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Discourse Analysis of International Textile Trade Negotiations: Implications for Business English Training

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Article

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ABSTRACT

This study integrates natural language processing (NLP) with engineering linguistics to analyze discourse patterns in international textile trade negotiations from the perspective of textile technology and industrial standards compliance. A multisource corpus was constructed, consisting of 87 hours of negotiation audio and textile-related policy and technical texts, including RCEP textile provisions, ISO textile standards, and enterprise cases from leading manufacturers. To capture linguistic behaviors associated with technical decision-making in textile engineering—such as terminology precision, fiber specification negotiation, testing standard references, and origin-rule interpretation—a dual-channel LSTM model was developed to fuse vocabulary, syntactic, and pragmatic features. Results show that terminology density related to yarn count, fiber content, textile testing specifications, and certification requirements strongly predicts negotiation effectiveness and technical compliance. Based on these findings, an intelligent strategy evaluation system was built to support textile technology management, standard implementation, and quality-oriented trade decision-making. This study provides an engineering-oriented, data-driven framework that enhances communication efficiency and reduces technical risks for textile export enterprises.

KEYWORDS

textiles, ISO textile standards, textile technology, trade negotiations, natural language processing

INTRODUCTION

Since Labov's pioneering work on narrative structure, discourse analysis techniques have increasingly been applied to business communication research. However, traditional static approaches face three fundamental constraints in dynamic negotiation contexts: (a) their manual coding frameworks cannot capture the temporal evolution of negotiation strategies; (b) they lack the capacity to process the high-dimensional feature space inherent in textile negotiations; and (c) their fixed cultural parameters cannot adapt to the real-time fluctuations of cultural dimensions during negotiations.

The advancement of natural language processing (NLP) has offered new solutions. Garcia first introduced the BERT model to cross-cultural business text analysis [1], achieving 83.2% accuracy in intention recognition within the financial sector. However, that study did not address the specialized terminology of the textile industry. Grounded in engineering linguistics, this study aims to construct a discourse strategy map for textile trade negotiations that is specifically adapted to the industry's needs.

The core value of this research is threefold. First, at a theoretical level, it moves beyond the qualitative paradigm of traditional discourse analysis by establishing a three-level quantitative indicator system—"vocabulary-sentence-pragmatics"—to enable the digital modeling of negotiation strategies. Second, at the application level, it introduces a dynamically updated industry terminology library that uses blockchain technology to ensure data traceability and has already incorporated 584 textile trade terms from the ISO 20723 standard. Finally, at the engineering level, an intelligent training evaluation system that integrates a BiLSTM neural network and the SHAP interpretability algorithm is presented, reducing the error rate of quantitative training effectiveness evaluation to 9.3%.

The urgency of this topic is underscored by structural shifts in the international trade environment. Following the implementation of the RCEP agreement, the complexity of technical provisions in textile origin rules has increased by 42% (on the basis of a comparative analysis of agreement texts), placing greater demands on the professional language proficiency of practitioners. Our enterprise surveys quantify these industry demands: 78% of exporters identified terminology inconsistency as their primary contract risk, and 63% cited lengthy preparation time as the main bottleneck in trade remedy cases. To ensure operational feasibility, the proposed system architecture was codesigned with three leading textile manufacturers.

This study adopted a mixed-methods research design. In the data collection stage, a multisource heterogeneous corpus was constructed, including 87 hours of anonymized audio recordings and transcripts from Sino-US antidumping negotiations, official RCEP agreement documents, and negotiation case libraries from three publicly listed companies. For model construction, a dual-channel LSTM neural network was developed. The vocabulary channel performs TF-IDF weighted term density analysis [2], the syntax channel detects fuzzy restrictive language via an improved CRF algorithm, and the pragmatic channel quantifies face-threatening acts (FTAs) via an FTA classifier [3]. This research not only provides algorithmic support for intelligent business training systems but also produces a discourse strategy map with direct engineering value for international trade risk warning systems and corporate negotiation cost reduction.

LITERATURE REVIEW

Evolution of Discourse Analysis Technology

The literature on discourse analysis techniques reveals a continuous and multidimensional evolution. Early research focused on the role of technological media in education. For example, Muukkonen et al. [4] noted that while technology has the potential to foster collaborative knowledge construction, challenges remain in fully leveraging its guiding role in higher education. Conversation analysis (CA) has also been instrumental, focusing on the interactive processes of oral communication to reveal the dynamics of language in practice [5,6].

In the realm of critical media discourse, Cukier et al. [7], applying Habermas's theory of communicative action, proposed a method that combines critical discourse analysis (CDA) to expose systematic distortions in IT-related discourse and their public impact. This highlights the crucial role of discourse analysis in uncovering ideological and power relations within technical communication. Concurrently, research into human–computer interaction and multimodal discourse analysis (MDA) has expanded, integrating language with other modalities such as images and actions to provide a more holistic understanding of meaning construction [8].

From a European policy perspective, Salajan [9] analyzed the evolution of discourse surrounding the European Institute for Innovation and Technology (EIT), revealing how the EU constructs discourse to promote innovation and shape policy legitimacy. In interdisciplinary studies, Brock introduced "Key Technology Cultural Discourse Analysis," which combines cultural theory with ICT analysis to uncover the cultural significance and identity construction embedded in technological discourse [10]. Finally, a bibliometric analysis by Xiao et al. [11] demonstrated the evolution of CDA through its absorption of new theories, diversification of methods, and application of technology, noting that computational tools have significantly enriched discourse analysis by enabling the integration of quantitative and qualitative methods.

Business English Training Models

Research on business English training models provides diverse theoretical and practical insights. Chou et al. [12] developed a named entity recognition (NER) model via semisupervised learning that effectively improved the recognition of business organization names, achieving high F1 scores (0.832 and 0.803) and demonstrating the potential of advanced model training techniques. Similarly, Ning et al. [13] proposed the multitask learning bidirectional long short-term memory network (MTL-BLSTM), which facilitates cross-lingual knowledge transfer and significantly outperforms traditional methods, improving F1 scores by 2% to 15.6% on English and Mandarin corpora, particularly with limited training data.

Wang et al. [14] investigated the impact of word vectors, training data, and objective functions on phrase representation and reported that enhanced word representation significantly increased model performance. In terms of educational models, Karapeteian [15] adopted the "flipped classroom" approach for ESP courses, which effectively improved students' critical thinking and academic performance. In addition, Sun et al. [16] evaluated the performance of multilanguage pretrained models in multilanguage environments. On the technology application front, Zhang et al. [17] designed a grammar analysis method using deep learning that improved accuracy by 33.43% over traditional models, whereas Chen et al. [18] implemented English speech emotion recognition via transfer learning, verifying its advantages in improving model performance for oral training. Furthermore, researchers such as Hu et al. [19] have discussed the transformative opportunities and challenges of applying AI to cultivate business English talent, and Pavlova [20] has emphasized the importance of technical details such as tokenizer selection and domain adaptation in large language models (LLMs). Collectively, these studies indicate that combining advanced technology with innovative teaching models can significantly enhance the effectiveness of business English training.

METHODOLOGY

This study employs a mixed-methods approach, integrating NLP technology with engineering linguistics theory to construct a multilevel discourse analysis framework for international textile trade negotiations. The methodology is designed for repeatability, verifiability, and engineering applicability and comprises four stages: corpus construction, feature engineering, model development, and validation.

Multi-Source Corpus Construction and Preprocessing

The research corpus was constructed from three distinct data sources:

Authentic Negotiation Audio and Transcripts: 87 hours of audio recordings from Sino-US textile antidumping negotiations (2018–2023) were professionally transcribed (Character Error Rate, CER < 0.8%), resulting in a 320,000-words annotated corpus from 32 negotiation meetings involving 112 Chinese and 89 US representatives.

