

Research on the Construction of Knowledge Graph for Textile Foreign Trade Negotiation and the Design and Practice of Personalized Recommendation System

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ABSTRACT Against the backdrop of the restructuring of the global textile trade pattern and the acceleration of digital transformation, textile foreign trade negotiations face multiple challenges arising from complex product specifications, evolving trade rules, and frequent cross-cultural communication. With the continuous development of intelligent information systems and electromagnetic-enabled digital communication technologies, traditional experience-driven negotiation models can no longer satisfy the demand for efficient and adaptive decision-making. Knowledge graphs, as a core technology for structured knowledge representation and intelligent reasoning, provide an effective approach for integrating multi-source heterogeneous information and supporting personalized decision-making in textile foreign trade negotiations. This study follows the technical framework of “knowledge graph construction–recommendation algorithm optimization–system development–practical verification” to investigate the construction of a knowledge graph and a personalized recommendation system for textile foreign trade negotiations. The proposed framework enhances semantic association analysis and user-oriented recommendation capability while providing a reference for intelligent information interaction and knowledge-driven decision support in data-intensive communication environments.

INDEX TERMS textile foreign trade negotiations, knowledge graph, personalized recommendation system, intelligent information systems, electromagnetic-enabled communication

I. INTRODUCTION

A. RESEARCH BACKGROUND

As a traditional advantageous industry and pillar industry of foreign trade in China, the textile industry will have a total export value of 338.95 billion US dollars for textiles and clothing in 2023, accounting for 38.2% of the global textile trade volume. As the core link of international trade, textile foreign trade negotiations directly affect the success rate of transactions, trade profits, and cooperation stability. It involves multiple repetitive and complex links such as product specification confirmation, price negotiation, trade term selection, payment method agreement, policy and regulation adaptation, cross-cultural communication, etc.

B. INNOVATION POINTS

The innovation of this article is mainly reflected in the following three aspects:

1. Construct a new “6 dimensions+full process” knowledge graph for textile foreign trade negotiations, achieving

structured integration of multi-dimensional knowledge such as products, trade, policies, and culture, covering 128000 entities and 356000 relationships, breaking through the limitations of existing research that focuses on a single dimension.

2. Propose a personalized recommendation algorithm driven by “knowledge association+user preference”, integrating collaborative filtering and knowledge graph embedding technology, introducing negotiation scenario features and user ability profiling to improve the accuracy and adaptability of recommendations.

3. Develop an intelligent system that integrates knowledge graph management, user profiling, personalized recommendations, and negotiation assistance, forming a complete technical path of “knowledge integration demand mining precise push decision support”, filling the gap in intelligent tools for textile foreign trade negotiations.

Relevant studies from 2019 to 2024 were retrieved through databases such as Web of Science and CNKI.

This study compares 28 core literatures from domestic and foreign sources in three dimensions:

1. Knowledge graph construction: Existing research mostly covers 3-4 dimensions, while this research has expanded to 6 core dimensions (products, trade, policies, markets, culture, strategies);

2. Recommendation algorithm design: Existing research rarely integrates negotiation scenarios and user ability characteristics, while this study introduces both to enhance recommendation adaptability;

3. System development: Existing systems mostly focus on knowledge queries and lack negotiation assistance functions, while this system integrates comprehensive functions such as negotiation plan generation and risk warning.

The comparative analysis clarifies the innovation and differentiation advantages of this research.

II. THEORETICAL AND TECHNICAL FOUNDATIONS

A. KNOWLEDGE SYSTEM FOR TEXTILE FOREIGN TRADE NEGOTIATION

The knowledge system of textile foreign trade negotiations is the foundation of knowledge graph construction and recommendation system design. Based on literature review, field research (visiting 20 textile foreign trade enterprises and 5 industry associations), and expert interviews (15 senior negotiation experts and industry scholars), the knowledge of textile foreign trade negotiations is divided into 6 core dimensions, and the core contents of each dimension are as follows:

Covering import and export country tariff policies, quota management, trade barriers (technical barriers, green barriers), environmental standards (REACH, OEKO-TEX, GOTS), intellectual property protection and other policy and regulatory content.

This includes market dynamics such as international market supply and demand conditions, price fluctuation trends, information on major competitors, raw material price trends, and exchange rate fluctuations. Involving negotiation etiquette, communication styles, values, taboo customs, etc. of different countries (regions), such as European and American countries emphasizing efficiency and contract terms, and Southeast Asian countries emphasizing interpersonal relationships and etiquette [1-4].

Including scenario based negotiation methods and techniques such as price negotiation strategy, concession strategy, dispute resolution strategy, new customer development strategy, and long-term cooperation maintenance strategy [5-7].

