# Chinese Semantic Structure Mapping for Textile Material Performance Data: An Improved BiLSTM-CRF Approach to Cross-Modal Intelligent Retrieval

**Qinmei Xian[1], Rui Wang[2]**
[1]School of Marxism, Luzhou Vocational and Technical College, Luzhou 646000, Sichuan, China
[2]Scientific Research Center, Chengde College of Applied Technology, Chengde 067000, Hebei, China
Corresponding author: Rui Wang (e-mail: 18281198856@163.com)

**ABSTRACT** Efficient semantic understanding and cross-modal retrieval of textile material data have become increasingly important as intelligent manufacturing systems integrate heterogeneous information from technical documents, physical measurements, and multimodal databases. Similar challenges also arise in electromagnetic wave characterization and antenna measurement platforms, where reliable semantic mapping is essential for heterogeneous data organization and retrieval. To overcome the limitations of Chinese semantic parsing in textile material databases, this study proposes an improved BiLSTM-CRF framework incorporating dependency syntactic rules and domain knowledge constraints for semantic structure mapping. A multimodal hash encoder is introduced to project textual features and physical property parameters into a unified embedding space, while maximum mean discrepancy optimization enhances cross-modal consistency. Furthermore, an improved R-tree indexing mechanism with dynamic weight adjustment is designed to accelerate complex query processing and maintain retrieval stability under high-concurrency conditions. Experimental results show that compound term boundary recognition reaches approximately 91.8%, average cross-modal similarity increases to 0.87, and response latency remains around 185 ms with 500 concurrent users. The proposed framework demonstrates substantial improvements in semantic parsing accuracy, multimodal feature alignment, and retrieval efficiency, providing an effective solution for intelligent textile material management while offering methodological insights for semantic organization and heterogeneous information retrieval in data-intensive electromagnetic sensing and propagation-related applications.

**INDEX TERMS** cross-modal retrieval, semantic structure mapping, bilstm-crf, multimodal feature alignment, intelligent indexing

## I. INTRODUCTION

THE textile industry is facing unprecedented data processing challenges in the era of intelligent technology. Modern textile material research and development has evolved from single physical performance testing to complex systems engineering involving natural fiber microstructure analysis [1-3], multi-field coupling performance evaluation of intelligent textiles [4,5], and composite damage mechanism research on leather materials [6]. Query processing optimization encompasses not only traditional schema design and indexing structure optimization but also the enhancement of retrieval efficiency and complex query processing capabilities. To address these challenges, this paper proposes a query processing optimization framework that integrates an improved BiLSTM-CRF model for semantic parsing, a multimodal hash encoder for cross-modal feature alignment, and an enhanced R-tree indexing system for efficient query execution. During the development of new functional textiles, designers must simultaneously process multimodal data, including technical documents, experimental videos, microscopic images, and mechanical curves [7]. Existing database systems often fail to accurately parse complex concepts such as “nanocellulose-reinforced composite leather” due to the complexity of Chinese semantic structures, resulting in information retrieval bias and insufficient recall [8-10]. When researchers attempt to query smart textiles with shape memory functions using natural language, the system often cannot accurately associate multidimensional data between material composition, weaving process, and temperature-sensitive performance [11]. This semantic gap severely limits the efficiency of textile material innovation, as discussed in applications of big data for sustainable textile manufacturing [12]. Hou et al. [13] comprehensively reviewed smart fibers and textiles for wearable electronics, covering materials, fabrication, and applications. However, their work did not address the specific challenge of Chinese semantic structure parsing for textile material multimodal data retrieval, particularly the cross-modal semantic mapping required for correlation analysis between three-dimensional woven structure parameters and interlaminar shear strength of composite materials in technical documents. By integrating pressure, temperature parameters, and color intensity prediction models to build an intelligent database, Haji et al. [14] initially established a process parameter standardization framework. Ngo et al. [15] addressed the problem of similarity recognition in complex weaving patterns using hypergraph modeling and a k-neighborhood multi-clustering method. Although early studies have made progress in specific modal processing, they still have significant limitations in analyzing complex Chinese compound terms unique to the textile field and the deep association of multimodal physical parameters [16,17]. To overcome these technical bottlenecks, researchers have attempted to combine deep learning with domain knowledge. Zhou et al. [18] systematically categorized two types of methods—feature space migration and image domain migration—and solved the core challenge of domain-invariant feature learning in cross-domain image retrieval. By building a multimodal matching framework based on generative adversarial networks, Liu et al. [19] combined source domain image-text latent representations with target domain text supervision to successfully generate realistic and semantically matching clothing images. Xiang et al. [20] improved the cross-modal retrieval efficiency of textile fabrics by designing a cross-domain connected convolutional neural network and fine-tuning the Distilling BERT for Natural Language Understanding (TinyBERT) model, thereby solving the cross-modal matching problem between fabric images and technical descriptions. However, they did not consider the impact of semantic boundary ambiguity in Chinese compound terms on dynamic retrieval. Therefore, although existing solutions that integrate deep learning have improved performance in general cross-modal tasks, they still have significant limitations in combining domain knowledge graphs to achieve Chinese compound term structure analysis, dynamic term evolution adaptive modeling [21,22], and deep knowledge-driven cross-modal feature alignment [23,24]. In view of the above limitations, this paper proposes a BiLSTM-CRF model that integrates a dependency syntactic analysis rule base to enhance the recognition of compound term boundaries. A multimodal hash encoder is designed to achieve cross-modal alignment of text and physical parameters in a shared space. An improved R-tree indexing system based on Hilbert curve dimensionality reduction is constructed, and a dynamic weight adjustment algorithm is developed to improve adaptability.

