ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Metaphor Mapping Mechanism and Cultural Cognitive Model Construction in Chinese New word formation

Wenqi Wang[1] *and Qian Cao*[1,*]

[1] College of Education, Science and Technology College of Hubei University of Arts and Science, Xiangyang, 441025, Hubei P.R. China

SUMMARY: *In the study of Chinese neologisms, the description of word formation is too much, and the explanation of metaphor generation mechanism and cultural cognition is insufficient. This paper proposes a computational framework for word formation analysis of Chinese neologisms. Based on 12,480 self-built corpora, this study constructs a joint model of metaphor mapping and cultural cognition of neologisms, focusing on word formation component identification, metaphor mapping extraction, cultural prototype modeling and relevance attention mechanism optimization. This method integrates character-level boundary recognition, contextual semantic representation and cultural prototype memory into a unified process, which can simultaneously depict the source-target correspondence and its socio-cultural orientation. The experimental results show that the Macro-F1 of the proposed model on the metaphor mapping recognition task reaches 0.913, and the Accuracy is 0.924. The Macro-F1 and Accuracy on the cultural cognitive classification task reach 0.879 and 0.891, respectively, which are better than rule matching, SVM+TF-IDF and Chinese BERT baselines. The research shows that the meaning generation of Chinese new words is not a simple lexical splicing, but a compressed cognitive construction process under the joint effect of metaphor mapping and cultural experience.*

KEYWORDS: *Chinese new words; Metaphor mapping; Cultural cognition model; Computational Language Analysis*

1 Introduction

Chinese neologisms are the product of social experience, media technology and cultural psychology. Especially in the context of the continuous acceleration of mobile Internet and platform communication, a large number of new words do not rely on the direct superposition of existing word meanings to complete the naming, but with the help of cross-domain projection such as "space-society", "body-emotion" and "object-relationship" to compress the abstract experience into a perceptible and marketable expression form [1-6]. This kind of word-formation phenomenon is reflected by word renewal on the surface, but it is deeply related to the choice of metaphor mapping path, the activation of cultural knowledge and the reorganization of group cognitive framework. Therefore, how to interpret the generative logic of the metaphorical meaning of neologisms from the perspective of the word-formation process has become a problem worthy of positive response in Chinese lexical research and computational language analysis.

Existing studies have provided solid discussions on conceptual metaphor, discourse

*cqcc8812@126.com
https://doi.org/10.65102/is2026250 Published: 30 April, 2026

metaphor, bilingual embodied cognition and Chinese metaphor recognition [7-20]. Relevant results show that metaphor is not a rhetorical appendage, but an important mechanism for language understanding and meaning organization. However, there are still two shortcomings in the existing work. One kind of research focuses on manual interpretation and can reveal the types of metaphor, but it is difficult to detail the combination of word-formation components, mapping trigger conditions and semantic evolution chain inside the new word. Although neural networks, dataset construction and interpretable computing frameworks have been introduced in the other research category [11-21], they are more oriented to sentence-level metaphor detection or generation tasks, and pay less attention to "how new words complete metaphor compression at the word-formation level and further carry cultural cognition". In other words, there is still a lack of a unified computing path that can connect the "word formation unit identification, mapping relationship extraction, cultural association modeling, and result interpretation verification" in the study of Chinese neologisms.

With the development of natural language processing, pre-trained language models and semantic representation learning, researchers have been able to capture word co-occurrence features, contextual semantic shifts and cross-domain association patterns from large-scale corpora, which provides new technical conditions for systematic analysis of the metaphor mechanism of new words. Combining word segmentation tagging, word-formation component coding, context vector representation and attention mechanism, we can not only identify the potential source-target domain correspondence in new words, but also further estimate the effect strength of different cultural semantic elements in word sense generation. Thus, the explanation process which relied on intuitionistic judgment in the past is transformed into an analysis process which can be calculated, compared and verified again.

Based on this, this paper focuses on three problems: first, how to accurately identify the word-forming components of Chinese new words in complex contexts and complete the text preprocessing of adaptation metaphor analysis; Second, how to extract the metaphorical mapping relationships within the new words and their contexts, and form the semantic representation for comparison. Thirdly, how to construct a deep semantic model oriented to cultural cognition to explain the association differences of different neologisms in social psychology, value orientation and cultural experience. To address these issues, this paper intends to construct a corpus of Chinese new word metaphor, and establish a set of analysis framework that takes into account both linguistic interpretability and computational realizability by combining deep semantic coding and cultural relevance attention mechanism. This study aims to provide a more detailed evidence chain for the study of Chinese new word formation, and also provide a transferable method basis for Chinese metaphor recognition, cultural semantic modeling and intelligent vocabulary analysis.

2 Related Research

In recent years, there has been a significant increase in the research on metaphorical expression, neologism generation and cultural interpretation in Chinese. It has been shown that metaphor is not a rhetorical decoration attached to the surface of words, but an important mechanism involved in concept organization, stance construction and social meaning generation. Ahrens et al. analyzed the dual functions of conceptual metaphor in reference and evaluation from the perspective of governmental discourse and public discourse. Wu et al. further investigated the evolution trajectory of legal metaphor in Chinese official texts through diachronic corpora, and these studies provided solid theoretical support for understanding the cognitive basis and discourse distribution of Chinese metaphor [1-3]. At the same time, discussions about network neologies and media neologies have been gradually carried out. Relevant studies have noted that the construction of neologies not only reflects language economy, but also reflects the rapid reorganization of platform culture, group identity and value judgment [4-6].

From the perspective of cognitive linguistics and psycholinguistics, scholars have conducted more detailed discussions on the embodiment, cross-lingual differences and abstract concept representation of Chinese metaphor understanding. Yu et al. pointed out that there is a significant correlation between metaphor comprehension and expression conventionality. Wei et al., Yang et al., and Yang and Reid respectively explained from the perspectives of spatial metaphor, temporal concept and power representation that Chinese users would be jointly influenced by body experience, language background and cognitive path in the process of concept extraction [7-10]. This kind of research illustrates that metaphorical mapping is not a word sense substitution occurring in isolation, but is closely related to cultural experience invocation, perceptual structure activation, and conceptual projection direction. For this paper, this means that the analysis of word formation of neologisms should not stop at the literal combination level, but should further investigate the cultural cognitive patterns behind them.

With the development of natural language processing technology, computational metaphor research has gradually shifted from rule matching to data-driven and deep representation learning. Ge et al. combined conceptual metaphor theory with interpretable models to improve the transparency of metaphor recognition. Li et al. and Yang et al. introduced context modeling and multiple constraint mechanism into Chinese metaphor and simile generation task, which promoted the improvement of generation quality and semantic adaptation [11-13]. Shao et al. constructed a Chinese metaphor dataset with explanatory annotation information, which laid a resource foundation for subsequent model training and evaluation [14]. These results show that cross-domain semantic associations can be captured more stably with the help of pre-trained language models, contextual semantic coding and labeled corpora. However, most of the research objects focus on sentence-level or document-level metaphors, and the discussion of internal word-formation components, mapping trigger locations and cultural-semantic coupling relationships of new words is still insufficient.

In order to more clearly present the distribution and shortcomings of the existing research, this paper briefly summarizes the relevant results, as shown in Table 1. In general, the existing research has made a certain accumulation in metaphor theory, Chinese new word observation and computational model construction, but the three have not been effectively connected. In other words, there is still a lack of an analysis path for "how Chinese new words complete metaphor mapping in the process of word formation and further form a computational cultural cognitive structure", which takes into account both language interpretability and model operability. On this basis, this paper proposes to introduce a joint framework of word formation component identification, metaphor relation extraction and cultural correlation modeling to bridge the gap between the micro word formation level and the deep cognitive level of related research.

