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Knowledge-Enhanced Semantic Reasoning Model for Implicit Sentiment Recognition

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Abstract: Existing methods for implicit sentiment identification in think tank documents face limitations in deep semantic understanding, including insufficient integration of domain knowledge and difficulty in modeling sentiment evolution in long texts. This study proposes an implicit sentiment recognition model that combines knowledge enhancement with semantic reasoning. The model builds a foundation for deep semantic understanding through a bidirectional encoder and enhances the modeling of implicit sentiment dependencies in text by combining the graph convolutional network's graph-structured reasoning mechanism. In metric tests, the model achieves 95.92% accuracy in implicit sentiment classification with 97.58% domain adaptability. The model also demonstrates strong performance in long-document sentiment modeling (96.87% accuracy) and cross-domain consistency (0.971). Based on the experimental evaluation, the model developed in this paper achieves superior performance compared with existing approaches in testing, while alleviating the limitations of implicit sentiment extraction and biases in domain-specific term comprehension observed in current methods, thereby offering valuable support for in-depth semantic analysis and decision-making in think tank documents.

Keywords: Bidirectional encoder; graph convolutional network; implicit emotion recognition; knowledge enhancement; semantic reasoning; think tank document.

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1. Introduction

Implicit sentiment attribute identification in think tank documents, as a core technology for intelligent information processing and achieving deep semantic understanding in the policy analysis domain, not only provides precise sentiment polarity judgment for think tank research reports, but also offers critical analytical support for strategic decision-making and public opinion awareness (Wagner et al., 2023). Implicit sentiment in this study refers to the emotional inclination that is not expressed through explicit sentiment words but is indirectly implied through context, sentence structure, domain terminology, logical relationships, etc. It is commonly seen in the positional inclination under objective statements in think tank documents. With the deep integration of natural language processing and knowledge graph technologies, the accuracy and interpretability of sentiment analysis models directly determine whether think tank documents can achieve deep semantic mining and extract multi-dimensional sentiment features (Gong et al., 2024). However, current sentiment analysis methods for think tank documents still suffer from inadequate capture of implicit sentiment, insufficient integration of domain knowledge, and difficulty modeling sentiment evolution in long texts (Ai et al., 2024). While existing sentiment analysis technologies can handle basic sentiment lexicon matching and explicit sentiment recognition, they struggle with complex tasks such as identifying sentiment reversal in intricate sentence structures and interpreting professional terminology (Li et al., 2024). To perform sentiment classification on text data, Gao and Yang (2023) proposed a multi-view semantic autoencoder algorithm that first extracts multi-view features, such as lexical and syntactic features from text, encodes and decodes them separately through autoencoders, learns deep semantic representations of each view, and after fusing multi-view features, trains classifiers and optimizes feature extraction and classification performance through self-supervised learning. The Shi et al. (2025) team proposed a multimodal sentiment analysis method to integrate sentiment into text signals. To analyze emotions in social media texts, Rifa'i et al. (2023) proposed a method that combines text mining with a Support Vector Machine (SVM). This method first collects social media text, converts it into vectors via feature extraction, and then inputs them into SVM models.

Although existing research has made progress in sentiment analysis of think tank documents, problems such as inadequate extraction of implicit sentiment features and weak semantic reasoning capabilities still persist. Therefore, how to construct a sentiment analysis model that integrates deep knowledge enhancement and semantic reasoning has become a research hotspot in intelligent text analysis. Among these approaches, Bidirectional Encoder Representations from Transformers (BERT) obtains deep semantic representations through pre-trained language models and demonstrates significant advantages in handling text semantic understanding and contextual feature extraction (Hu et al., 2024; Luo et al., 2025). To improve network security rates, Alferaidi et al. (2025) proposed a BERT-based network intrusion detection system that feeds network traffic data into a pre-trained BERT model for deep semantic learning to uncover hidden patterns in the traffic. To improve the detection efficiency of communication detection models, Wang et al. (2023) proposed a BERT-based auxiliary model that first extracts key features and performs lightweight representation, then inputs them into the BERT model to focus on core semantic association learning. Graph Convolutional Networks (GCNs), as deep learning models for graph-structured data, can effectively model such data through node feature aggregation and neighborhood information propagation, providing structured semantic reasoning capabilities for sentiment analysis of think tank documents (Li et al., 2025). To improve the efficiency of automatic modulation recognition technology, Ghasemzadeh et al. (2023) proposed a GCN-based optimization method that first extracts time-frequency features from received signals and constructs graph structures, then learns node and neighborhood associations through GCN, optimizes feature aggregation and propagation mechanisms, incorporates attention mechanisms to strengthen key feature weights, and finally inputs them into classifiers to complete modulation type recognition. To address the serious information loss problem in connected nodes, Yuan et al. (2025) proposed a GCN-based node collaboration model that first constructs graph nodes from signal time-frequency features, adopts multi-head attention mechanisms to strengthen inter-node associations, optimizes neighborhood information aggregation strategies through GCN, introduces residual connections and layer normalization to reduce information loss, enables nodes to collaboratively complement missing features, and inputs them into classifiers after multi-layer iterative refinement.

Therefore, this research focuses on developing an implicit sentiment attribute identification model that effectively integrates domain knowledge, enhances semantic reasoning capabilities, and is suitable for modeling long-text sentiment evolution. This approach is intended to remedy the shortcomings of existing think tank document analysis methods, namely their failure to adequately capture implicit sentiment and their limited domain adaptability. This study hypothesizes that combining BERT's deep semantic understanding with GCN's structured reasoning can significantly improve implicit sentiment identification. The model further incorporates knowledge enhancement, attention alignment, and context perception mechanisms to strengthen accuracy and robustness. The innovation of this study lies in using the BERT-GCN collaborative architecture as the core, integrating auxiliary modules such as Attention Enhancement (AE), Semantic Alignment Mechanism (SAM), Knowledge Graph (KG), Domain Adaptation (DA), Context Awareness (CA), and Temporal Modeling Network (TMN) to strengthen the model's semantic understanding and sentiment reasoning capabilities for complex think tank documents. On this basis, we construct an implicit sentiment attribute identification model for think tank documents under multi-module collaboration. From an engineering application perspective, the proposed model can be integrated as a core algorithmic module into automated public opinion monitoring systems and policy intelligence analysis platforms, enabling real-time processing and sentiment classification of massive amounts of unstructured text. In practical production organizations, this technology has the potential to replace manual rapid screening and annotation of large-scale think tank literature, effectively reducing information processing costs in policy analysis and strategic decision-making, and providing key technical support for building efficient and intelligent decision support systems.

