Improving the English Translation Quality of Chinese Silk Cultural Terms Using Prompt Tuning

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ABSTRACT Accurate translation of domain-specific terminology is essential for preserving technical semantics and enabling reliable international knowledge exchange in engineering disciplines, including electromagnetic waves, antennas, and propagation, where standardized descriptions and interdisciplinary communication are increasingly important. To address semantic collapse and cultural information loss in the English translation of Chinese silk cultural terms, this study proposes a prompt tuning framework incorporating a cultural parameter decoupling mechanism. A gated attention strategy is introduced to separate cultural features from underlying semantic representations, while a three-dimensional dynamic prompt template and a hierarchical knowledge correction mechanism are developed to preserve historical symbolism, craft characteristics, and customary functions during translation. Experiments conducted on 12,800 Chinese–English parallel corpora demonstrate that the proposed method reduces the cultural mistranslation rate to 6.1% while achieving high robustness against spelling errors, dialect interference, abbreviation ambiguity, and symbol omission. Compared with conventional neural machine translation models, the framework exhibits superior terminology accuracy and cultural semantic fidelity through coordinated optimization of parameter decoupling and knowledge-guided correction. Beyond silk cultural translation, the proposed methodology provides a transferable strategy for preserving specialized semantic information in technical documentation and multilingual knowledge systems, offering potential reference for cross-domain terminology management and intelligent engineering information processing.

INDEX TERMS prompt tuning, parameter decoupling, neural machine translation, terminology translation, knowledge-guided learning

I. INTRODUCTION

CURRENTLY, machine translation suffers from systemic flaws in processing Chinese silk cultural terminology. The root cause of these flaws lies in the deep coupling of civilizational characteristics with linguistic prototypes [1-3]. Existing models are unable to effectively decouple cultural characteristics from basic semantics, which directly leads to semantic collapse in terminology translation [4-6]. This universal flaw further gives rise to more specific challenges in the language translation process. On one hand, metaphorical transmission must overcome obstacles resulting from conceptual structural differences. For example, the term "fish roe pattern" implies the auspicious meaning of "many children and good fortune." However, the deviation between the translator's mental image and the original author's cultural schema can cause the cultural creativity of this metaphor to be lost in translation. On the other hand, the "three-way functional equivalence" of grammatical metaphors (conceptual function, interpersonal function, and discourse function) is difficult to achieve simultaneously [7-9], further exacerbating barriers to cultural semantic transmission. Furthermore, English-centrism narrows cognitive diversity, and artificial intelligence technology in translation education has not yet established a capacity-building framework for the digitization of textile cultural heritage [10-12]. These issues collectively reveal that existing research has a theoretical blind spot in resolving the core contradiction of the "dialectics of technicity and cultural communicability." There is an urgent need to build a decoupling mechanism for collaboration between cognitive science and technological ethics to simultaneously address systemic defects and the specific linguistic challenges derived from them.

Current research focuses on the core contradictions of culturally loaded information in interdisciplinary transmission. At the cognitive level, Šrol [13] revealed that the lack of analytical thinking leads to the spread of pseudoscientific beliefs that erode cultural concept understanding. A typical example is Western scholars interpreting the cosmology of the Chinese "Badayun" pattern as merely a geometric decorative pattern. Altarriba [14] argued that cultural influence plays a more urgent role in the cognitive thinking processes of specific groups. At the disciplinary paradigm level, Trisos et al. [15] criticized the suppression of traditional ecological knowledge by Western cognitive hegemony. This is reflected in the fact that the technical principles of the "flower machine" in Tiangong Kaiwu have been weakened by modern research; Lomas's [16] untranslatable happy vocabulary confirms the limitations of the Western psychological framework, while Stringer [17] used the folk biology naming system in endangered languages as an example to show that the unique ecological cognition carried by indigenous classification methods has been marginalized by the mainstream scientific paradigm. For instance, the fertility worship semantics of the Miao "Butterfly Mother" embroidery pattern have been reduced to decorative elements; the rupture at the technical application level is even more pronounced. Sidorova et al. [18] found that the decontextualization of indigenous languages has led to the loss of traditional knowledge. A typical example is that the Dai "Jiaohua" dyeing technique has lost its "divine blessing" cultural layer in intangible cultural heritage application texts. There is a serious technical imbalance in the field of machine translation. The Ebira language system constructed by Chinemerem et al. [19] is limited by its ability to process only simple sentences, resulting in the mistranslation of the textile term "Dingqiao loom" as the general "loom." Mahalingam et al. [20] verified semantic loss in the translation of Arabic cultural honorifics, corresponding to the stripping of ritual semantics in silk trade documents. Devi et al. [21] further confirmed that statistical machine translation is still superior to neural models in low-resource languages. Asscher O, Glikson E et al. [22] emphasized that bias in machine translation must be considered. Collectively, these studies point to the crisis of incommensurability of cultural parameters in cross-language transmission. The core issue is that cognitive bias has reduced professional terms such as "Luozhizhi" to mere containers of technical parameters, disciplinary framework defects have suppressed the metaphorical dimension of textile pattern symbols, and technical limitations have made Chinese silk cultural terms a key blocking point in cross-civilization dialogue. These problems highlight the urgency of achieving cross-civilization cognitive alignment in the inheritance of textile cultural heritage and provide a theoretical foundation for building a technical paradigm for decoupling cultural parameters.