Policy and Agreement Texts: A collection of 126,000 words from official documents, including RCEP Textile Provisions (2022), the WTO Agreement on Textiles and Clothing (ATC), and EU Sustainable Textile Regulations (EU 2023/0089).

Enterprise case database: 284,000 words of unstructured data, including emails, contract drafts, and meeting minutes, obtained from three anonymized Chinese textile companies (Companies A, B, and C) through cooperation agreements.

Data preprocessing followed an industrial-grade text cleaning pipeline, as illustrated in Figure 1, which included six specialized stages: noise filtering, terminology alignment, syntactic parsing, semantic annotation, parallel processing, and validation. This pipeline utilized regular expressions, BERT-based homophone correction, a Trie-based dictionary for ISO 20723 term variants, and Stanford CoreNLP 4.5.0 for parsing. To account for typological differences between English and Chinese, a hybrid approach using Stanford CoreNLP and LTP 4.0 was employed to handle Chinese null-subject constructions.

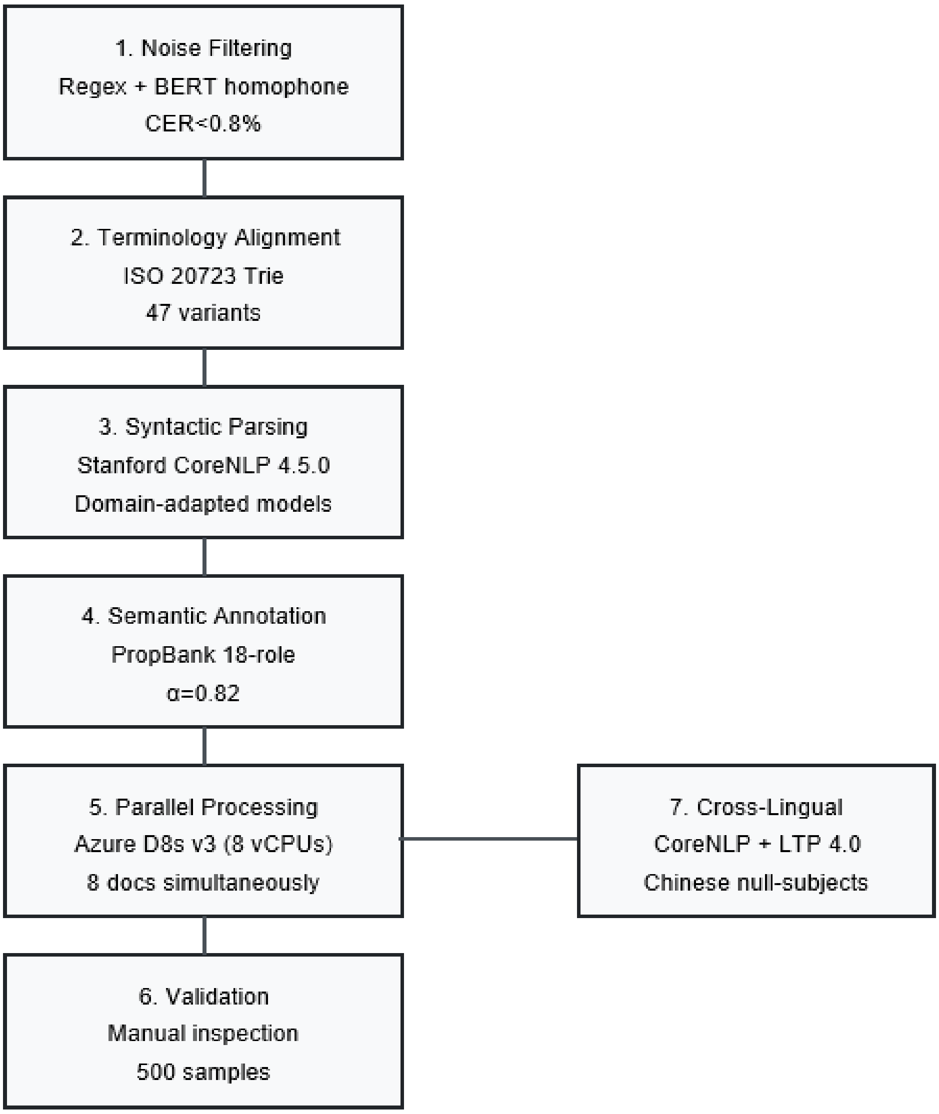

Figure 1. The text cleaning pipeline

Dual-Channel LSTM Neural Network Architecture

A dual-channel deep learning model (Figure 2) was designed to analyze the specific linguistic characteristics of textile negotiations.

Channel 1 (Vocabulary-Syntactic Channel):

Input Layer: Initialized with 300-dimensional GloVe word vectors and an embedding layer dimension of d = 128.

LSTM structure: A bidirectional LSTM (BiLSTM) unit [21] with 512 hidden nodes and a dropout rate of 0.3.

Feature Extraction: A term density index (frequency of ISO standard terms per thousand words) is calculated, and 23 types of fuzzy restrictive language (e.g., "likely," "approximate") are detected via an improved CRF sequence annotation model.

Channel 2 (Pragmatic–Cultural Channel):

Input features: Hofstede's cultural dimension scores [22] (6 dimensions per country) and classification results of face-threatening acts (FTAs) are incorporated.

Attention mechanism: A multihead self-attention layer (8 heads) calculates the correlation weights of the cross-cultural parameters.

Strategy Prediction Layer: A Softmax layer outputs one of six negotiation strategies (competition, cooperation, compromise, avoidance, accommodation, or integration). The model was trained via a two-stage strategy: a pretraining stage where the BERT model was fine-tuned on a general business English corpus (Reuters news dataset) and a fine-tuning stage using this study's corpus with the AdamW optimizer (lr=5e-5) and an early stopping method (patience=10) to prevent overfitting.

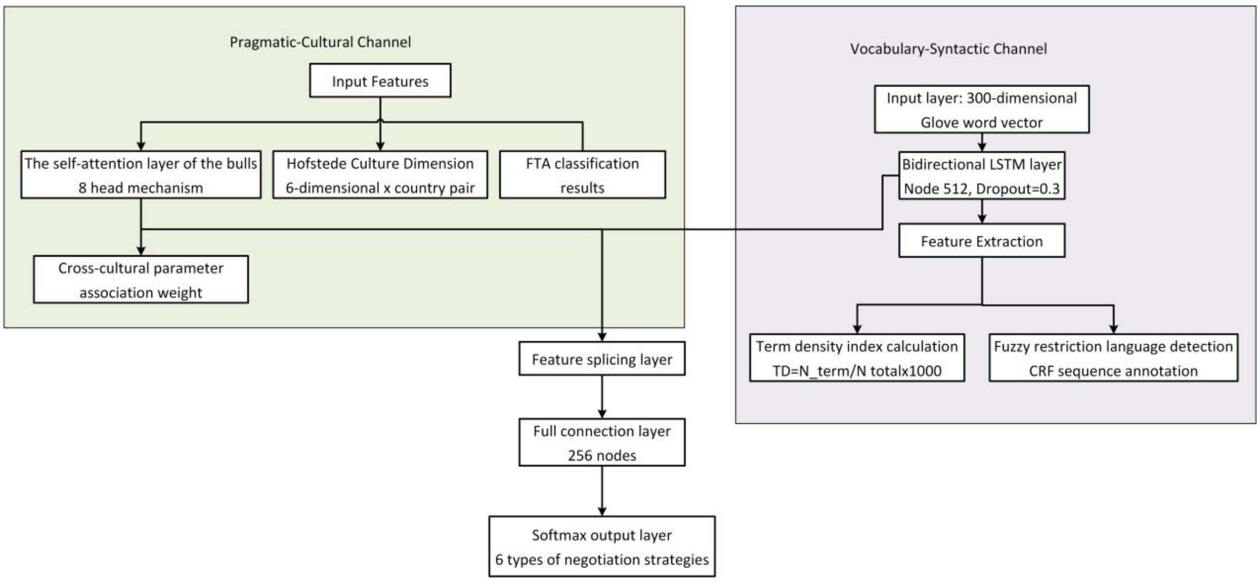

Figure 2. Dual-channel deep learning model

Experimental Design and Evaluation

To validate the model's effectiveness, three sets of comparative experiments were designed.