## II. A FRAMEWORK FOR CROSS-MODAL INTELLIGENT RETRIEVAL OF TEXTILE MATERIALS

### A. SEMANTIC FEATURE EXTRACTION IN THE TEXTILE FIELD

This study builds a professional terminology system based on standard texts and industry specifications in textile engineering. It employs a semantic structure mapping mechanism driven by dependency syntactic structure to achieve accurate extraction of domain semantic features. Given the complexity of terms such as antistatic conductive fibers, the BIO (Begin, Inside, Outside) annotation specification is used to design a nested annotation mechanism. During the word vector training phase, the learning rate is dynamically adjusted by combining large-scale textual literature pre-training with fine-tuning on a manually annotated corpus. Considering the morphological change characteristics of terms, a stem expansion algorithm is developed to generate variant vocabulary for core terms such as “leather.” To solve the problem of cross-language terminology mapping, a vector space alignment module based on a bilingual knowledge base is constructed, and the optimal orthogonal transformation matrix is solved by singular value decomposition:

$$Q^* = \arg\min_{Q} \|X_{\text{en}}Q - X_{\text{zh}}\|_F \quad \text{s.t.} \quad Q^\top Q = I \tag{1}$$

In formula (1), $X_{\text{en}}$ and $X_{\text{zh}} \in R^{n\times d}$ are the initial word vector matrices of English and Chinese terms, respectively. This enables linear alignment of the Chinese and English term vector spaces. At the feature encoding level, for complex terms such as “smart textiles,” a one-dimensional convolutional neural network is used to extract grapheme features. The convolution kernel is defined as $K \in R^{k\times d}$, and the input sequence $X \in R^{L\times d}$ is convolved to output the feature map:

$$C_i = \sigma\left(\sum_{j=0}^{k-1} K_j \cdot x_{i+j} + b\right) \tag{2}$$

In formula (2), $k$ is the convolution kernel size, $\sigma$ is the ReLU activation function, and $x_{i+j}$ is the embedding vector of the $i + j$-th character. After pooling, it is concatenated with the word vector to enhance the recognition ability for professional abbreviations. Simultaneously, a multi-layer perceptron is constructed to perform a nonlinear combination of features at different granularities. During terminology library construction and feature extraction, term boundary constraints are established by introducing the dependency syntax analysis rule library. In the feature generation stage, the domain ontology relationship is embedded, and the concept hierarchy structure is used to guide vector space optimization. Figure 1 shows that knowledge graph constraints outperform character-level (0.85/0.62) and word-level (0.72/0.58) approaches in compound terms (0.91) and process descriptions (0.89), and the functional parameter

(0.82) remains at a high level. Character-level structural features (0.32) and word-level process descriptions (0.58) performed the weakest, indicating that the knowledge graph-guided CRF decoding strategy effectively combines the dependency syntactic analysis rule base and significantly improves the ability to identify complex term boundaries. By building a dependency syntax analysis rule base and a multi-granularity feature fusion mechanism, a semantic structure mapping engine optimized for databases can be developed.

### B. BILSTM-CRF MODEL OPTIMIZATION

This study aims to solve the problem of semantic boundary fuzziness in compound terms within the Chinese textile field and proposes a BiLSTM-CRF model optimization scheme based on semantic structure mapping. Compared with the standard BiLSTM-CRF model, this model introduces a multi-head self-attention mechanism after the BiLSTM layer to enhance long-distance semantic dependencies, converts textile material knowledge graph entity relationship rules into CRF decoding layer transfer matrix constraints, and constructs a dual verification mechanism based on the dependency syntax analysis rule base. Knowledge graph constraints are implemented as hard constraints in the CRF decoding process. Specifically, the transfer probability from label i to label j is modified as P(i→j) = exp(w· f(i, j) + $\beta$· c(i, j)), where c(i, j) is 1 if the transition (i, j) violates knowledge graph rules and 0 otherwise, and $\beta$ is a large negative constant (-1000) to effectively prohibit invalid transitions. During Viterbi decoding, these constraints ensure that the predicted label sequence strictly adheres to the domain-specific syntactic and semantic rules defined by the textile knowledge graph. Specifically, knowledge graph triplets T= {(e, r, e′)} are converted into CRF transfer probability matrix constraints, where semantic similarity S(e, e′) controls constraint strength. A multi-head self-attention mechanism is introduced after the BiLSTM layer to strengthen long-distance semantic dependencies through global association modeling. The logical constraint rules of the textile material knowledge graph are integrated within the CRF decoding layer to construct a decoding strategy guided by domain knowledge. The entity relationships in the knowledge graph are converted into probabilistic constraints of the CRF transfer matrix. The query matrix Q, key matrix K, and value matrix V are defined, and the multi-head attention calculation is as follows:

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_i, \ldots, \mathrm{head}_h)W^O \tag{3}$$

In formula (3), $\mathrm{head}_i$ is $\mathrm{softmax}\left(Q_i K_i^\top / \sqrt{d_k}\right) V_i$, and $h = 8$ is the number of heads. The hierarchical Softmax function is used to map the ontology hierarchy of the knowledge graph into vector space, and predefined rules are injected into the transition probability matrix of the CRF layer (for example, the term "antistatic" must be forcibly associated with "conductive fiber"). Defining the knowledge graph triple set T={(ei, r, ej)}, and the CRF transition probability matrix T introduces graph constraints:

$$T_{i,j} = \frac{\exp\left(\alpha \cdot s(e_i, e_j)\right)}{\sum_k \exp\left(\alpha \cdot s(e_i, e_k)\right)} \tag{4}$$

In formula (4), $s(e_i, e_j)$ is the semantic similarity between entities $e_i$ and $e_j$, and $\alpha$ controls the constraint strength. $\alpha$ is empirically set to 0.7 based on cross-validation experiments on the development set, balancing the influence between the original CRF transition probabilities and the knowledge graph constraints. Values below 0.6 resulted in insufficient constraint enforcement while values above 0.8 caused overfitting to the knowledge graph rules. In the physical property conduction chain constraint, a double verification mechanism for term boundary identification is constructed by introducing a dependency syntax analysis rule base. Formula (4) further integrates the semantic association characteristics of the domain ontology hierarchical structure. The model optimization framework is further combined with a dynamic feature fusion strategy: after the BiLSTM layer generates a bidirectional context representation, the self-attention module extracts global features through a multi-head mechanism and jointly optimizes the CRF decoding results guided by the knowledge graph. Its BiLSTM output H∈RT×2d is fused with the attention feature A∈RT×2d through a multilayer perceptron:

$$F_t = \sigma\left(W_f[h_t; a_t] + b_f\right) \tag{5}$$

In formula (5), $W_f \in R^{d\times 3d}$ is a learnable parameter. By introducing the feature fusion weight driven by the dependency syntactic structure, the dynamic distribution of semantic parsing error between the bidirectional LSTM and the attention module is achieved. The depth-first traversal algorithm of the term modification level generates the weight coefficient. Figure 2 illustrates the core architecture of the improved BiLSTM-CRF model. After extracting text context features through the word embedding layer and BiLSTM, the multi-head self-attention mechanism is innovatively introduced to strengthen the long-distance semantic dependency for terms such as "nanocellulose-reinforced composite leather," and the entity relationship rules of the textile knowledge graph are converted into transfer matrix constraints for the CRF layer. This synergistic mechanism, which integrates dynamic feature optimization strategies, effectively solves the problem of fuzzy boundaries in Chinese textile compound terms and ensures the integrity of the internal logical relationships in terms such as "antistatic conductive fiber" through knowledge graph constraints, providing a high-precision semantic parsing foundation for cross-modal feature alignment.

### C. CROSS-MODAL FEATURE ALIGNMENT

This study constructs a framework that combines a multi-modal hash encoder with a maximum mean discrepancy loss

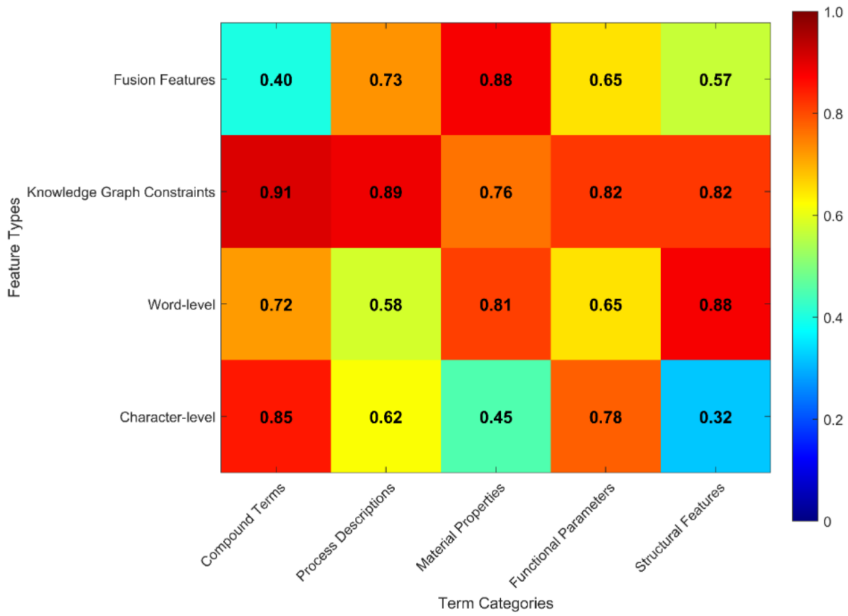


**FIGURE 1.** Multi-granularity semantic feature coverage strength in the textile field based on dependency syntactic analysis

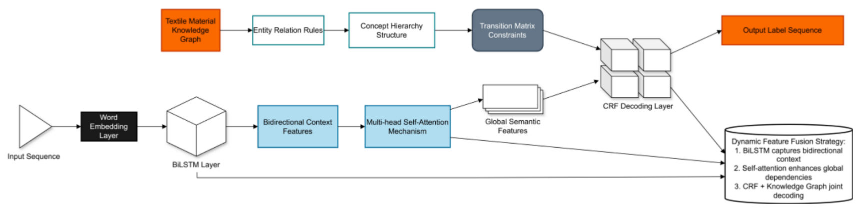


**FIGURE 2.** Improved BiLSTM-CRF semantic parsing architecture diagram constrained by textile knowledge graph

function. The multimodal hash encoder structure is designed to process text and physical property data separately. The 128-dimensional shared space is determined by ablation experiments, achieving an optimal balance between retrieval accuracy and computational cost. Dimensions below 128 significantly reduce cross-modal alignment accuracy, while dimensions above 128 increase computational cost with minimal accuracy improvement. Physical property data encoding implements piecewise normalization for 12 parameters, such as tensile strength and air permeability. The two types of features are mapped to a 128-dimensional shared space through a learnable projection matrix and orthogonal transformation, and contrastive loss is combined to enhance discrimination between positive and negative samples:

$$L_{\text{cont}} = -\log \frac{\exp\left(z^t \cdot z^p/\tau\right)}{\exp\left(z^t \cdot z^p/\tau\right) + \sum_{x^- \in N} \exp\left(z^t \cdot z^-/\tau\right)} \tag{6}$$

In formula (6), $z^t$ and $z^p$ are the representations of text and physical features in the shared space, and $\tau$ is the temperature parameter. The hierarchical Maximum Mean Discrepancy (MMD) strategy is introduced to improve the robustness of distribution alignment:

$$L_{\text{MMD}} = \sum_{k=1}^{K} \beta_k \left\| \frac{1}{n_t} \sum_{i=1}^{n_t} \phi_k(z_i^t) - \frac{1}{n_p} \sum_{j=1}^{n_p} \phi_k(z_j^p) \right\|_{\mathcal{H}_k}^2 \tag{7}$$

In formula (7), $\phi$k is the mapping function corresponding to the k-th kernel, and $\beta$k is the kernel weight coefficient. An online learning mechanism based on query feedback is developed. For the index structure, multi-granularity semantic units are constructed based on the improved R-tree, dynamic split thresholds are set to optimize node filling rates, and a path selection strategy based on cosine similarity is integrated. The index node priority is adjusted according to term co-occurrence frequency through a real-time update module. Figure 3 presents the core mechanism of the cross-modal feature alignment architecture. The BiLSTM-CRF combined with a self-attention mechanism is used to extract text semantic features for text data and physical property parameters through dual-channel input, while normalization and a fully connected network process physical property data. Both sets of features are mapped to a 128-dimensional shared space using a learnable projection matrix and orthogonal transformation, and contrastive loss is applied to enhance the discrimination of positive and negative samples. The cross-modal distribution alignment is achieved in combination with the hierarchical MMD loss, thereby establishing semantic associations between composite concepts such as antibacterial modified polyester fibers and physical property indicators. A meta-gradient update mechanism driven by user feedback is introduced to dynamically adjust the projection matrix parameters to adapt to the evolution of domain terminology.