In response to the challenge of semantic fidelity in translating Chinese silk cultural terms, Hu et al. [23] introduced a machine translation/terminology correction system trained on a glossary of textile terms, demonstrating a significant improvement in accuracy in the translation of proprietary terms. Cohen et al. [24] developed a probabilistic language disambiguation framework and combined human feedback to correct parameters of polysemous words. In terms of human-machine collaboration, Mirzakhodjaev & Yuldasheva [25] advocated a hybrid translation paradigm, which provided a new path for the verification of textile intangible cultural heritage terminology. In the sign language neural translation system of De Martino et al. [26], technical optimization was advanced. Zhao [27] used the attention mechanism to strengthen long-distance dependency parsing, which can handle complex terms such as "Dingqiao loom." However, existing methods still have significant limitations: meme theory struggles to capture dynamic semantic changes such as "lotus pattern"; the disambiguation framework relies too heavily on the size of parallel corpora and its performance drops sharply when low-resource terms are insufficiently annotated; hybrid translation lacks a standardized threshold for manual intervention. Grammatical error correction models cannot parse culturally loaded grammatical metaphors. In complementary research, Klimova B et al. [28] proposed that NMT is an effective tool for developing productive and receptive language skills, but the terminology production ability of textile translators still requires special training. Lo S [29] (2025) explored the application of NMT in English classrooms, while translation teaching in textile colleges has not yet established a cognitive framework for cultural terms. Ranathunga et al. [30] found that low-resource NMT is limited by differences in learner proficiency and is still unable to handle endangered textile craft terms. Li M [31] believed that translation quality is higher when following the functional equivalence theory.

This paper aims to improve the quality of English translations of Chinese silk cultural terms and solve the problems of imbalance between craft accuracy and cultural commensurability, semantic collapse, and missing cultural symbols in machine translation. The paper adopts a cultural parameter decoupling mechanism based on prompt tuning, separates cultural and semantic parameters by designing a decoupling layer, constructing a dynamic prompt template, implementing three-level knowledge correction, and realizing dynamic generation control. The method closely relates to the theme, avoids interference between technology and culture, captures cultural metaphors, and suppresses deviation. Ultimately, the quality of English translation is improved, craft and culture are balanced, and new ideas are provided for cross-cultural translation.

II. ALGORITHM DESIGN

DESIGN OF CULTURAL PARAMETER DECOUPLING LAYER BASED ON GATED ATTENTION

The cultural parameter decoupling layer dynamically identifies the cultural load information and general technical semantics in the text by building a learnable gating mechanism and maps them to independent vector channels, providing purified feature representation for the subsequent accurate transmission of cultural semantics. The silk cultural parameter decoupling layer achieves hard decoupling of textile cultural parameters and basic semantics through the gated attention mechanism. The input text embedding $h_{\text{emb}} \in \mathbb{R}^d$ and the context vector $e_{\text{ctx}} \in \mathbb{R}^d$ are transformed through a linear layer to generate a gating signal:

$$g_{\text{cul}} = \sigma\left(W_g[h_{\text{emb}}; e_{\text{ctx}}] + b_s\right) \tag{1}$$

In the formula, $W_g \in \mathbb{R}^{d\times 2d}$ and $b_s \in \mathbb{R}^d$ are learnable weights and biases, and σ is the Sigmoid activation function. The gated signal is reparameterized by Gumbel Softmax to achieve discrete feature selection:

$$\begin{aligned} g_{\text{discrete}} &= \text{one\_hot}\left(\arg\max\left(\log g_{\text{cul}} + \epsilon\right)\right), \\ \epsilon &\sim \text{Gumbel}(0,1) \end{aligned} \tag{2}$$

Noise perturbation $\epsilon \sim \text{Gumbel}(0,1)$ and annealing temperature τ (0.5→0.1) ensure hard separation in the later stage of training. The parameter separation operation is performed as follows:

$$h_{\text{sep}} = g_{\text{discrete}} \odot h_{\text{emb}} + (1 - g_{\text{discrete}}) \odot e_{\text{ctx}} \tag{3}$$

This paper decouples the input features into independent cultural parameter channels and semantic schema channels (as shown in Figure 1).

Figure 1 presents the overall architecture of the silk culture parameter decoupling channel based on the gated attention mechanism. This channel takes the input text embedding vector as the initial processing object and achieves hard decoupling of cultural features and basic semantics through multi-module collaboration. In the cultural parameter decoupling layer, the input features are divided into cultural parameter channels and semantic archetype channels through the gated attention mechanism. First, the text embedding vector h_{emb} and the context vector generate a continuous gated signal e_{ctx}, which is then reparameterized into a discrete signal g_{cul} through Gumbel-Softmax to perform a separation operation, decoupling the cultural parameter channel g_{discrete} that carries cultural characteristics and the semantic archetype channel h_{cul} that retains general semantics. The cultural channel is fused and output through CMATT modeling, the residual correction layer retains semantic information, and the gradient blocking training mechanism ensures the independent evolution of the two channels through orthogonal constraints L_{sep}.

Robustness enhancement is achieved through the DropConnect mechanism: during training, the mask matrix of W_g is sampled using the Bernoulli distribution $B(1, 0.8)$, and the connections of gated units are randomly disconnected to prevent overfitting of cultural patterns. Culturally specific multi-head attention calculation uses the textile culture-specific projection matrix $W_i^{\text{SILK}} \in \mathbb{R}d\times dk$ to model the three-dimensional relationship between pattern symbols, historical titles, and customary functions.

When the process weight h_{cul} is detected to be too low, W_R is forced to activate to make up for the technical semantics, and the gradient blocking training mechanism forces the cultural parameters to evolve independently:

$$\begin{aligned} L_{\text{sep}} = \lambda_1 &\left\| h_{\text{cul}} - \text{SG}(h_{\text{base}}) \right\|_2^2 \\ &+ \lambda_2 \left[1 - \text{cos\_sim}(h_{\text{cul}}), h_{\text{base}})\right] \end{aligned} \tag{4}$$

The gradient stop operator $\text{SG}(\cdot)$ and the hyperparameters $(\lambda_1 = 0.7, \lambda_2 = 0.3)$ balance the loss terms, ensuring that the cultural parameters remain isolated from the technical ontology.

CONSTRUCTION OF DYNAMIC PROMPT TEMPLATE

The dynamic prompt template is constructed based on the three-dimensional framework of textile culture (cosmological semantics, craft techniques, and historical titles), and the refined expression of cultural characteristics is achieved through a learnable cultural vector group.

