vectors of different source information is calculated (semantic vectors are derived from the semantic framework). If the similarity is <0.6, the semantic annotation is corrected by referring to the domain thesaurus; if the similarity is <0.4 after correction, the information is marked as "to be verified" and excluded from the current fusion process. Through semantic alignment, the redundancy and ambiguity of multi-source information are eliminated, and the accuracy of information fusion is improved.

#### *4.4.3 Conflict resolution mechanism*

Conflict resolution mechanism is used to solve the information conflict existing in multi-source information fusion, with detailed technical implementation as follows:

First, an information credibility evaluation index system is established, including three first-level indicators: source reliability (weight 0.4), logical consistency (weight 0.3), and timeliness (weight 0.3). Source reliability is graded according to the information source type (explicit demand declaration: 0.9, strategic planning: 0.8, platform behavior: 0.7, attribute information: 0.85); logical consistency is evaluated by the semantic similarity between conflicting information and other related information (similarity ≥0.7: 0.9, 0.5-0.7: 0.6, <0.5: 0.3); timeliness is scored based on the information update time (within 6 months: 0.9, 6-12 months: 0.6, more than 12 months: 0.3).

Second, the credibility score of conflicting information is calculated using the weighted sum method. For two conflicting pieces of information, if the credibility score difference is ≥0.2, the information with the higher score is retained; if the score difference is <0.2, a logical reasoning verification is performed using the domain rule base (e.g., "short-term R&D demand" is logically consistent with "small-budget investment", inconsistent with "large-scale industrialization investment").

Finally, if the conflict cannot be resolved through the above steps, the conflicting information is recorded in the "conflict information repository", and the demand reconstruction result is marked with "uncertainty" to remind subsequent users to verify through manual intervention. This mechanism ensures that the fused information is accurate and logically consistent.

#### *4.4.4 Technological demand reconstruction logic*

Based on the above multi-source information fusion mechanism, the technical logic of technological demand reconstruction is as follows: first, through layered fusion, the multi-dimensional information is integrated into a systematic feature set; then, through semantic alignment, the consistency of feature semantic connotation is ensured; finally, through conflict resolution, the accuracy of feature information is ensured. On this basis, the systematic integration of core demand features, potential demand features and constraint features is carried out to form a structured and systematic abstraction of enterprise technological demand, that is, the enterprise user portrait oriented to technological demand identification. This portrait realizes the comprehensive and in-depth understanding of enterprise technological demand, and provides a technical basis for the accurate matching of technological supply and demand.

## 5 CONTRIBUTION AND APPLICATION PROSPECT

### 5.1 Methodological Contribution

This study has three core methodological contributions: first, it enriches the application of user portrait theory in the specific field of technology transfer. By clarifying the connotation and structural system of enterprise technological demand portraits with operability, it realizes the extension of user portrait theory to the professional field of technology, and expands the methodological boundary of user portrait research.
Second, it develops an integrated multi-source information fusion approach for demand identification, breaking through the methodological limitations of traditional single-dimensional text-driven demand identification. The approach clarifies the technical basis and logical path of multi-source information integration, and enriches the methodological system of technological demand identification.
Third, it explores the multi-source information fusion and technological demand reconstruction mechanism, clarifying the logical relationship between multi-source information and demand identification. The constructed layered fusion, semantic alignment and conflict resolution mechanisms provide a systematic technical method for multi-source information integration in the field of technological demand identification, and improve the methodological depth of demand identification research.

### 5.2 Practical Application Prospect

From the perspective of practical application, the approach developed in this study has important guiding significance for the practice of technology transfer. First, it can guide technology transfer institutions to establish a scientific demand identification system, avoid the one-sidedness of demand understanding caused by single information sources, and improve the accuracy of technological supply and demand matching.
Second, it can provide technical guidance for enterprises to clarify their own technological demand connotation. By guiding enterprises to systematically sort out multi-dimensional information related to technological demand, they can realize the in-depth understanding of their own demand, which is conducive to improving the efficiency of enterprise technology introduction and R&D.
Third, it can provide a methodological basis for the construction of technology transfer information platforms. The multi-source information source dimension and feature extraction module defined in the approach can guide the design of information collection and processing modules of the platform, and promote the intelligent and efficient development of technology transfer platforms.

### 5.3 Research Limitations and Future Research Directions

This study is a methodological exploration, and there are certain limitations: first, the integrated approach developed needs to be further verified in practice. Although the approach is based on solid theoretical basis and logical derivation, its practical applicability needs to be tested in specific technology transfer scenarios.
Second, the research on the dynamic adjustment mechanism of portraits is insufficient. Enterprise technological demand is dynamic with the change of internal and external environment, and the current approach does not fully consider the dynamic characteristics of demand. Future research can focus on the following directions: first, carry out empirical research based on the integrated approach, verify and optimize the approach through practical data; second, explore the dynamic adjustment mechanism of enterprise technological demand portraits, and develop a dynamic approach that adapts to the changes of enterprise demand; third, expand the application scope of the approach, and explore its application in different types of enterprises and different technology fields.

## 6 CONCLUSION

This study develops an integrated multi-source information fusion approach for enterprise user portrait construction oriented to technological demand identification. The study clarifies the connotation and structural system of enterprise technological demand portraits, defines the multi-source information source dimension of portrait construction, constructs a demand feature extraction module based on the dual dimensions of explicit and potential demands, and explores the multi-source information fusion and technological demand reconstruction mechanism. The research breaks through the methodological limitations of traditional single-dimensional text-driven demand identification, enriches the methodological system of user portrait and technological demand identification, and provides technical support for breaking the information asymmetry in technology transfer.
The core conclusion of this study is that the accurate identification of enterprise technological demand can only be realized through the systematic integration of multi-source information. The multi-source information source dimension, demand feature extraction module and information fusion mechanism developed in the integrated approach form a complete technical logic chain, which provides systematic technical guidance for the practice of enterprise technological demand identification. Future research should focus on the empirical verification and dynamic optimization of the approach, so as to further improve the theoretical and practical value of the research.

## COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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