2. Materials and Methods

2.1. Design of BERT-GCN-Based Identification Algorithm

BERT demonstrates strong contextual modeling ability for text semantic understanding but suffers from local semantic interference when processing long texts for implicit sentiment, leading to bias in sentiment polarity judgments. GCN's graph-structured modeling can effectively capture implicit semantic relations and sentiment dependencies in text (Narayana et al., 2024; Ren et al., 2024). To address this limitation, this study combines BERT and GCN to construct the BERT-GCN algorithm. The algorithm enhances text representation quality through BERT's semantic encoding and strengthens implicit sentiment relation modeling via GCN's graph reasoning, thereby achieving effective coordination between semantic understanding and structural reasoning for think tank document sentiment recognition. Fig. 1 illustrates the operational flow of BERT-GCN.

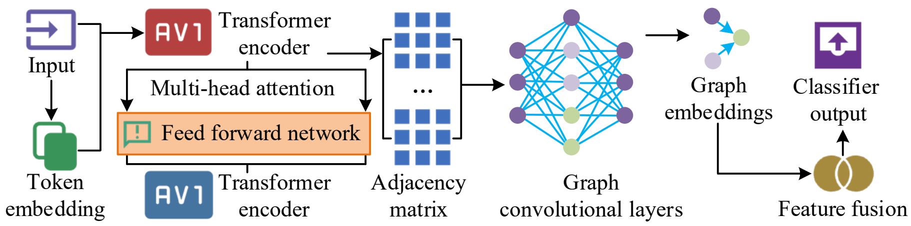


Fig. 1. Operational flow of the BERT-GCN algorithm

As shown in Fig. 1, BERT-GCN first preprocesses the input think tank document and uses BERT to generate contextual embeddings of vocabulary. GCN captures implicit emotional dependencies on the graph through neighborhood feature aggregation, while BERT enhances contextual semantic representation through Transformer encoding layers. Finally, the sentiment classifier evaluates implicit sentiment discrimination ability based on fused representations. GCN node feature aggregation is shown in Eq. (1).

$$h_i^{(l+1)} = \sigma(\sum_{j\in N(i)} \frac{1}{c_{ij}} W_{GCN}^{(l)} h_j^{(l)}) \tag{1}$$

In Eq. (1), $h_i^{(l+1)}$ represents the feature of node i at $l+1$-th layer, $W_{GCN}^{(l)}$ is the trainable weight matrix of the GCN layer, $N(i)$ is the neighborhood node set of node i, c_{ij} is the normalization factor, and $h_j^{(l)}$ is the feature of a neighbor node j at l-th layer (Yang et al., 2023). BERT semantic-enhanced representation is expressed in Eq. (2).

$$H_{BERT}^{(l+1)} = LayerNorm(Z + FFN(Z)) \tag{2}$$

In Eq. (2), $H_{BERT}^{(l+1)}$ is the BERT encoding output at $l+1$-th layer, $LayerNorm$ is the normalization operation, FFN is the feedforward neural network, and Z is the hidden layer output (Liu et al., 2025). Although BERT-GCN achieves collaborative modeling of semantics and structure, it still suffers from semantic drift and insufficient capture of sentiment dependencies in long texts. AE-SAM combines attention dynamically focusing on key sentiment segments and aligns semantic representations with the sentiment label space (Hou et al., 2023). Therefore, this study introduces AE-SAM into BERT-GCN to improve its implicit sentiment recognition accuracy and robustness. The operational flow of AE-SAM is shown in Fig. 2.

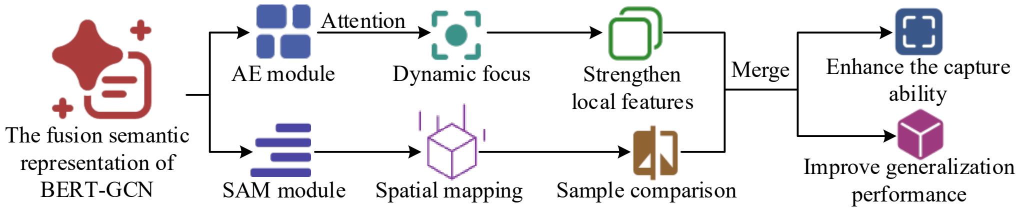


Fig. 2. Operational flow of the AE-SAM

As shown in Fig. 2, the AE-SAM module takes the fused semantic representation produced by BERT-GCN as input and enhances the local features of implicit emotions using an AE. At the same time, SAM maps the enhanced semantic representation to the sentiment label space and uses contrastive learning to narrow the representation distance between similar emotions and widen the representation distance between dissimilar emotions. The final output is an emotionally enhanced, focused and optimized representation. AE attention weight computation is expressed in Eq. (3).

$$\alpha_i = \frac{exp(h_i W_q (h_i W_k)}{\sum_{j=1}^{n} exp(h_j W_q (h_j W_k)} \tag{3}$$

In Eq. (3), α_i is the sentiment attention weight of the i-th semantic unit, h_i is the BERT-GCN fused semantic representation, and W_q and W_k are the query and key projection matrices (Dong et al., 2024). The SAM loss function is expressed in Eq. (4).

$$L_{align} = max(0, \|h_a - h_p\|^2 - \|h_a - h_n\|^2 + \alpha) \tag{4}$$

In Eq. (4), L_{align} is the semantic alignment triplet loss, h_a, h_p, and h_n are the semantic representations of anchor, positive, and negative samples, and α is the margin hyperparameter. BERT-GCN and AE-SAM are combined to construct the BERT-GCN-AE-SAM implicit sentiment recognition algorithm, named BGA. BGA uses BERT-GCN's semantic understanding and structural modeling capabilities, combined with AE-SAM's sentiment-focused and space alignment mechanisms, to capture and integrate multi-level implicit sentiment features in think tank documents. The stacking order of BERT and GCN in the algorithm is based on the design philosophy of prioritizing semantic comprehension over structural inference. First, BERT is used to obtain deep contextual representations, followed by a GCN for graph-structured sentiment dependency modeling, in line with the cognitive logic of moving from local semantics to global relationships. The operational flow of BGA is shown in Fig. 3.

As shown in Fig. 3, BGA begins by preprocessing input think tank documents and constructing a document semantic graph through BERT before entering multi-level feature fusion. Document semantic graph construction is expressed in Eq. (5).

$$A_{ij} = \frac{exp(sim(e_i, e_j))}{\sum_{k=1}^{N} exp(sim(e_i, e_k))} \tag{5}$$

In Eq. (5), A_{ij} is the semantic association strength between nodes i and j, and e_i and e_j are BERT embeddings of tokens, sim is the cosine similarity function.

