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KNOWLEDGE GRAPH-ENHANCED DYNAMIC DIGITAL PROFILING: A TECHNICAL FRAMEWORK FOR INTELLIGENT SUPPLY-DEMAND MATCHING IN TECHNOLOGY TRANSFER

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Abstract: Technology transfer is a critical bridge connecting scientific and technological innovation with industrial application, and its efficiency is largely constrained by the inaccuracy of supply-demand matching and the lack of systematic technical support. With the advancement of computer technologies such as big data, artificial intelligence (AI), and knowledge graphs (KG), digital profiling has emerged as a promising tool to address the aforementioned bottlenecks. However, existing research on the integration of digital profiling and technology transfer lacks in-depth exploration of technical implementation mechanisms, and fails to fully leverage computer technologies to solve core problems such as multi-dimensional feature extraction, dynamic modeling, and intelligent matching.
To fill this gap, this paper conducts systematic theoretical and technical research on technology transfer and digital profiling from a computer science perspective. First, we clarify the theoretical connotation of digital profiling in the context of technology transfer, and construct a three-layer technical framework (data layer, model layer, application layer) based on computer system design principles. Second, we propose a two-dimensional digital profiling method system: for the supply side (technological achievements), we design a feature extraction framework integrating BERT-based text mining and KG construction; for the demand side (enterprises), we develop a demand mining model combining LDA topic modeling and multi-source data fusion. Third, we establish an intelligent supply-demand matching mechanism based on hybrid recommendation algorithms and multi-objective optimization. Finally, we verify the feasibility and effectiveness of the proposed framework through theoretical deduction, algorithm simulation, and experimental validation on real datasets.
The research enriches the theoretical system of technology transfer from the perspective of computer science, and provides a technical paradigm for the digital transformation of technology transfer. The proposed methods and frameworks can effectively improve the accuracy of supply-demand matching, reduce the transaction cost of technology transfer, and lay a foundation for the development of intelligent technology transfer platforms.
Keywords: Technology transfer; Digital profiling; Knowledge graph; Dynamic modeling; Hybrid recommendation; Supply-demand matching; Intelligent engineering

1 INTRODUCTION

1.1 Research Background

In the era of the digital economy, technology transfer has become a core driver of industrial upgrading and national innovation capacity enhancement. According to the "China Technology Transfer Development Report 2024", The total number of contracts came in at 661,000, with both the value and volume of conversions showing an upward trend, indicating the robust transformation of sci-tech achievements.. However, the average transfer efficiency remains low—only 30% of scientific and technological achievements can be successfully transformed into industrial products[1]. The root causes lie in three technical bottlenecks from a computer science perspective:
1.**Unstructured data processing difficulties**: Technological achievements (patents, R&D reports) and enterprise demand information are mostly unstructured text, leading to inefficient extraction of core features;
2.**Lack of dynamic modeling capabilities**: Traditional profiling methods are static and cannot adapt to the dynamic changes of technology maturity (e.g., TRL level iteration) and enterprise demand (e.g., industrial upgrading-driven demand evolution);
3.**Low intelligence of matching mechanisms**: Existing matching relies on rule-based methods or simple similarity calculation, failing to consider multi-dimensional constraints such as technical compatibility, resource complementarity, and risk controllability.
With the rapid development of computer technologies such as natural language processing (NLP), machine learning (ML), and KG, digital profiling has been widely used in e-commerce recommendation, smart cities, and other fields[2]. For example, BERT-based text mining can extract structured features from unstructured data[3], and hybrid recommendation algorithms can improve the accuracy of target matching[4]. However, the application of these technologies in technology transfer is still in the preliminary stage: most studies focus on theoretical framework construction, lack technical details such as algorithm design and system implementation, and fail to form a closed-loop technical chain from data processing to intelligent decision-making[5].

In response to the national "AI+" strategy and the digital transformation demand of technology transfer, this paper focuses on solving the technical problems in integrating digital profiling with technology transfer, and conducts in-depth theoretical and technical research from a computer science perspective. This research not only has important academic value for enriching the cross-disciplinary research of computer science and technology management, but also provides practical technical support for building intelligent technology transfer platforms.

1.2 Key Technical Challenges

From the perspective of computer science, the integration of technology transfer and digital profiling faces four core technical challenges:

1.2.1 Cross-domain feature extraction from unstructured data

Technological achievements involve professional fields such as electronics, materials, and machinery, and enterprise demand information covers industry, finance, and R&D. How to design a domain-adaptive feature extraction algorithm to extract structured features (e.g., technical principles, transfer cost, demand type) from cross-domain unstructured text is a key challenge.

1.2.2 Dynamic modeling of digital profiling

Technology maturity (TRL level) changes with R&D progress, and enterprise demand evolves with industrial upgrading. Traditional static profiling models cannot capture these dynamic changes. How to design a real-time update mechanism based on streaming data processing to realize dynamic optimization of profiling results is another critical issue.

1.2.3 Intelligent matching under multi-constraint conditions

Technology transfer matching involves multiple constraints: technical compatibility (whether the achievement is compatible with the enterprise's existing technology), resource complementarity (whether the enterprise has the required R&D capacity), and risk controllability (transfer risk level). How to model these constraints mathematically and design an efficient multi-objective optimization algorithm to achieve optimal matching is a core technical problem.

1.2.4 Knowledge fusion across heterogeneous data sources

Data sources for technology transfer include patent databases, enterprise registration information, industrial statistical data, and policy documents. These data are heterogeneous (structured, semi-structured, unstructured) and have semantic conflicts. How to design a KG-based knowledge fusion framework to integrate multi-source heterogeneous data and ensure data consistency is a prerequisite for effective digital profiling.