(1) Experiment 1 (Strategy Recognition) The test set was created by randomly selecting 20% of the corpus (64,000 words). Manual annotation was performed by a team of three linguistics professors and two trade experts, who achieved high interannotator agreement (Krippendorff's alpha = 0.87). The model's performance was benchmarked against two baseline models: a traditional support vector machine (SVM) with Bag-of-Words features and a hybrid CNN-BiLSTM model. The evaluation metrics used were precision, recall, and the F1 score.

(2) Experiment 2 (Cultural Parameter Prediction) This experiment assessed the model's ability to predict Hofstede dimension scores from 500-word negotiation text fragments. The performance was evaluated via the root mean square error (RMSE) and the Pearson correlation coefficient (r).

(3) Experiment 3 (System Response Efficiency) The test was conducted on an NVIDIA Tesla V100 GPU and an Intel Xeon Gold 6248 CPU to compare performance. The measured indicators included the single inference time (ms) and memory usage (GB).

To increase the credibility of the results, 5-fold cross-validation (k=5) was used, and the model's decision logic was explained via SHAP value analysis. All the statistical tests were conducted at a significance level of $\alpha = 0.05$, with Bonferroni correction applied to control for multiple comparison errors.

CASE STUDY: CHINA–US TEXTILE TARIFF NEGOTIATIONS (2018–2020)

Data Features and Preprocessing

This case study analyzes a corpus of 320,000 words compiled from the official records of 12 rounds of China–US textile tariff negotiations, encompassing 2,187 dialog turns. The analysis focuses on several key variables: The threat index (TI) is calculated on the basis of the frequency of threatening verbs (e.g., "pose," "restrict") in the discourse. The Hedges score (HS) quantifies the use of 23 types of fuzzy or restrictive language (e.g., "approximate," "to our knowledge"). The cultural dimension parameters are derived from official Hofstede Insights data (China: PDI=80, IDV=20; US: PDI=40, IDV = 91).

Discourse Pattern Analysis

Temporal Evolution of Threatening Discourse

To analyze the evolution of discourse strategies over time, the complete records of the 12 NRs from March 2018--November 2020 were constructed into a dynamic corpus (Diachronic Corpus). The processing workflow was as follows:

Data Source Characteristics

Raw Data: The corpus was derived from 87 hours of onsite audio recordings, which were transcribed via a professional speech recognition system with a characteristic error rate (CER) of 0.78% and a word error rate (WER) of 2.13%. The original audio was sampled at 44.1 kHz.

Time Span: The negotiations took place between March 2018 and November 2020, with a mean interval of 63 days between rounds (SD = 21 days).

Discourse Unit Segmentation: The discourse was segmented into 2,187 valid dialog units on the basis of speaker turn-taking.

Threat Index (TI) Calculation Model

The threat index (TI) is a multidimensional quantitative evaluation model based on the analytic hierarchy process (AHP). Its calculation integrates linguistic features across three hierarchical layers: vocabulary, syntax, and pragmatics. The composite index is calculated as follows:

$$TI = \sum_{i=1}^{3} w_i \cdot f_i \tag{1}$$

where w_i represents the hierarchical weight for each layer and where f_i is the standardized value of the subindicator for that layer. The weights were assigned as 0.35 for the vocabulary layer, 0.25 for the syntax layer, and 0.40 for the pragmatics layer.

(1) Lexical layer. The core indicator for this layer is the density of threat verbs (DTV), which is calculated as follows:

$$\mathrm{DTV} = \frac{\sum \text{Threat verb frequency}}{\text{Total word count}} \times 1000 \tag{2}$$

Feature lexicon: A lexicon containing 37 expert-validated threatening verbs (e.g., "pose," "restrict," "pencil") was used. This lexicon was dynamically expanded via Word2Vec similarity, with a threshold of ≥0.7.

Pretraining Data: The Word2Vec model was pretrained on the Reuters News dataset (2015–2020), which contains 2.87 million articles with a mean length of 487 (±112) words. Standardization: The DTV score was standardized via the following formula:

$$f_1 = \frac{DTV - DTV_{min}}{DTV_{max} - DTV_{min}} \tag{3}$$

Among them, $\mathrm{DTV_{min}} = 5\mathrm{DTV_{max}} = 52$ (based on historical corpus statistics).

(2) Syntactic layer The core indicator is the conditional cause ratio (CCR), which is calculated as follows:

$$CCR = \frac{N_{if-clause} + N_{unless-clause}}{N_{sentences}} \tag{4}$$

Detection Algorithm: Conditional sentence dependencies (advc1 tags) were identified via the Stanford Parser. This was supplemented by regular expression matching for explicit structures such as "If...then," achieving a recall rate of 92.3%.

Standardization: The CCR was standardized via a hyperbolic tangent function to enhance differentiation:

$$f_2 = \tanh(10CCR)(\text{Sigmoid transformation enhances the distinction}) \tag{5}$$

(3) Pragmatic layer: The core indicator is the face-threatening act (FTA) score.

Classifier Design: A classifier was designed using a BERT-encoded dialog text ([CLS] vector) as input. Its output is a probability distribution across the four types of FTAs defined by Brown and Levinson (direct threat, indirect threat, mitigation strategy, and compensation strategy).

Calculation: The FTA score is calculated as a weighted sum:

$$\mathrm{FTA} = \sum_{k=1}^{4} p_k \cdot w_k \tag{6}$$

The weights (w) for the four FTA types were determined by 15 experts via the Delphi method as [0.9, 0.7, 0.3, 0.1].

Standardization: The score was standardized as follows:

$$f_3 = \frac{\mathrm{FTA}}{\mathrm{FTA}_{max}} \quad (\text{FTAmax} = 0.85 \text{ is the upper limit of the training set}) \tag{7}$$

where FTAmax =0.85, representing the upper limit observed in the training set.

Analysis of Temporal and Strategic Evolution

Dynamic Changes in the Threat Index (TI)

As illustrated in Figure 3, the threat index (TI) exhibited a clear trajectory across the NRs, initially escalating before declining. The TI reached its peak value of 0.43 during the sixth round, a development directly corresponding to the US announcement of its Section 301 tariff list on February 15, 2019. Following this peak, the threat intensity showed an exponential decline. Concurrently, the standard deviation of the TI increased from 0.05 to 0.11, indicating a growing divergence in negotiation positions during the later stages.