B. KNOWLEDGE GRAPH RELATED TECHNOLOGIES

1) Knowledge Graph Construction Techniques

The construction of knowledge graph mainly includes three core steps: knowledge extraction, knowledge fusion, and knowledge processing:

Knowledge extraction: Extracting entity, relationship, and attribute information from unstructured (literature,

cases), semi-structured (tables, web pages), and structured (database) data. Core technologies include Named Entity Recognition (NER), Relationship Extraction (RE), and Attribute Extraction (AE), with commonly used algorithms such as BERT and BiLSTM CRF [8];

Knowledge fusion: de duplication, alignment, and conflict resolution of extracted knowledge to achieve integration of knowledge from different sources. Common methods include entity alignment (based on string similarity and semantic similarity), attribute fusion, and relationship fusion;

Knowledge processing: including knowledge reasoning and knowledge storage, mining hidden relationships through logical reasoning (such as rule-based reasoning, ontology based reasoning), using graph databases (such as Neo4j, ArangoDB) for storage, supporting efficient graph queries and association analysis [9-10].

C. PERSONALIZED RECOMMENDATION RELATED TECHNOLOGIES

Common personalized recommendation algorithms include:

Collaborative Filtering (CF): Recommendation based on user behavior similarity or item similarity, divided into user collaborative filtering and item collaborative filtering. The advantage is that there is no need to rely on item content features, but the disadvantage is the existence of cold start problems [11];

Hybrid Recommendation: Integrating the advantages of multiple recommendation algorithms, such as collaborative filtering+content recommendation, collaborative filtering+knowledge graph recommendation, to improve recommendation accuracy and robustness [12-14];

III. CONSTRUCTION OF KNOWLEDGE GRAPH FOR TEXTILE FOREIGN TRADE NEGOTIATION

A. OBJECTIVES AND PRINCIPLES OF KNOWLEDGE GRAPH CONSTRUCTION

1) Building Objectives

Comprehensive goal: Covering the six core knowledge dimensions of textile foreign trade negotiations, achieving structured integration of knowledge throughout the entire process;

Accuracy goal: Ensure the accuracy and consistency of entity, relationship, and attribute information to meet the reliability requirements of negotiation decisions;

Practical objective: To support rapid retrieval, association queries, and inference of knowledge, and provide data support for personalized recommendations;

Scalability goal: Design a flexible knowledge system that supports dynamic updates and extensions of entities, relationships, and attributes.

2) Construction Principles

Ontology driven principle: Based on the knowledge system of textile foreign trade negotiations, construct an ontology model to standardize the definition of entities, relationships, and attributes;

Principle of authoritative data sources: Priority should be given to selecting authoritative data sources (such as the General Administration of Customs, WTO, industry association reports, and core journals) to ensure the reliability of knowledge;

Practicality priority principle: Focus on high-frequency knowledge and core needs in negotiation practice, and prioritize the construction of key entities and relationships;

Standardization principle: Adopt standardized knowledge representation formats and coding standards to ensure the reusability and interoperability of knowledge.

B. KNOWLEDGE GRAPH ONTOLOGY DESIGN

Ontology design is the core of knowledge graph construction, used to define the concepts, categories, relationships, and constraints of knowledge. Based on the knowledge system of textile foreign trade negotiations, a Protégé tool is used to construct an ontology model, which includes three parts: entity class, relationship class, and attribute class

1) Definition of Entity Classes

A total of 8 core entity classes are defined, each containing several subclasses. Some entity classes and subclasses are as follows:

Product: Subcategories include Fiber, Fabric, Garment, and Accessory;

Trade Rules: Subcategories include Trade Terms, Payment Methods, and Transport Modes;

Policy: Subcategories include Tariff Policy, Environmental Standards, and Trade Barrier;

Market: Subcategories include Regional Market, Customer Type, and Competitor;

Culture: Subcategories include Negotiation Etiquette and Communication Style;

Strategy: Subcategories include Pricing Strategy, Concession Strategy, and Dispute Resolution Strategy;

User class: subclasses include Enterprise User and Negotiator;

Scenario: Subclass includes New Customer Development, Renewal Negotiation, and Dispute Resolution[15,16].

2) Definition of Relationship Classes

Define 12 core relationships and describe semantic associations between entities, with some relationships as follows:

Product Specification: such as "Pure Cotton Fabric Weight: 180g/m²";

Trade term applicable scenario: such as "FOB sea freight scenario";

Policy Applicable Region: such as "REACH - EU Region";

Scenario Strategy: such as "New customer development - gradual concession strategy";

User Focus Market: such as "Enterprise A - European Market";

Product Environmental Standard: such as the "Organic Cotton Clothing GOTS Standard" [17-19].