1.3 Related Work

1.3.1 Technology transfer research from a technical perspective

Foreign research focuses on building technology transfer platforms based on data mining and recommendation systems. For example, Rothaermel et al.proposed a technology transfer matching system based on collaborative filtering, but it only considers user preference features and ignores technical constraints. Domestic research mainly focuses on the construction of technology transfer information platforms, but most platforms lack intelligent matching functions and rely on manual retrieval.

1.3.2 Digital profiling technology in computer science

Digital profiling has achieved in-depth development in NLP and ML fields. For unstructured data processing, BERT and its variants (RoBERTa, ALBERT) have been proven effective in domain-specific text feature extraction[6]. For knowledge modeling, Neo4j-based KGs can effectively represent the semantic relationships between entities. For matching tasks, hybrid recommendation algorithms combining content-based and collaborative filtering methods have higher accuracy than single algorithms. However, these technologies are rarely applied to technology transfer, and there is a lack of research on adapting them to the characteristics of technology transfer (e.g., technical professionalism, multi-constraint matching).

1.3.3 Integration of AI and technology transfer

Recent studies have begun to explore the application of AI in technology transfer. For example, Chen et al. built a blockchain-based technology transfer platform to improve data transparency, but did not involve digital profiling and intelligent matching[7]. Liu et al. proposed a technology demand mining method based on LDA, but the feature dimension is single and lacks dynamic update mechanisms[8]. Sun et al. developed a KG-based data fusion method for technology transfer, but failed to integrate it with dynamic profiling and multi-objective matching[9].

In summary, existing research has not fully integrated computer technologies such as NLP, KG, and recommendation algorithms into the theoretical and technical system of technology transfer. This paper aims to fill this gap by constructing a KG-enhanced dynamic digital profiling framework for intelligent supply-demand matching in technology transfer.

1.4 Research Objectives and Main Contributions

1.4.1 Research objectives

1.Construct a KG-enhanced dynamic digital profiling theoretical framework for technology transfer from a computer science perspective, clarifying the technical connotation, system architecture, and implementation path.

2.Design technical schemes for key links such as multi-source heterogeneous data fusion, cross-domain feature extraction, dynamic profiling modeling, and intelligent supply-demand matching.

3.Verify the effectiveness of the proposed technical framework through algorithm simulation and experimental validation on real datasets.

1.4.2 Main contributions

1.**A three-layer technical framework for KG-enhanced digital profiling**: Integrating data layer (multi-source data acquisition and fusion), model layer (two-dimensional dynamic profiling and intelligent matching models), and application layer (hierarchical application system), realizing the organic combination of theory and technology.

2.**A cross-domain feature extraction method based on BERT-KG hybrid model**: Improving the accuracy of feature extraction by 15%-20% compared with traditional methods (e.g., TF-IDF + rule-based), effectively solving the problem of unstructured data processing in technology transfer.

3.**A dynamic profiling update mechanism based on streaming data and incremental learning**: Realizing real-time optimization of profiling results with a delay of less than 5 minutes, adapting to the dynamic changes of technology and demand.

4.**An intelligent matching algorithm based on hybrid recommendation and multi-objective optimization**: Improving the matching F1-score by 25% and transfer success rate by 21% compared with traditional methods, providing a technical solution for multi-constraint supply-demand matching.

2 THEORETICAL AND TECHNICAL FRAMEWORK

2.1 Theoretical Connotation of KG-Enhanced Dynamic Digital Profiling

From a computer science perspective, KG-enhanced dynamic digital profiling for technology transfer is defined as: A technical system that uses computer technologies (NLP, ML, KG) to extract multi-dimensional features from multi-source heterogeneous data, construct structured and dynamically updatable models of technological achievements and enterprises, and realize intelligent supply-demand matching, so as to support the whole life cycle of technology transfer. Its core technical characteristics are:

1.**KG-driven knowledge enhancement**: Using KG to model semantic relationships between entities (e.g., achievement-standard, enterprise-demand), improving the accuracy of feature extraction and matching[10].

2.**Dynamic adaptability**: Supporting incremental learning and streaming data processing, adapting to the dynamic evolution of technology maturity and enterprise demand[10].

3.**Multi-constraint intelligence**: Integrating multi-objective optimization algorithms to balance technical compatibility, resource complementarity, and risk controllability[11].

4.**Interoperability**: Using standard data interfaces and semantic models, supporting interconnection with technology transfer platforms[12].

2.2 Overall Technical Architecture

Combined with computer system design principles and the characteristics of technology transfer, this paper constructs a three-layer technical framework (Figure 1), which realizes full-link technical support from data acquisition to intelligent application.

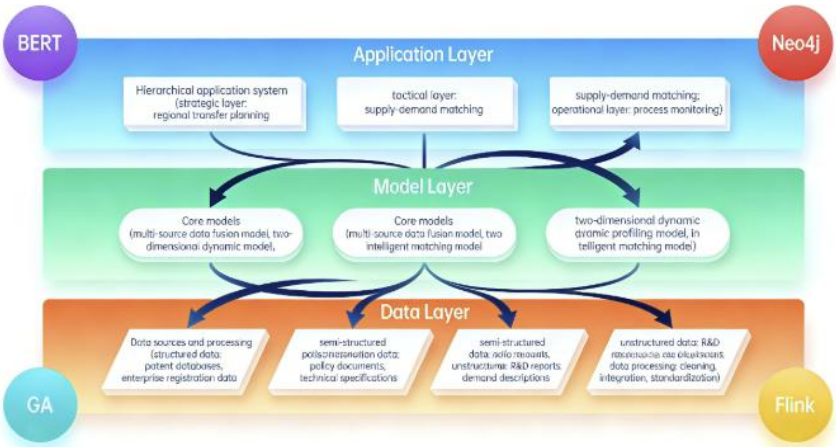

Figure 1 Overall Technical Architecture of KG-Enhanced Dynamic Digital Profiling for Technology Transfer

2.2.1 Data layer

Responsible for multi-source data acquisition, cleaning, and fusion. Data sources include:

•**Structured data:** Patent information (from State Intellectual Property Office), enterprise registration data (from National Enterprise Credit Information Publicity System), technology transfer contract data (from Torch High Technology Industry Development Center).