Table 1: Summary of relevant results of Chinese new word metaphor research

Research Direction	Representative References	Main Content	Limitation
Conceptual Metaphor and Discourse Analysis	[1–3]	Analyzes the referential, evaluative, and evolutionary functions of metaphor in government discourse, public discourse, and diachronic texts	Mostly focuses on macro-level discourse, with limited attention to neologism word-formation
Neologisms and Media Rhetoric Research	[4–6]	Discusses metaphorical phenomena in internet neologisms, media rhetoric, and gendered neologisms	Lacks computational characterization of mapping mechanisms
Embodied Cognition and Cross-Linguistic Understanding	[7–10]	Reveals the relationships between metaphor comprehension of abstract concepts such as space, time, and power, and bodily experience and linguistic background	Mainly focuses on cognitive experiments, with limited coverage of neologism corpora
Computational Metaphor Identification and Generation	[11–14]	Improves metaphor identification and generation using interpretable models, neural generation frameworks, and Chinese datasets	Primarily targets sentence-level tasks, while cultural cognition modeling remains insufficient

3 Methods

3.1 Word formation identification and text preprocessing methods

When Chinese new words enter the real propagation scene, they often show the characteristics of boundary loosening, semantic compression and emotional attachment. Different from general vocabulary, many words are not expanded layer by layer according to stable dictionary meaning, but are rapidly spliced, expanded and solidified in hot events, platform interaction and group imitation. If the original corpus is directly input into the subsequent model, the system is easy to mistake the platform symbol, noise collocation or accidental co-occurrence as the basis for word formation, thus affecting the accuracy of metaphor mapping recognition. Based on this, we set up word formation recognition and text preprocessing before model analysis, so that the original text can be transformed into an analysis object with clear boundaries, traceable sources and computable structures. Its processing flow is shown in Figure 1.

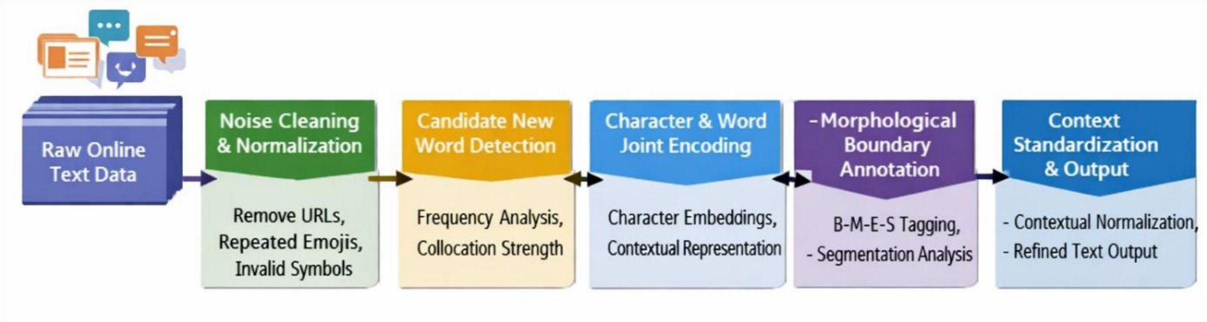

Figure 1: Process of word formation component identification and text preprocessing

The starting point of preprocessing is corpus cleaning. The corpus of new words collected in this paper mainly comes from news comments, social media, public forums and Internet special pages. Although these texts retain the most active generation sites of new words, they also contain a large number of invalid links, emoticons, retweet fragments and non-standard writing. In order to avoid these factors destroying character boundaries, this paper defines a character normalization function $\phi(\cdot)$, which converts the original character sequence $X = \{x_1, x_2, \dots, x_n\}$ as the normalized sequence $X' = \{x'_1, x'_2, \dots, x'_n\}$:

$$x'_i = \phi(x_i), \quad i = 1,2, \dots, n \tag{1}$$

Among them, $\phi(\cdot)$ is used to complete the combination of foreign symbols, the compression of repeated characters, the deletion of outer chain marks, and the unification of Chinese and English punctuation. This step is not simply to reduce the length of the text, but to preserve the writing information that is really useful for word formation judgment.

After cleaning, the system performs candidate new word discovery on the text. Considering that new words often have the characteristics of "local combination is tight, the overall appearance is new, and the context diffusion is fast", this paper uses the joint index of internal solidification and external activity to screen candidate segments. Let a character fragment c consist of m characters and its internal binding strength can be expressed as follows.

$$\mathrm{PMI}(c) = \log \frac{P(c)}{\prod_{j=1}^{m} P(c_j)} \tag{2}$$

where, P(c) represents the overall occurrence probability of the fragment and $P(c_j)$ represents the marginal probability of the constituent characters. If a segment has a high PMI value and maintains a strong reproduction ability in different contexts, it can be included in the set of candidate new words. This setting can better identify those expressions that have not yet entered the dictionary, but have shown a stable tendency to use in the public opinion field.

After candidate word identification, instead of directly adopting traditional word segmentation results, this paper uses a joint character-level and word-level encoding to locate word-formation boundaries. The reason is that Chinese new words often contain condensation, metonymy, misalignment modification and other phenomena. If we completely rely on the existing word segmenter, it is easy to fragment the internal structure, or mistakenly incorporate the word-forming components that can be analyzed separately into the regular word chunks. Let the normalized sequence be embedded into a vector representation $E = \{e_1, e_2, \dots, e_n\}$, which is processed by the context encoder to obtain the hidden state $H = \{h_1, h_2, \dots, h_n\}$:

$$h_i = \mathrm{Encoder}(x'_i \mid X'), \quad i = 1,2, \dots, n \tag{3}$$

Among them, Encoder is used to extract the dynamic semantics of characters in the concrete context. Compared with static vector, this representation is more beneficial to deal with new word samples with "uncertain semantics but active collocations".

In the boundary detection stage, sequence labeling method is used to determine the position of each character in the word formation structure, and B-M-E-S tags are used to indicate whether the character belongs to the beginning, middle, end or single character component. Given a sequence of labels $Y = \{y_1, y_2, \dots, y_n\}$, the optimal boundary path is defined as follows.

$$Y^* = \arg\max_{Y} \left(\sum_{i=1}^{n} s_i\,(y_i) + \sum_{i=1}^{n-1} t\,(y_i, y_{i+1}) \right) \tag{4}$$

Here, $s_i(y_i)$ denotes the emission score of position i taking tag yi, and $t(y_i, y_{i+1})$ denotes the transfer score between adjacent tags. Through this process, the system not only segmented the complete new words, but also further identified the modification components, central components and potential trigger components.

In order to make the subsequent metaphor analysis more targeted, this paper adds metaphor potential prediction after boundary labeling to screen the semantic deviation degree of candidate word-formation fragments. Let the metaphor trigger strength of candidate segment c be M(c), which combines semantic offset, cross-domain co-occurrence and cultural cue information:

$$M(c) = \alpha D_{sem}(c) + \beta C_{cross}(c) + \gamma K_{cult}(c) \tag{5}$$

$D_{sem}(c)$ represents the offset of the fragment relative to the conventional sense, $C_{cross}(c)$ represents its co-occurrence strength with heterogeneous semantic domain components, $K_{cult}(c)$ represents its association degree with cultural labels, and α, β, γ are weight parameters. Only when M(c) exceeds the threshold, the segment will be retained as the focus object for subsequent metaphor mapping analysis.

After the above processing, the original web corpus is transformed into structured samples with clear word formation boundaries, context Windows, and metaphor trigger markers. The resulting input no longer stays on the loose surface text, but can provide stable and fine-grained analysis units for subsequent mapping relation extraction.