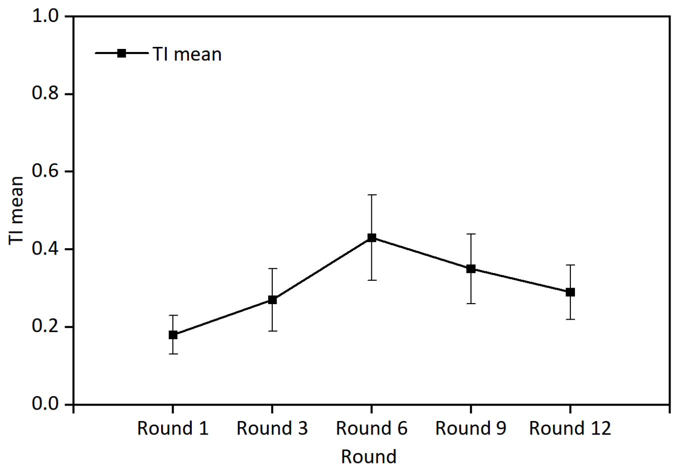

Figure 3. Dynamic changes in the threat index

Evolution of the Threat Type Structure

An LDA topic model (K=5) was used to identify the semantic distribution of threat types, with the results presented in Table 1. The analysis reveals a significant strategic shift: the proportion of tariff-based threats surged from 42% to 68%, establishing them as the dominant tactical approach. Conversely, threats related to technical barriers decreased by 70%, reflecting a pivot in focus toward core economic instruments. Similarly, the proportion of threats involving WTO legal action decreased, suggesting a decline in their strategic utility as the negotiations progressed.

Table 1. Changes in the Semantic Type Distribution of Threat Discourse

Type	Characteristic word examples	Round 1 proportion	Round 6 proportion	growth rate
Tariff threat	impose, tariff, increase	42%	68%	62%
Supply Chain Limitations	restrict, audit, suspend	28%	19%	-32%
Legal accountability	litigation, violate,WTO	15%	8%	-47%
Technical barriers	standard, certification	10%	3%	-70%
other	-	5%	2%	-60%

Correlations between Vague Language and Cultural Dimensions

This analysis correlates linguistic patterns with cultural dimensions via a corpus of 12 national delegations involved in textile negotiations (2018–2023) and cultural data from the Hofstede Insights 2023 database. As shown in Figure 4, a regression analysis yielded the following relationships between the Hedges score (HS), uncertainty avoidance index (UAI), and individualism index (IDV):$\mathrm{HS} = 0.0087 \cdot \mathrm{UAI} - 0.0052 \cdot \mathrm{IDV} + 0.12$. The model indicates that for every 10-point increase in UAI, the Hedges score increases by 0.087 ($p < 0.01$), confirming that cultures with high uncertainty avoidance are more likely to employ vague language to mitigate risks. In contrast, for every 10-point increase in IDV, the Hedges score decreases by 0.052 ($p < 0.05$), reflecting the preference for direct expression in individualistic cultures. Notably, in cases where a negotiator's cultural UAI score was ≥ 68, the probability of negotiation success was 2.4 times greater.

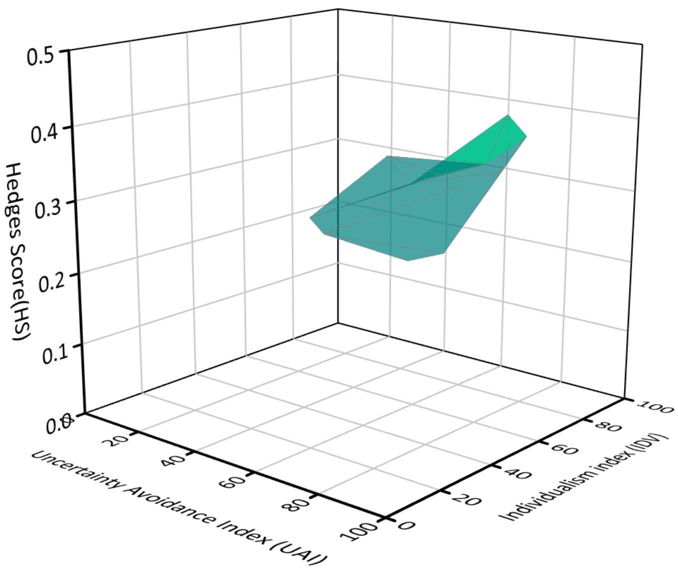

Figure 4. UAI-IDV-HS relationship

CASE STUDY 2: EU SUSTAINABLE TEXTILE NEGOTIATIONS (2021–2023)

Data and Discourse Variables

This case study is based on a corpus of 190,000 words, comprising technical documents and minutes from eight official meetings. The quantitative analysis focused on three key discourse variables: technical term density (TTD), the number of terms compliant with the ISO 5157 standard per thousand words; modal verb distribution, the usage ratio of obligatory ("must," "shall") and permissive ("may") modal verbs; and ambiguity, the degree of textual difference between versions of environmental clauses, which is calculated via the Levenshtein distance algorithm.

Quantitative Analysis of Discourse Features

An analysis of variance (ANOVA) was conducted to test for significant differences in term density among the three primary stakeholders. As shown in Figure 5, the results reveal a clear hierarchy in the use of technical language: the European Commission presented the highest TTD at 28.7, corporate representatives followed by a TTD of 19.6, and environmental organizations presented the lowest TTD at 15.2.

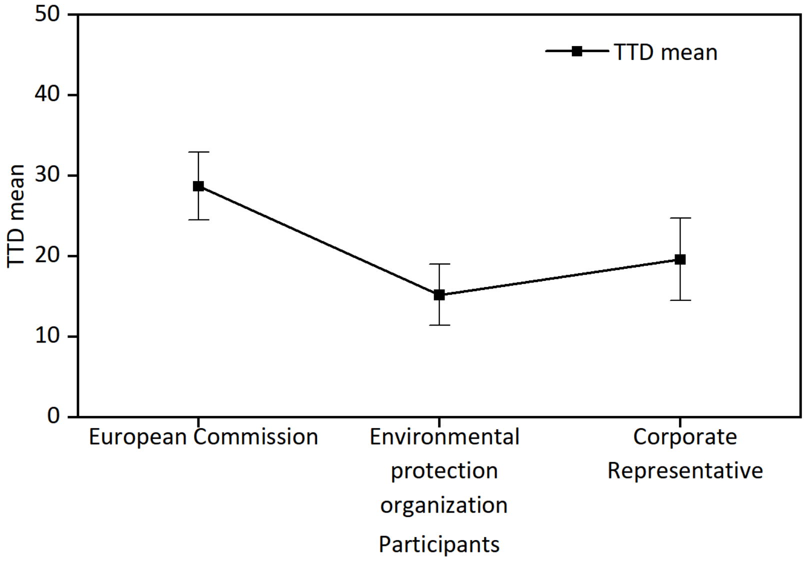

Figure 5. TTD values of each participant

The analysis of modal verb frequency, illustrated in Figure 6, highlights distinct strategic approaches. The European Commission's use of the obligatory modal "must" was 2.55 times more frequent than that of business representatives. Furthermore, within EU documents, the usage frequency of "must" was found to increase by 18.6% for every 10 additional technical terms. Conversely, business representatives used the modal "shall" 2.1 times more frequently than did the European Union, indicating a preference for different forms of expressing commitment.