3) Definition of Attribute Classes

Each entity class contains several attributes that describe the characteristic information of the entity. Some attributes are as follows:

Product entity attributes: product code, material, specifications, purpose, quality standards;

Trade term attributes: applicable transportation mode, risk classification point, and cost bearing party;

Policy attributes: implementation time, validity period, applicable product scope, penalty rules;

Negotiator attributes: level, years of experience, expertise in the market, negotiation style.

C. KNOWLEDGE EXTRACTION AND FUSION

1) Data Source

The data sources for this study include:

Structured data: Textile product database (national standard GB/T 29862-2013), customs tariff database, Incoterms 2020 official document;

Semi structured data: industry reports (annual report of China Chamber of Commerce for Import and Export of Textiles), negotiation manuals for enterprises, and product detail pages for trade platforms;

Unstructured data: Literature related to textile foreign trade negotiations (CNKI, Web of Science), negotiation case collections, expert interview records (transcribed text).

2) Three-Level Quality Control Process for Expert Interview Data

Expert screening: When selecting 15 experts, ensure that they cover "frontline negotiation experts (8), industry scholars (4), and foreign trade policy researchers (3)" to avoid cognitive bias of experts with a single background;

Interview standards: Adopt standardized interview outlines to avoid guiding questions, record the entire interview process and transcribe it independently by two people to ensure data authenticity;

Coordination of opinions: Organize specialized seminars to reach consensus on divergent viewpoints among experts (such as the applicable scenarios of certain negotiation strategies). For viewpoints that cannot reach consensus, mark them as "controversial points" and supplement multiple sources of data to support them.

3) Implementation of Knowledge Extraction

Using a combination of "rule extraction+machine learning extraction" method, knowledge extraction is completed step by step:

1. Entity extraction: Directly extract entities from structured data through SQL queries; Extract semi-structured data using XPath and regular expressions; For unstructured data, named entity recognition is performed based on the BERT-NER model, and the dictionary and training data are optimized for the textile foreign trade field. The accuracy of entity recognition reaches 89.6%;

2. Relationship extraction: For structured data, extract relationships based on inter table associations in the database; For unstructured data, the BiLSTM ATT model is used for relationship extraction, combined with domain rules (such as “applicable”, “suitable”, “used” and other relationship trigger words) to improve the extraction effect, and the accuracy of relationship extraction reaches 85.3%;

3. Attribute extraction: Extract entity attributes from product manuals and standard documents, using rule-based methods (such as “attribute name: attribute value” format matching) combined with machine learning methods. The accuracy of attribute extraction reaches 90.1% [20].

4) Knowledge Fusion

Adopting a multi-step fusion strategy to achieve knowledge integration and optimization:

1. Entity alignment: Based on string similarity (edit distance, Jaccard similarity) and semantic similarity (BERT vector cosine similarity), duplicate entities (such as “pure cotton fabric” and “100% cotton fabric”) are aligned with an accuracy rate of 92.8%;

2. Relationship fusion: Standardize different relationship descriptions (such as “applicable” and “adapted”) for the same entity pair, and unify them into ontology defined relationship types;

3. Conflict resolution: Prioritize conflict attributes (such as differences in the implementation time of the same policy) based on the authority of data sources (official documents>industry reports>cases) and data freshness, and retain the optimal data [21-22].

Multi-source cross validation: The construction of the knowledge graph adopts the principle of “authoritative data priority+multi-source cross validation”.

1. Structured authoritative data is prioritized for core knowledge (such as customs tariff databases and WTO official documents), and expert interview data is only used to supplement unstructured knowledge (such as negotiation experience and cultural customs);

2. For unstructured knowledge provided by experts, triple verification is conducted through “cross validation of enterprise manuals, industry report evidence, and historical case tracing”. For example, the “negotiation etiquette of a certain region” proposed by experts needs to match at least 2 enterprise manuals and 1 industry report, otherwise it will not be entered.

D. KNOWLEDGE PROCESSING AND STORAGE

1) Knowledge Reasoning

Using a combination of rule-based reasoning and ontology reasoning to uncover hidden knowledge:

Rule reasoning: Based on domain rules, a reasoning rule library is constructed, such as “If the enterprise mainly operates in the European market, it must comply with REACH regulations” and “If the negotiation scenario is for new customer development, a gradual concession strategy is recommended”. A total of 120 rules are designed;

Ontology reasoning: Based on the semantic constraints of OWL ontology language, infer the implicit relations between entities, such as inferring that “Product A complies with GOTS standards” and “GOTS standards are applicable to organic textiles”, and inferring that “Product A is an organic textile” [23-24].

2) Knowledge Storage

Adopting a hybrid storage architecture of “graph database+relational database”:

Graph database: Neo4j is selected to store entity, relationship, and attribute information, supporting efficient graph queries (such as shortest path queries and associated entity queries), and adapting to the association analysis requirements of knowledge graphs;

Relational database: MySQL is used to store structured data such as user behavior data and system configuration data, complementing the graph database [25].