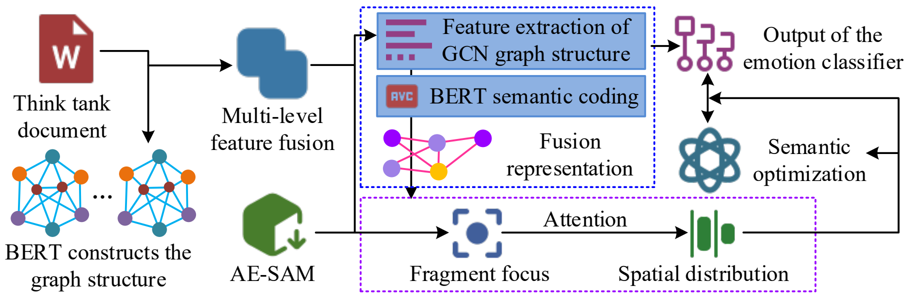


Fig. 3. Operational flow of the BGA algorithm

2.2. BGA Think Tank Document Implicit Sentiment Recognition Algorithm Optimization

In the BGA algorithm, the AE-SAM module is positioned after the BERT-GCN, aiming to perform sentiment focusing and spatial alignment based on existing semantic and structural representations, while avoiding premature introduction of attention mechanisms that may interfere with the original semantic modeling. KG-DA combines KG and DA to introduce external domain knowledge via a knowledge graph, thereby enriching the semantic representation (Zhong et al., 2023; Xu et al., 2024). Therefore, this study integrates KG-DA into BGA to enhance its cross-domain adaptability. The KG used in the study is constructed from domain-specific terminology and a public policy corpus, thereby forming structured knowledge through entity linking and relation extraction. The graph uses a regular incremental update mechanism, incorporating newly released think tank documents to dynamically expand entities and relationships, thereby maintaining its timeliness and domain coverage. The operational flow of KG-DA is shown in Fig. 4.

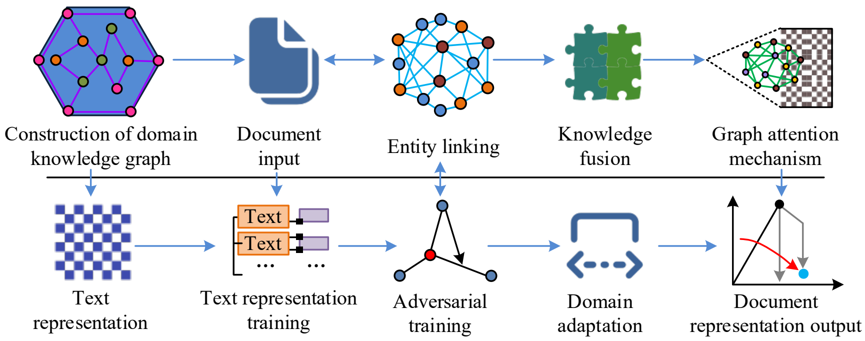


Fig. 4. Operational flow of the KG-DA

As shown in Fig. 4, KG-DA first builds a domain knowledge graph and links professional terms in the document with concept nodes in the graph through entity linking. It then performs knowledge fusion by integrating semantic relations and attribute information from the graph into the text representation through a graph attention mechanism. DA uses adversarial training to align feature distributions across domains and reduces domain differences that affect sentiment analysis. This process generates the enhanced document representation. The KG fusion attention mechanism is expressed in Eq. (6).

$$\beta_{ij} = \frac{exp(\sigma(v_k^T[h_{i1} \| e_{j1}]))}{\sum_{k \in N(i)} exp(\sigma(v_k^T[h_{i1} \| e_{k1}]))} \tag{6}$$

In Eq. (6), β_{ij} is the fusion weight between the i-th word in the document and the j-th entity in the knowledge graph, h_{i1} is the semantic representation of the word, e_{j1} is the embedding of the entity, and v_k^T is a trainable parameter vector (Liang et al., 2025). KG-DA is integrated with BGA to construct the KG-DA-BGA implicit sentiment recognition algorithm, which is named KBGA. KBGA addresses insufficient understanding of technical terms via KG-based semantic enhancement and improves cross-document sentiment stability via DA, thereby achieving more reliable implicit sentiment recognition in complex real-world scenarios. The operational flow is shown in Fig. 5.

As shown in Fig. 5, KBGA preprocesses think tank documents and uses BERT to generate word embeddings and to construct a semantic graph that integrates domain knowledge. In the feature fusion stage, the BERT-GCN module extracts graph features and performs deep semantic encoding, while KG-DA enriches semantic representation by injecting domain knowledge graph information, forming knowledge-enhanced fused features. In the sentiment enhancement stage, AE-SAM focuses on key sentiment segments and optimizes the distribution of the representation space. DA aligns cross-domain feature distributions through adversarial training. Finally, the sentiment classifier outputs implicit sentiment attributes. GCN graph convolution is expressed in Eq. (7).

$$Z = ReLU(\overline{D}^{-\frac{1}{2}}\overline{A}\overline{D}^{-\frac{1}{2}}XW_g + EW_k) \tag{7}$$

In Eq. (7), Z is the knowledge-enhanced graph node representation, $\overline{A}$ is the adjacency matrix with self-connections, X is the original node feature matrix, W_g is the graph convolution weight, E is the external knowledge embedding matrix, and W_k is the knowledge projection weight.

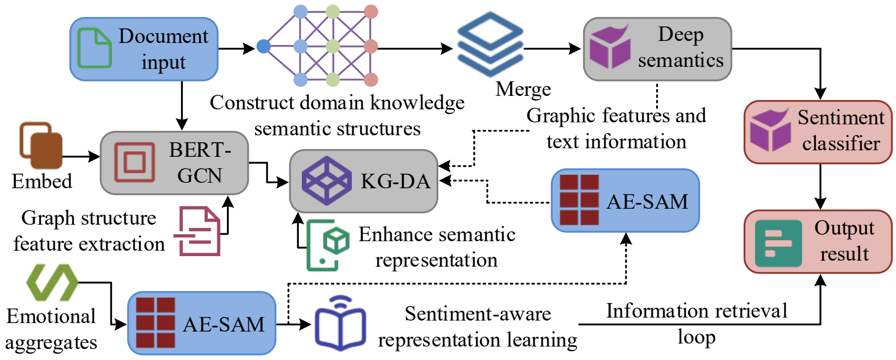


Fig. 5. Operational flow of the KBGA algorithm

2.3. Implicit Sentiment Recognition Model Construction

KBGA achieves knowledge enhancement and cross-domain adaptation in standard think tank document sentiment analysis. However, in multi-source, heterogeneous, and dynamically evolving think tank documents, it still shows low sensitivity to contextual variation and has difficulty modeling long text sentiment evolution. CA-TMN combines CA and TMN to perceive contextual variation through CA and capture fine-grained sentiment cues. It uses TMN's sequence-modeling ability to learn patterns of sentiment evolution in long documents, improving adaptability in complex contexts and amid sentiment shifts (Bang et al., 2025; Xiang et al., 2024). Therefore, this study integrates CA-TMN into KBGA to enhance its ability to model dynamic context and the evolution of sentiment. The parallel design of CA and TMN aims to simultaneously capture the static characteristics of context and the dynamic evolution of emotions. The two are weightily integrated through a gated fusion mechanism to balance the influence of global context and local temporal information. The operational flow of CA-TMN is shown in Fig. 6.