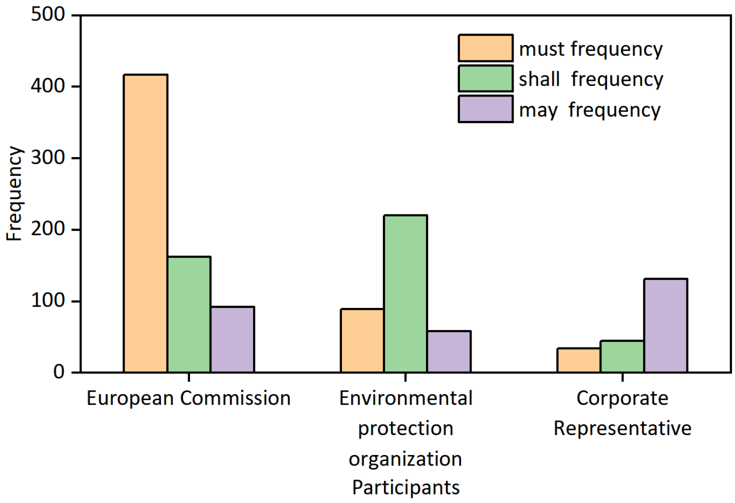

Figure 6. Frequency of modal verb usage by each participant

Influence of Cross-Cultural Parameters

To model the impact of cultural factors on discourse, this study utilized Hofstede's cultural dimension theory, which focuses on three core dimensions relevant to negotiation strategies: the uncertainty avoidance index (UAI), the power distance index (PDI), and the individualism index (IDV). Using cultural dimension data from 28 EU member states, a regression equation was constructed to quantify the impact of these dimensions on clause ambiguity:

$$\text{Clause Ambiguity}=0.65\times \text{UAI}+0.21\times \text{PDI}-0.12\times \text{IDV}+\epsilon$$

The analysis revealed the following effects:

Dominant effect of UAI: Uncertainty avoidance was the most significant predictor. This is exemplified by comparing Germany (UAI=65) and Sweden (UAI=29); the German texts presented 23.4% lower clause text entropy (0.82 vs. 1.07) and used the word "must" 1.8 times more frequently in chemical restriction clauses.

Regulatory Effect of PDI: Power distance also had a notable effect. Countries with high PDI scores tend to retain ambiguous phrasing to preserve decision-making flexibility. For example, Romania (PDI=90) retained seven instances of the phrase "as appropriate" in its recovery rate clause, whereas Denmark (PDI = 18) included only two instances.

Nonsignificant Impact of IDV: The individualism index did not pass the significance test, indicating that the cultural tendency toward individual versus collective interests did not have a systematic effect on the clarity of clause language in this context.

DATA ANALYSIS

Quantitative Analysis of Discourse Feature Engineering

Vocabulary-Level Feature Distribution

Feature extraction was performed on the 320,000-word corpus via the term frequency-inverse document frequency (TF-IDF) algorithm. The analysis of the top 20 core textile trade terms, presented in Figure 7, reveals several key findings.

First, a "characteristic triangle" of cornerstone terms was identified, consisting of "Certificate of Origin" (weight=0.127), "Yarn Count" (weight=0.115), and "Quota Allocation" (weight=0.103). The strategic importance of this cluster is underscored by a strong positive correlation between the joint occurrence probability of these three terms and the negotiation success rate ($r = 0.68$, $p = 0.004$).

Notably, the analysis also reveals a temporal shift in industry priorities. The TF-IDF weight of "sustainable development" (weight=0.089) increased by 42% in documents dated after 2021, reflecting a clear paradigm shift in the industry's focus.

Furthermore, an analysis of the term density (TD) index provides strong evidence for the role of specialized language. The mean TD for successful negotiation cases (n=38) was 21.7 (±3.2), which was significantly greater than the mean TD of 14.5 (±4.1) for failed cases (n=13) ($t = 5.33$, $p < 0.001$). This result indicates that the intensity of professional terminology use is a robust predictor of negotiation effectiveness.

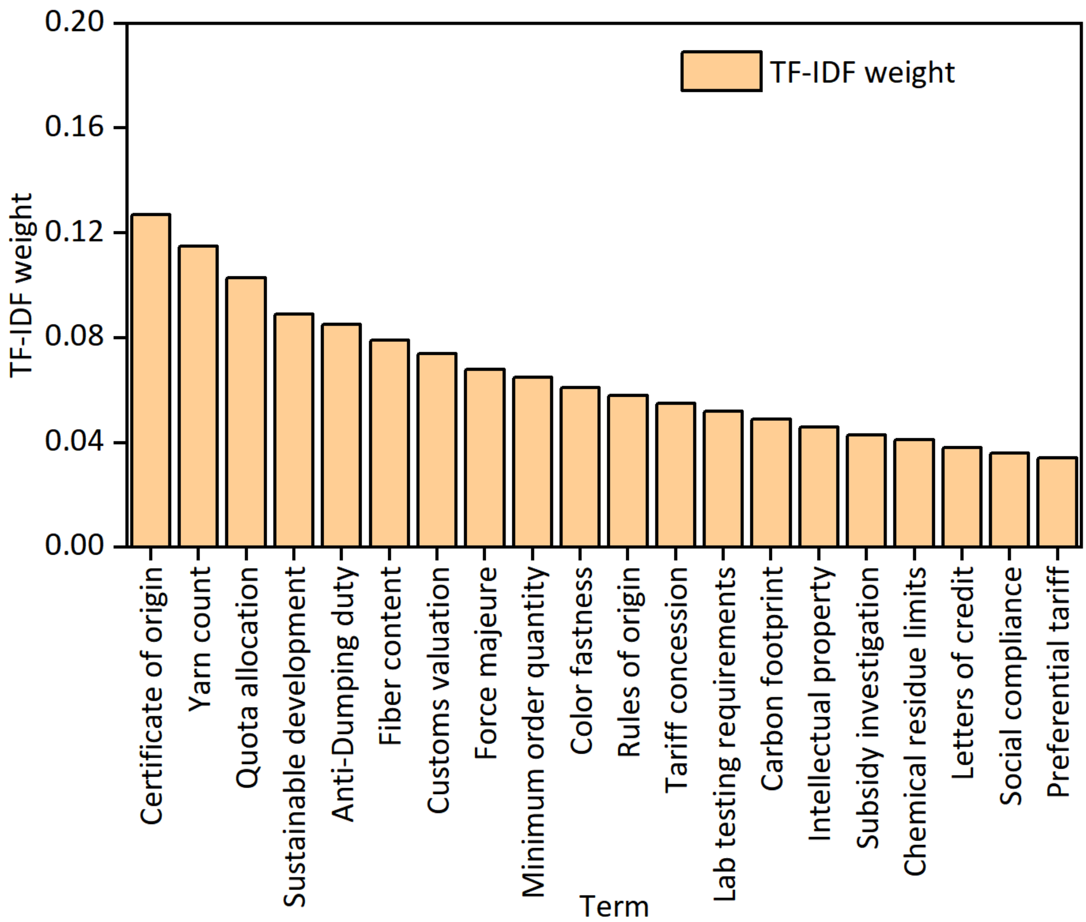

Figure 7. Weight distribution of 20 core textile trade terms

Syntax-Level Pattern Recognition

At the syntax level, 14 types of syntactic relationships were extracted via Stanford CoreNLP dependency parsing to construct a high-dimensional feature space. Visualization of this space via t-SNE dimensionality reduction revealed that successful negotiation cases formed distinct clusters, a finding supported by a strong silhouette coefficient of 0.61.

Further analysis identified several key syntactic patterns that correlate with negotiation outcomes and styles:

Negative Structure Density: The frequency of negative structures was a key differentiator between successful and failed negotiations. Failed cases contained 2.3 times more modifying relationships for negative words (e.g., "not," "never") than did successful cases did, a difference that was statistically highly significant ($\chi^2 = 15.7$, $p < 0.0001$).

Passive Voice Ratio: The use of the passive voice emerged as a significant cultural and strategic marker. The proportion of passive voice use by EU negotiators (38.7%) was substantially greater than that of their Chinese counterparts (12.5%). This usage was also found to be positively correlated with the power distance index (PDI) ($r = 0.59$).