E. CORE PARAMETERS AND VISUALIZATION OF KNOWLEDGE GRAPH

1) Core Parameters

The core parameters of the knowledge graph for textile foreign trade negotiations constructed in this study are as follows:

Number of entities: 128000, including 35000 product entities, 12000 trade rule entities, 21000 policy and regulation entities, 8000 market entities, 6000 cultural entities, 15000 strategy entities, 3000 user entities, 2000 scenario entities, and 26000 other entities;

Number of relationships: 356000, including 82000 product specification relationships, 31000 trade rule applicable scenario relationships, 45000 policy applicable region relationships, 38000 scenario strategy relationships, 9000 user market attention relationships, and 151000 other relationships;

Number of attributes: 583000, with an average of 4.5 attributes per entity;

Knowledge coverage: Covering the six core dimensions of textile foreign trade negotiations, with a high-frequency knowledge coverage rate of over 95%.

2) Visualization of Knowledge Graph

Implementing knowledge graph visualization based on Neo4j Bloom tool, supporting multi-dimensional graph queries and interactions:

Entity query: supports precise and fuzzy queries based on entity name, type, and attributes, such as querying applicable products and regions for the OEKO-TEX standard;

Relationship query: supports querying direct and indirect relationships between entities, such as querying trade terms, policies, regulations, and negotiation strategies related to “pure cotton clothing exports to Europe”;

Association analysis: supports graph based association mining, such as mining core knowledge association networks in the “new customer development” scenario [26-29].

IV. USER PROFILE CONSTRUCTION AND PERSONALIZED RECOMMENDATION ALGORITHM DESIGN

A. CONSTRUCTION OF USER PROFILE FOR TEXTILE FOREIGN TRADE NEGOTIATION

1) User Profile Dimension Design

Based on the particularity of textile foreign trade negotiation scenarios, construct a four-dimensional user portrait model of “static attributes+dynamic behavior+scenario features+preference features”:

Static attributes: enterprise attributes (enterprise type: production-oriented/trade-related, product category: fabric/clothing/home textiles, export region: Europe/America/Southeast Asia), negotiator attributes (level: novice/intermediate/senior, years of experience, professional background);

Dynamic behavior: knowledge query records (query keywords, query frequency), content click behavior (click duration, bookmark operation), negotiation case usage records (view count, application scenario);

Scenario features: negotiation objectives (new customer development/renewal/dispute resolution), transaction size (small/medium/large), cooperation stage (preliminary negotiation/contract negotiation/execution stage);

Preferred features: commonly used trade terms, policy areas of concern, preferred negotiation strategies, and product specifications of particular focus.

2) User Tag System

Based on the four-dimensional portrait model, construct a three-level user tagging system:

First level tags: enterprise attribute tags, negotiator attribute tags, behavior tags, scenario tags, preference tags;

Secondary labels: such as “Product Category Label” and “Export Region Label” under the Enterprise Attribute Label, and “High Frequency Query Label” and “Favorite Label” under the Behavior Label;

Third level tags: specific tag values, such as “clothing export”, “European market”, “Incoterms 2020 query”, “concession strategy preference”.

3) User Profile Construction Process

1. Data collection: static data is collected through system registration, dynamic behavior data is collected through user operation logs, and scene feature data is collected through scene selection modules;

2. Feature extraction: Preprocess the collected data (denoising, standardization) to extract key features, such as extracting keyword features such as “REACH” and “FOB” from query records;

3. Label generation: Adopting a combination of “rule generation+machine learning generation” method, rule generation is used to clarify labels (such as “less than 1 year of experience → novice negotiator”), and machine learning generation (such as mining potential preference labels based on K-means clustering);

4. Profile update: Establish a dynamic update mechanism to update tag weights and content in real-time based on the latest user behavior data, ensuring the timeliness of the profile.

B. PERSONALIZED RECOMMENDATION ALGORITHM DESIGN

The algorithm framework is divided into three core modules:

Knowledge Graph Representation Module: Using the TransR model to map entities (users, knowledge, scenes) and relationships to a low dimensional vector space, obtaining entity vectors and relationship vectors;

Collaborative filtering module: Based on user behavior data, calculate user similarity and knowledge similarity to generate a collaborative filtering recommendation list;

Fusion recommendation module: Combining the semantic similarity of the knowledge graph with the behavioral similarity of collaborative filtering, a weighted fusion strategy is used to generate the final recommendation list.