3.2 Metaphor mapping relation extraction and semantic representation analysis

After the word formation elements are identified, the focus of the problem turns to how the internal meaning of the new word is transferred across domains. For Chinese new words, metaphor does not always appear as explicit "like" or "like". More often, it is compressed into the internal composition collocation and context traction. Some components are responsible for the activation of the source domain experience, and the other part carries on the social evaluation or abstract concept, and the two gradually form a stable correspondence in the high-frequency propagation. If we only look at surface co-occurrences, the model may misjudge general modification relations as metaphorical structures. If we only look at static word senses, it is also difficult to find the temporary projection and situational reinterpretation that are common in new words. To solve this problem, this paper constructs the analysis process of "trigger identification-source domain/target domain pairing - structural constraint screening - semantic aggregation representation", whose structure is shown in Figure 2.

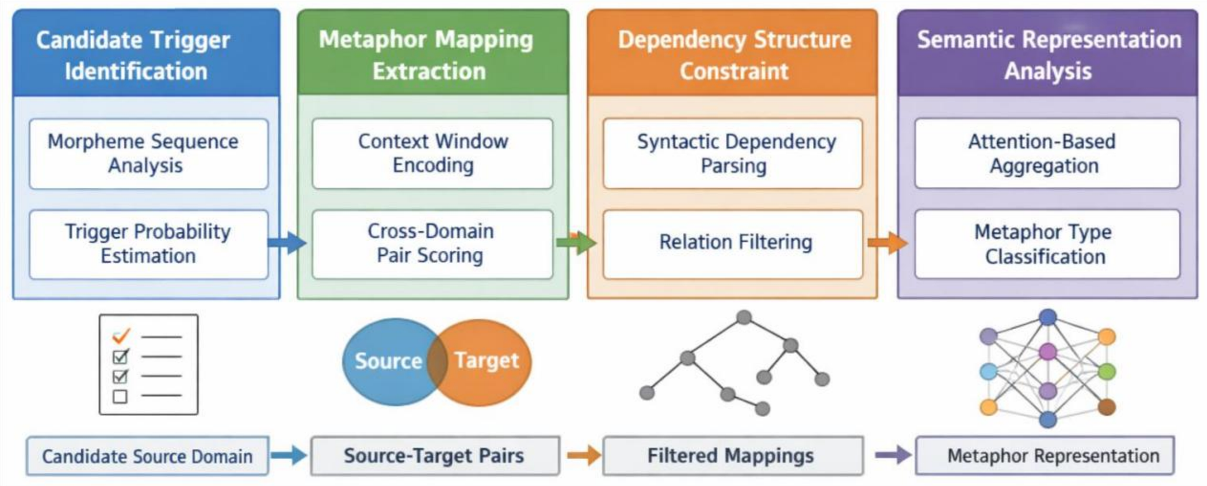

Figure 2: Process of metaphor mapping relation extraction and semantic representation analysis

The starting point of mapping extraction is trigger item identification. Let the sequence of word-forming constituents output in Section 3.1 be $C = \{c_1, c_2, \ldots, c_m\}$, each component corresponds to the context representation h_i. In this paper, h_i is fed into the discriminator to estimate the probability that the component assumes the function of metaphor activation:

$$p_i = \sigma(W_t h_i + b_t) \tag{6}$$

where p_i represents the probability of c_i as a metaphor trigger, W_t and b_t are learnable parameters. High probability components are usually not directly equal to the "source domain" itself, but they are often the entrance to trigger cross-domain transfer, such as body part words, spatial location words, object action words, and consumption behavior words.

After identifying the potential trigger items, the system further constructs the source domain and target domain candidate pairs. The core of metaphor mapping is not that the components themselves exist in isolation, but that the cross-domain connections between them form. For any pair of components (c_i, c_j), this paper uses the bilinear relationship function to calculate the mapping strength:

$$r_{ij} = h_i^T W_r h_j \tag{7}$$

Here, r_{ij} represents the relevance score that forms the metaphorical relationship between c_i and c_j, and W_r is the relationship parameter matrix. When a component biased towards concrete experience shows strong correlation with a component biased towards abstract evaluation in semantic space, the system will include it into the set of potential mappings.

However, vector correlation alone does not guarantee a reliable mapping. There are frequent but non-metaphorical collocations in the context of neologisms. Without structural constraints, the model will amplify the impact of accidental co-occurrence. To this end, we introduce dependency path constraints to perform a secondary screening of candidate relations. Let d_{ij} be the shortest path length of components c_i and c_j in the dependency graph, then the mapping score after structure modification is as follows.

$$\tilde{r}_{ij} = r_{ij} \cdot \exp(-\lambda d_{ij}) \tag{8}$$

Here, λ is the attenuation coefficient. The meaning of this expression is that the elements that really participate in the construction of metaphor usually do not stray from each other in the syntactic structure. On the contrary, most of them are closely related to the core predicate, evaluation center or key modification chain. With this processing, the system is able to exclude semantically related but loosely structured pairs.

After determining the effective relations, the model needs to integrate multiple sets of candidate mappings into a unified metaphor representation of the neologisms. Considering that the same new word may contain several cross-domain cues at the same time, this paper uses the attention weighting method to aggregate the filtered mappings. Let M be the set of valid mappings, then the mapping semantic vector z of a new word is defined as follows.

$$z = \sum_{(i,j)\in M} \alpha_{ij} [h_i; h_j], \alpha_{ij} = \frac{\exp(\tilde{r}_{ij})}{\sum_{(u,v)\in M} \exp(\tilde{r}_{uv})} \quad (9)$$

Here, $[h_i; h_j]$ is the concatenation representation of the component pair, and α_{ij} represents the contribution weight of the relation to the overall metaphorical meaning. The obtained representation is no longer a fuzzy overall similarity, but can clearly reflect "which set of cross-domain correspondences really supports the meaning generation of the new word".

Based on the aggregated results, the system then feeds the mapping representation to the classification layer for type merging. The category here is not just "whether metaphor is not", but is refined into several explanatory patterns, such as "body-emotion", "space-order", "instrument-identity", "consumption-value" and so on. After relation extraction and semantic aggregation, the source-target correspondence within a new word is no longer just an empirical judgment, but is represented as a computable and comparable mapping structure. This result provides a direct basis for subsequent semantic interpretation at the level of cultural cognition.

3.3 Construction of deep semantic model for Cultural cognition

The identification of metaphorical mappings alone is not enough to explain the rapid popularity of new words in a particular period. The reason why many new words have spread power is not only because they have completed cross-domain substitution, but also because they have accurately touched a certain group experience and cultural feelings. The same word-formation way may point to completely different value judgments when it enters into different contexts. Similar source domain components in different groups may also be assigned different emotional temperatures. Therefore, above the metaphor mapping, a further explanatory framework is needed to describe how the new words connect the linguistic forms, social experiences and cultural archetypes. Based on this consideration, this paper constructs a deep semantic model for cultural cognition, which integrates context representation, mapping structure and cultural prototype memory into the same computational process, and its structure is shown in Figure 3.