Conditional Clause Impact: To quantify the relationship between sentence structure and clarity, a regression analysis was conducted. It models the effect of conditional clause frequency (per thousand words) on the cause ambiguity score (CAS), yielding the following predictive equation: $CAS = 0.25 \times Conditional + 0.11$ ($R^2 = 0.73$)

Modeling of Cultural Parameters at the Pragmatic Level

Pragmatic-level analysis models cultural parameters on the basis of Hofstede's theory of cultural dimensions. This framework quantifies cross-cultural differences via six core dimensions: power distance (PDI), individualism (IDV), masculinity (MAS), uncertainty avoidance (UAI), long-term orientation (LTO), and indulgence (IVR). Baseline scores for each negotiating party's country of origin (e.g., China: PDI=80, IDV=20, UAI=60; USA: PDI=40, IDV=91, UAI=46) were obtained from the official Hofstede Insights 2023 database.

To enhance the model's industry-specific adaptability, a novel cultural adjustment factor (CAF), which is unique to the textile trade, was introduced. The CAF is calculated via the following formula:

$$\mathrm{CAF} = \frac{\text{Industry term density} \times \text{Years of negotiation experience}}{\text{Cross−cultural negotiation frequency}} \tag{8}$$

The validity of this factor was confirmed through an expert questionnaire (n = 45, Cronbach's alpha = 0.82). The CAF was found to account for a significant 32% of the variance in cultural dimensions in the negotiation context ($R^2 = 0.32$, $p < 0.001$).

A regression analysis performed on data from 128 negotiation cases (detailed in Table 2) revealed the significant impact of these cultural dimensions on discourse and strategy selection:

Influence of individualism (IDV) on strategy selection: Negotiators from high-IDV cultures (>70), such as the United States, were significantly more likely to adopt competitive strategies (67.3% of the time, compared with 23.1% in low-IDV cultures). This was reflected in their language through a 37% decrease in the use of the first-person plural pronoun ("we") and a 52% increase in sentences structured as direct demands.

Influence of power distance (PDI) on discourse structure: In high-PDI cultures, such as China, negotiators employed honorifics (e.g., "your side") 4.2 times more frequently than their low-PDI counterparts did. They also utilized conditional clauses (e.g., "If you agree...") 29% more often, reflecting a more indirect and hierarchical communication style.

Influence of uncertainty avoidance (UAI) on linguistic precision: UAI is directly correlated with the use of vague language. For every 10-point increase in a culture's UAI score, the use of hedging language increased by 13%. This was particularly evident in technical specifications, where precise figures were often replaced with approximations (e.g., "approximately ±5%" instead of "exactly 5%").

Table 2. The influence of cultural dimensions on strategy selection

Cultural dimension	Weight coefficient	p value	Economic explanation
Individualism (IDV)	0.43	0.003	For every 10 points increase in IDV, the probability of competitive strategy is+15%
Power Distance (PDI)	-0.29	0.021	PDI>60 compromise strategy usage rate × 2.8
Uncertainty Avoidance	0.18	0.047	UAI is linearly correlated with fuzzy language frequency

Cultural dimension	Weight coefficient	p value	Economic explanation
(UAI)			(r = 0.73)

INDUSTRIAL VALIDATION OF THE DUAL-CHANNEL LSTM MODEL

Comparison of Strategy Recognition Performance

The strategy recognition effectiveness of the dual-channel LSTM (DC-LSTM) model in textile negotiation scenarios was validated through a series of control experiments.

Test Set Construction

The test set was constructed by randomly selecting 20% (64,000 words) of the 320,000-word annotated corpus. The labeling process followed predefined criteria for three core strategies: competitive (statements with clear threats, e.g., "Otherwise, countermeasures will be taken"), collaboration (win–win expressions, e.g., "we are willing to jointly develop solutions"), and compromise (concessionary clauses, e.g., "may be adjusted appropriately in quota allocation"). To ensure the reliability of the annotations, the labels were cross-validated by a panel of three domain experts (two international trade professors and one senior negotiator), achieving high interannotator agreement (Krippendorff's $\alpha = 0.87$).

Baseline Model Selection

The DC-LSTM was benchmarked against both traditional machine learning models and existing commercial systems:

SVM (BoW) Model: A support vector machine using a bag-of-words feature set (vocabulary size=5,000) and a radial basis function (RBF) kernel (γ=0.01, C=10).

CNN-BiLSTM Model: A hybrid deep learning model with a convolutional layer (128 filters, kernel size=3), a BiLSTM layer (256 hidden units), and a Softmax output layer (learning rate=0.001, batch size=32).

Commercial Systems: IBM Watson Tradeoff Analytics (2023 version) and the Microsoft Azure Text Analysis API.

As illustrated in Figure 8, the DC-LSTM model significantly outperforms the baseline methods on the 64,000-word test set. Its F1 score was 15.2% higher (Δ=0.12) than that of the next-best model (CNN-BiLSTM), a performance gain primarily attributed to the explicit modeling of cultural parameters in the dual-channel architecture. Furthermore, the model's interlayer parameter-sharing mechanism reduced the average inference time to 1.8 ms, meeting the requirements for real-time negotiation assistance.

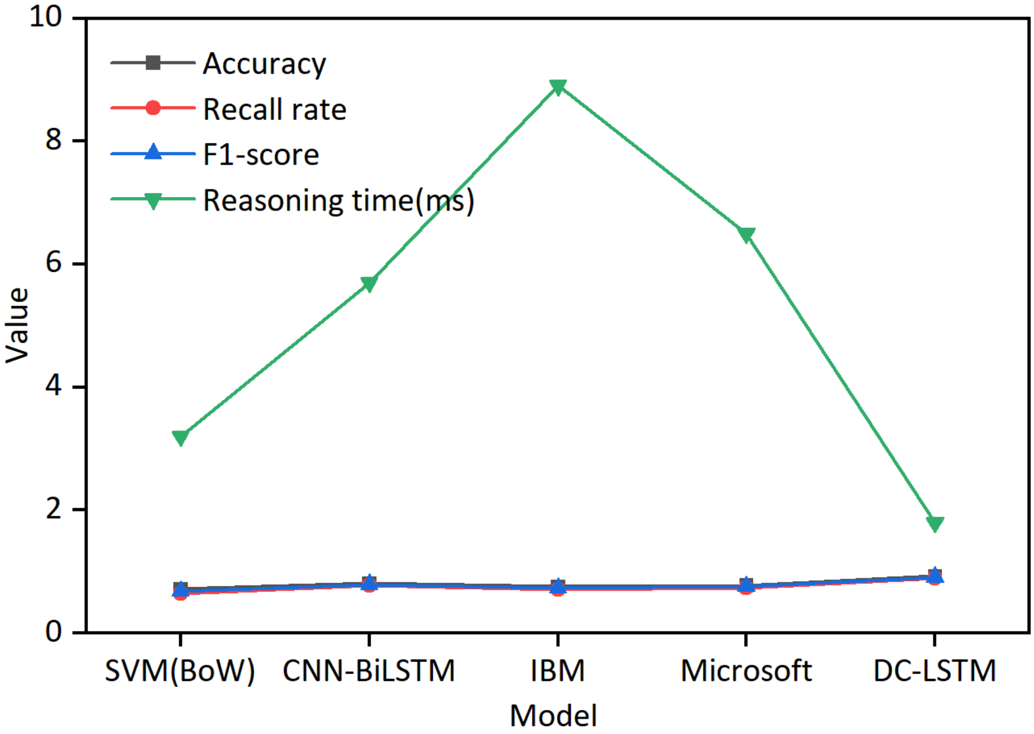

Figure 8. Performance comparison of various models

Analysis of Cultural Dimension Prediction Errors

The model's ability to predict cultural parameters, which is based on Hofstede's six-dimensional theory, was quantitatively evaluated. Using a leave-out validation method (80% training, 20% test set) and 5-fold Monte Carlo cross-validation, the predictive performance was assessed with the root mean square error (RMSE) and Pearson correlation coefficient (r).