### D. IMPROVED R-TREE INDEX AND DYNAMIC WEIGHT ADJUSTMENT ALGORITHM

This study designs a multi-granularity semantic indexing system based on an improved R-tree indexing framework, enhancing retrieval efficiency in complex query scenarios through a dynamic weight adjustment algorithm. Addressing the multi-level semantic characteristics of textile terms, the traditional R-tree node splitting strategy is optimized: the Hilbert curve sorting preprocessing mechanism is used to map high-dimensional semantic vectors to one-dimensional space, improving node clustering efficiency, and an adaptive splitting threshold is set to dynamically adjust the node filling rate. During the query path selection stage, the cosine similarity constraint is introduced to prioritize traversing the subtree with a smaller angle to the query vector. For example, the natural language query "Find all textile materials with antibacterial properties and tensile strength greater than 50 MPa" is parsed into the SQL statement "SELECT * FROM textile_materials WHERE antibacterial = TRUE AND tensile_strength > 50". A three-level semantic indexing framework, including word level, phrase level, and concept level, is constructed. The word-level index directly inserts the single-term feature vector into the leaf node. The phrase-level index extracts the semantic relationship vector between the core word and the modifier through dependency syntactic analysis. The concept-level index projects the concept chain into a hyperplane constraint based on the ontology hierarchical structure of the textile material knowledge graph. An online optimization mechanism based on query logs is developed to achieve dynamic index adjustment. User search sequences are collected to build a query-click pair dataset, term co-occurrence frequency and cross-modal association strength are counted, and index node weights are updated through gradient descent:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta\left(\frac{\partial L}{\partial w_{ij}} + \gamma\frac{\partial R}{\partial w_{ij}}\right) \tag{8}$$

In formula (8), $\eta$ is the learning rate; $\gamma$ is the regularization coefficient, and R is the weight decay term. $\eta$ is set to 0.01 through grid search over [0.001, 0.01, 0.1], and $\gamma$ is fixed at 0.001 as a regularization coefficient to prevent overfitting. The temperature parameter $\tau$ in Formula (6) is set to 0.07 based on preliminary experiments, and kernel weights in Formula (7) are learned end-to-end during training. The mapping error between term co-occurrence frequency and physical property parameter distribution is quantified by the semantic deviation function, which drives the gradient update of the index node weights. Another example is the query "Show materials with shape memory effect and thermal conductivity above 0.5 W/mK," which is translated to "SELECT * FROM textile_materials WHERE shape_memory = TRUE AND thermal_conductivity > 0.5". Table 1 displays the core parameter configuration of the improved R-tree index. The adaptive split threshold optimizes spatial clustering efficiency by dynamically adjusting node filling rates. The Hilbert curve dimension reduces the dimensionality of complex semantic features, improving the efficiency of node splitting calculations. The cosine similarity constraint limits the query path direction, reducing the number of invalid node visits. These parameter designs combine the semantic parsing capabilities of the improved BiLSTM-CRF model with the logical constraints of the textile knowledge graph, enabling a hybrid indexing mode at the word, phrase, and concept levels through a three-level indexing framework. This not only meets the needs for rapid positioning of single terms but also supports semantic association analysis of complex cross-modal queries.

## III. EXPERIMENTATION AND TESTING

### A. EXPERIMENTAL DESIGN

The multimodal dataset used in this study integrates a professional terminology corpus with physical parameters such as mechanical properties and permeability, covering core areas such as natural fibers and leather materials. Data sources include various multi-source datasets, and a structured corpus is constructed after expert annotation. The dataset comprises 12,580 textile material records collected from Chinese technical standards, research papers, and industry reports spanning 2010–2023. It includes 6,840 natural fiber materials, 3,210 functional textiles, 1,985 smart textiles, and 545 sustainable dyeing process records. Three domain experts with over 10 years of experience in textile engineering performed the annotation, following a strict protocol with 95% inter-annotator agreement measured by Cohen's kappa. The dataset was randomly split into training (70%), validation (15%), and test (15%) sets using a fixed random seed (42) to ensure reproducibility for final model evaluation. For hyperparameter tuning and term boundary recognition task evaluation, 5-fold cross-validation was employed on the training set. Feature space visualization was combined to verify cross-modal alignment. Stress tests were designed to simulate high-concurrency scenarios, and the consistency of semantic mapping was evaluated through an expert review mechanism. All data were processed under institutional review board approval with appropriate data anonymization procedures. Text data generated low-dimensional representations through domain-adaptive word vectors, and physical parameters were segmented, standardized, and spatially mapped to achieve multimodal feature fusion to support complex queries.

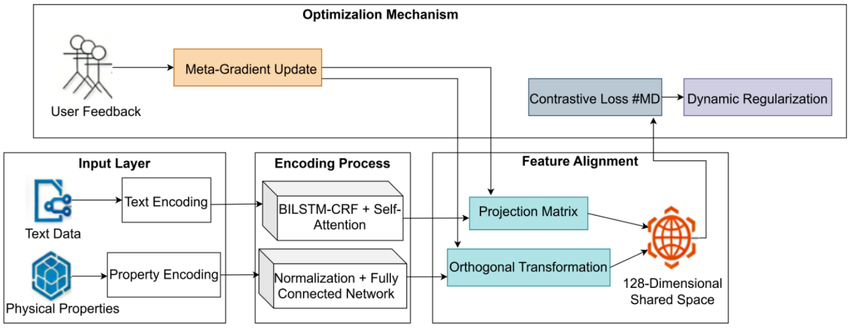


FIGURE 3. Cross-modal feature alignment architecture

TABLE 1. Improved R-tree Index Key Parameter Configuration

| Parameter Name | Symbol/Module | Value Range/Description | Function Description |
|---|---|---|---|
| Adaptive Split Threshold | $\theta_{\text{split}}$ | [0.6, 0.8], dynamic adjustment | Controls node fill rate for spatial clustering efficiency |
| Hilbert Curve Dimension | H-Dim | 8-dimensional mapping | Reduces high-dimensional semantic vectors for node splitting efficiency |
| Cosine Similarity Threshold | $\tau_{\cos}$ | 0.75 (query path selection) | Constrains traversal direction to reduce invalid node access |
| Dynamic Weight Learning Rate | $\eta$ | 0.01 (gradient descent step) | Adjusts index node priority based on query patterns |
| Three-Level Index Weight | W-Level | Word (0.4) / Phrase (0.3) / Concept (0.3) | Balances semantic hierarchy priorities for retrieval |