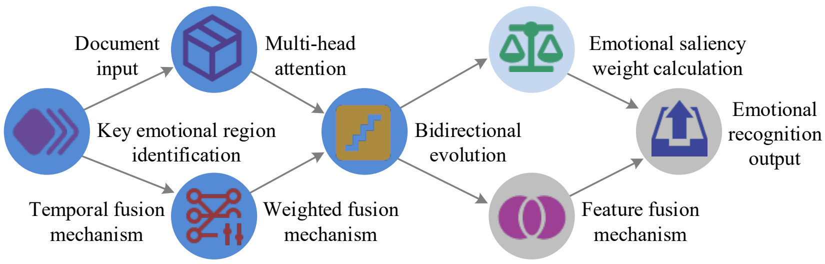


Fig. 6. Operational flow of the CA-TMN

As shown in Fig. 6, CA-TMN receives the document representation produced by KBGA as input. CA analyzes global context relations through multi-head attention, computes sentiment salience weights for different text segments, and identifies key sentiment regions. TMN uses bidirectional gated recurrent units to capture temporal patterns in sentiment evolution and model long-range dependencies. The outputs of both modules are fused using a weighted mechanism to produce an enhanced sentiment representation that incorporates global context awareness and temporal dynamics. The CA gated fusion computation is expressed in Eq. (8).

$$g = \sigma(W_g[h_{i2} \| c_{i2}] + b_g) \tag{8}$$

In Eq. (8), g is the CA gate vector, h_{i2} is the original feature of the i-th text segment, c_{i2} is the context feature computed through attention, and W_g and b_g are weights and biases of the gating network. TMN multi-scale temporal convolution is shown in Eq. (9).

$$s_t = LayerNorm(h_t + \sum_{k=1}^{K} Conv1D_k(H_{t-\tau:t+\tau})) \tag{9}$$

In Eq. (9), s_t is the multi-scale temporal feature at time step t, $Conv1D_k$ is the k-th temporal convolution kernel of a different scale, $H_{t-\tau:t+\tau}$ is the local temporal window centered at t, and K is the number of multi-scale convolution kernels (Yu et al., 2025). CA-TMN is combined with KBGA to construct the CA-TMN-KBGA implicit sentiment recognition model, named CKBGA. CA-TMN improves KBGA's modeling of long-text sentiment evolution and enhances understanding of global context through context-aware mechanisms. It achieves more accurate implicit sentiment recognition in dynamic and complex think tank document scenarios. The operational flow of CKBGA is shown in Fig. 7.

As shown in Fig. 7, CKBGA preprocesses document data and then uses BERT-GCN to extract semantic graph features, while KG-DA integrates domain knowledge to form a knowledge-enhanced document representation. CA analyzes global context through multi-head attention and identifies key sentiment regions. TMN captures sentiment evolution patterns through multi-scale temporal convolution. The outputs of all modules are fused through a gating mechanism to produce multi-level integrated features. The sentiment classifier then outputs implicit sentiment attributes. The model is trained end-to-end and achieves both context awareness and temporal modeling on top of knowledge enhancement, improving sentiment analysis accuracy and robustness in complex think tank document scenarios. Multimodal feature interaction fusion is expressed in Eq. (10).

$$F_{fusion} = LayerNorm(F_k + F_c + F_t + F_k \odot F_c \odot F_t) \tag{10}$$

In Eq. (10), F_{fusion} is the final multimodal fused feature. F_k, F_c, and F_t are feature representations of knowledge enhancement, context awareness, and temporal modeling. $\odot$ is the interaction operation between features.

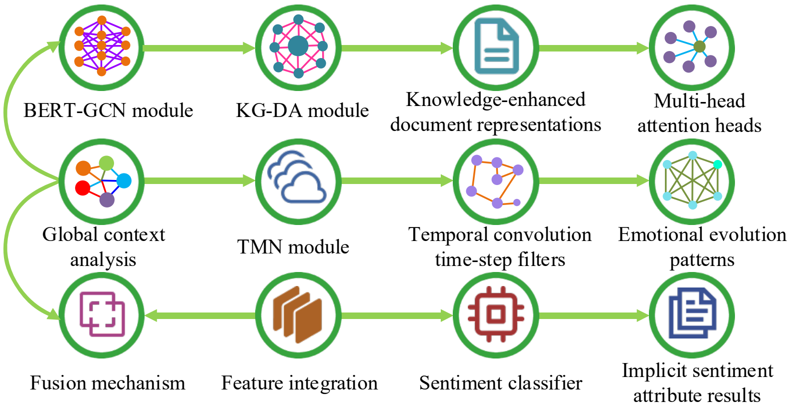


Fig. 7. Operational flow of the CKBGA model

3. Results and Analysis

3.1. Performance Analysis of the BGA Algorithm

To verify the performance of the proposed BGA implicit sentiment attribute identification algorithm, this study conducted performance comparison tests with the BERT-TCN algorithm based on BERT and Text Convolutional Network (TCN), the GAT-SVM algorithm based on Graph Attention Network (GAT) and Support Vector Machine (SVM), and the CNN-ATT algorithm based on Convolutional Neural Network (CNN) and Attention Mechanism (ATT). When processing semantic modeling and sentiment feature extraction tasks on long think tank texts, the system efficiently performed semantic encoding and graph structure reasoning on large-scale documents, leveraging powerful parallel computing capabilities and high memory capacity. The operating system used Ubuntu 20.04, and the programming language was Python 3.8. This study developed the proposed algorithm and model using the PyTorch and Hugging Face Transformers libraries and implemented semantic graph construction and graph convolution operations with the NetworkX library. In addition, the development and debugging environment used VS Code, combined with the Seaborn and Matplotlib libraries, to visualize and analyze sentiment classification results. Model hyperparameters (such as the number of GCN layers, KG fusion dimension, etc.) are tuned on the validation set, and the test set is not used for parameter selection at any point to ensure fairness in evaluation. In this study, the Ruiyan Chinese News Database was merged with the NewsMTSC dataset and randomly stratified in a 7:2:1 ratio to generate training, validation, and testing sets, ensuring that the emotional category distributions of the three sets were consistent and that the samples did not overlap. Among them, the Ruiyan Chinese News Database covers policy interpretations and social public opinion reports from mainstream media such as People's Daily. The NewsMTSC dataset contains a large number of annotated emotional news titles and abstracts, which can be used as benchmarks for emotional attribute recognition. Table 1 presents the distribution of sample sizes for each sentiment category in the dataset.