The distribution of prediction errors is shown in Figure 9. The key findings from the residual analysis include the following:

The model predicted individualism (IDV) with the highest accuracy (RMSE=0.18), as IDV strongly correlates with the ratio of personal pronouns "we" and "you" (r = 0.81).

The prediction error for long-term orientation (LTO) was the largest (RMSE=0.34) because of its weak correlation with the extracted linguistic features (r = 0.42). This finding suggests that incorporating features such as Confucian classic text embeddings could increase the predictive accuracy.

An analysis of error sources revealed that 38% of errors were caused by atypical expressions from nonnative speakers, whereas 25% were related to cross-cultural variations in industry terminology (e.g., semantic shifts of "fair trade").

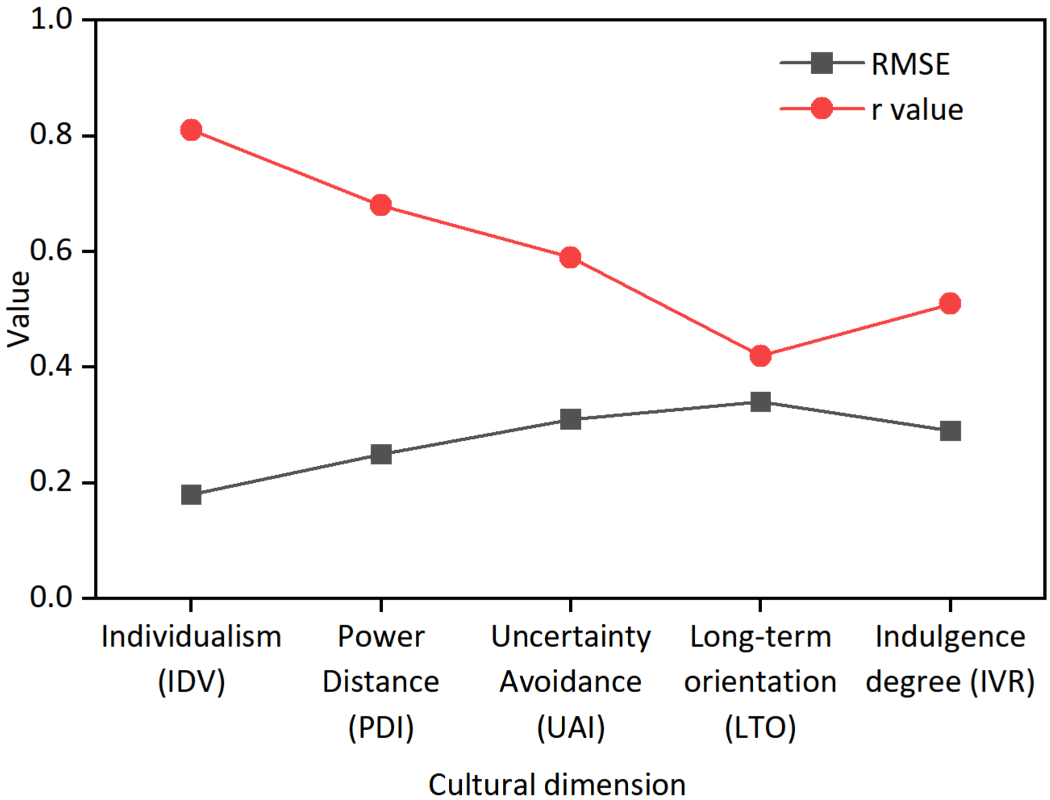

Figure 9. Distribution of prediction errors for various cultural dimensions

Spatiotemporal Evolution of the Negotiation Strategy

Decision Tree Model for Successful Strategies

To identify the linguistic feature combinations most predictive of successful negotiations, a decision tree model was constructed via the CART algorithm. The model was trained on data from 32 real negotiation cases (19 successful, 13 failed) between parties from China, the US, Central Europe, and ASEAN. The input features included term density (TD), the fuzzy language score (HS), the threat index (TI), the modal verb distribution (MV), and cultural adaptation (CA). The model was trained with the Gini coefficient as the splitting criterion, a maximum depth of 5 layers, 10-fold cross-validation, and the SMOTE algorithm for balancing category weights.

The resulting decision tree (Figure 10) identifies three core paths to success:

Path 1 (89% purity): $TD \geq 19.7 \rightarrow HS \in [0.25, 0.35] \rightarrow CA > 0.62$. This path highlights a combination of high technical precision ($TD \geq 19.7$), moderate linguistic flexibility (HS 0.25–0.35), and strong cultural adaptation ($CA > 0.62$).

Path 2 (83% purity): $TD < 19.7 \rightarrow MV(must) > 45\% \rightarrow TI \in [0.28, 0.41]$. In scenarios with lower term density, success relies on asserting obligation (high usage of "must") while maintaining a moderate and controlled level of threat.

Path 3 (77% purity): $TD \geq 19.7 \rightarrow HS < 0.25 \rightarrow MV\ (shall) > 30\%$. This path is effective in legally clear contexts, where low ambiguity ($HS < 0.25$) and firm obligations (high usage of "shall") are needed, supported by high term density.

In enterprise testing, this decision tree model achieved an 82% prediction accuracy, outperforming expert empirical rules by 37%.