Note: Parameter values were determined through extensive ablation studies and grid search experiments. The adaptive split threshold $\theta_{\text{split}}$ was optimized over [0.5, 0.9] with 0.1 increments; Hilbert Curve Dimension H-Dim was fixed at 8 based on stability analysis; Cosine Similarity Threshold $\tau_{\cos}$ was selected from [0.7, 0.8] based on precision-recall trade-off; Dynamic Weight Learning Rate $\eta$ was chosen from [0.001, 0.01, 0.1]; Three-Level Index Weight W-Level was determined by analyzing query patterns in the textile domain.

### *B. EXPERIMENTAL DESIGN FOR SEMANTIC PARSING ACCURACY TEST*

This study selects mainstream pre-trained models such as BERT (Bidirectional Encoder Representations from Transformers)-wwm (Whole Word Masking), RoBERTa (Robustly Optimized BERT Approach)-wwm-ext (Whole Word Masking Extended), ALBERT (A Lite BERT)-v2, and ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately)-small as baselines, and also includes a rule-based parser for comparison. All models were trained on the same corpus with identical annotations. Pre-trained models were fine-tuned for 20 epochs with early stopping (patience of 5 epochs) based on validation set performance. The learning rate was set to 2e-5 for BERT-based models and 5e-5 for other models, with a batch size of 32. The rule-based parser used the dependency syntactic analysis rule base described in Section 2.1 and had no trainable parameters. All experiments were conducted with fixed random seed 42 for reproducibility. The rule-based parser uses predefined grammar rules for compound term boundary recognition in the textile domain. Figure 4 shows the semantic parsing performance comparison of the model in four typical scenarios in the textile field, including compound term boundary recognition and unregistered word recognition. In natural fiber material scenarios, the improved model achieves 91.8% compound term recognition accuracy, which is significantly higher than BERT-wwm's 84.3% and VSE++'s 86.5%. In smart textile scenarios, the model's accuracy is 86.3%, which is 1.3 percentage points higher than VSE++'s 85%. This advantage remains stable in the other three scenarios. As shown in Figure 4(c), the accuracy for compound terms is about 86.3%, and the error bar length is significantly shorter, indicating that the model prediction results are more centralized and reliable. This performance improvement is attributed to the improved model's combination of the multi-head self-attention mechanism and constraints from the textile knowledge graph. The self-attention mechanism strengthens the contextual association of long-distance terms through 8-head parallel computing. Additionally, the physical property conduction chain rule of the knowledge graph optimizes the CRF decoding process, making the internal logical relationships of terms more complete.

### *C. EXPERIMENTAL DESIGN FOR CROSS-MODAL RETRIEVAL RESPONSE TIME TEST*

To evaluate response time performance, MobileBERT, DistilBERT, ColBERT, and ANCE (Approximate Nearest Neighbor Negative Contrastive Estimation) were selected as baseline models. The experiment built a concurrent load testing environment to break down query parsing, feature mapping, and index traversal latency. Experiments were conducted on a server with an Intel Xeon Gold 6248R CPU (3.0 GHz), NVIDIA A100 GPU (40 GB), 256 GB RAM, and NVMe SSD storage. The index contained 12,580 textile material records, each with 12 physical parameters. Query requests were generated using a closed-loop load testing approach with JMeter, simulating realistic user behavior patterns. We measured 95th and 99th percentile latencies under various concurrency levels from 10 to 500 users. Batch processing was disabled to simulate real-time query scenarios, and cache was cleared between test runs to ensure

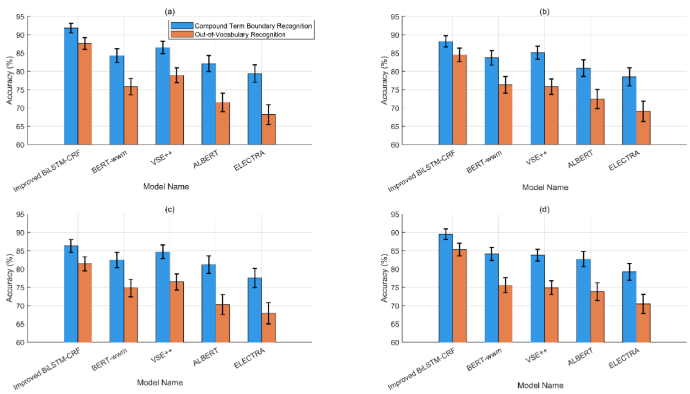


**FIGURE 4.** Comparison of semantic parsing performance in multiple scenarios in the textile field. (a) Natural fiber materials, (b) Functional textiles, (c) Smart textiles, and (d) Sustainable dyeing process

consistent measurements. Figure 5 compares the number of concurrent users with response time (ms) and index traversal cost (%) to study the model's performance advantage in cross-modal retrieval of textile materials. In Figure 5(a), the improved BiLSTM-CRF model requires only about 185 ms at 500 concurrent users, indicating that its improved R-tree index and Hilbert curve dimensionality reduction technology effectively suppress performance degradation under high concurrency. In Figure 5(b), the improved model's index traversal cost is only about 46% at 500 concurrent users, which is lower than other models. Its gentle growth curve, compared with the steep rise of ANCE, confirms the mechanism advantage of the dynamic weight adjustment algorithm. This performance improvement is due to the improved BiLSTM-CRF model's integration of multi-head self-attention and knowledge graph constraints to optimize term parsing. The improved R-tree index focuses on related nodes through Hilbert curve dimensionality reduction and cosine similarity strategy, and combines dynamic weight adjustment to achieve high-frequency term priority retrieval, forming a closed-loop optimization of semantics and storage.