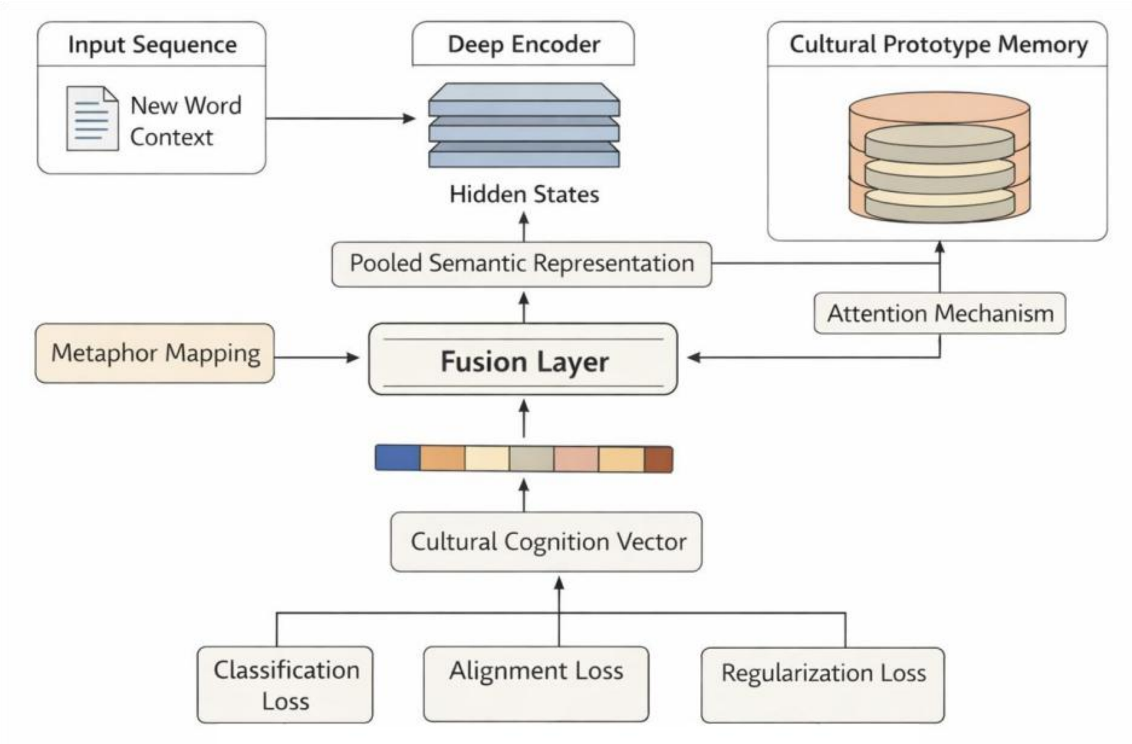

Figure 3: Framework of deep semantic model for cultural cognition

The model takes the new word and its context sequence $X = \{x_1, x_2, \dots, x_n\}$ is the input, and the hidden state $H = \{h_1, h_2, \dots, h_n\}$. In order to obtain the sentence-level core semantics, the local representations are pooled to obtain the global vector h^c:

$$h^c = \text{Pool}(H) \tag{10}$$

where Pool(·) represents the pooling operation. hc here is used to summarize the overall meaning of the context in which the new word is located and serves as the initial semantic entry for cultural cognitive inference.

In order to make the model move from "language similarity" to "cultural interpretation", this paper introduces the cultural prototype memory $P = \{p_1, p_2, \dots, p_K\}$. Each prototype vector corresponds to a relatively stable empirical framework, such as body perception, spatial order, social role, consumption logic, emotional attitude and group identity. When the deep semantics of a new word enters the module, it does not directly make a category judgment, but first matches with each cultural prototype to estimate which interpretation path is more likely to be activated. For the KTH cultural prototype p_k, its attention weight is defined as follows.

$$\alpha_k = \frac{\exp((h^c)^\top W_p p_k)}{\sum_{j=1}^{K} \exp((h^c)^\top W_p p_j)} \tag{11}$$

Here, W_p is a parameter matrix, and α_k represents the degree of semantic fit between the current new word and the KTH cultural prototype. Through this mechanism, culture is no longer just a post-hoc interpretation by the analyst, but is transcribed into a semantic resource that can be called and compared by the model.

After obtaining the associated weights of each prototype, the system aggregates the cultural prototypes with weights to form the cultural cognition vector c^* :

$$c^* = \sum_{k=1}^{K} \alpha_k\, p_k \tag{12}$$

This vector does not replace the metaphor mapping representation extracted in the previous section, but provides a higher level of cognitive background for it. In other words, the mapping structure answers "how does word meaning move across domains", and the cultural vector answers "why can this cross-domain be understood and accepted by the group".

In order to combine the context semantics, mapping structure and cultural prototype, this paper sends the sentence-level representation h^c, mapping representation z^m and cultural cognitive vector c^* into the fusion layer to obtain the final semantic representation z^* :

$$z^* = \tanh(W_h h^c + W_m z^m + W_c c^* + b) \tag{13}$$

Here,W_h, W_m, W_c and b are the parameters to be learned. This formula reflects the basic position of our model: the deep meaning of a new word is not determined by the isolated context alone, but is gradually stabilized by the interaction of word-formation mapping, context distribution and cultural prototype. In the training phase, the model uses a joint loss function to make it capable of both cultural category discrimination and representation alignment.

$$\mathcal{L} = \lambda_1 \mathcal{L}_{cls} + \lambda_2 \mathcal{L}_{align} + \lambda_3 \mathcal{L}_{reg} \tag{14}$$

Among them, $\mathcal{L}_{cls}$ is used for cultural cognitive category prediction, $\mathcal{L}_{align}$ is used to constrain the alignment degree between semantic representation and prototype space, $\mathcal{L}_{reg}$ is the regularization term, and $\lambda_1, \lambda_2, \lambda_3$ are weight parameters. This optimization method can weaken the squeeze of high-frequency popular expressions on the semantic space, and make the new words that belong to the same surface expression but have different cultural orientations obtain a clearer distinction boundary.

On this basis, the semantic generation process of new words can be explained along the path of "word-formation component-metaphor mapping-cultural prototype". The output of the model is not only used to determine the category, but also to reveal the way of cultural cognitive differentiation behind different new words. Therefore, the model can establish a relatively stable computational relationship between metaphor mapping structure and cultural cognitive interpretation.

3.4 Optimization of metaphor mapping and cultural relevance attention mechanism

After completing the identification of word-formation components, mapping relationship extraction and cultural cognition modeling, the model has been able to obtain the basic semantic structure of new words. However, for some words with strong compressibility and obvious context dependence, the common attention mechanism is still prone to two types of deviations: One is to mistake high-frequency neighboring components as core mapping triggers, and the other is to ignore the traction effect of cultural cues on semantic focus direction. The former will weaken the accuracy of the source-target domain pairing, and the latter will make the model drift in cultural classification when explaining similar new words. Based on this, this paper further directs the attention mechanism to explicitly embed metaphor boundary information and cultural relevance signals into the weight calculation process, whose structure is shown in Figure 4.