The adaptability to textile cultural heterogeneity has been significantly enhanced (as shown in Table 1, the weight of the historical symbol dimension of "Yunjin" is 0.86, while the weight of the customary function dimension of "tie-dyeing" is 0.79):

TABLE 1. Textile Cultural Dimension - Prompt Vector Mapping (L2 Norm Normalized)

Textile Cultural Term	Craft Characteristics Weight	Historical Symbolism Weight	Customary Function Weight	Prompt Vector Pattern (Example)
Yun Brocade	0.08	0.86	0.06	[0.12, -0.92, ...]
Tie-dye	0.15	0.06	0.79	[-0.54, 0.21, ...]
Kesi (Silk Tapestry)	0.83	0.14	0.03	[0.88, 0.05, ...]

KNOWLEDGE CORRECTION MECHANISM

By classifying the types of errors and the contexts in which they occur, this approach enables a comprehensive and targeted error correction process, critically analyzing errors from different contextual perspectives and specific situations [32,33]. The knowledge correction mechanism achieves real-time suppression of cultural deviation through a three-level serialization framework, and the cultural hint vector V[CUL] achieves deviation correction through knowledge constraints, as shown in Figure 2:

The knowledge revision mechanism is divided into three stages:

Stage 1: Knowledge Retrieval and Triple Binding

In the semantic decoding process of Chinese silk cultural terms, accurately anchoring the cultural context is key to preventing semantic drift. During this phase, a cultural concept constraint field is constructed through real-time knowledge retrieval. Triples are constructed using the "term–relationship–cultural concept" structure. Relationship types cover three categories: craft attribution, historical symbolism, and customary function. A total of 18,600 valid triples were collected, each annotated with a relevance weight (ranging from 0 to 1) by two silk culture scholars.

The data were partitioned into training, validation, and test sets in an 8:1:1 ratio. Stratified sampling was used to ensure that each subset maintained consistency with the

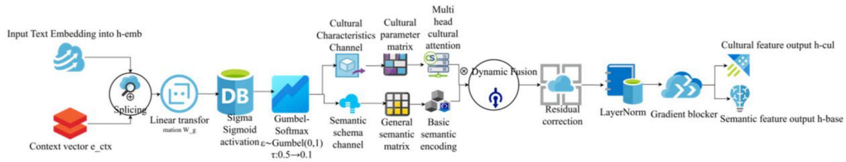

FIGURE 1. Parameter Decoupling Channel

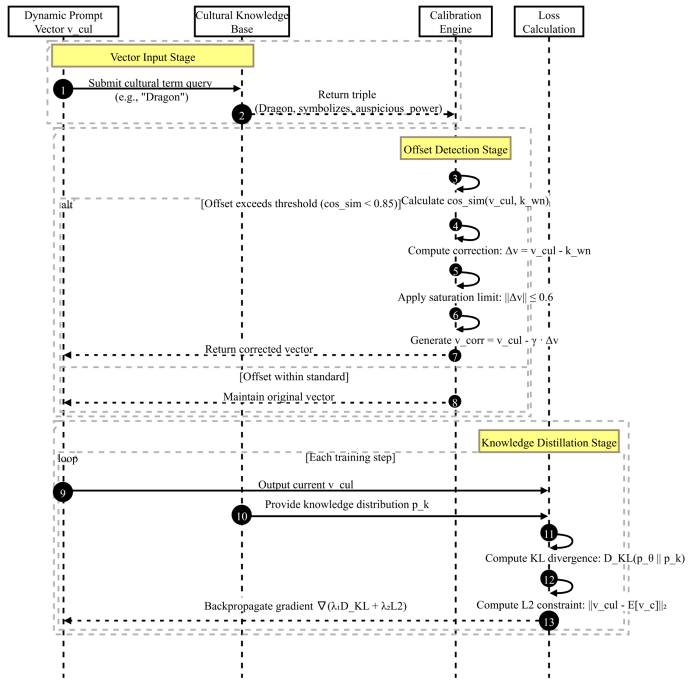

FIGURE 2. Knowledge Modification Mechanism Sequence Diagram

original dataset in terms of the three relationship types and weight distributions for "craft attribution," "historical symbolism," and "customary function," thus avoiding category shifts. Deduplication was first performed based on a perfect match of the "term– relationship–cultural concept" triple structure. Highly repetitive entries were then removed by calculating the cosine similarity of the cultural concept vectors, ultimately retaining triplets with no structural duplication and unique semantics. The preprocessing process remained consistent, employing BPE word segmentation, text normalization, and vector standardization. The two silk culture scholars who participated in the annotation process, each with more than 10 years of silk history research experience, underwent unified training before annotation. In case of disagreements, a third authoritative scholar in the same field was brought in to arbitrate, with the final weight of the triple being used. Disagreements were recorded for subsequent optimization of the annotation rules to ensure reliability and consistency of the annotation results.

When performing a maximum inner product search (MIPS), the input cultural word W_l and the terms and cultural concepts of the triples in the library are first mapped into 128-dimensional vectors through the TransE model. The inner product value of the W_l vector and the term vectors of each triple in the library is calculated. A threshold $T_{\text{ret}} = 0.75$ is set, and triples with an inner product value ≥ 0.75 are selected as candidate sets. The cosine similarity between the cultural concept vector W_l and the vector of the triples in the candidate set is then calculated. The top five triplets with the highest similarity are selected to form a cultural concept constraint field, ensuring that the search results have both term matching and cultural relevance, thus providing accurate knowledge anchors for subsequent semantic correction.