Table 1. Distribution of sample numbers according to various emotional categories in the dataset

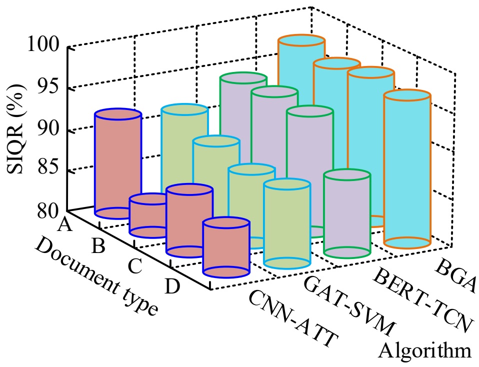
Emotion category	Number of samples in the training set	Number of validation set samples
Positive emotion	4,200	1,050
Negative emotion	4,100	1,030
Neutral emotion	4,150	1,040
Complex emotions	3,950	980
Total	16,400	4,100

As shown in Table 1, the distribution of sample sizes across categories is relatively balanced, indicating that the dataset is overall balanced, which is conducive to model training and evaluation. Three researchers with backgrounds in policy analysis independently annotated the implicit sentiment labels of the dataset, and the inter-annotator consistency was evaluated using the Kappa coefficient. The final Kappa value of the annotation results was 0.85, indicating high consistency in the annotations. In case of disagreement during the annotation process, consensus was reached through discussion. Typical sample examples from the Ruiyan Chinese News Database and NewsMTSC dataset are shown in Table 2.

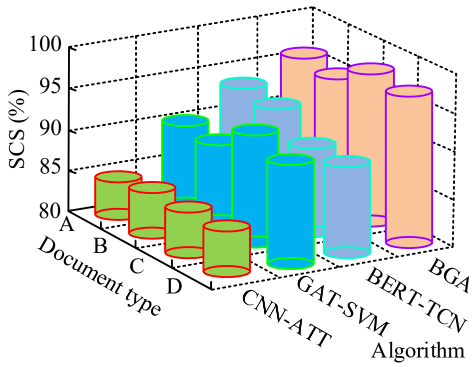
Next, the experiment employed four algorithms to conduct sentiment attribute identification tests on four types of think tank documents: economic policy, diplomatic white papers, technology reports, and national defense strategy reports, and calculated the Sentiment Identification Qualification Rate (SIQR) and Sentiment Consistency Score (SCS). SIQR is a ratio indicator used to evaluate the degree of agreement between the emotional intensity values predicted by the model and the true labeled values. The SCS measures the model's stability in maintaining the same sentiment polarity judgment results across different contexts. The four types were labeled as A, B, C, and D in sequence, and the test results are shown in Fig. 8.

Table 2. Typical sample examples in the dataset

Dataset	Text sample (excerpt)	Emotion category	Split
Ruiyan Chinese News Database	Although the policy has achieved phased results in its implementation, it has not fundamentally resolved structural contradictions.	Negative	Training
	After the subsidy for this industry is reduced, some small and medium-sized enterprises are facing transformation pressure, but the advantages of leading enterprises are highlighted.	Complex	Validation
	The balance of international payments is basically balanced, and the scale of external reserves remains stable.	Neutral	Test
NewsMTSC	The Foreign Minister reiterated that dialogue and consultation are the only viable path to resolving differences.	Neutral	Training
	The sales of new energy vehicles have reached a new high, and the overall profit expectation of the industry chain is improving.	Positive	Validation
	Some real estate companies' credit risks have not been fully released, and the foundation for industry recovery is not yet solid.	Negative	Test



(a) SIQR results



(b) SCS results

Fig. 8. Test results under different document types

Fig. 8(a) shows that the BGA algorithm achieved an SIQR of 97.52% for economic policy documents, 96.89% for diplomatic white papers, 97.13% for technology reports, and 96.75% for national defense strategy reports. The CNN-ATT algorithm performed the worst, with SIQR of 83.35% and 85.92% for diplomatic white papers and national defense strategy reports, respectively. As shown in Fig. 8(b), the SCS of the BGA algorithm across different types was also higher than those of the comparison algorithms, at 95.67%, 94.82%, 96.35%, and 95.18%, respectively. The BGA algorithm's excellent performance stemmed from the AE-SAM module in its architecture, which dynamically focused on sentiment-critical segments and optimized the distribution of the representation space through attention enhancement and semantic alignment mechanisms, enabling it to maintain stable sentiment identification performance across different types of think tank documents. The study extracted a segment of text from the training set and employed four algorithms to conduct recognition tests on the extracted text, calculating their text recognition response time and recognition accuracy. The test results are shown in Fig. 9.

As shown in Fig. 9(a), in the BGA algorithm's recognition of the extracted text, only one character was recognized as garbled, with a recognition response time of 0.002 s and a recognition accuracy of 97.12%. As shown in Fig. 9(b), (c), and (d), the BERT-TCN and GAT-SVM algorithms had more garbled text during recognition. The GAT-SVM algorithm's recognition response time was 0.031s, and its recognition accuracy was 81.78%. Although the CNN-ATT algorithm had less garbled text in recognition, its response time was longer at 0.028s. In summary, the BGA algorithm performed significantly better than the comparison algorithms in text recognition tests. To comprehensively evaluate the performance of the algorithms, accuracy, recall, F1 score, and Sentiment Stability (SS) were assessed for four algorithms on the training and validation sets for sentiment attribute identification. Among them, the SS index can reflect the model's output sentiment tendency fluctuation smoothness when processing large-scale or long-sequence data. The test results are presented in Table 3.