1) Implementation of Key Steps

Dataset construction: Using user entities, knowledge entities, scenario entities, and their relationships (such as user attention knowledge, user participation scenario, and scenario association knowledge) in the knowledge graph as training data, a total of 150000 triplets are included. Note that the 128000 entities and 356000 relationships in the knowledge graph cover the full amount of textile foreign trade negotiation knowledge (including low-frequency and marginal associations). When training the TransR model, the focus is on the core association triplets of “user-knowledge-scenario”, excluding isolated entities, redundant relationships (such as historical invalid policy entities and repeated association relationships) and knowledge combinations unrelated to user behavior that have no actual recommendation value. The 150000 highvalue core triplets specifically include four types of core associations: “User-Attention-Knowledge” (42000), “User-Participation-Scenario” (38000), “Scenario-Association-Knowledge” (55000), and “Knowledge-Association-Knowledge” (15000), covering the key semantic associations required by the recommendation algorithm.

Sampling rationality verification: Through stratified sampling, the representativeness of core triplets is verified

- comparing the knowledge dimension coverage (both 95.3%) and scenario distribution consistency (chi-square test $p > 0.05$) between core triplets and full data, it is proved that core triplets can fully preserve the core semantic structure of the full knowledge graph. Although the size of training data is smaller than the total number of relationships, it has sufficient representativeness and rationality.

Vector generation: Generate user vector (U), knowledge vector (K), and scene vector (S) through the trained TransR model.

2) Algorithm Advantages

Solving the cold start problem: Based on semantic association of knowledge graph, even new users (without behavioral data) can generate recommendations through semantic matching between user profiles and knowledge;

Improve interpretability: The recommended results can be explained through the association path of the knowledge graph (such as “recommending REACH regulation knowledge, as your company mainly operates in the European market”);

Enhance accuracy: Integrate behavioral similarity and semantic similarity, while considering user preferences and knowledge associations, to improve recommendation adaptability.

V. DESIGN AND DEVELOPMENT OF PERSONALIZED RECOMMENDATION SYSTEM FOR TEXTILE FOREIGN TRADE NEGOTIATION

A. OVERALL SYSTEM DESIGN

1) Design Objectives

Functional objective: To achieve core functions such as knowledge query, knowledge visualization, personalized recommendation, negotiation assistance, and user management;

Performance goals: Knowledge query response time ≤ 0.5 seconds, recommendation list generation time ≤ 1 second, system concurrent user count ≥ 1000 ;

Usability goal: The interface is simple and intuitive, the operation process is simple, and it supports multi terminal (PC, mobile) access;

Scalability goal: Adopting modular design to support functional expansion and knowledge updates.

2) Design Principles

User centered: Design functions based on user profiles and scenario requirements to enhance user experience;

Data driven: with knowledge graph and user behavior data as the core, supporting intelligent functions;

Modular design: Divide the system into multiple independent modules to reduce coupling and facilitate maintenance and expansion;

Security principle: To ensure the security of user data and knowledge data, measures such as permission management and data encryption are adopted.

B. SYSTEM FUNCTION MODULE DESIGN

The system adopts a layered architecture design, which is divided into a presentation layer, a business logic layer, and a data layer. The core functional modules include a knowledge graph management module, a user profile management module, a personalized recommendation module, a negotiation assistance module, and a system management module. The specific functions are as follows:

1) Knowledge Graph Management Module

Knowledge query: supports entity query, relationship query, attribute query, fuzzy query, and provides multi condition filtering function;

Knowledge visualization: using graph visualization components to display entity association relationships, supporting zooming, dragging, and path highlighting;

Knowledge update: Supports administrators to manually add, edit, and delete knowledge, and supports batch import of knowledge data;

Knowledge reasoning: Provides a rule management interface that supports administrators to add and modify reasoning rules, triggering reasoning tasks.

2) User Profile Management Module

Portrait construction: Automatically collect user data, generate user tags, and support administrators to manually supplement tags;

Profile viewing: Users can view personal profiles, administrators can view all user profiles, and support profile filtering and export;

Portrait update: Real time update of portrait labels based on user behavior data, supporting label weight adjustment.

3) Personalized Recommendation Module

Homepage recommendation: Based on user profiles and recent behavior, push personalized knowledge and negotiation strategies on the system homepage;

Scenario based recommendation: After the user selects a negotiation scenario (such as “new customer development”), the core knowledge and adaptation strategies for that scenario are pushed;

Related recommendation: When users view a certain knowledge (such as “FOB trade terms”), push related knowledge (such as applicable scenarios, risk points, negotiation skills);

Recommendation feedback: Support users to evaluate the recommendation results as “useful” or “useless” and optimize the recommendation algorithm.

4) Negotiation Assistance Module

Negotiation plan generation: Based on user input of negotiation scenarios, product information, and partners, automatically generate scenario based negotiation plans;

Risk warning: Combining policy regulations and market knowledge from the knowledge graph, warning potential risks in negotiations (such as tariff changes and non-compliance with environmental standards);

Case reference: Recommend successful cases similar to the current negotiation scenario and provide reference experience;

Terminology tool: integrates practical tools such as a dictionary of commonly used textile foreign trade terms, unit converters, and exchange rate queries.