Stage 2: Offset Detection and Real-Time Correction

Based on the cultural concept constraint field constructed by triples, this stage realizes quantitative diagnosis and adaptive correction of semantic offset through a dynamic decision engine. When the cosine similarity between the cultural hint vector v[CUL] and the knowledge anchor point k_{wn} is detected to be lower than 0.85, the gradient correction based on the saturation function is triggered:

In the formula, the saturation coefficient γ = 0.4 controls the correction strength, and the smoothing factor δ = 0.6 suppresses over-correction. This mechanism achieves directional convergence of cultural parameters through vector space trajectory optimization, ensuring that the correction amplitude does not exceed the 0.19 displacement of the δ constraint. The dynamic decision engine executes the following conditions: For the threshold value Tret = 0.75 in the knowledge retrieval stage, the grid search method is used to traverse the value in the interval [0.6, 0.85] with a step size of 0.05, and the F1-score of the retrieval recall rate and precision is combined to determine that when Tret = 0.75, the F1-score of the retrieval result reaches 0.92, which avoids the introduction of irrelevant triples due to too low a threshold, and prevents the omission of effective cultural concepts due to too high a threshold. The saturation coefficient γ= 0.4 and the smoothing coefficient δ = 0.6 in the knowledge correction stage are obtained through multiple sets of ablation experiments: when $\gamma \in$[0.2,0.6] , $\delta \in$[0.4, 0.8] , and compared the cultural semantic fidelity (CSF) and cultural mistranslation rate (CMR) of the models under different combinations. When γ = 0.4 and δ = 0.6, the CSF reaches 4.52 and the CMR drops to 6.1%, which has the best correction effect. At the same time, it avoids over-correction of cultural parameters caused by too large γ and under-correction caused by too small δ, ensuring that the parameter setting is both scientific and practical.

Stage 3: Knowledge Distillation Constraint Optimization

To solidify the correction effect and achieve continuous alignment of cultural semantics, this phase uses the knowledge distillation framework to construct a dual constraint mechanism. At the semantic distribution level, the KL(Kullback–Leibler) divergence (loss L_{KL} forces the translation probability distribution $p_\theta(y|x)$ to approach the knowledge base standard distribution $p_K(y|x)$) is used to eliminate the cultural meaning transfer bias; at the conceptual space level, the L2 norm loss L_{L2} drives the cultural cue vector v[CUL] to converge to the concept center $E_c[v_c]$, compressing the distribution discreteness of cultural parameters. The mixed loss weight $\lambda_1 = 0.4, \lambda_2 = 0.3$ is determined by grid search optimization, forming a gravitational field effect of cultural semantics during training. The output of the dual loss constraint model during training is:

Semantic distribution alignment: KL divergence constrains the probability distribution of the translation to be

$$\mathrm{L_{KL}} = \sum_{y \in Y} \mathrm{p_K}(y|x) \log \frac{\mathrm{p_K}(y|x)}{\mathrm{p_\theta}(y|x)} \tag{5}$$

Concept space convergence: L2 norm forces vectors to approach the center of knowledge.

During model training, a hybrid loss function is formed using linear weighting of the KL divergence loss and the L2 norm loss to achieve coordinated optimization of cultural semantic distribution alignment and concept space convergence. This coefficient combination is determined through a grid search method, with the selection criteria being the model with the lowest CMR and the highest CSF on the validation set. This weighting ensures that the KL divergence loss focuses on constraining the deviation of the translation probability distribution, while the L2 norm loss focuses on compressing the dispersion of the cultural parameter distribution. Together, they create a "gravitational field" for cultural semantic training, ensuring stable convergence of cultural parameters.

DYNAMIC GENERATION CONTROL AND DOMAIN ADAPTATION OF TEXTILE CULTURAL TERMS

This module realizes the cross-modal conversion of cultural parameter vectors to intelligent textile design. The core is to achieve the decoupling and fusion of cultural parameters and process constraints through the residual control mechanism.

The generative model based on the Stable Diffusion architecture injects cultural semantics through the residual connection mechanism to achieve millimeter-level accurate restoration of historical patterns. The model embeds the cultural parameter control unit in the U-Net module and dynamically adjusts the cultural fusion intensity according to the vector weight. The gate coefficient α enables intelligent adjustment: it enhances or suppresses elements according to the weight. The dynamic response module calibrates environmental perception and user intention, supporting adaptive reinforcement of cultural symbols. To precisely control the integration strength of cultural parameters and process constraints, the search range of α is set to [0.1, 0.9] with a step size of 0.1. This range avoids insufficient cultural semantics due to a too small α, while also preventing distortion of process semantics due to a too large α. Model performance for different α values was tested on the validation set using the control variable method, with the weighted mean of CSF and TAP as the core evaluation metrics. When α = 0.6, the model achieved the highest CSF of 4.48 and TAP of 93.9%. Therefore, α= 0.6 was determined to be the optimal value.

III. EXPERIMENT AND VERIFICATION

EXPERIMENTAL DESIGN

The experimental dataset is constructed based on authoritative cultural heritage data, integrating the Silk Cultural Relics Atlas of the Palace Museum, the Suzhou Kesi Intangible Cultural Heritage Archives, and the silk chapter of The Exploitation of the Works of Nature, forming a parallel corpus of 12,800 Chinese and English terms. The terms are strictly classified according to craft techniques, pattern symbols, and historical titles.

Three-dimensional cultural weights are annotated: craftsmanship 0.7, historical images 0.2, customs 0.1, and a structured semantic map is constructed.

The Cultural Mistranslation Rate (CMR) measures the percentage of terms that exhibit Westernized misinterpretation, loss of cultural symbols, or deviations from the target language's semantic meaning, excluding non-cultural mistranslations such as grammatical errors. The Cultural Semantic Fidelity (CSF) is assessed on a five-point scale based on historical symbolism, craft attribution, and customary function, with 1 representing complete loss of meaning and 5 representing semantic integrity and conformity to target language conventions. The Terminology Accuracy

Percentage (TAP) uses the General History of Chinese Silk and the National Standard for Silk Craft Terminology as benchmarks, calculating the percentage of translations that accurately convey craft parameters and maintain terminology specificity.