Table 3 indicates that the BGA algorithm achieved accuracy, recall, F1 score, and SS of 97.52%, 96.84%, 98.18%, and 0.961, respectively, all of which are significantly better than the comparison models. The model also achieved 96.87%, 95.93%, 96.40%, and 0.948 on the validation set, respectively. Overall, the BGA algorithm achieves superior overall performance by integrating BERT's deep semantic encoding, GCN's graph-structure inference, and AE-SAM's sentiment-focused alignment mechanism, thereby enabling accurate identification of implicit sentiment attributes in think tank files.

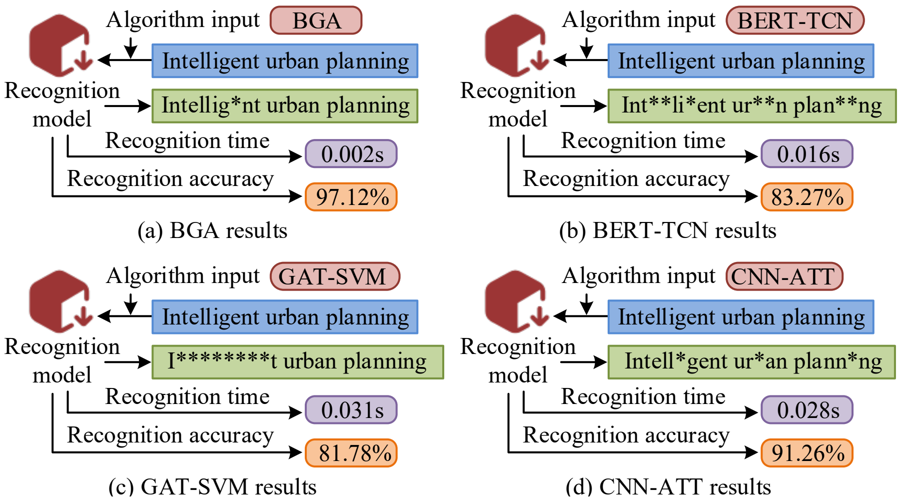


Fig. 9. Text recognition test results of various algorithms

Table 3. Performance evaluation of algorithms on semantic and sentiment metrics

Dataset	Algorithm	Precision (%)	Recall (%)	F1 (%)	SS
Training	BGA	97.52	96.84	98.18	0.961
	BERT-TCN	92.18	90.75	91.46	0.892
	GAT-SVM	88.39	87.26	87.82	0.831
	CNN-ATT	89.67	88.53	89.10	0.845
Validation	BGA	96.87	95.93	96.40	0.948
	BERT-TCN	90.84	89.12	89.97	0.874
	GAT-SVM	86.25	85.08	85.66	0.812
	CNN-ATT	87.93	86.41	87.17	0.829

3.2. Performance Validation of the CKBGA Implicit Sentiment Recognition Model

To further evaluate the performance of the CKBGA implicit sentiment attribute identification model, which is based on the BGA algorithm, this study conducted comparative tests with sentiment analysis models built using the BERT-TCN, GAT-SVM, and CNN-ATT algorithms. To ensure uniformity of test conditions and comparability of results, this study continued to use the Ruiyan Chinese News Database as the training set and the NewsMTSC dataset as the validation set. This study assessed the number of completions and the effective quantity of sentiment-identified document generation by performing implicit sentiment-attribute identification tasks on 800 think tank documents within 60 minutes, and calculated the Sentiment Identification Effectiveness Rate (SIER). SIER refers to the ratio of the number of valid emotional samples successfully identified by the model per unit time to the total number of processed samples. The test results are shown in Fig. 10. The 800 think tank documents used for testing were sourced from multi-field policy documents and think tank reports filtered from the Ruiyan Chinese News Database.

As shown in Fig. 10(a), the CKBGA model completed sentiment identification for 142 documents in 10 minutes, generated 118 effective identifications, and achieved an SIER of 83.09%. At task completion, the CKBGA model identified sentiment in 782 documents and generated 758 effective identifications, achieving an SIER of 96.93%. As shown in Fig. 10(b), the BERT-TCN model identified 698 documents and generated 612 effective documents at the end of the task. As shown in Fig. 10(c) and (d), the SIER of the CNN-ATT model was 85.67% at the end of the task, and the GAT-SVM model only completed the identification of 554 documents and generated 486 effective documents at the end of the task. In summary, the CKBGA model proved its performance advantage through verification. The performance advantage of CKBGA stemmed from the combination of CA-TMN's contextual awareness and temporal modeling, which reduced invalid identifications caused by context changes and sentiment drift by dynamically modeling the global context and the evolution of document sentiment. Subsequently, to systematically evaluate the training stability and generalization capability of the CKBGA model, this study conducted Average Loss Value (AL) analyses on the training and validation sets, respectively, and introduced significance testing to quantify the statistical significance of differences in model performance. AL represents the average error amplitude between the predicted output and the true label during the training process of the model, which is used to measure the convergence degree of the model. This study applied a one-way ANOVA to examine differences in average loss values across groups between the CKBGA model and each comparison model, and considered results statistically significant when p was below 0.05. The test results are shown in Fig. 11.