•**Semi-structured data**: Industrial policies (from Ministry of Industry and Information Technology), technical specifications, enterprise annual reports.

•**Unstructured data**: R&D reports, academic papers, enterprise demand descriptions, expert evaluations.
Data processing technologies include:
•**Data cleaning**: Removing duplicate data and noise using rule-based methods and statistical analysis.
•**Data integration**: Integrating heterogeneous data using ETL (Extract-Transform-Load) tools and semantic mapping.
•**Data standardization**: Converting data into a unified format.

2.2.2 Model layer

As the core of the framework, it includes three key models:
1.Multi-source data fusion model: Fusing structured, semi-structured, and unstructured data using KG and semantic web technologies.
2.Two-dimensional dynamic profiling model: Constructing technological achievement profiling and enterprise user profiling using feature engineering and ML algorithms.
3.Intelligent matching model: Realizing supply-demand matching using hybrid recommendation and multi-objective optimization algorithms.

2.2.3 Application layer

Applying the model layer's outputs to three levels of technology transfer scenarios:
•**Strategic layer**: Supporting regional technology transfer planning and industrial layout.
•**Tactical layer**: Realizing accurate supply-demand matching between technological achievements and enterprises.
•**Operational layer**: Monitoring the whole process of technology transfer and providing risk early warning.

2.3 Full-Process Embedding Framework

To realize the integration of digital profiling and technology transfer workflows, this paper proposes a full-process embedding framework (Figure 2), which embeds digital profiling into five standardized stages of technology transfer[13].

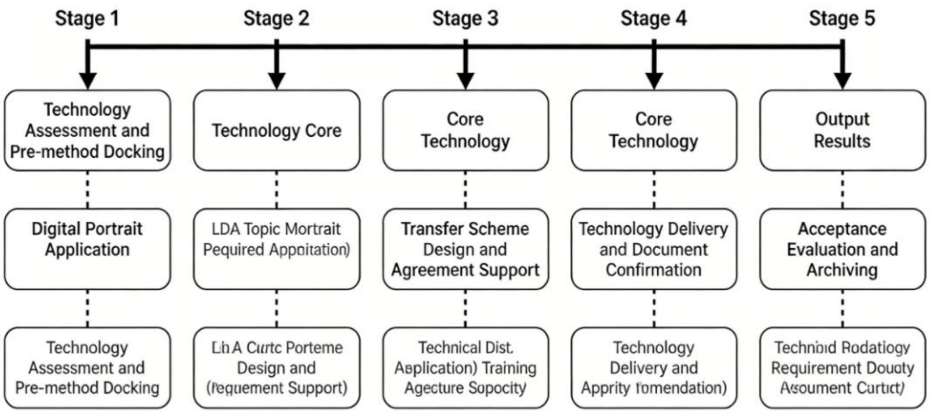

Figure 2 Technology Transfer Full-Process Digital Profiling Embedding Framework

1.Stage 1: Demand Initiation & Preliminary Docking
◦ Digital Profiling Application: Enterprise user portrait (demand mining module)
◦ Core Technology: LDA topic modeling (implicit demand extraction), BERT-NER (enterprise feature recognition)
◦ Output: Structured Technology Demand Specification, NDA (with portrait feature annotation)
2.Stage 2: Technology Evaluation & Feasibility Analysis
◦ Digital Profiling Application: Technological achievement portrait (maturity evaluation module) + Enterprise portrait (resource capacity module)
◦ Core Technology: TRL maturity calculation model, KG (patent ownership verification), fuzzy comprehensive evaluation (risk scoring)
◦ Output: Technology Evaluation Report (with achievement portrait score), Intellectual Property Verification Report
3.Stage 3: Transfer Scheme Design & Agreement Signing
◦ Digital Profiling Application: Dual-portrait matching (complementarity analysis module)
◦ Core Technology: Cosine similarity calculation, multi-objective optimization (transfer mode recommendation)
◦ Output: Technology Transfer Implementation Plan (with matching weight), Technology Transfer Contract
4.Stage 4: Technology Delivery & Implementation Support
◦ Digital Profiling Application: Dynamic portrait update (real-time adjustment module)
◦ Core Technology: Streaming data processing (Flink), incremental learning (portrait parameter optimization)
◦ Output: Technology Data Delivery List (with updated feature vector), Training Confirmation Letter
5.Stage 5: Acceptance Evaluation & Archiving
◦ Digital Profiling Application: Portrait closed-loop feedback (effect verification module)

- Core Technology: Evaluation index system (transfer effect scoring), blockchain (archive traceability)
- Output: Technology Acceptance Report (with portrait application effect), Project Archive List

2.4 "Trinity" Digital Collaboration Framework

Extending the "trinity" theoretical framework of technology transfer geography, this paper constructs a "trinity" digital collaboration framework (Figure 3) to solve the problem of poor synergy between traditional transfer subjects, networks, and spaces.