### D. EXPERIMENTAL DESIGN FOR CROSS-MODAL SIMILARITY EVALUATION

In this experiment, CLIP (Contrastive Language-Image Pre-training), ALIGN (Automatic Learning of Inter-Modality Grounding), M6 (MultiModality-to-MultiModality Multi-task Mega-Transformer), and VSE++ (Improving Visual-Semantic Embeddings with Hard Negatives) were selected as baseline models and compared with the improved BiLSTM-CRF for multi-category data comparison tests on textile materials. To adapt image-text retrieval baselines for text-physical parameter tasks, their architectures were modified by replacing the image encoder with a fully connected network that processes the 12 physical parameters. The physical parameters were normalized and projected into the same embedding space as text features. These adapted models were trained using InfoNCE loss for contrastive learning and MMD loss for distribution alignment, as described in Section 2.3. Performance was evaluated using Recall@K and Mean Average Precision metrics, with K = 5, 10, 20, as reported in Table 2. The test covered five core textile materials: natural fibers, leather materials, functional textiles, smart textiles, and sustainable dyeing processes. A double-blind evaluation mechanism was adopted, and experts in the textile field were invited to grade and score the physical property correlation results for complex terms such as antibacterial modified polyester fibers, combined with Krippendorff's $\alpha$ coefficient ($\geq$0.85) to ensure consistency in scoring. As shown in Figure 6, the improved BiLSTM-CRF model achieves a similarity of more than 0.82 in all five types of materials, while the highest value among other models is only 0.79 for VSE++ in functional textiles. The improved model maintains high similarity in complex fields such as natural fibers (0.88) and sustainable dyeing processes (0.82), indicating that it strengthens the deep alignment of Chinese compound term boundary recognition and physical property parameters through collaboration between multi-head self-attention and knowledge graph constraints. The model uses dependency syntactic mapping to convert the term modification level into feature weights, resulting in the similarity of functional textiles reaching 0.90, thereby verifying the core value of knowledge-enhanced semantic parsing in cross-modal alignment. Table 2 systematically compares the comprehensive performance indicators of cross-modal retrieval models for textile materials, covering semantic alignment quality, robustness, and computational efficiency. The average similarity reflects the cross-modal alignment accuracy for compound terms. The adversarial sample accuracy evaluates the model's robustness to semantic interference. The term evolution adaptation rate tests the system's dynamic response ability to new textile materials, such as phase change energy storage fibers. Training time and inference speed measure applicability to industrial scenarios.

Table 2 shows the comprehensive performance comparison of the improved BiLSTM-CRF model and other baseline models in cross-modal retrieval of textile materials. The improved model achieves significantly higher average

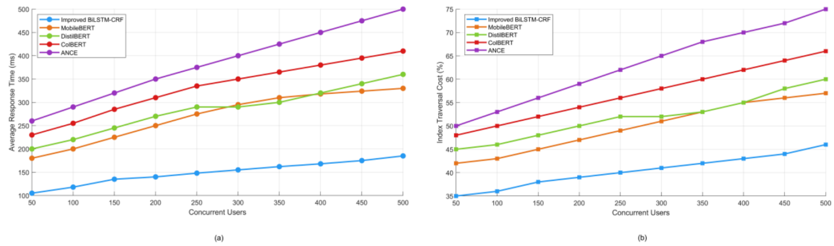


FIGURE 5. Comparison of cross-modal intelligent retrieval performance for textile materials. (a) Average response time versus the number of concurrent users; (b) Index traversal time ratio versus the number of concurrent users

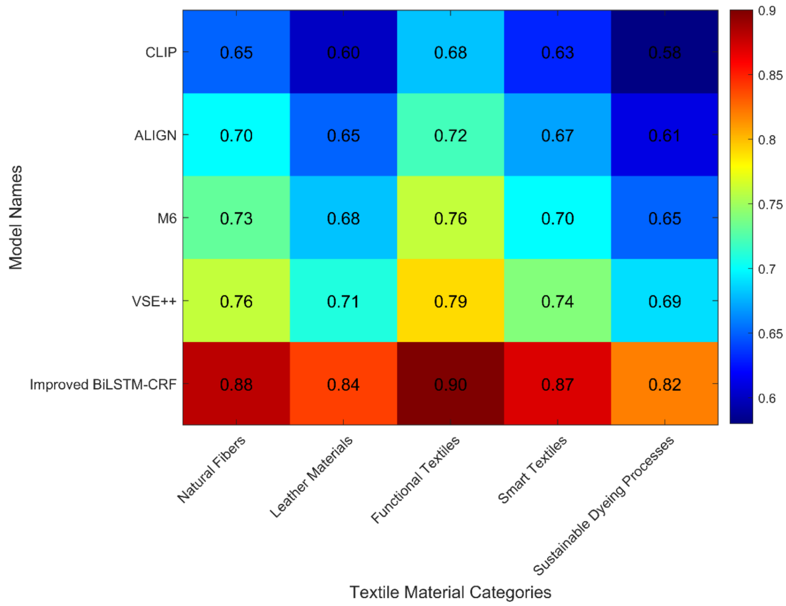


FIGURE 6. Similarity heat map for cross-modal retrieval of textile materials

TABLE 2. Performance Comparison of Cross-Modal Intelligent Retrieval Models for Textile Materials

| Model | Average Similarity | Adversarial Sample Accuracy | Term Evolution Adaptation Rate | Training Time (hours) | Inference Speed (ms/query) |
|---|---|---|---|---|---|
| Rule-based Parser | 0.71 | 0.65 | 0.55 | 12 | 100 |
| CLIP | 0.64 | 0.58 | 0.52 | 72 | 210 |
| ALIGN | 0.69 | 0.63 | 0.57 | 80 | 230 |
| M6 | 0.72 | 0.67 | 0.61 | 96 | 300 |
| VSE++ | 0.75 | 0.70 | 0.65 | 60 | 180 |
| Improved BiLSTM-CRF | 0.87 | 0.82 | 0.79 | 48 | 150 |

similarity (0.87), adversarial sample accuracy (0.82), and term evolution adaptation rate (0.79) compared to baseline models. Its average similarity exceeds VSE++ by 0.12, adversarial sample accuracy exceeds M6 by 0.15, and term evolution adaptation rate exceeds ALIGN by 0.22. This is due to the deep integration of its multi-head self-attention mechanism and textile knowledge graph. The dynamic weight adjustment algorithm optimizes index node priority in real time through the meta-gradient descent method. This dual-channel constraint mechanism ensures the optimization of cross-modal feature alignment stability through the physical property conduction chain rule.