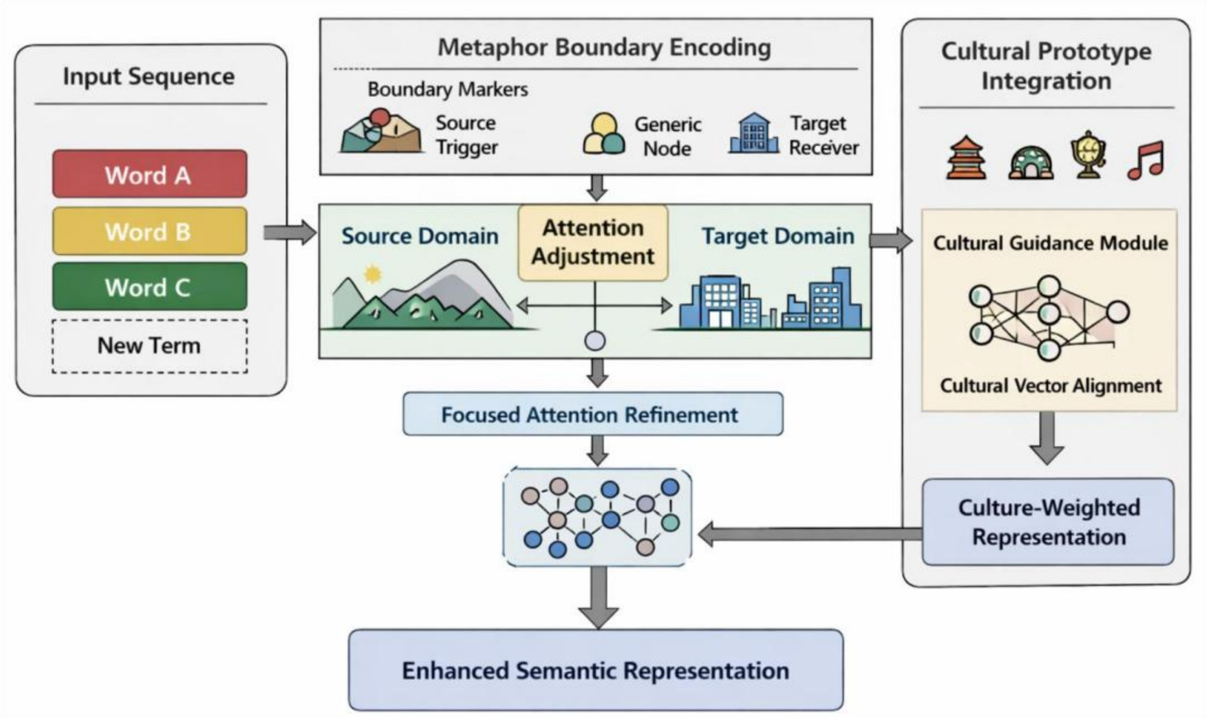

Figure 4: Optimization structure of metaphor mapping and cultural relevance attention mechanism

In order to make the model more accurately distinguish between "common collocation" and "metaphor trigger chain", this paper first adds metaphor boundary markers to the input sequence. Let the representation of the ith word-forming component in the sequence be h_i, and its metaphoric role label be denoted as m_i, where m_i can represent source domain trigger, target domain undertake or ordinary semantic unit. Based on this marker, the original attention weights are corrected to:

$$\widehat{A}_{ij} = \frac{\exp\left(\frac{Q_i K_j^\top}{\sqrt{d}}\right) \cdot \delta(m_i, m_j)}{\sum_k \exp\left(\frac{Q_i K_k^\top}{\sqrt{d}}\right) \cdot \delta(m_i, m_k)} \tag{15}$$

where $\delta(m_i, m_j)$ is the metaphor boundary adjustment function. When the two components were located in the key positions of the source domain and the target domain respectively, the system improved their mutual attention strength. If the two are only ordinary adjacent components, the regular weight is maintained. After this process, the model's attention focus is no longer drawn by the surface co-occurrence frequency, but more focused on the word-formation chain that is really involved in the metaphor generation.

Boundary enhancement alone is not enough to ensure the stability of cultural interpretation, because although some new words have similar mapping structures, their cultural orientations are different. Therefore, this paper continues to introduce the cultural archetype guidance term to make a secondary correction of the attention distribution. Let the association score between the ith component and the cultural prototype vector c be g_i, then the culture-weighted representation of the component is written as follows.

$$\tilde{h}_i = g_i h_i, g_i = \sigma(W_g[h_i; c] + b_g) \tag{16}$$

Here, W_g and b_g are the parameters to be learned, and $\sigma(\cdot)$ is the activation function. The function of this formula is to give higher retention weight to those components that have both metaphorical trigger and cultural direction, and moderately weaken those components that only have local modification function. In this way, when dealing with "emotional expressions", "identity teasing" or "value naming", the model can more clearly distinguish between their cultural origins, rather than only merging based on superficial semantic similarity.

Based on this, this paper combines boundary enhanced attention and culturally weighted representation to form the final optimized output:

$$z' = \sum_i \sum_j \widehat{A}_{ij} \, \tilde{h}_j \tag{17}$$

Here, z 'represents the optimized fusion semantic vector. Compared with the ordinary semantic aggregation results above, this representation highlights the key connection positions in the metaphor mapping, and can better retain the difference information at the level of cultural cognition. Therefore, the deep interpretation of new words is no longer just "which components have cross-domain correspondence", but further implemented as "which correspondences are highlighted, amplified and fixed under what cultural framework".

Through this optimization process, the analysis path of the model for complex new words is further narrowed: the metaphor boundary marker is responsible for limiting the scope of attention, and the cultural correlation signal is responsible for correcting the focus direction, which jointly improves the consistency between mapping recognition and cognitive interpretation. The attention mechanism established in this way not only helps to improve the subsequent classification and discrimination performance, but also makes the model output closer to the real meaning generation process of Chinese new words.

4 Dataset construction and experimental setup

4.1 New Word Metaphor Corpus dataset

In order to ensure that metaphor mapping analysis and cultural cognition modeling are based on computable and reviewable data, this paper constructs a specialized metaphor corpus dataset for Chinese neologisms research. The corpus of Chinese new words used in this paper is mainly from the hot word list of microblog, news comment sections, network forum special pages and annual new word sorting texts, and the collection time span covers January 2022 to December 2025. On the one hand, new words are often generated and diffused in high-frequency interaction scenes. On the other hand, these texts can retain the initial use context, emotional orientation and cultural evaluation information of words. A total of 18,642 candidate texts were obtained from the original sample after crawling and duplication removal.

In the data screening stage, this paper removes the fragmented text containing only emojis and without complete semantic support, removes the AD forwarding, mechanical copy and pure topic tag samples, and merges the temporary splicing expression of the same form and different sources but without stable semantic support. After cleaning, 12,480 valid texts were retained, including 7,936 new word samples with clear metaphor word-formation mechanisms and 4,544 common new word control samples. In order to improve the usability of the corpus, this paper combines manual review and semi-automatic annotation, and synchronously records the new word ontology, context window, word formation boundary, candidate source domain, candidate target domain and cultural semantic label for each sample. The annotation work was completed by three linguistic researchers and two computational language processing researchers, and the double-round cross-validation mechanism was used to deal with the disagreement samples. The final consistency coefficient Cohen's Kappa reached 0.86, indicating that the annotation results have good stability.

In terms of data organization, this paper divides the corpus into training set, validation set and test set with a ratio of 7:1:2. This division can not only ensure that the deep semantic model obtains enough training samples, but also help to test the generalization ability of the model on the independent test set. For the purpose of this paper, the focus of corpus annotation is not on general sentiment classification, but on the fine-grained description of the relationship between word-formation mechanism and cultural cognition. The specific annotation dimensions are shown in Table 2.

Table 2: Annotation dimensions and descriptions of the new word metaphor corpus dataset

Annotation Dimension	Annotation Content	Description
Neologism Entity	Target term and its variants	Records the standard form, abbreviated form, and synonymous alternative forms
Morphological Component Boundary	Component segmentation results	Identifies the core component, modifier component, and combination pattern
Metaphorical Mapping Relation	Source-domain–target-domain correspondence	Determines whether cross-domain projection exists and its direction
Contextual Semantic Information	Context window and evaluative tendency	Preserves the core semantic environment in which the neologism appears
Cultural Cognition Label	Social emotion, identity relations, value orientation, etc.	Annotates the cultural interpretive framework behind the neologism
Sample Category	Metaphorical / Non-metaphorical	Used for model training and comparative experiments

4.2 Acquisition of Chinese new words corpus and configuration of experimental environment

After clarifying the data sources and annotation dimensions in Section 4.1, this paper further explains the process of corpus storage, cleaning, label backfilling and experiment deployment.

(1) Corpus acquisition

The corpus of Chinese new words used in this paper is mainly from the hot words list of microblogs, news comments, special pages of network forums and the annual new words collating text. The collection program was written in Python, and the original text was obtained through the combination of directional crawling and keyword expansion, and the release time, source platform, topic label and context window information were synchronously recorded. Considering that new words often show strong semantic drift in the early stage of event propagation, this paper does not directly take a single sentence as the analysis unit, but retains two sentences before and after the target word as the context fragment, so that the subsequent model can identify its metaphor trigger position and cultural orientation. After the original text is entered into the database, the processing steps such as duplication removal, noise cleaning, sentence segmentation, candidate new word detection, manual review and label backfilling are completed in turn, and the structured corpus for training and testing is finally formed. The overall process is shown in Figure 5.