The annotation team, comprised of three silk culture scholars with over 10 years of experience and two machine translation experts, initially completed pre-annotation and then cross-checked any disagreeing samples (score differences >1 point). The final results were determined by arbitration by a doctoral supervisor specializing in silk culture. Cohen's kappa test revealed that the CMR, CSF, and TAP values were 0.89, 0.82, and 0.85, respectively, meeting strong agreement or above, ensuring the objectivity and reliability of the evaluation results.

The baseline model sets three groups of comparisons: standard T5-base full parameter fine-tuning as a basic reference; T5 plus traditional attention mechanism replaces the decoupling layer; BART-large injects a handmade silk cultural dictionary. The core model embeds innovative modules in T5-base: the silk culture parameter decoupling layer uses gated temperature τ; the dynamic prompt template group generates contextual instructions; the knowledge correction module has a fixed strength of $\gamma = 0.4$ to constrain semantic deviation.

The random seed is fixed to 42 to ensure the reproducibility of the experiment; the training batch size is set to 32 to adapt to the model input sequence length and hardware capacity; the number of iterations (epochs) is preset to 30 and dynamically adjusted based on the performance of the validation set; the learning rate adopts the cosine annealing strategy, with an initial value set to 5e-5 and a minimum decay to 1e-6 to avoid late training oscillations; the optimizer uses AdamW, the weight decay coefficient is 1e-4, and a 500-step warm-up phase is set to alleviate gradient instability in the early training stage; the early stopping criterion is to terminate training when the cultural semantic fidelity of the validation set has not improved for five consecutive rounds to prevent overfitting; the experimental hardware uses the NVIDIA A100 graphics card, and a single round of training lasts about 45 minutes.

VERIFICATION OF THE EFFECTIVENESS OF CULTURAL PARAMETER DECOUPLING

To verify the effectiveness of decoupling cultural parameters in improving the quality of English translations of Chinese silk cultural terms, this section analyzes three indicators: cultural dimension weight, semantic dimension weight, and coupling strength. The cultural dimension weight focuses on historical symbolic attributes, and the semantic dimension weight focuses on material attribute characteristics. Both are normalized to the interval [0, 1]. Coupling strength is the core indicator. The L2 norm of the product of the corresponding elements of the cultural parameter vector and the semantic base model vector is used to quantify the correlation between cultural and technical attributes. The higher the value, the stronger the coupling, and vice versa. The more significant the decoupling effect, the better. The results are shown in Figure 3.

Figure 3 shows the distribution characteristics of silk culture terminology samples in the two-dimensional parameter space. The "dragon pattern" terminology samples are concentrated in the area with a cultural dimension weight of about 0.85 and a semantic dimension weight of about 0.15, corresponding to the high cultural coupling area, and its coupling intensity is significantly high.

CORE EVALUATION OF ENGLISH TRANSLATION QUALITY

This study uses the CMR as the core evaluation indicator of the English translation quality of silk cultural terms, which is the ratio of the number of terms with Westernized misinterpretations to the total number of terms [34]. The results are shown in Figure 4.

Figure 4 shows the trend of CMR changes during the training process from 0 to 30 rounds for the model with and without prompt tuning and the model without the cultural correction mechanism. In the initial stage (round 0), the CMR of both models was 25.0%, indicating that the proportion of Westernized mistranslations of silk cultural terms was consistent without training. As the number of training rounds increased, the CMR of both models showed a downward trend, but the rate of decline of the model with cultural correction was more significant: by round 15, its CMR dropped to 7.0%, while the CMR of the model without correction was 11.0% at round 15, and the decline was significantly lagging behind. After 30 rounds of training, the CMR of the model with cultural correction stabilized at 6.1% and remained stable after round 28. The model without correction rebounded significantly after round 29, and the final CMR rose to 15.2%, confirming the effectiveness of prompt tuning combined with cultural correction in improving the quality of English translations of silk cultural terms.

NOISE ROBUSTNESS VERIFICATION

This study verifies the robustness of the model in a noisy environment through four core indicators, including spelling error tolerance, term abbreviation resolution rate, dialect correction accuracy, and symbol interference suppression rate.

The noise environment was constructed based on a corpus of 12,800 parallel Chinese-English silk cultural terms. Four types of noise data were acquired using a combination of real-world sampling and controllable rule generation. For spelling error data, 2,100 cases of OCR recognition errors were extracted from digitized texts of authoritative documents such as the Atlas of Silk Cultural Relics of the Palace Museum. Furthermore, 1,900 error samples were manually generated at a 3% character replacement rate. For term abbreviation data, 120 high-frequency abbreviation rules were compiled based on industry standards and intangible