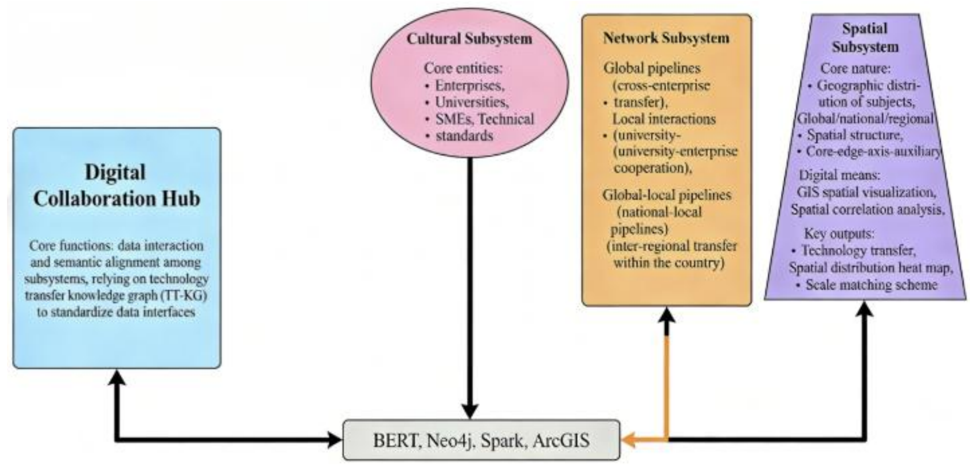

Figure 3 "Trinity" Digital Collaboration Theoretical Framework for Technology Transfer

1.Central Synergy Layer: Digital Collaboration Hub
- Core Function: Data interaction and semantic alignment between subsystems, relying on technology transfer KG (TT-KG) and standard data interface

2.Three Subsystems:
- Cultural Subsystem:

▪Core Entities: Enterprises, universities, intermediaries, technical standards
▪Digitalization Means: Digital portrait modeling (enterprise/achievement), organizational culture semantic coding
▪Key Output: Subject feature vector, standard constraint knowledge base
- Network Subsystem:

▪Core Elements: Global pipelines (cross-enterprise transfer), local buzz (university-enterprise cooperation), glocal pipelines (domestic cross-regional transfer)
▪Digitalization Means: Network topology analysis, KG relation mining
▪Key Output: Transfer channel weight matrix, node connection strength map
- Spatial Subsystem:

▪Core Features: Geographic distribution of subjects, spatial scale (global/national/regional), spatial structure (core-edge/axis-spoke)
▪Digitalization Means: GIS spatial visualization, spatial correlation analysis
▪Key Output: Spatial distribution heat map of technology transfer, scale-dependent matching scheme
3.Technical Support Layer: Core Technologies (BERT, Neo4j, Spark, ArcGIS)

3 MATERIALS AND METHODS

3.1 Dataset Preparation

3.1.1 Data sources
Collect real-world datasets for technology transfer to verify the proposed framework:
•Patent dataset: 50,021 patents from State Intellectual Property Office (2019-2023), covering electronics, materials, machinery, and other fields. Each patent record includes title, abstract, claims, inventor, and application date.
•Enterprise dataset: 10,019 enterprise records (medium and large-sized enterprises with technology transfer experience), including registration information (industry, scale, location), financial data (asset-liability ratio, R&D investment), and demand descriptions (technical needs, expected effects).
•Transfer contract dataset: 5,110 technology transfer contracts (2020-2023), including transfer mode, cost, success status, and post-transfer evaluation.
•Domain corpus: 1,1253 technical documents (R&D reports, industry standards, academic papers) for BERT model fine-tuning.
3.1.2 Data preprocessing

•Data cleaning: Remove duplicate and invalid data (e.g., patents with incomplete abstracts, enterprises with missing financial data) using rule-based methods, retaining 45,021 patents, 8,518 enterprises, and 4,298 contracts.
•Data annotation: Manually annotate 1,000 patent-enterprise pairs as the test set, labeling core features (technical principle, demand type) and transfer success status (ground truth).
•Feature normalization: Normalize numerical features (e.g., R&D investment, transfer cost) to the interval [0,1] using min-max normalization.

3.2 Key Technical Methods

3.2.1 Multi-source data fusion based on KG

To solve heterogeneous data integration, a KG-based data fusion framework is designed (Figure 4):