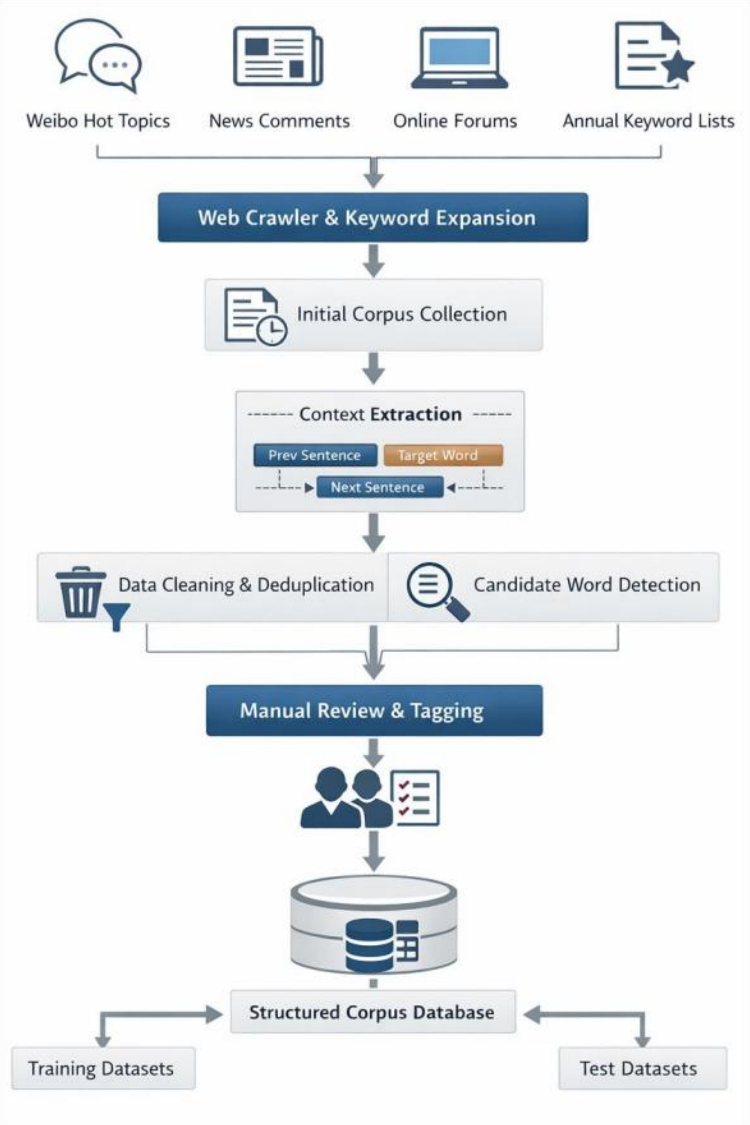

Figure 5: Chinese new word corpus acquisition and experimental process

(2) Experimental environment configuration

The experimental part focuses on the three tasks of "word formation identification, metaphor mapping extraction and cultural cognitive modeling", so the environment configuration should not only meet the coding requirements of the Chinese pre-training model, but also support the optimization of the attention mechanism and batch corpus training. This paper completed the experiment on Ubuntu 22.04 platform, using Python 3.11, PyTorch 2.1 and Transformers 4.38 to build the model framework, word segmentation and dependency analysis call jieba and HanLP toolkit respectively. PostgreSQL 14 was used for data storage. A single NVIDIA RTX 4090 GPU with 24 GB memory was used in the training phase. AdamW is used as the optimizer, the initial learning rate is set to 2×10^{-5}, the batch size is 32, and the maximum sequence length is 128. In order to weaken the interference of occasional hot words on the training results, this paper conducts early stop monitoring on the validation set after each round of training, and retains the model parameters with the highest Macro-F1. The core experimental environment is shown in Table 3.

Table 3: Experimental environment and core parameter configuration

Item	Configuration
Operating System	Ubuntu 22.04
Programming Language	Python 3.11
Deep Learning Framework	PyTorch 2.1
Pre-trained Model Toolkit	Transformers 4.38
Word Segmentation and Syntactic Analysis	jieba, HanLP
Database	PostgreSQL 14
GPU	NVIDIA RTX 4090, 24 GB
Optimizer	AdamW
Learning Rate	2×10^{-5}
Batch Size	32
Maximum Sequence Length	128

5 Experimental evaluation and discussion of results

Based on the Chinese neologisms metaphor corpus constructed in Chapter 4, this paper completes the model training, parameter selection and final evaluation on the training set, validation set and test set respectively. The total number of samples was 12,480, including 8,736 in the training set, 1,248 in the validation set and 2,496 in the test set. The test set contains 1,587 metaphorical new words and 909 non-metaphorical control words. According to the research goal, the experimental evaluation is no longer limited to general text classification, but sets up two connected tasks. The first task is to identify the metaphor mapping relationship, which is to determine whether there is an effective source-target correspondence inside the new word, and further identify its mapping direction. The second is cultural cognitive classification, that is, on the basis of mapping recognition, the samples are classified into five types of cultural cognitive labels: "body-emotion", "space-order", "object-identity", "consumption-value" and "compound mixture". To ensure the comparability of the evaluation, Accuracy, Precision, Recall and Macro-F1 are uniformly used as the main indicators in this paper. For the mapping recognition task, the model output is recorded as correct only if the source domain, the target domain, and the mapping direction match at the same time.

Four kinds of methods are selected for comparison experiments: rule matching method, SVM+TF-IDF method, Chinese BERT baseline and the joint model proposed in this paper. The rule method mainly relies on the metaphor word list, PMI threshold and manual rules to complete the matching, which can give a more direct judgment, but it is sensitive to the change of context. SVM+TF-IDF can deal with some statistical features, but it is difficult to describe the internal cross-domain structure of word formation. Chinese BERT has good context modeling ability, but it does not explicitly introduce metaphor boundary and cultural prototype information. Table 4 presents the overall results of each method on the two tasks.

Table 4: Comparison of results of different models on metaphor mapping identification and cultural cognitive classification tasks

Model	Mapping Recognition P	Mapping Recognition R	Mapping Recognition Macro-F1	Mapping Recognition A	Cultural Classification P	Cultural Classification R	Cultural Classification Macro-F1	Cultural Classification A
Rule Matching + Lexicon	0.756	0.729	0.742	0.761	0.695	0.668	0.681	0.704
SVM + TF-IDF	0.812	0.791	0.801	0.819	0.749	0.721	0.734	0.756
Chinese BERT	0.872	0.850	0.861	0.874	0.824	0.801	0.812	0.829
Proposed Model	0.918	0.909	0.913	0.924	0.886	0.873	0.879	0.891

Table 3 shows that the proposed model achieves optimal results on both tasks. In the metaphor mapping recognition task, the Macro-F1 of our model reaches 0.913, which is 5.2 percentage points higher than that of the best comparison model Chinese BERT. In the cultural cognition classification task, Macro-F1 reaches 0.879, which is 6.7 percentage points higher than that of Chinese BERT. The Accuracy of the two tasks reaches 0.924 and 0.891 respectively, indicating that the model not only has a strong ability to recognize metaphorical new words, but also maintains a relatively stable output in the discrimination of higher level cultural cognition. In other words, the three-level linkage framework of "word-forming boundary-mapping relations-cultural prototype" proposed in the previous article is not only more complex in structure, but also shows clear gains in the result level.