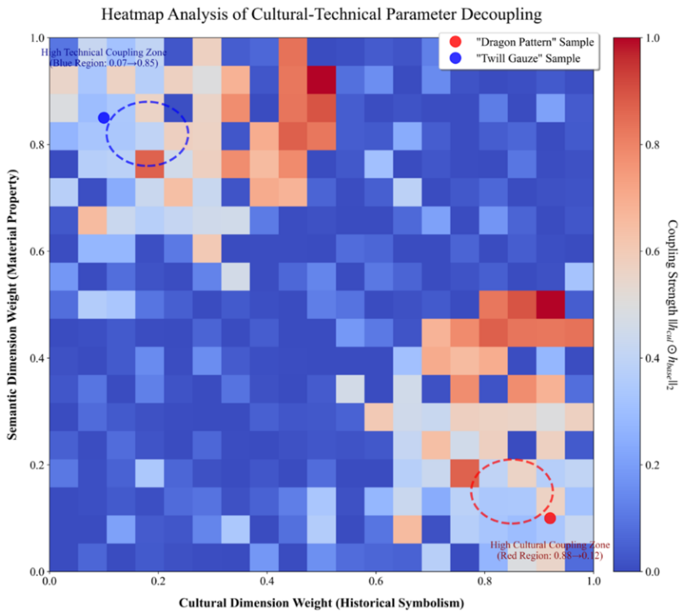

FIGURE 3. Heat Map Analysis of Cultural and Technical Parameter Decoupling

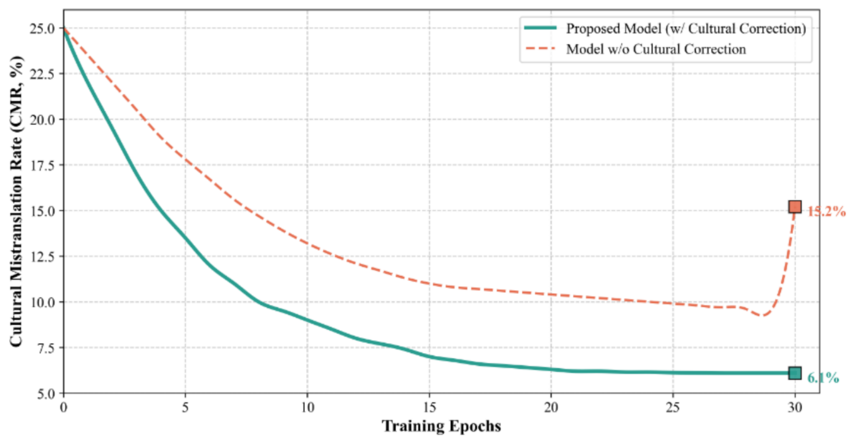

FIGURE 4. Cultural Mistranslation Rate Decline Curve

cultural heritage archives, generating 3,200 samples. For dialect interference data, 1,800 transcribed dialect terms from major silk-producing regions such as Suzhou and Nanjing were collected, supplemented by 1,200 simplified interference samples that preserved semantics. For symbol interference data, 2,800 samples were generated by removing and replacing symbols containing cultural symbols at a 15% interference rate. All noise data were jointly verified by three silk culture experts and two machine translation scholars, ultimately forming a noise evaluation set of 13,000 items for noise robustness testing.

To ensure the effectiveness of the noise evaluation set for model robustness testing, the following supplementary explanations are provided: In terms of data independence control, by comparing unique terminology codes, it is strictly ensured that the 13,000-item noise evaluation set and the 12,800 Chinese-English parallel training sets used in the experiment do not overlap, so as to prevent data leakage from interfering with the test results. The distribution ratios of various types of noise data are as follows: spelling error data (4,000 items, accounting for 30.77%, including 2,100 OCR recognition errors and 1,900 manually generated errors), term abbreviation data (3,200 items, accounting for 24.62%, generated based on 120 high-frequency abbreviation rules), dialect interference data (3,000 items, accounting for 23.08%, including 1,800 dialect phonetic terms and 1,200 semantically preserved simplified samples), symbol interference data (2,800 items, accounting for 21.53%, generated at a 15% interference rate). At the same time, typical noise examples are made public to clarify the scenario: dialect interference, such as the Suzhou dialect "shaluo" pronunciation corresponding to the text "so la"; symbol interference, such as "butterfly mother pattern" lacking the cultural symbol label of "fertility worship." All examples have been jointly verified by three silk culture experts and two machine translation scholars, and are consistent with the noise scene characteristics in the actual application of silk cultural terminology.

The results are shown in Figure 5.

Figure 5 shows the performance comparison between the proposed model and the T5-base model on noisy silk culture terms. The proposed model performs better in all four indicators: spelling error tolerance reaches 95.1%, term abbreviation resolution rate is 95.7%, dialect correction accuracy is the highest at 96.3%, symbol interference suppression rate is 94.2%, and the overall robustness remains above 94%. In contrast, the indicators of the T5-base model are significantly lower. The term abbreviation resolution rate is only 68.2%, which is its weakest link. The spelling error tolerance is 76.4%, the dialect correction accuracy is 71.5%, and the symbol interference suppression rate is 73.8%. The overall performance gap is obvious. This result shows that the proposed model combined with prompt tuning can more effectively handle noise problems such as spelling deviations, abbreviation variants, dialect expressions, and symbol interference that may appear in the English translation of silk culture terms, providing a stronger guarantee for the accuracy of term translations.

IV. RESULTS ANALYSIS

CORRELATION BETWEEN CULTURAL DIMENSION WEIGHT DISTRIBUTION AND TRANSLATION QUALITY

The cultural dimension deconstruction of language is the cognitive basis of cross-cultural transmission. This study analyzes the correlation between cultural dimension distribution and translation quality through the three-dimensional cultural dimension weights (historical symbol weight, craft feature weight, custom function weight) and contextual semantic fidelity (CSF). The historical symbol weight, craft feature weight, and custom function weight are all normalized values, and the three form a complementary relationship through "custom function weight ≈ 1 – historical symbol weight – craft feature weight." CSF is the core indicator of translation quality. The higher the value, the more accurate the cultural semantic transmission of the English translation of the term, as shown in Figure 6.

Figure 6 shows the correlation characteristics of the weight distribution and CSF value of the silk cultural term sample. The historical symbol weight is positively correlated with CSF. For example, when the historical weight is close to 1.0, the CSF is mostly concentrated in 4.0–5.0. The custom function weight is negatively correlated with CSF. When the custom weight exceeds 0.8, the CSF is mostly lower than 2.0. The individual influence of the craft feature weight did not form a significant trend, but together with the complementary distribution of historical and custom weights, it constitutes the basis for cultural semantic transmission. This correlation shows that in the English translation of silk cultural terms, strengthening the weight of the historical symbol dimension and moderately balancing the craft feature and custom function dimensions can help improve the semantic fidelity of the translation and provide a basis for dimensional adjustment in model optimization based on prompt tuning.