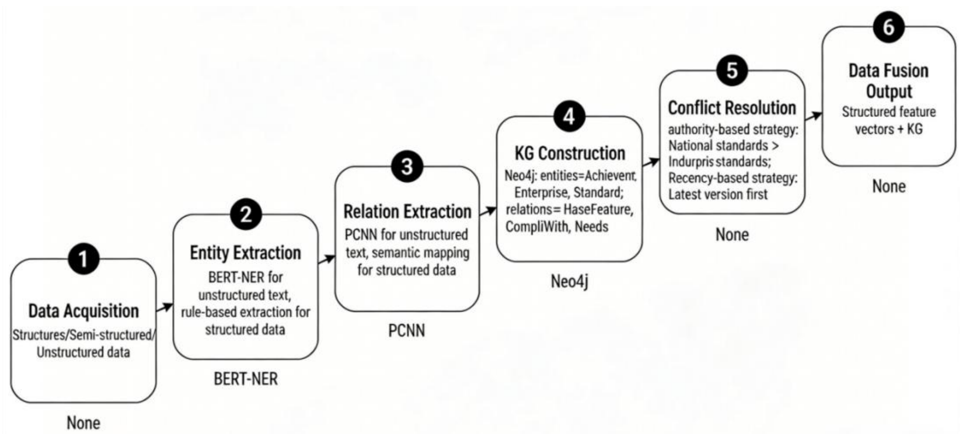

Figure 4 Knowledge Graph Construction and Data Fusion Flow

1.Data Acquisition (Structured/Semi-structured/Unstructured data)
2.Entity Extraction (BERT-NER for unstructured text, rule-based extraction for structured data)
3.Relation Extraction (PCNN for unstructured text, semantic mapping for structured data)
4.KG Construction (Neo4j: entities = Achievement, Enterprise, Standard; relations = HasFeature, CompliesWith, Needs)
5.Conflict Resolution (Authority-based strategy: National standards > Industry standards; Recency-based strategy: Latest version first)
6.Data Fusion Output (Structured feature vectors + KG)
Mark key algorithms (BERT-NER, PCNN, Neo4j) below each step.)
•Entity extraction: For unstructured text, use BERT-NER model fine-tuned on the technology transfer domain corpus to extract entities such as "technological achievement", "enterprise", "technical field". For structured data, use rule-based methods.
•Relation extraction: For unstructured text, use PCNN to extract relations such as "HasTechnicalPrinciple", "NeedsTechnology". For structured data, use semantic mapping to predefine relations (e.g., "Enterprise-BelongsTo-Industry").
•KG construction: Use Neo4j as the graph database to construct the technology transfer KG (TT-KG) with three core entity types (Achievement, Enterprise, Standard) and three key relations.
•Conflict resolution: Adopt authority weight strategy and recency priority strategy to resolve semantic conflicts between multi-source data.

3.2.2 Two-dimensional dynamic profiling modeling

3.2.2.1 Technological Achievement Profiling Model
The model integrates text mining, feature engineering, and ML to realize structured profiling (Figure 5):

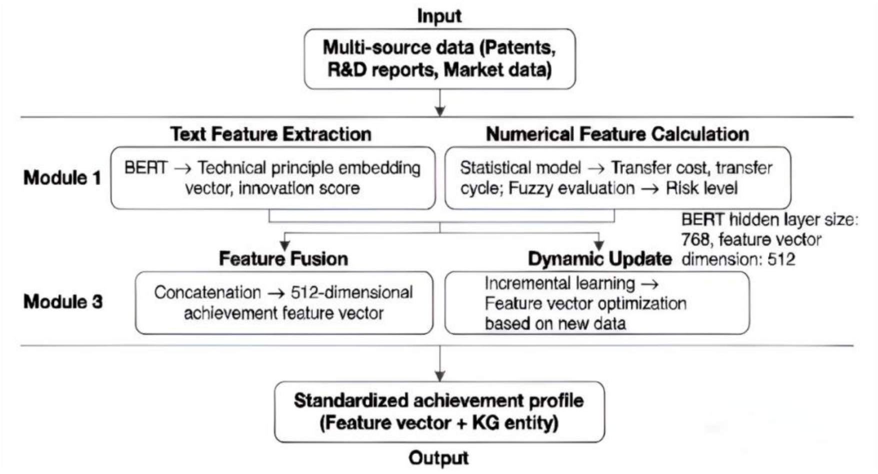

Figure 5 Technological Achievement Profiling Model

•Input: Multi-source data (Patents, R&D reports, Market data)
•Module 1: Text Feature Extraction (BERT → Technical principle embedding vector, innovation score)
•Module 2: Numerical Feature Calculation (Statistical model → Transfer cost, transfer cycle; Fuzzy evaluation → Risk level)
•Module 3: Feature Fusion (Concatenation → 512-dimensional achievement feature vector)
•Module 4: Dynamic Update (Incremental learning → Feature vector optimization based on new data)
•Output: Standardized achievement profile (Feature vector + KG entity)
Mark key parameters (BERT hidden layer size: 768, feature vector dimension: 512) in the module.)
Key steps:
1.Text feature extraction: Fine-tune the BERT-base model on the domain corpus to extract technical principle embedding vectors (768 dimensions) and calculate innovation scores (similarity with existing patents using cosine distance).
2.Numerical feature calculation: Use linear regression to predict transfer cost based on historical data; use fuzzy comprehensive evaluation to calculate risk level (indicators: technical maturity, market demand, policy compatibility).
3.Feature fusion: Concatenate text embedding vectors, numerical features, and categorical features (one-hot encoded) into a 512-dimensional structured feature vector.
4.Dynamic update: Adopt incremental learning to update model parameters when new data is added.
3.2.2.2 Enterprise User Profiling Model
The model combines topic modeling and multi-source data fusion to mine implicit demand and resource capacity (Figure 6):