To present the model differences more intuitively, Figure 6 plots the Macro-F1 comparison results of the four methods on the two tasks. It can be seen that the rule method and SVM method can still achieve a certain effect in the mapping recognition stage, but once they enter the cultural cognitive classification task, the performance decreases rapidly. The curves of Chinese BERT on the two tasks are relatively smooth, indicating that the pre-trained semantic representation is indeed helpful for new word analysis. The proposed model maintains the highest position on both task lines, especially in the cultural classification task. This indicates that it is still not enough to explain the cultural cognitive differentiation behind new words by relying solely on contextual semantics, and it is necessary to explicitly introduce cultural prototypes and correct attention mechanisms.

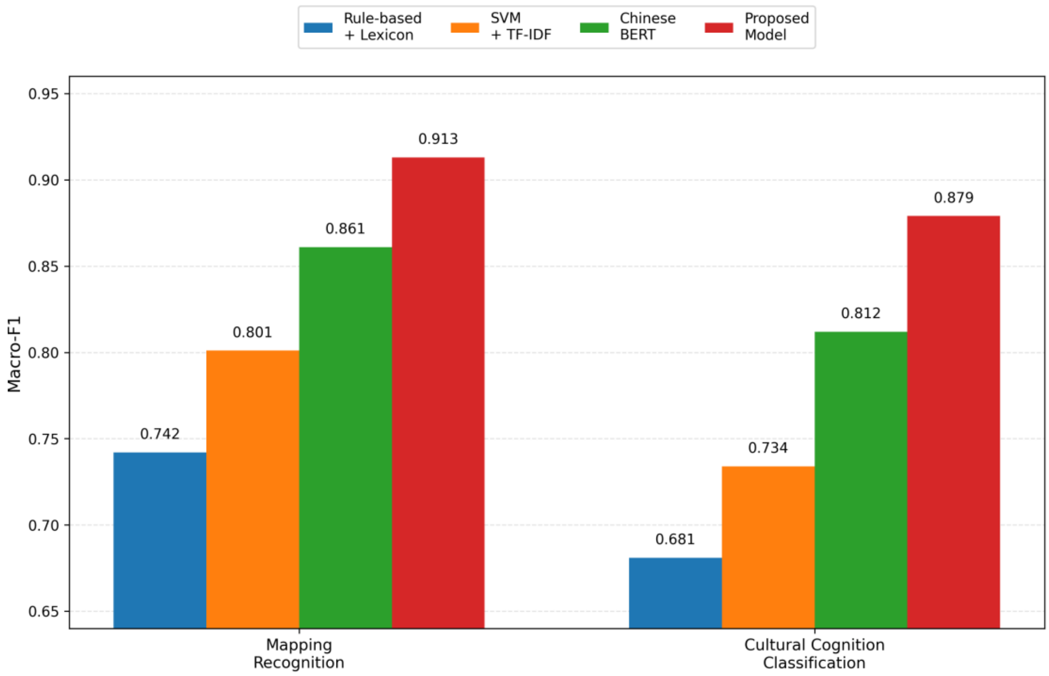

Figure 6: Macro-F1 comparison plots of different models on the two tasks

Looking at the population mean alone is still not enough to reveal the detailed performance of the model. Further observation by cultural cognitive types shows that the proposed model performs most stably on the samples of "Body-emotion" and "space-order", with Precision reaching 0.924 and 0.905, and Recall reaching 0.918 and 0.891, respectively. The "instrument-identity" class is next, with Precision of 0.886 and Recall of 0.874. Recall for the "consumption-value" class decreased to 0.851; The "composite hybrid" class has the lowest Precision of 0.841 and Recall of 0.806. Figure 7 shows the corresponding results. Such differences are not unexpected. The source domains of body experience and spatial location have strong stability in Chinese new words, the trigger components are clear, and the mapping direction is easy to be captured by the model. Consumption logic and compound mixed category expressions are more dependent on the specific event context, and some words also contain irony, joke or secondary escape, resulting in relatively fuzzy category boundaries and more significant impact on recall.

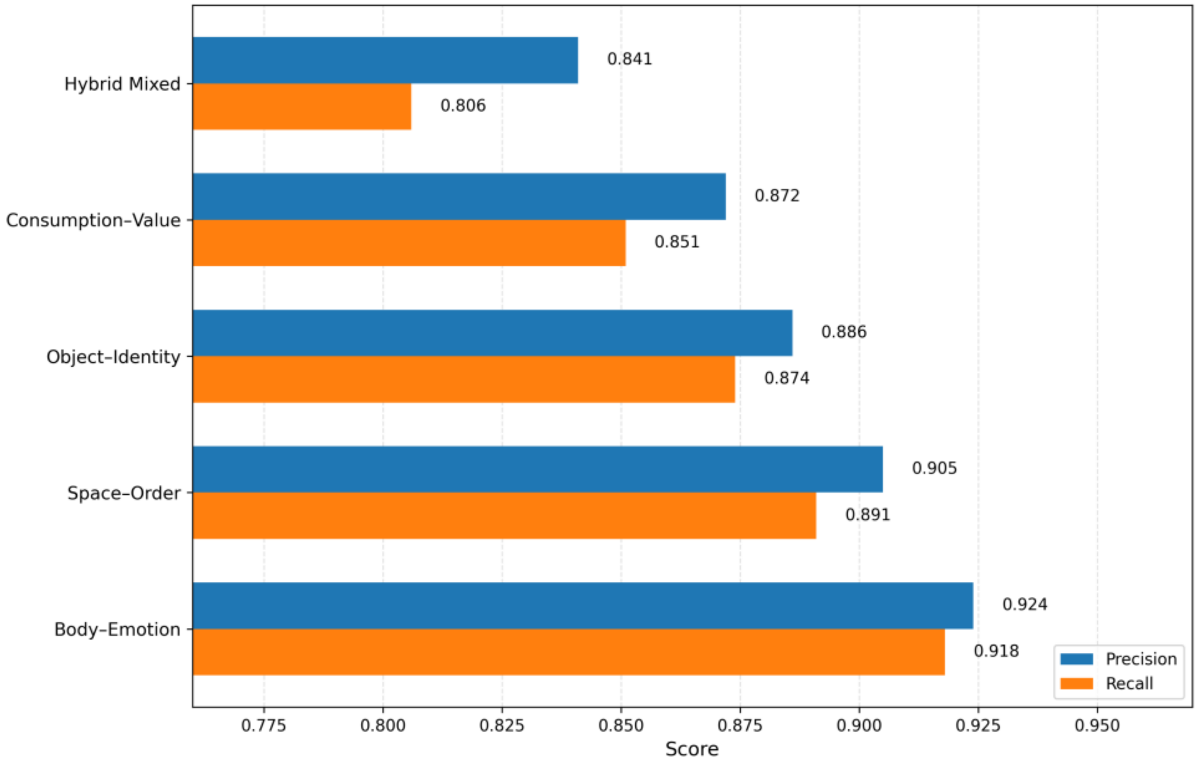

Figure 7: Precision and Recall of the proposed model on different cultural cognitive types

Looking back from the error samples, the model misjudgment mainly concentrated in two cases. One is the new words with short word formation form and narrow context, such as the evaluation words formed by only double-character compression. The source domain cue of such samples is weak, and the model is easy to judge them as ordinary new words. The other is the compound expression with obvious color of group slang, which seems to belong to consumption semantics on the surface, but actually points to identity attitude or emotional projection. At this time, if the context window is too short, the model may drift. Nevertheless, the proposed model still significantly outperforms the baseline on these complex samples, which indicates that metaphor boundary labeling and cultural relevance attention mechanism indeed improve the model's ability to perceive deep semantic differences. In order to further verify the practical contribution of each module, an ablation experiment is carried out. The ablation setting removes metaphor boundary markers, cultural prototype memory, and attention mechanism optimization modules, respectively, and compares them with the full model. The results are presented in Table 5.