5) System Management Module

User management: supports user registration, login, and permission allocation (administrator, regular user, guest);

Data management: supports data backup, recovery, and cleaning, and provides data statistical reports;

Log management: Record user operation logs and system operation logs, support log query and export;

System configuration: Supports system parameter configuration (such as recommendation algorithm weights, knowledge update frequency).

C. SYSTEM TECHNICAL ARCHITECTURE

1) Performance Optimization Technology

The system uses three key technical methods to ensure that actual performance exceeds design goals:

1. Distributed Cache (Redis): Optimize query response by caching high-frequency access knowledge and user profile data, reducing database query pressure;

2. Service Cluster Deployment: Deploy backend services in a cluster mode to improve concurrent processing capabilities and support large-scale user access;

3. Knowledge Graph Precomputation: Precompute common semantic associations and reasoning results during off-peak hours, reducing real-time inference time during user access.

2) Front End Architecture

Using Vue.js as the front-end development framework, combined with the Element UI component library to build the user interface, the core technologies include:

View layer: Vue.js is responsible for page rendering and data binding, while Element UI provides standardized components;

State management: Vuex manages global state and enables data sharing between components;

Route management: Vue Router implements page routing redirection;

Visualization components: ECharts implements data statistics visualization, D3.js implements knowledge graph visualization;

Adaptation technology: adopting responsive design, supporting PC and mobile access.

3) Backend Architecture

Using Spring Boot as the backend development framework, implemented in Java language, the core technologies include:

Business logic layer: Spring Boot implements core business logic, while Spring MVC handles HTTP requests;

Data access layer: MyBatis Plus operation relational database, Neo4j Java Driver operation graph database;

Algorithm module: Integrated recommendation algorithm developed in Python (based on TensorFlow implementation), providing services through RESTful API;

Security framework: Spring Security implements user authentication and authorization, JWT implements token management;

Message queue: RabbitMQ handles asynchronous tasks such as knowledge updates and logging.

4) Data Layer

Adopting a hybrid storage solution of “relational database+graph database+file storage”:

Relational database: MySQL stores structured data such as user information, operation logs, system configurations, etc;

Graph database: Neo4j stores knowledge graph data for textile foreign trade negotiations;

File storage: MinIO stores unstructured data such as uploaded documents and images.

D. SYSTEM DEVELOPMENT AND DEPLOYMENT

1) Development Environment

Operating systems: Windows 10 (development environment), Linux CentOS 7 (deployment environment);

Database versions: MySQL 8.0, Neo4j 4.4.0;

Framework versions: Spring Boot 2.7.0, Vue.js 3.0, TensorFlow 2.8.0.

2) System Deployment

Adopting Docker containerization deployment solution to achieve rapid deployment and expansion of the system:

Front end deployment: Package the Vue.js project as a static file and deploy it on the Nginx server;

Backend deployment: Package the Spring Boot project as a Docker image and deploy it in a Docker container;

Database deployment: MySQL and Neo4j are deployed in separate Docker containers, and service communication is achieved through the network;

Load balancing: Nginx is used to achieve load balancing and improve the system's concurrent processing capability.

VI. EMPIRICAL TESTING AND APPLICATION VERIFICATION

A. EMPIRICAL TEST DESIGN

1) Test Objectives

Verify the completeness and accuracy of the knowledge graph;

Verify the accuracy of personalized recommendation algorithms;

Verify the functional integrity and performance of the system;

Collect user feedback and evaluate the practicality and usability of the system.

2) Test Object

Select 120 negotiators from 30 textile foreign trade enterprises (covering production and trade types, involving fabrics, clothing, home textiles and other categories) as

test users, including 40 novice negotiators, 50 intermediate negotiators, and 30 senior negotiators. Informed consent was obtained from all participants.

3) Test Indicators

Knowledge graph indicators: knowledge coverage (the proportion of covering the 6 core dimensions), entity accuracy (the accuracy of randomly selected entity verification), relationship accuracy (the accuracy of randomly selected relationship verification);

Recommendation algorithm metrics: accuracy (the proportion of useful knowledge in the recommendation list), recall (the proportion of knowledge that users need recommended), F1 score (the harmonic average of accuracy and recall), user satisfaction (the user's evaluation of the recommendation results);

System performance indicators: query response time, recommendation response time, concurrent user count;

System application indicators: negotiation preparation efficiency (comparison of negotiation preparation time before and after using the system), negotiation success rate (comparison of transaction success rate during testing).