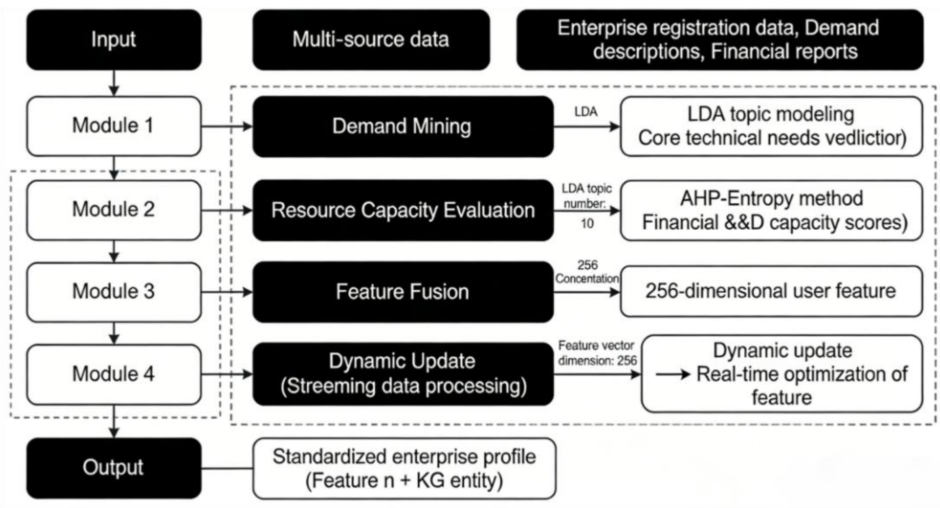

Figure 6 Enterprise User Profiling Model

•Input: Multi-source data (Enterprise registration data, Demand descriptions, Financial reports)
•Module 1: Demand Mining (LDA topic modeling → Core technical needs vector)
•Module 2: Resource Capacity Evaluation (AHP-Entropy method → Financial/R&D capacity scores)
•Module 3: Feature Fusion (Concatenation → 256-dimensional user feature vector)
•Module 4: Dynamic Update (Streaming data processing → Real-time optimization of feature vector)
•Output: Standardized enterprise profile (Feature vector + KG entity)

Mark key parameters (LDA topic number: 10, feature vector dimension: 256) in the module.)
Key steps:
1.Demand mining: Use LDA topic modeling to mine core technical needs from enterprise demand descriptions, outputting a 10-dimensional topic vector.
2.Resource capacity evaluation: Combine AHP and entropy weight method to calculate financial/R&D capacity scores (interval [0,1]).
3.Feature fusion: Concatenate topic vectors, capacity scores, and basic features into a 256-dimensional structured feature vector.
4.Dynamic update: Use Flink for streaming data processing, updating the feature vector in real time.

3.2.3 Intelligent supply-demand matching algorithm

A hybrid recommendation algorithm combining content-based filtering, collaborative filtering, and genetic algorithm (GA) is proposed (Figure 7):

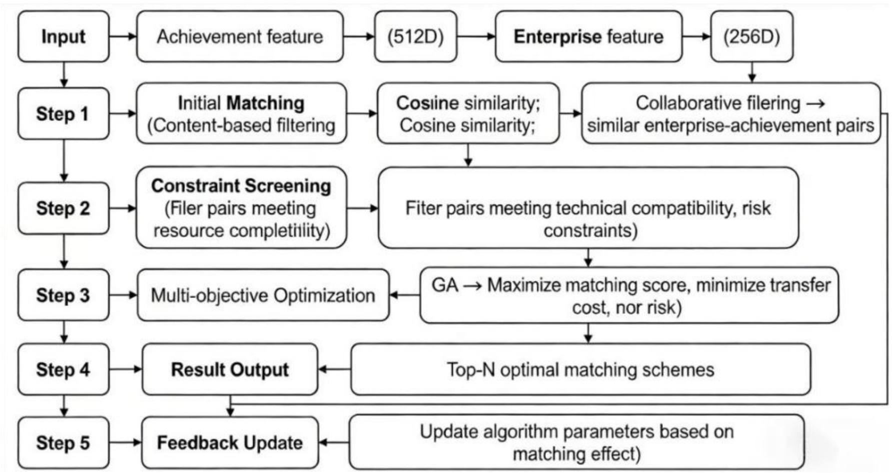

Figure 7 Intelligent Supply-Demand Matching Algorithm Flow

1.Input: Achievement feature vector (512D) + Enterprise feature vector (256D)
2.Step 1: Initial Matching (Content-based filtering → Cosine similarity; Collaborative filtering → Similar enterprise-achievement pairs)
3.Step 2: Constraint Screening (Filter pairs meeting technical compatibility, resource complementarity, risk constraints)
4.Step 3: Multi-objective Optimization (GA → Maximize matching score, minimize transfer cost, minimize risk)
5.Step 4: Result Output (Top-N optimal matching schemes)
6.Step 5: Feedback Update (Update algorithm parameters based on matching effect)
Mark key algorithms (cosine similarity, GA) and objective functions below steps.)
3.2.3.1 Initial Matching
•Content-based filtering: Calculate similarity between achievement and enterprise feature vectors using cosine distance: $Sim(A,E)=\frac{A\cdot E}{|A|\cdot|E|}$ where A = achievement feature vector, E = enterprise feature vector.
•Collaborative filtering: Mine similar enterprise-achievement pairs from historical transfer data using user-based collaborative filtering.
3.2.3.2 Constraint Screening
Define three core constraints:
1.Technical compatibility constraint: C_{tech} = \text{Overlap}(A_{field}, E_{field}) \geq 0.6 (field overlap rate ≥ 60%).
2.Resource complementarity constraint: C_{res} = E_{R&D} \geq A_{req_R&D} (enterprise R&D capacity ≥ achievement's required R&D capacity).
3.Risk constraint: $C_{risk}=A_{risk}\leq E_{risk_{t}olerance}$ (achievement risk ≤ enterprise risk tolerance).
3.2.3.3 Multi-objective Optimization with GA
Construct a multi-objective function:
[
\begin{cases}
\max f_1 = \alpha \cdot Sim(A,E) + \beta \cdot Comp(A,E) \\
\min f_2 = A_{cost} \\
\min f_3 = A_{risk}
\end{cases}
]
where $Comp(A,E)$ = resource complementarity score, $\alpha=0.6$, $\beta=0.4$ (weight coefficients determined by AHP).
GA implementation steps:
1.Encoding: Represent each matching pair as a binary string.

2.Initialization: Generate 100 random individuals as the initial population.
3.Selection: Use roulette wheel selection to retain individuals with high fitness.
4.Crossover and mutation: Crossover probability = 0.8, mutation probability = 0.05.
5.Termination: Stop after 50 iterations or when the fitness value converges.