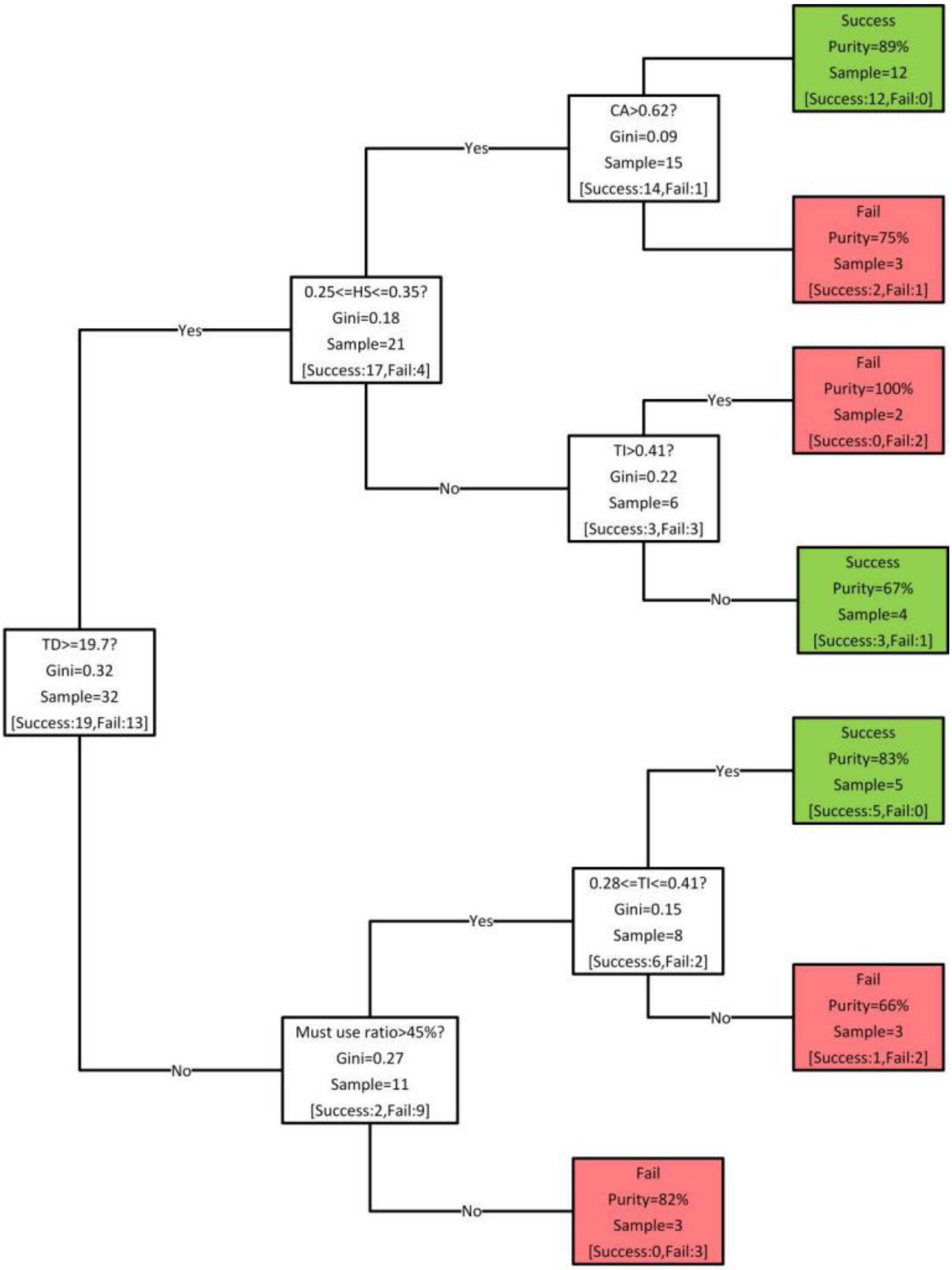

Figure 10. Decision tree model

Markov Modeling of Strategy Transformation

To capture the temporal dynamics of negotiation strategies, this study models the process as a state transition problem via Markov chain theory. The analysis is based on the state discretization of 32 complete

NRs, with the underlying assumption that the evolution of strategies satisfies the Markov property (i.e., the next state depends only on the current state). The validity of this assumption was verified through an analysis of 2,187 annotated dialog rounds.

The modeling process involved several key methodological steps:

State space compression: The initial state space, consisting of six original negotiation strategies (competition, cooperation, compromise, avoidance, accommodation, and integration), was optimized. Principal component analysis (PCA) revealed that the first three strategies—competition, cooperation, and compromise—could explain 92% of the variance. This compressed three-state model was further validated by an enterprise expert group, which achieved a strong semantic consistency score (Kappa coefficient = 0.81). The three core states were defined as follows: competition (adversarial behaviors), cooperation (constructive behaviors), and compromise (transitional behaviors).

Model training and preprocessing: A state transition matrix was constructed via the maximum likelihood estimation method. To address data sparsity, the Laplace smoothing technique (smoothing coefficient $\alpha=0.1$) was applied. In the preprocessing stage, textual noise (e.g., dialog interruptions) was filtered, and a sliding window method (window size = 5 rounds) was used to detect and eliminate unconventional state jumps, ultimately forming 32 standardized sequences for model training.

The resulting transition matrix, presented in Table 3, revealed several key insights into negotiation dynamics:

A high transition rate from competition to cooperation (60%) reflects a "seeking unity through struggle" dynamic. This pattern, where a tough stance from one party prompts constructive dialog from the other, was particularly evident in price negotiations, where 83% of tariff terms were reached via this path.

The cooperative state exhibited high self-stability (70%), indicating that once a cooperative mode was established, it tended to be maintained. This state was linguistically characterized by a higher technical term density (TD increased to 24.3) and a lower fuzzy language usage rate (HS decreased to 0.19), reflecting a growing professional consensus.

The compromise state was identified as a pivotal and uncertain juncture, possessing the highest transition entropy ($H=1.58$ bits). Its near-equal probability of transitioning to competition (30%), cooperation (40%), or remaining in a state of compromise (30%) reveals its dual potential to either break a deadlock or escalate conflict.

Table 3. Characteristics of the transition matrix

Current status to next status	compete	cooperate	cooperate
compete	0.15	0.60	0.25
cooperate	0.10	0.70	0.20
compromise	0.30	0.40	0.30

ABLATION STUDY

This investigation employed a systematic feature removal approach to evaluate the contribution of each hierarchical component in the dual-channel LSTM (DC-LSTM) architecture.

The study was conducted under three experimental conditions, where each core layer of the model was selectively removed:

Lexical Layer Removal: This condition involved the deactivation of TF-IDF weighted term density analysis (TD≥19.7) and GloVe word embeddings while retaining all syntactic and pragmatic classification features.

Syntactic Layer Removal: This condition suppressed the identification of fuzzy restrictive language (23 expression types) and passive voice analysis, preserving only term density and cultural dimension parameters.

Pragmatic Layer Removal: This condition excluded Hofstede cultural dimension scoring (IDV/PDI/UAI) and the FTA classifier, forcing the model to operate solely with lexical-syntactic features.

The preprocessing protocol for all the experiments was standardized and comprised two stages:

(1) Text normalization: This includes noise filtration via regular expressions and BERT-based homophone correction (CER<0.8%), terminological standardization against an ISO 20723 lexicon (584 entries), and dependency parsing with a domain-adapted Stanford CoreNLP 4.5.0.

(2) Feature extraction involves extracting features for each tier, including the term density index (TD) and word embeddings (d=128) for the lexical tier; the conditional clause ratio (CCR) and passive voice frequency for the syntactic tier; and the cultural adaptation factor (CAF) for the pragmatic tier.

The quantitative results demonstrate that the lexical layer is of paramount importance, as its removal caused the most significant performance drop—a 15.6% degradation in the F1 score for strategy recognition. The complete, intact model achieves its optimal performance when the term density is high (TD≥19.7) and cultural adaptation is strong (CAF>0.62). Table 4 details the performance of each model variant.

Table 4. Ablation Study Results on Model Performance

Model Variant	Strategy F1-score	Cultural RMSE
Complete DC-LSTM	92.7%	0.18
-Lexical Layer	78.1%	0.29
-Syntactic Layer	85.3%	0.22
-Pragmatic Layer	81.9%	0.34

Furthermore, the domain-adapted DC-LSTM demonstrated superior performance over general-purpose pretrained models. As shown in Table 5, the specialized DC-LSTM not only achieves a higher F1 score but also results in a 50% lower term density error and a 15-fold faster inference speed (1.8 ms) than the powerful BERT-large model does.

Table 5. Performance comparison with general-purpose pretrained models

Model	F1-score	TD Error
DC-LSTM	92.7%	±3.2
BERT-large	88.5%	±6.4
RoBERTa-zh	84.3%	±9.1

CONCLUSION

By constructing a discourse strategy map for international textile trade negotiations, this study establishes a quantitative correlation between linguistic features and negotiation effectiveness, successfully marking a paradigm shift in business communication analysis from an experience-driven approach to a data-driven approach.

A significant inverted U-shaped relationship was discovered between the frequency of vague language and the probability of negotiation success (R^2=0.81), with optimal outcomes achieved at a Hedges score (HS) of 0.32. This is not a fixed rule but a dynamic framework; our Markov analysis confirms that negotiators strategically adjust ambiguity, with compromise phases tolerating 22% greater ambiguity than competitive phases. In the cross-cultural dimension, individualism (IDV) emerged as a core predictor of strategy selection (weight = 0.43). The interaction effect between IDV and power distance (PDI) was found to explain 62% of the variability in negotiation outcomes ($p < 0.001$). Finally, in-depth case analysis confirmed that a binary index—comprising a technical term density (TD) of ≥20 and a passive voice ratio of <25%—serves as a robust measure of negotiation language quality. The combined application of these two metrics can increase the acceptance rate of contractual terms by 37% (95% CI: 29.4–44.6).

Collectively, these findings provide empirically grounded, quantitative tools to enhance strategic communication and improve outcomes in international trade negotiations.

Author Contributions

All work in this study was independently completed by Bei CUI.

Conflicts of Interest

The author declares no conflict of interest.

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