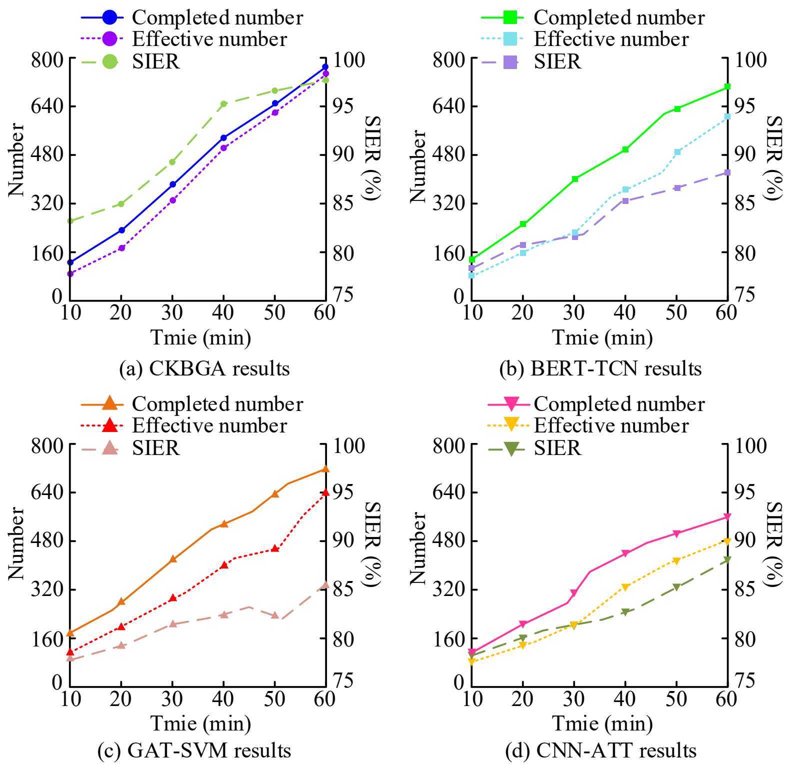


Fig. 10. Test results of each model within 60 minutes

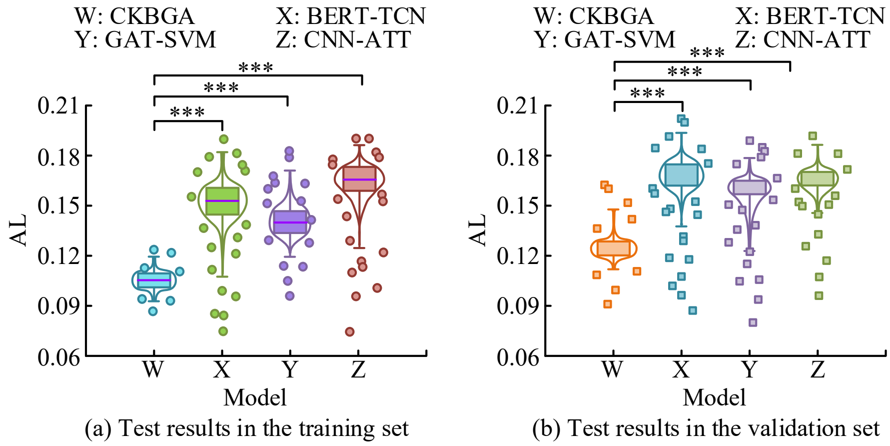


Fig. 11. Average loss value test during training
Note: "***" indicates p<0.05, indicating significant inter-group differences.

As shown in Fig. 11, the box represents the typical fluctuation range of loss values, and the center line represents the average loss value. If too many patterns appear around the fitted line beside the box, this indicates unstable model operation. As shown in Fig. 11(a), when the CKBGA model performed implicit sentiment attribute identification tasks in the training set, its AL was 0.102, significantly lower than the comparison models ($p < 0.05$). The AL of the CNN-ATT model was the highest at 0.164. As shown in Fig. 11(b), when the CKBGA model performed implicit sentiment attribute identification tasks on the validation set, its AL was significantly lower than that of the comparison models ($p < 0.05$), at 0.124. In summary, the CKBGA model significantly outperformed the comparison models, demonstrating strong fitting capability and training stability. Finally, to comprehensively evaluate the CKBGA model's core performance, this study tested key indicators across four models performing implicit sentiment attribute identification tasks in the training set and validation set, including Implicit Sentiment Classification Accuracy (ISCA), Domain Adaptation Ability (DAA), Long Document Sentiment Modeling Precision (LDSMP), and Cross-Domain Sentiment Consistency (CDSC). ISCA is specifically used to measure the accuracy of models in classifying implicit emotional texts that lack clear emotional vocabulary. DAA can characterize the model's ability to generalize and maintain high recognition performance on unseen target-domain data, such as from news to policy. LDSMP is used to evaluate a model's grasp of the overall emotional theme of a lengthy think tank report. CDSC is used to measure the logical coherence and consistency of the output results when a model performs sentiment analysis across different knowledge domains. The test results are shown in Table 4. ISCA is calculated as shown in Eq. (11).

$$ISCA = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

In Eq. (11), TP represents true positive instances, TN represents true negative instances, FP represents false positive instances, and FN represents false negative instances. DAA is defined as the ratio of target-domain accuracy to source-domain accuracy. LDSMP is calculated through the F1 score of long text sentiment classification. CDSC is measured by the correlation coefficient (Pearson) of sentiment classification results across different domains.

Table 4. Core performance test results of each model

Dataset	Indicator	CKBGA	BERT-TCN	GAT-SVM	CNN-ATT
Training	ISCA (%)	95.92	93.45	89.67	91.28
	DAA (%)	97.58	88.93	85.14	87.62
	LDSMP (%)	96.87	89.76	84.35	86.91
	CDSC	0.971	0.865	0.822	0.841
Validation	ISCA (%)	98.14	92.18	87.59	89.74
	DAA (%)	96.83	86.45	82.37	84.96
	LDSMP (%)	95.92	87.31	81.68	83.52
	CDSC	0.962	0.842	0.798	0.819

As shown in Table 4, the ISCA of the CKBGA model on the training-set test was 95.92%. The improvement in ISCA was attributed to the deep semantic and structural reasoning coordination of BERT-GCN. The DAA was 97.58%, and the leading DAA was attributed to the domain knowledge integration and adversarial adaptation mechanism of KG-DA. The LDSMP achieved 96.87%, and its excellent performance was attributed to the contextual awareness and multi-scale temporal modeling of CA-TMN. The CDSC was 0.971, and its stability was attributed to the sentiment consistency constraint in multi-task joint optimization. The results of the CKBGA model on the validation set were also higher than those of the comparison models, with ISCA, DAA, LDSMP, and CDSC achieving 98.14%, 96.83%, 95.92%, and 0.962, respectively. In summary, the CKBGA model further demonstrated its superior performance in the test. This performance advantage stemmed from the synergy among modules, enabling the CKBGA model to accurately identify implicit sentiment attributes in complex think tank document scenarios.

4. Discussion

The proposed BGA algorithm demonstrated significant performance superiority in comparative experiments. This result stemmed from the integration of BERT's deep semantic encoding, GCN's graph structure reasoning, and AE-SAM's sentiment focusing and alignment mechanisms. Through multi-level feature fusion and spatial distribution optimization, it strengthened the model's ability to capture implicit sentiment dependencies and improved the stability of sentiment polarity judgments in complex sentence structures. This finding aligns with the comprehensive review by Zhang et al. (2024) on natural language processing applications in text sentiment analysis. It emphasizes the importance of deep coordination between semantic and structural features to improve analysis accuracy and to verify the effectiveness of hybrid architectures in implicit sentiment analysis. In sentiment identification tests of multiple think tank document types, the SIQR of the BGA algorithm for economic policy and diplomatic white papers exceeded 96.5%, and the SCS remained stable above 95%, significantly higher than the comparison algorithms. This advantage stemmed from the semantic and structural collaborative modeling of BERT-GCN, combined with the dynamic attention mechanism of AE-SAM, which effectively reduced the impact of local semantic interference on sentiment judgment. Compared with the unsupervised text sentiment analysis method of Jiang et al. (2023), the BGA algorithm enhanced the controllability and discriminability of the semantic representation, as well as the capability to capture implicit sentiment clues through attention enhancement and graph convolution mechanisms, thereby achieving further breakthroughs in complex contextual adaptability.