Table 5: Ablation experimental results of the proposed model

Model Variant	Mapping Recognition Macro-F1	Cultural Classification Macro-F1	Overall Accuracy
Without Metaphor Boundary Markers	0.887	0.846	0.864

Without Cultural Prototype Memory Bank	0.901	0.833	0.857
Without Attention Mechanism Optimization	0.895	0.851	0.869
Full Model	0.913	0.879	0.891

Table 4 shows that all three core modules have a substantial impact on the final performance. After removing the metaphor boundary marker, the Macro-F1 of mapping recognition decreases to 0.887, indicating that if the model is not explicitly prompted which components are more likely to participate in cross-domain correspondence, the attention is easily drawn by high-frequency adjacent items, which affects the mapping judgment. After removing the cultural prototype memory bank, the Macro-F1 of cultural classification decreases the most significantly, only 0.833, which indicates that cultural cognition discrimination cannot be completed only by the universal context vector, but still needs the support of relatively stable prototypes. After removing the attention mechanism optimization, the two tasks also decreased, especially in the compound mixed class samples, indicating that the attention distribution corrected by both boundary and culture can indeed help the model find a more effective focus path in complex contexts.

It should also be pointed out that although the Accuracy of the proposed model on the cultural cognitive classification task has reached 0.891, there is still room for improvement from complete stability. The problems mainly focus on low-frequency new words, temporary hot expressions, and multiple metaphor superposition samples. They tend to span two or even three cognitive domains, and single-label classification will compress their true semantic hierarchy. The following research can consider introducing the hierarchical label system, multi-label discrimination strategy and time evolution information, and incorporate the dynamic process of "generation, spread and stereotypes of new words" into the model, so as to observe in more detail how metaphors are accepted by society at different stages and transformed into relatively fixed cultural cognitive formats.

6 Conclusions

Focusing on the problem of metaphorical meaning generation in Chinese new word formation, this paper constructs a computational analysis framework consisting of word formation component identification, metaphor mapping extraction, deep semantic modeling of cultural cognition and correlation attention mechanism optimization. The system is verified on a self-built corpus of metaphor new words. The results show that the generation of Chinese new words is not a simple splicing of words, but a compressed process of meaning construction under the joint action of source domain experience, target domain concept and cultural prototype. After transforming this process into a computable task, the model can more stably identify the cross-domain correspondence within the new words, and further explain the cultural cognitive direction behind them. A total of 12,480 samples were used in the experimental part, including 8,736 in the training set, 1,248 in the validation set, and 2,496 in the test set. The results show that the Precision, Recall, Macro-F1 and Accuracy of the proposed model on the metaphor mapping recognition task reach 0.918, 0.909, 0.913 and 0.924 respectively, and it reaches 0.886, 0.873, 0.879 and 0.891 respectively on the cultural cognition classification task. It is significantly better than the comparison methods such as rule matching, SVM+TF-IDF and Chinese BERT. Ablation experiments also show that metaphor boundary labeling, cultural prototype memory bank and attention mechanism optimization all have practical contributions to the performance improvement. After removing the cultural prototype memory bank, the

Macro-F1 of cultural classification decreases from 0.879 to 0.833, indicating that the explicit injection of cultural knowledge plays an irreplaceable role in the deep interpretation of new words. The significance of this paper is not only to improve the performance of metaphor recognition indicators for neologisms, but also to provide a feasible path from language description to computational modeling for Chinese neologisms research. Of course, there are still some limitations in current research, such as the recognition of low-frequency new words, compound metaphor samples and strong event-dependent expressions still fluctuate. In the future, the scale of the corpus can be further expanded, and the time evolution information, multi-label discrimination mechanism and finer-grained cultural prototype hierarchical structure can be introduced to further characterize the dynamic cognitive laws of Chinese new words in the process of propagation, solidification and semantic transfer.

References

[1] Ahrens K, Zeng W H. Referential and evaluative strategies of conceptual metaphor use in government discourse[J]. Journal of Pragmatics, 2022, 188: 83-96.

[2] Zeng W H, Ahrens K. Corpus-based metaphorical framing analysis: WAR metaphors in Hong Kong public discourse[J]. Metaphor and Symbol, 2023, 38(3): 254-274.

[3] Wu Z, Cheng L. Exploring metaphorical representations of law and order in China’s government work reports: A corpus-based diachronic analysis of legal metaphors[J]. Critical Arts, 2022, 36(5-6): 96-112.

[4] Qi H, Zhang H. Characteristics of Internet neologisms in Chinese networks in 2023[J]. Modern scientist, 2024 (7): 21-26.

[5] Changchao L, Zhenkui S. Digital Rhetoric in Media: Conceptual Metaphors in Chinese Editorial Stories[J]. Journal of Interdisciplinary Perspectives, 2024, 2(2): 134–144.

[6] Zhang L, Mu Y. “A strong diewei”–A critical investigation of gendered neological metaphors on Weibo[J]. Discourse, Context & Media, 2024, 61: 100805.

[7] Yu Y, Gu F, Li Y, et al. Conventionality matters in Chinese metaphor but not simile comprehension: evidence from event-related potentials[J]. Frontiers in psychology, 2024, 15: 1404498.

[8] Wei Y F, Yang W W, Oppenheim G, et al. Embodiment for spatial metaphors of abstract concepts differs across languages in Chinese–English bilinguals[J]. Language Learning, 2024, 74(S1): 224-257.

[9] Yang T, Yang Y. How Mandarin–English bilinguals interpret qián/forward: impact of language proficiencies on retrieval of temporal concepts[J]. Frontiers in Psychology, 2024, 15: 1370605.

[10] Yang H, Reid J N. The embodiment of power as upward/downward movement in Chinese-English bilinguals[J]. Applied Psycholinguistics, 2024, 45(4): 647-665.

[11] Ge M, Mao R, Cambria E. Explainable metaphor identification inspired by conceptual metaphor theory[C]//Proceedings of the AAAI conference on artificial intelligence. 2022,

36(10): 10681-10689.

[12] Li Y, Lin C, Guerin F. Cm-gen: A neural framework for chinese metaphor generation with explicit context modelling[C]//Proceedings of the 29th international conference on computational linguistics. 2022: 6468-6479.

[13] Yang K, Liu D, Lei W, et al. Fantastic expressions and where to find them: Chinese simile generation with multiple constraints[C]//Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2023: 468-486.

[14] Shao Y, Yao X, Qu X, et al. CMDAG: A Chinese metaphor dataset with annotated grounds as CoT for boosting metaphor generation[C]//Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024). 2024: 3357-3366.

[15] Tong X, Choenni R, Lewis M, et al. Metaphor understanding challenge dataset for LLMs[C]//Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024: 3517-3536.

[16] Jia K, Li R. Metaphor detection with context enhancement and curriculum learning[C]//Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers). 2024: 2726-2737.

[17] Tian Y, Zhang R, Xu N, et al. Bridging word-pair and token-level metaphor detection with explainable domain mining[C]//Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2024: 13311-13325.

[18] Li Y X, Peng B, Hsu Y Y, et al. Embodiedbert: cognitively informed metaphor detection incorporating sensorimotor information[C]//Findings of the Association for Computational Linguistics: EMNLP 2024. 2024: 16868-16876.

[19] Mao R, He K, Ong C, et al. MetaPro 2.0: Computational metaphor processing on the effectiveness of anomalous language modeling[C]//Findings of the Association for Computational Linguistics: ACL 2024. 2024: 9891-9908.

[20] Chen P, Yang C, Huang Q. Merely judging metaphor is not enough: Research on reasonable metaphor detection[C]//Findings of the Association for Computational Linguistics: EMNLP 2024. 2024: 5850-5860.

[21] Qu X, Zhang G, Wu S, et al. Overview of the nlpcc 2024 shared task on chinese metaphor generation[C]//CCF International Conference on Natural Language Processing and Chinese Computing. Singapore: Springer Nature Singapore, 2024: 181-192.