4) Test Plan

1. Knowledge graph testing: Randomly select 500 entities, 500 relationships, and 500 attributes, and have 5 industry experts verify their accuracy;

2. Recommendation algorithm testing: Divide the test users into an experimental group (using the KG-CF algorithm designed in this article) and a control group (using traditional collaborative filtering algorithm), with 60 people

in each group. Record the recommendation accuracy, recall, F1 score, and user satisfaction of both groups;

3. System performance testing: Use JMeter tool to simulate 100, 500, and 1000 concurrent users to test the system's response time and stability;

4. System application testing: Test the user's use of the system for a 3-month negotiation practice, record the negotiation preparation time and transaction success rate, and compare them with the data before using the system.

5) Standardization Design of Query Tasks and External Variable Control

Task difficulty stratification: Divide query tasks into three categories: "basic queries (such as single product specification queries), medium difficulty (such as policy+scenario association queries), and high difficulty (such as cross-dimensional knowledge association queries)", and assign the same proportion of each difficulty task to each group of users (3:4:3);

Task authenticity guarantee: All query tasks are sourced from real negotiation scenarios of 30 companies, without extremely difficult tasks designed manually;

User group balance: Independent sample t-test was used to verify that there was no significant difference ($p>0.05$) in negotiation experience and computer proficiency among the four groups of users, and the impact of individual differences on efficiency was excluded.

B. TEST RESULTS AND ANALYSIS

1) Knowledge Graph Test Results

TABLE 1. Test Results of Textile Foreign Trade Negotiation Knowledge Graph

Test Indicator	Test Result
Knowledge Coverage	95.3%
Entity Accuracy	92.7%
Relationship Accuracy	90.5%
Attribute Accuracy	93.2%

2) Recommended Algorithm Test Results

TABLE 2. Comparison of Personalized Recommendation Algorithm Test Results

Test Indicator	Experimental Group (KG-CF Algorithm)	Control Group (Traditional CF Algorithm)	Improvement
Precision	0.82	0.65	26.2%
Recall	0.78	0.61	27.9%
F1 Score	0.80	0.63	27.0%
User Satisfaction (Points)	4.5 (5-point scale)	3.2 (5-point scale)	40.6%

The test results show that the KG-CF algorithm designed in this paper is significantly better than traditional collaborative filtering algorithms in all indicators:

The accuracy and recall rates have increased by 26.2%

and 27.9% respectively, indicating that the recommendation results are more accurate and can better match user needs;

User satisfaction has increased by 40.6%, reaching 4.5 points (on a 5-point scale), indicating a high level of

recognition from users towards the recommendation results.

This result validates the advantages of integrating knowledge graph and collaborative filtering, and improves the accuracy and adaptability of recommendations through semantic association mining.

Technical details of the benchmark model: The traditional collaborative filtering benchmark model adopts the standard UserCF algorithm, which does not integrate domain knowledge and scene features. It only calculates similarity based on surface behavior data such as user clicks and queries, and does not solve the cold start problem (the accuracy of new user recommendations is only 0.32). It belongs to the basic version of the recommendation system field, rather than a deliberately weakened benchmark model. Relevant research data in recent years shows that the hybrid algorithm of knowledge graph and collaborative filtering in the textile field has an average improvement of 18%-25% compared to traditional CF. This study, due to the integration of scene features and user capability portraits, has a slightly higher improvement than the average, which is within a reasonable range.

Rationality verification of test data: The test data adopts a dual source of “real business data+public dataset”.

TABLE 3. System Performance Test Results

Number of Concurrent Users	Query Response Time (Seconds)	Recommendation Response Time (Seconds)	System Stability (Fault-Free Operation Time)
100	0.12	0.35	72 hours
500	0.31	0.68	72 hours
1000	0.48	0.92	72 hours

The test results show that the response time of the system meets the design goals (query response time ≤ 0.5 seconds, recommended response time ≤ 1 second) under different concurrent user numbers, and runs without faults for 72 hours, indicating that the system has good performance and stability, and can support large-scale simultaneous user access.

4) Supplementary Long-term Stability and Pressure Test Results

Long-term stability test: The system stability testing cycle has been extended to 30 days (720 hours), simulating continuous access by 1000 concurrent users (including high-frequency operations such as knowledge queries, recommendation requests, and data entry). The system has accumulated 712 hours of fault-free operation, with only 8 hours of failure time (due to routine database backups). The system availability has reached 98.9%, far exceeding the minimum requirement of 85% for enterprise-level software. The fluctuation range of query response time within 30 days is ± 0.05 seconds, and the fluctuation range of recommendation response time is ± 0.08 seconds, proving the long-term stability of the system operation.

1. Real data: 3-month real negotiation behavior data of 120 users from 30 enterprises (including 28000 queries and 53000 clicks), the data distribution follows a power-law distribution, and there is no deliberate filtering;

2. Public dataset: Using the Amazon Textile Reviews public dataset (including 120000 user-product interaction records) to validate algorithm performance across datasets. The overfitting test results show that the accuracy

difference between the training and testing sets of the model is only 2.3%, and the F1 score difference is 1.8%, indicating no overfitting issue.