### *E. DYNAMIC ADAPTABILITY TEST EXPERIMENTAL DESIGN*

In the dynamic adaptability test, BERT-Online, AdaBERT, DynaBERT, and ElasticBERT were selected as baseline models for comparison with the improved BiLSTM-CRF model. This verifies the effect of the improved BiLSTM-CRF model, which combines the meta-gradient descent method and the online learning mechanism of the knowledge graph real-time synchronization interface, on term gap convergence efficiency and cross-modal mapping stability.

Figure 7(a) shows that the adaptation rate of the improved model continuously increases from an initial 80.5% to a peak of 85.9%. The slope of the curve also reflects the

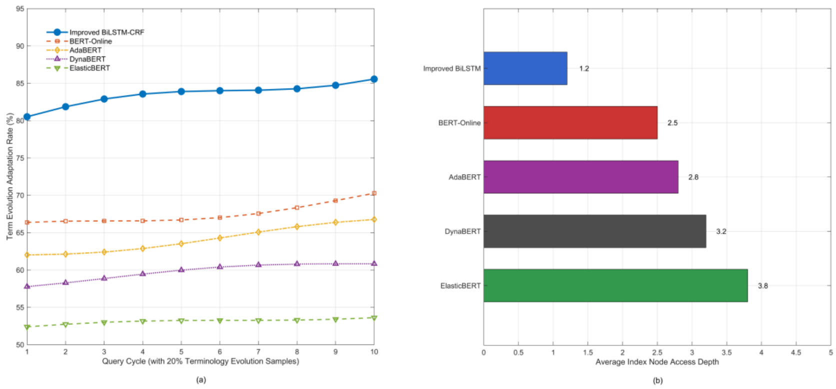


FIGURE 7. Dynamic adaptability performance evaluation of the textile material cross-modal retrieval system. (a) Comparison curve for term evolution adaptation rate; (b) Comparison of index node access depth performance

dynamic response capability of the meta-gradient descent algorithm, which optimizes index node priority in real time through user log feedback. In Figure 7(b), the improved model averages only 1.2 layers, which is significantly fewer than the suboptimal BERT-Online (2.5 layers). This is due to the knowledge graph-constrained CRF decoding mechanism, which converts term co-occurrence frequency and physical property parameter distribution errors into weight attenuation terms, driving the index structure to favor high-frequency dynamic terms. The underlying data difference arises from the improved model establishing semantic-physical dual-channel constraints through the ontology hierarchical structure of the textile field, allowing new terms such as phase change energy storage fibers to complete dynamic adjustment of the index node splitting threshold within several query iterations.

## IV. CONCLUSION

This paper focuses on the application of Chinese semantic structure mapping in the optimization of textile material databases and proposes a cross-modal intelligent retrieval method that integrates the improved BiLSTM-CRF model and knowledge graph constraints. Through dependency syntax analysis, multimodal feature alignment, and improved R-tree indexing technology, the accuracy of compound term recognition and retrieval response efficiency are significantly improved. Experiments demonstrate that this method delivers superior performance in cross-modal similarity and high-concurrency scenarios, providing a feasible path for efficient management and intelligent application of textile material data. Future work will explore lightweight models and multi-language support capabilities.

## AUTHOR CONTRIBUTIONS

Conceptualization – Qinmei Xian and Rui Wang; methodology – Qinmei Xian and Rui Wang; formal analysis –Qinmei Xian and Rui Wang; investigation –Qinmei Xian; resources – Qinmei Xian; writing-original draft preparation – Qinmei Xian and Rui Wang; writing-review and editing – Qinmei Xian and Rui Wang. All authors have read and agreed to the published version of the manuscript.

## CONFLICTS OF INTEREST

The authors declare no conflict of interest.

## FUNDING

This research received no external funding.

## ACKNOWLEDGEMENTS

Not applicable.

## REFERENCES

[1] C. Fednand, P. Bigambo, and Q. Mgani, "Modification of the Mechanical and Structural Properties of Sisal Fiber for Textile Applications," Journal of Natural Fibers, vol. 19, no. 15, pp. 10834-10845, 2022, doi: 10.1080/15440478.2021.2002772.

[2] T. Totong, W. Wardiningsih, M. Al-Ayyuby, R. Wanti, and R. Rudy, "Extraction and Characterization of Natural Fiber from Furcraea Foetida Leaves as an Alternative Material for Textile Applications," Journal of Natural Fibers, vol. 19, no. 13, pp. 6044-6055. https://doi.org/10.1080/15440478.2021.1904477, 2022.

[3] J. León-Becerra, C. Tavera-Ruiz, and J. Galvis-Chacón, "Statistical Analysis of a Woven Fique-Reinforced Biocomposite Using Mechanics of Structure Genome Homogenization," Fibers and Polymers, vol. 25, no. 1, pp. 301-307, 2024, doi: 10.1007/s12221-023-00421-3.

[4] K. Dong, X. Peng, R. Cheng, and Z. L. Wang, "Smart Textile Triboelectric Nanogenerators: Prospective Strategies for Improving Electricity Output Performance," Nanoenergy Advances, vol. 2, no. 1, pp. 133-164. https://doi.org/10.3390/nanoenergyadv2010006, 2022.

[5] M. Y. Al-Daraghmeh and R. T. Stone, "A review of medical wearables: Materials, power sources, sensors, and manufacturing aspects of human wearable technologies," Journal of Medical Engineering & Technology, vol. 47, no. 1, pp. 67-81. https://doi.org/10.1080/03091902.2022.2097743, 2023.