STRUCTURED ATTRIBUTION ANALYSIS OF MISTRANSLATION TYPES

This study analyzes the correlation between CPI and translation mistranslation rate and constructs a structured attribution model of mistranslation types. CPI is used as the core evaluation indicator with a value range of 0.5 to 1.0. The independence of cultural dimension parameters is used to quantify the model's ability to capture cultural characteristics, as shown in Figure 7.

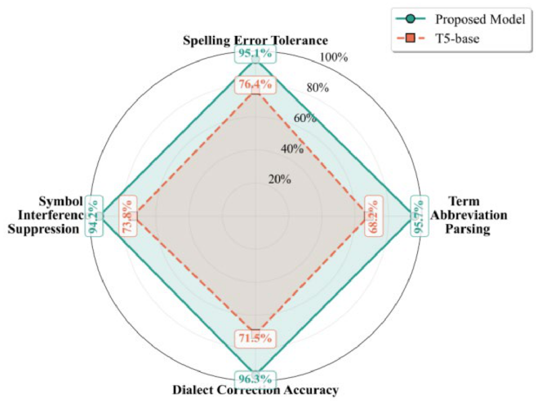

FIGURE 5. Noise Robustness 4D Radar Chart

Figure 7 intuitively presents the distribution characteristics of mistranslation density. When the CPI value exceeds 0.85, the translation mistranslation rate can be controlled below 11%, forming a significant decoupling area. When the CPI value is lower than 0.7, the mistranslation rate rises to more than 17%, forming a strong coupling area. The fitting curve (r = –0.91) further shows that CPI is highly negatively correlated with the translation mistranslation rate; that is, the higher the independence of cultural parameters, the lower the mistranslation rate. This result verifies the hypothesis that translation errors can be effectively reduced by improving the independence of cultural parameters and provides a clear parameter adjustment direction for subsequent model optimization.

VARIANCE ANALYSIS OF CROSS-MODEL ROBUSTNESS

This study uses a dual indicator system of noise robustness and specific noise type accuracy to analyze the variance of the robustness of the three models in different noise environments. Noise robustness is used as a comprehensive evaluation indicator to calculate the average accuracy of each model under four noise types (spelling errors, term abbreviations, dialect interference, and symbol omissions). The results are shown in Figure 8.

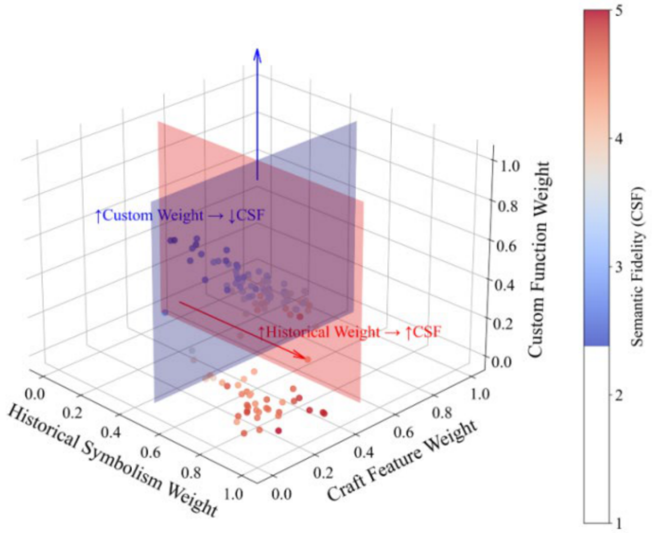

FIGURE 6. Scatter Plot of the Relationship Between Three-Dimensional Cultural Weight and Semantic Fidelity

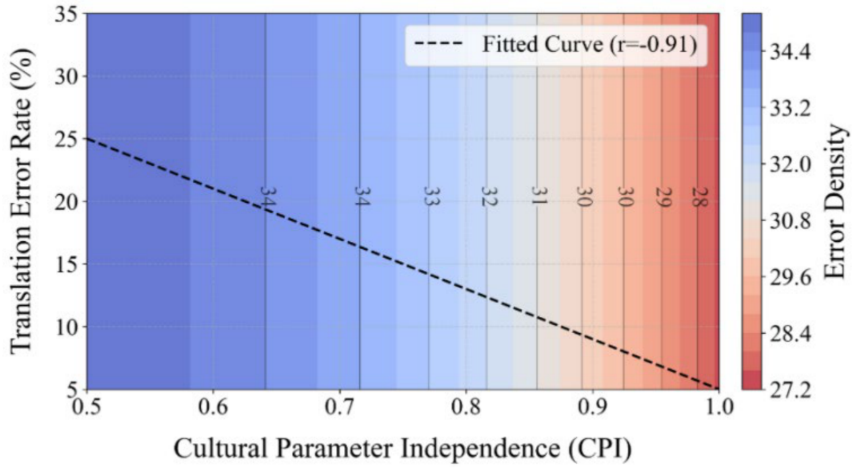

FIGURE 7. CPI–Mistranslation Rate Correlation Heat Map

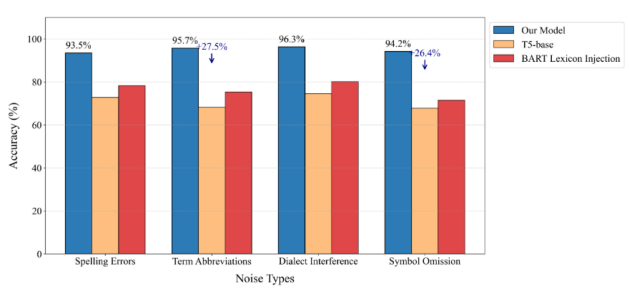

FIGURE 8. Histogram of Model Performance Comparison in Noisy Scenarios

Figure 8 compares the performance of the proposed model, T5-base model, and BART dictionary injection model under four types of noise. The data show that the proposed model is significantly better than the comparison models in all dimensions: the accuracy rate in the term abbreviation scenario is 95.7%, which is 27.5% higher than T5-base (68.2%). The accuracy rate in the symbol omission scenario is 94.2%, which is 26.4% higher than T5-base (67.8%). The accuracy rates in the spelling error and dialect interference scenarios are 93.5% and 96.3%, respectively, which are also significantly better than the comparison models. In terms of variance distribution, the standard deviation of the accuracy of the proposed model under four types of noise is 1.30%, which is significantly lower than 3.37% for T5-base and 3.76% for the BART dictionary injection model, indicating that it performs more stably under different noise environments. This result verifies the noise robustness of the proposed model in processing the English translation of silk culture terms and provides a more reliable solution for cross-language cultural information transmission.