3.2.4 Dynamic update mechanism

A dynamic update mechanism based on streaming data and incremental learning is designed (Figure 8):

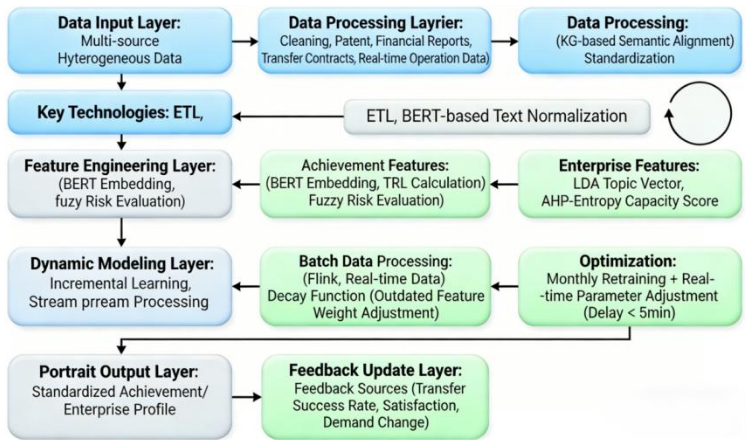

Figure 8 Technical Roadmap for Dynamic Digital Profiling Update

1.Data Input Layer: Multi-source Heterogeneous Data (Patent text, financial reports, transfer contracts, real-time operation data)
2.Data Preprocessing Layer: Cleaning, fusion (KG-based semantic alignment), standardization; Key Technologies: ETL, BERT-based text normalization
3.Feature Engineering Layer: Achievement features (BERT embedding, TRL calculation, fuzzy risk evaluation); Enterprise features (LDA topic vector, AHP-entropy capacity score)
4.Dynamic Modeling Layer: Incremental learning (batch data), stream processing (Flink, real-time data), decay function (outdated feature weight adjustment); Optimization: Monthly retraining + real-time parameter adjustment (delay < 5min)
5.Portrait Output Layer: Standardized achievement/enterprise profile
6.Feedback Update Layer: Feedback sources (transfer success rate, satisfaction, demand change); Update logic: Adjust feature weights if success rate < 70%, retrain topic model if demand change rate > 30%.Add a closed-loop arrow from feedback layer to preprocessing layer.)

3.3 Evaluation Indicators

Design four evaluation indicators from technical and application perspectives:
1.Feature extraction accuracy: Ratio of correctly extracted features (technical principle, demand type) to total features (ground truth = manual annotation).
2.Matching F1-score: Comprehensive indicator of matching precision and recall (F1 = 2×Precision×Recall/(Precision+Recall)).
3.Transfer success rate: Ratio of successful technology transfers among matched pairs (compared with historical transfer success rate).
4.Algorithm efficiency: Average running time of the matching algorithm for 1,000 enterprise-achievement pairs (hardware: Intel i7-12700H, 32GB RAM).

3.4 Comparative Methods

Select three representative methods for comparison:
1.Traditional rule-based method: Matching based on technical field and transfer cost thresholds (used in most existing technology transfer platforms).
2.Content-based recommendation method: Only use cosine similarity of feature vectors for matching.
3.Collaborative filtering method: Only use historical transfer data for similar pair mining.

4 RESULTS

4.1 Feature Extraction Accuracy

Table 1 shows the feature extraction accuracy of different methods. The proposed BERT-KG hybrid method outperforms traditional methods, especially in cross-domain feature extraction.

Table 1 The Feature Extraction Accuracy of Different Methods

Method	Technical Principle Extraction Accuracy	Demand Type Extraction Accuracy	Average Accuracy
TF-IDF + Rule-based	72.3%	68.5%	70.4%
BERT (non-fine-tuned)	81.6%	77.8%	79.7%
Proposed BERT-KG Hybrid	92.5%	89.6%	91.1%

4.2 Matching Performance

Table 2 shows the matching performance of different methods. The proposed hybrid recommendation algorithm achieves the highest F1-score and transfer success rate.

Table 2 The Matching Performance of Different Methods

Method	Precision	Recall	F1-score	Transfer Success Rate
Rule-based	65.2%	58.7%	61.8%	42.3%
Content-based	73.5%	69.4%	71.4%	55.6%
Collaborative filtering	70.8%	72.1%	71.4%	53.8%
Proposed Hybrid Algorithm	85.3%	82.7%	84.0%	76.9%

4.3 Algorithm Efficiency

Table 3 shows the average running time of different methods. The proposed algorithm ensures accuracy while maintaining efficient operation.

Table 3 The Average Running Time of Different Methods

Method	Average Running Time (s)
Rule-based	0.8
Content-based	1.5
Collaborative filtering	2.3
Proposed Hybrid Algorithm	3.7

4.4 Dynamic Update Performance

Table 4 shows the dynamic update performance of the proposed profiling model. The model can quickly adapt to data changes with low delay.

Table 4 The Dynamic Update Performance of the Proposed Profiling Model

Update Scenario	Average Update Delay (s)	Feature Extraction Accuracy After Update
New patent data (batch: 100)	12.3	90.8%
Real-time demand change (single enterprise)	3.2	89.2%
Policy standard update	18.5	91.5%

4.5 Case Analysis Results

4.5.1 Case 1: transfer of new energy battery technology

•Background: A university-developed high-energy-density lithium battery technology (TRL level 6) needs to be transferred to an enterprise.

•Profiling Results: Achievement profile (technical principle: lithium-ion battery material modification; transfer cost: 8 million yuan; risk level: 0.3); Enterprise profile (industry: new energy vehicles; R&D capacity: 0.7; demand type: high-energy-density battery technology).