Ablation experiment results: The source of performance improvement is decomposed through ablation experiments.

- 1. Knowledge graph semantic fusion contributes 15.7%;
- 2. The introduction of scene features contributes 7.3%;
- 3. The optimization of user capability profile contributes 3.9%.

The collaborative implementation of the three achieves an overall improvement of 26.2%, and the improvement of each module is consistent with domain cognition.

3) System Performance Test Results

Extreme stress test: Using JMeter tool for extreme stress testing.

1. When there are 1500 concurrent users, the query response time is 0.68 seconds, the recommended response time is 1.25 seconds, and there is no request loss;

2. When the peak concurrency is 2000 people, the system automatically triggers the load

balancing mechanism, and the response time is controlled within 1.8 seconds without any crashes or data anomalies.

The system adopts distributed caching (Redis), database read-write separation, and service cluster deployment to ensure stability in high concurrency scenarios, far exceeding the design goal of 1000 concurrent users.

Actual deployment verification: The system has been piloted and deployed in 5 textile foreign trade enterprises for 6 months, serving a total of 830 users and processing 12000 requests per day without major failures. The average availability of the system is 99.2%, and its stability and reliability in real business scenarios have been verified through practical application.

5) System Application Test Results

TABLE 4. System Application Effect Comparison (Before vs. After Using the System)

Test Indicator	Before Using the System	After Using the System	Improvement
Negotiation Preparation Time (Hours/Time)	8.5	5.0	41.3%
Negotiation Success Rate (%)	62.3	78.5	26.0%
Knowledge Query Efficiency (Items/Hour)	15.2	38.7	154.6%
User Comprehensive Satisfaction (Points)	—	4.4 (5-point scale)	—

The application test results show that the application of the system significantly improves the efficiency and success rate of textile foreign trade negotiations:

The negotiation preparation time has been reduced from 8.5 hours per session to 5.0 hours per session, an increase of 41.3%, mainly due to the rapid retrieval of knowledge and personalized recommendations, which have reduced information screening time;

The success rate of negotiations has increased from 62.3% to 78.5%, an increase of 26.0%, due to the scenario based strategies and risk warnings provided by the system, which help negotiators make more scientific decisions;

The efficiency of knowledge query has increased by 154.6%, and the overall user satisfaction has reached 4.4 points, indicating that the practicality and usability of the system have been recognized by users.

Calculation logic: The calculation method for “knowledge query efficiency” is “the number of effective queries completed per unit time”, where “effective queries” are defined as “the query behavior in which the user successfully obtains the target knowledge and marks it as ‘useful’”. The raw data shows that before using the system, users completed an average of 15.2 valid queries per hour, which increased to 38.7 after use. The

calculation process is $(38.7 - 15.2)/15.2 \times 100\% \approx 154.6\%$. The accuracy of the data comes from the automatic statistics of the system operation log (accurate to the second level), rather than manual estimation.

Hierarchical verification results based on query difficulty:

1. Basic query: increased by 128.3%;
2. Medium difficulty query: increased by 165.7%;
3. High difficulty queries: increased by 182.5%.

The more significant improvement in high difficulty queries is in line with the core advantage of the system’s “cross-dimensional knowledge association recommendation”. Industry research data shows that the efficiency improvement range of intelligent query systems compared to traditional query tools is 100%-180%, and the results of this study are within a reasonable range.

VII. CONCLUSION

A four-dimensional user portrait model of “static attributes+dynamic behavior+scene features+preference features” was proposed, and a multi-dimensional user label system was constructed to provide accurate user demand

support for personalized recommendations; Developed a textile foreign trade negotiation personalized recommendation system that integrates knowledge query, personalized recommendation, and negotiation assistance. The system has complete functions, stable performance, query response time ≤ 0.5 seconds, and concurrent user count ≥ 1000 ; Empirical testing and enterprise application verification show that the system can significantly improve negotiation preparation efficiency (by 41.3%), negotiation success rate (by 26.0%), and knowledge query efficiency (by 154.6%), with a comprehensive user satisfaction score of 4.4 (on a 5-point scale), demonstrating good practicality and application value.

AUTHOR CONTRIBUTIONS

Nanyan Shen designed, collected and analyzed the data, and drafted the manuscript. Nanyan Shen conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Nanyan Shen participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research was supported by, Research and Practice on Knowledge Graph Construction and Personalization in Foreign Trade Negotiation, Research Output(s) of the Special Project on Foreign Language Teaching Reform and Practice in Undergraduate Universities of Guangdong Province for the Year 2025 (Project Number: 25GWYB25).

ACKNOWLEDGEMENTS

Not applicable.

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