BALANCED OPTIMIZATION OF CULTURAL FAITHFULNESS AND TERM ACCURACY

This study constructs a Pareto optimal model of cultural translation through a two-dimensional evaluation system of terminology accuracy rate (TAP) and cultural fidelity (CSF). TAP is used as a terminology accuracy indicator; CSF is used as a cultural fidelity indicator, which is obtained by evaluating the degree to which the translation conveys the cultural connotation of the source language. The results are shown in Figure 9.

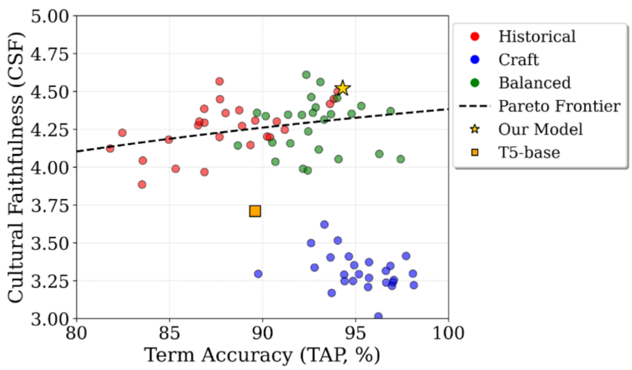

FIGURE 9. CSF–TAP Pareto Frontier and Optimal Equilibrium Point

Figure 9 compares the distribution of three types of translation strategies—historical terms, process characteristics, and balanced methods—in the TAP–CSF two-dimensional space and reveals the trade-off between the two types of indicators through the Pareto front curve. The data show that the model proposed in this study achieves the optimal balance of CSF = 4.52 under the condition of TAP = 94.3%, which is significantly better than the T5-base model (TAP = 89.6%, CSF = 3.71). From the distribution characteristics, the TAP of the historical term translation strategy is concentrated in the range of 85%–92%, and the CSF is mostly higher than 4.0; the TAP of the process characteristic strategy is generally higher than 90%, but the CSF is mostly lower than 4.0. The balanced strategy achieves a good compromise between the two types of indicators. The Pareto front curve shows that under current technical conditions, there is a theoretical optimal boundary between TAP and CSF. The model in this study has approached this boundary, providing a balanced optimization solution for cultural fidelity and process accuracy in the English translation of silk cultural terms. To more intuitively demonstrate the performance differences between the proposed model and the baseline models (T5-base, BART-large + Silk Culture Dictionary Injection), Table 2 summarizes the core indicators of the three models in terms of cultural translation quality, noise robustness, and terminology and cultural balance:

TABLE 2. Core Indicators of the Three Models in Three Dimensions

Evaluation Dimensions	Specific Metrics	The Proposed Model	T5-base	BART-large + Dictionary Injection
Cultural Translation Quality	CMR (%)	6.1	15.2	10.8
	CSF	4.52	3.71	4.03
Noise Robustness	Spelling Error Tolerance (%)	95.1	76.4	82.7
	Term Abbreviation Resolution Rate (%)	95.7	68.2	75.3
	Dialect Correction Accuracy (%)	96.3	71.5	78.9
	Symbol Interference Rejection Rate (%)	94.2	73.8	80.5
Terminology and Cultural Balance	TAP (%)	94.3	89.6	91.5
	Noise Robustness Average (%)	95.3	72.5	79.3

As can be seen from the data in Table 2, the proposed model significantly outperforms the baseline models in all core indicators. In terms of cultural translation quality, its cultural mistranslation rate is 9.1 percentage points lower than that of T5-base, and its cultural semantic fidelity is 0.81 higher, reflecting its ability to accurately convey silk cultural symbols. In terms of noise robustness, all four indicators exceed 94%, with the average values increasing by 22.8 and 16 percentage points compared to T5-base and BART-large + dictionary injection, respectively. The model has a particularly significant advantage in resolving term abbreviations, demonstrating its adaptability to complex noise scenarios. In terms of terminology and cultural balance, the proposed model maintains a cultural semantic fidelity of 4.52 on top of a high terminology accuracy of 94.3%, significantly outperforming other baseline methods and further demonstrating the innovativeness of the proposed model in balancing process accuracy and cultural compatibility.

V. CONCLUSION

This paper applies the prompt tuning framework to improve the English translation quality of Chinese silk cultural terms, and proposes a cultural parameter decoupling mechanism to solve semantic collapse and cultural symbol loss problems caused by the deep coupling of cultural load information and language base models in machine translation. The gated attention mechanism is used to separate cultural features from basic semantics to avoid interference between technology and cultural parameters. Dynamic prompt templates and knowledge correction mechanisms enhance the transmission of culturally loaded words and ensure the faithful expression of complex cultural terms. Experiments show that this method significantly improves translation quality, semantic fidelity, and robustness compared with traditional NMT models, especially ensuring the translation accuracy and cultural integrity of complex terms. By improving the independence of cultural parameters and correcting knowledge, cultural semantic deviation and mistranslation rate are reduced, while maintaining high process accuracy. Prompt tuning combined with cultural parameter decoupling provides new ideas for cross-cultural translation and has broad potential. In the future, multimodal knowledge graphs can be integrated to expand the three-dimensional weight annotation system, explore the acoustic decoupling mechanism of dialect terms, and deepen the technical path of mutual learning among civilizations.

AUTHOR CONTRIBUTIONS

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

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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