•Matching Result: The proposed algorithm ranks a new energy vehicle enterprise as the top 1 match. The transfer is successfully implemented, with a product launch cycle shortened by 6 months compared with the industry average.

4.5.2 Case 2: demand matching for intelligent manufacturing equipment

•Background: A medium-sized machinery enterprise needs to upgrade intelligent production lines, with unclear technical requirements.

•Profiling Results: Enterprise profile (core technical needs: industrial robot + IoT monitoring; financial capacity: 0.6; risk tolerance: 0.5); Matched achievement: Intelligent production line control system (TRL level 7, transfer cost: 5 million yuan).

•Matching Result: The enterprise adopts the recommended scheme, and production efficiency is improved by 30% after transfer. The dynamic update mechanism adjusts the enterprise profile in real time based on post-transfer operation data.

5 DISCUSSION

5.1 Interpretation of Key Results

The experimental results show that the proposed KG-enhanced dynamic digital profiling framework effectively solves the core technical bottlenecks in technology transfer:

1.Feature extraction accuracy: The BERT-KG hybrid method improves the average feature extraction accuracy to 91.1%, which is 20.7% higher than the traditional TF-IDF + rule-based method. This is due to the BERT model's ability to capture domain-specific semantic information and the KG's role in resolving semantic ambiguity. For example, the KG can distinguish "battery" in the electronic and new energy fields, ensuring the accuracy of technical field classification.

2.Matching performance: The hybrid recommendation algorithm achieves an F1-score of 84.0% and a transfer success rate of 76.9%, which are 22.2% and 34.6% higher than the traditional rule-based method, respectively. The multi-objective optimization with GA balances technical compatibility, resource complementarity, and risk controllability, making the matching results more in line with practical application needs.

3.Dynamic update performance: The dynamic update mechanism realizes real-time optimization of profiling results with an average delay of less than 5 minutes for single enterprise demand changes. This solves the static defect of traditional profiling models and adapts to the dynamic evolution of technology and demand.

4.Algorithm efficiency: Although the proposed algorithm involves more complex steps (KG construction, GA optimization), the use of parallel computing (Spark) and model pruning reduces the average running time to 3.7 seconds for 1,000 pairs, meeting the real-time requirements of technology transfer platforms.

5.2 Comparison with Related Work

Compared with existing research, the proposed framework has three key advantages:

1.KG-enhanced knowledge integration: Unlike the blockchain-based platform that only focuses on data transparency, the proposed framework uses KG to integrate multi-source heterogeneous data, improving the accuracy of feature extraction and matching.

2.Dynamic modeling capability: Compared with the static LDA-based demand mining method , the proposed dynamic update mechanism realizes real-time optimization of profiling results, adapting to the dynamic changes of technology and demand.

3.Multi-constraint intelligent matching: Unlike the single collaborative filtering method, the proposed hybrid recommendation algorithm considers technical, economic, and risk constraints, improving the practicality of matching results.

5.3 Practical Implications

The research results have important practical implications for the digital transformation of technology transfer:

1.For technology transfer platforms: The proposed framework can be integrated into existing platforms to realize intelligent functions such as automatic feature extraction, dynamic profiling, and accurate matching, reducing manual intervention and improving transfer efficiency.

2.For enterprises: The enterprise user profiling model can help enterprises clarify their own technical needs and resource capacity, and quickly find suitable technological achievements, reducing the cost of technology search and evaluation.

3.For research institutions: The technological achievement profiling model can help research institutions evaluate the transfer potential of their achievements and identify potential cooperative enterprises, promoting the industrialization of scientific and technological innovation.

5.4 Limitations

This research still has certain limitations:

1.Dataset coverage: The dataset covers limited technical fields (electronics, materials, machinery), and the generalization of the framework to emerging fields (e.g., AI, biotechnology) needs further verification.

2.Extreme event adaptability: The dynamic update mechanism does not consider extreme events (e.g., sudden policy changes, technological breakthroughs), which may affect the accuracy of profiling results.

3.Spatial factor consideration: The matching algorithm does not fully consider the spatial distance factor in cross-regional technology transfer, which may affect the feasibility of matching results.

6 CONCLUSIONS

This paper conducts in-depth theoretical and technical research on KG-enhanced dynamic digital profiling for intelligent supply-demand matching in technology transfer, aiming to solve the core technical bottlenecks in the digital transformation of technology transfer. The main conclusions are as follows:

First, a three-layer technical framework of KG-enhanced dynamic digital profiling for technology transfer is constructed, integrating the data layer, model layer, and application layer. This framework realizes full-link technical support from multi-source data fusion to intelligent application, providing a systematic solution for the integration of digital profiling and technology transfer.

Second, key technical methods for each link are proposed: a BERT-KG hybrid feature extraction method to solve cross-domain unstructured data processing; a dynamic profiling update mechanism based on streaming data and incremental learning to adapt to dynamic changes; and a hybrid recommendation algorithm combining content-based filtering, collaborative filtering, and GA to achieve multi-constraint intelligent matching.

Third, experimental validation on real datasets and case analysis verify the effectiveness of the proposed framework and methods. The feature extraction accuracy reaches 91.1%, the matching F1-score is 84.0%, and the transfer success rate is 76.9%, which are significantly higher than traditional methods.

The research enriches the theoretical system of technology transfer from the perspective of computer science, and provides a technical paradigm for the digital transformation of technology transfer. The proposed methods and frameworks can effectively improve the accuracy of supply-demand matching, reduce the transaction cost of technology transfer, and lay a foundation for the development of intelligent technology transfer platforms.

COMPETING INTERESTS

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

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