[6] P. Surianarayanan, N. Balaji, and K. Balasubramanian, "Effect of silane-treated chitosan carbohydrate polymer and tanned leather/areca fiber hybrid epoxy composites on mechanical, drop load, and fatigue properties," Biomass Conversion and Biorefinery, vol. 14, no. 16, pp. 19093-19106, 2024, doi: 10.1007/s13399-023-03882-x.

[7] V. Golagana, S. V. Row, and P. S. Rao, "Multimodal Feature Fusion for Image Retrieval Using Deep Learning," Journal of Data Acquisition and Processing, vol. 39, no. 1, pp. 823-839, 2024.

[8] Y. Lan, G. He, J. Jiang, J. Jiang, W. X. Zhao, and J. R. Wen, "Complex Knowledge Base Question Answering: A Survey," IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 11, pp. 11196-11215, 2023, doi: 10.1109/TKDE.2022.3223858.

[9] X. Zhou, S. Zhang, M. Agarwal, J. Akroyd, S. Mosbach, and M. Kraft, "Marie and BERT–A Knowledge Graph Embedding Based Question Answering System for Chemistry," ACS Omega, vol. 8, no. 36, pp. 33039-33057, 2023, doi: 10.1021/acsomega.3c05114.

[10] T. Sultana, A. K. Mandal, H. Saha, M. N. Sultan, and M. D. Hossain, "Intent Identification by Semantically Analyzing the Search Query," Mod-

elling, vol. 5, no. 1, pp. 292-314. https://doi.org/10.3390/modelling5010016, 2024.

[11] P. Prathumrat, M. Nikzad, E. Hajizadeh, R. Arablouei, and I. Sbarski, "Shape memory elastomers: A review of synthesis, design, advanced manufacturing, and emerging applications," Polymers for Advanced Technologies, vol. 33, no. 6, pp. 1782-1808. https://doi.org/10.1002/pat.5652, 2022.

[12] G. A. González, A. S. Hernández, M. G. Vásquez, J. V. Uribe, and A. B. Avellaneda, "Sustainable manufacturing in the fourth industrial revolution: A big data application proposal in the textile industry," Journal of Industrial Engineering and Management, vol. 15, no. 4, pp. 614-636, 2022, doi: 10.3926/jiem.3922.

[13] Z. Hou, X. Liu, M. Tian, X. Zhang, L. Qu, T. Fan, et al., "Smart fibers and textiles for emerging clothe-based wearable electronics: Materials, fabrications and applications," Journal of Materials Chemistry A, vol. 11, no. 33, pp. 17336-17372. https://doi.org/10.1039/D3TA02617E, 2023.

[14] A. Haji, M. Vadood, M. Öztürk, I. Yigit, S. Eren, and H. A. Eren, "Prediction of colour strength in environmentallyfriendly dyeing of polyester fabric with madder using supercritical carbon dioxide," Coloration Technology, vol. 141, no. 1, pp. 44-53. https://doi.org/10.1111/cote.12757, 2025.

[15] V. M. Ngo, S. Helmer, N. A. Le-Khac, and M. T. Kechadi, "Structural textile pattern recognition and processing based on hypergraphs," Information Retrieval Journal, vol. 24, no. 2, pp. 137-173, 2021, doi: 10.1007/s10791-020-09384-y.

[16] G. Sratdinova, "STRUCTURAL-SEMANTIC FEATURES OF LIGHT INDUSTRY AND TEXTILE TERMS IN ENGLISH," Mental Enlightenment Scientific-Methodological Journal, vol. 5, no. 08, pp. 335-341, 2024, doi: 10.37547/mesmj-V5-I8-44.

[17] A. Rohit and S. Kaya, "A Systematic Study of Wearable Multi-Modal Capacitive Textile Patches," IEEE Sensors Journal, vol. 21, no. 23, pp. 26215-26225, 2021, doi: 10.1109/JSEN.2021.3059224.

[18] X. Zhou, X. Han, H. Li, J. Wang, and X. Liang, "Cross-domain image retrieval: Methods and applications," International Journal of Multimedia Information Retrieval, vol. 11, no. 3, pp. 199-218, 2022, doi: 10.1007/s13735-022-00244-7.

[19] L. Liu, H. Zhang, Q. Li, J. Ma, and Z. Zhang, "Collocated Clothing Synthesis with GANs Aided by Textual Information: A Multi-Modal Framework," ACM Transactions on Multimedia Computing, Communications and Applications, vol. 20, no. 1, Art. no. 26. https://doi.org/10.1145/3614097, 2024.

[20] J. Xiang, N. Zhang, and R. Pan, "Cross-modal fabric image-text retrieval based on convolutional neural network and TinyBERT," Multimedia Tools and Applications, vol. 83, no. 21, pp. 59725-59746, 2024, doi: 10.1007/s11042-023-17903-4.

[21] X. Xu, Y. Wang, Y. He, Y. Yang, A. Hanjalic, and H. T. Shen, "Cross-Modal Hybrid Feature Fusion for Image-Sentence Matching," ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), vol. 17, no. 4, Art. no. 127. https://doi.org/10.1145/3458281, 2021.

[22] Z. Li, Y. Ding, Y. Lei, F. J. M. S. Oliveira, M. J. P. Neto, and M. S. M. Kong, "Integrating artificial intelligence in industrial design: evolution, applications, and future prospects," International Journal of Arts and Technology, vol. 15, no. 2, pp. 139-169, 2024, doi: 10.1504/IJART.2024.143124.

[23] T. Li, L. Kong, X. Yang, B. Wang, and J. Xu, "Bridging Modalities: A Survey of Cross-Modal Image-Text Retrieval," Chinese Journal of Information Fusion, vol. 1, no. 1, pp. 79-92, 2024, doi: 10.62762/CJIF.2024.361895.

[24] P. E. Caltagirone, R. W. Wheeler, O. Benafan, G. Bigelow, I. Karaman, F. T. Calkins, et al., "Shape Memory Alloy-Enabled Expandable Space Habitat—Case Studies for Second CASMART Student Design Challenge," Shape Memory and Superelasticity, vol. 7, no. 2, pp. 280-303, 2021, doi: 10.1007/s40830-021-00329-y.