In realistic think tanks document analysis application scenarios, the CKBGA model, which is built on the BGA algorithm, also had significant advantages. The CKBGA model completed sentiment identification for 782 documents in 60 minutes, produced 758 effective identifications and achieved an SIER of 96.93%. This is because the KG-DA model's integration of domain knowledge and its adversarial adaptation mechanism has improved understanding of professional terminology by leveraging external knowledge graphs and reduced distributional differences among documents through domain-alignment strategies. Compared with the research by Hajek and Munk (2023), which combined speech emotion recognition and text sentiment analysis for financial risk prediction, the CKBGA model demonstrated innovation in domain adaptability and long-document modeling through knowledge enhancement and contextual awareness mechanisms, thereby further improving the reliability of sentiment analysis results. In core indicator tests, the ISCA of the CKBGA model on the training and validation sets was 95.92% and 98.14%, respectively, and the LDSMP was 96.87% and 95.92%, respectively, both significantly higher than those of the comparison models. Similar to Hosseinalipour and Ghanbarzadeh (2023) meta-heuristic optimization approach for text sentiment analysis, the CKBGA model effectively captured dynamic sentiment evolution patterns and global contextual dependencies through contextual awareness and temporal modeling of CA-TMN, combined with knowledge enhancement of KG-DA, further proving the important value of multi-module collaboration in complex think tank document sentiment analysis. Compared to the BERT baseline, the CKBGA model, which incorporates multiple modules such as GCN, attention enhancement, and knowledge graph, incurs increased computational overhead during both training and inference stages. However, its significant improvements in implicit sentiment recognition accuracy and cross-domain adaptability demonstrate a reasonable trade-off between performance and efficiency. To visually demonstrate the model's advantage in implicit sentiment reasoning, this study used the think tank sentence with implicit negative sentiment: "Although the policy has achieved phased results during its implementation, it has not fundamentally resolved structural contradictions." The baseline model's output was neutral and failed to recognize the negative implication of the phrase "not fundamentally resolved." However, the CKBGA model's output was negative and recognized the negative implication of the phrase "structural contradictions not resolved" through the perception and enhancement of contextual knowledge.

At the practical application level, the CKBGA model's high accuracy in sentiment analysis of think tank documents (such as an ISCA of 95.92%) can be transformed into a practical tool for policy analysis. For example, in diplomatic white papers or economic policy reports, the model can automatically identify implicit sentiment tendencies in the text, helping analysts quickly grasp the emotional tone and evolution of stance in policy documents, and providing data support for public opinion research, policy evaluation, and risk warning. This not only enhances the objectivity and efficiency of policy interpretation but also provides an interpretable basis for sentiment analysis in intelligent decision-making systems. The model's high performance is partly due to the structural and domain specific characteristics of implicit emotional cues in the selected dataset. For example, policy documents often convey emotional tendencies through specific terminology, sentence structures, or contexts, and these cues are effectively captured by knowledge graphs and context modeling.

This study made three main contributions. First, it proposed the BGA algorithm, which integrates BERT-GCN and AE-SAM, thereby improving the accuracy and robustness of implicit emotion recognition in think tank files through the synergy of semantic understanding and structural reasoning. Second, it constructed the CKBGA model, introducing knowledge augmentation and dynamic contextual modeling to solve the challenges of domain adaptability and capturing the emotional evolution of long documents. Third, the model has proven successful in sentiment analysis of various kinds of think tank documents, providing technical support for policy and public opinion analysis. The above-mentioned works not only provide new solutions for implicit sentiment analysis in think tanks, but also provide new ideas for semantic understanding and calculation of sentiment of complex texts.

5. Conclusion

Existing implicit sentiment analysis methods for think tank documents face challenges in domain knowledge fusion and modeling long text sentiment evolution. Therefore, it is difficult to meet the accuracy and domain adaptability requirements in complex semantic environments, and the current study proposed a CKBGA implicit sentiment attribute identification model. This model is based on the BERT-GCN collaborative architecture and combines it with the AE-SAM algorithm to optimize the distribution of sentiment representations. It utilizes the KG-DA algorithm to integrate domain knowledge and achieve cross-domain adaptation, and enhances context perception and temporal modeling capabilities through the CA-TMN algorithm. Multi-module collaboration effectively improves implicit sentiment recognition accuracy for think tank documents in complex semantic environments. The experiments showed that the model performs well in implicit sentiment classification accuracy and cross-domain adaptability, and can meet the requirements of deep semantic analysis. The core algorithmic framework of this research is highly portable. By adapting to the language features of the target region (such as constructing localized word vectors and sentiment dictionaries) and cultural context, it can be directly applied to public opinion monitoring, policy analysis, and social emotion perception in other countries and regions, providing technical support for cross-cultural semantic understanding and global governance research. In addition, the high-precision sentiment analysis tool provided in this study can also assist managers in optimizing the decision-making process. Specifically, by accurately understanding public opinion trends and the SS of the public, managers can adjust the timing and communication strategies for public policy releases. Meanwhile, by using the model to enhance LDSMP, managers can more efficiently extract key emotional information from large volumes of think tank reports, thereby improving the scientific rigor and responsiveness of strategic planning. However, the model's understanding of specific rhetorical structures and cultural metaphors remains limited, and its sentiment reasoning in complex rhetorical and cross-cultural contexts requires further improvement. In addition, the current model primarily targets Chinese think-tank texts, and its performance on cross-lingual think-tank documents, such as English ones, still requires further verification and optimization. Future work will conduct in-depth research on deep semantic understanding and cross-cultural sentiment analysis by combining domain knowledge graphs with multilingual pre-training technologies and optimizing contextual awareness mechanisms and knowledge integration strategies, enabling the model to better adapt to complex multilingual and cross-cultural analysis scenarios, and provide more powerful technical support for intelligent analysis and decision-making support of think tank documents.

Author Contributions

Yuhui Sun contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, and draft preparation. Feng Tian contributed to manuscript editing, visualization, supervision and project administration. All authors have read and agreed with the manuscript before its submission and publication.

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Declaration of Artificial Intelligence (AI) Tools

The author only uses ChatGPT for language editing and readability improvement. The author has reviewed and verified all content and takes full responsibility for the accuracy and completeness of the manuscript.

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