

Analyzing and Recommending Network User Behavior Using Natural Language Processing

Bing Zhang¹ and Chenhe Yang²

¹ Lecturer, School of Foreign Languages, Guangdong University of Science and Technology, Dongguan 523083, China

² Lecturer, School of Foreign Languages, Guangdong University of Science and Technology, Dongguan 523083, China,
E-mail: ChenheYangz@outlook.com (corresponding author).

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Abstract: With the rapid development and popularization of network technology, the internet has become an indispensable part of people's daily lives. At the same time, the analysis and recommendation of online user behavior have become important links in the development of the internet. This study proposes a unified framework that integrates fine-grained sentiment analysis and an Attention-Guided recommendation Algorithm (AGA), enhances model robustness through FreeLB adversarial training, and dynamically captures user-item associations using a collaborative attention mechanism. This study focuses on its potential application in engineering management and project operation, such as analyzing team behavior and feedback from textual data, such as equipment logs and engineering reports, in order to provide intelligent support for optimizing project management decisions, resource allocation, and risk response. The experimental results show that using the FreeLB model can improve the accuracy of fine-grained sentiment analysis and increase the model's recall rate for positive and negative samples. Compared to other models, the recommendation model's loss decreased by 3.6% and 5.2%, respectively. The results indicate that the model can still maintain high prediction accuracy when processing data from different fields. The research results provide strong support for the analysis and recommendation of online user behavior.

Keywords: User behavior analysis; natural language processing; recommendation algorithm; fine grained sentiment analysis; convolutional neural network; decision-support systems; operations management; digital platforms in engineering.

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1. Introduction

With the proliferation of Internet platforms and media, networks have become an indispensable part of people's daily lives. They are quietly integrating into people's daily lives and changing them. Meanwhile, the increase in the number of online users and the frequency of online activities has also generated massive amounts of user behavior data, providing rich data sources for analyzing online user behavior. Analyzing online user behavior can help businesses better understand users and provide more personalized products and services. It also identifies problems and deficiencies in products and services, and makes timely improvements and optimizations. At the same time, product and market strategies can be adjusted based on user feedback and changes in demand, but human analysis cannot handle such a large database. The value of online user behavior analysis and recommendation technology is not limited to the general Internet platform. Such technologies also have significant applications in engineering management, production operations, and project-based environments. For example, in large-scale engineering projects or complex production systems, massive textual data from equipment logs, engineer reports, collaborative platform communication, and user feedback also constitute domain-specific "user behavior" data. Through fine-grained sentiment analysis, project members' attitudes towards specific processes, tools, or collaboration patterns can be identified, or evaluations of different engineering attributes of products can be extracted from customer feedback. The recommendation algorithm that integrates semantic understanding can provide data-driven decision support for resource allocation, risk response strategy recommendations, or supply chain optimization in project management. In recent years, some researchers have begun to introduce Natural Language Processing (NLP) to open new avenues for analyzing online user behavior, leveraging its powerful language comprehension capabilities. Although NLP technology has made remarkable progress, it still faces many challenges, including insufficient depth of semantic understanding, difficulties in multilingual processing, and low-quality knowledge graph construction (Guess et al., 2023). Fine-grained sentiment analysis is an effective NLP method for understanding users' diverse emotions. By preprocessing network user behavior data and constructing samples that meet pre-training requirements, it achieves visualization of sentiment analysis (Lin et al.,

2022). Existing research on the analysis and recommendation of network user behavior primarily follows two technical paths. The first approach focuses on mining patterns from macro behavioral data. Although such research can effectively capture users' group trends and explicit preferences, it often lacks in-depth interpretation of users' subjective intentions and emotional motivations. The second path begins to introduce NLP technology to extract value from user-generated comments. However, most of these studies have the following limitations: (1) Coarse application granularity: They often remain at the stage of making overall and coarse-grained sentiment judgments on comments, unable to analyze users' contradictory emotions towards different attributes of the same product, thus losing a large amount of precious detailed information. (2) Insufficient model robustness: When dealing with comment data in the real world that is full of noise and adversarial samples, the generalization ability and stability of the model are challenged. In this context, this study seeks to develop an innovative NLP technology that combines fine-grained sentiment analysis with recommendation algorithms. The proposed analysis framework can be directly transferred and applied to typical engineering and management scenarios. For example, in the operation and maintenance platform of infrastructure systems, text reports and logs submitted by engineers can be analyzed to identify their concerns and satisfaction with different device states or maintenance processes through fine-grained sentiment analysis; In production environments or project management collaboration platforms, members' emotional tendencies towards task allocation, resource coordination, or technical solutions can be extracted from communication records and feedback, and recommendation algorithms can be used to provide data-driven intelligent suggestions for project process optimization, risk planning, or team collaboration mode improvement. This proves that deeply integrating natural language processing technology into engineering management systems is a feasible path to perceive personnel status, understand behavioral motivations, and assist management decisions from massive text data.

2. Related Works

With the rapid growth of the Internet, a large number of comments have been generated in cyberspace, making effective analysis of network user behavior an important approach in information mining. Many scholars have conducted research on online user behavior. Gan et al. (2024) proposed an integrated emotion model to understand potential mechanisms underlying user behavior on social media. By investigating changes in user usage processes and incorporating gender-regulatory differences, the factors that affect social media interruptions can be analyzed. The findings showed that the raised model could precisely determine the mechanism of the impact of user behavior. Jupalle et al. (2022) proposed a classifier technique using Ludwig to predict user purchasing behavior. During the process, machine learning algorithms were used to extract evaluations from the network, classify them, analyze and predict them, and finally represent them using fuzzy matrices. The experimental results showed that the advanced technology achieved extremely high precision in forecasting user behavior. Luo et al. (2022) raised a deep learning approach for deploying and managing mobile network user behavior. Artificial intelligence driven states were mapped to perception, and then cognition and decision-making were combined to achieve dynamic adaptation of the system. The experiment indicated that the raised method was highly effective and offered advantages. Schneider et al. (2023) proposed a new encoding method, Cebra, for the learning problem of joint behavior and neural analysis. By using supervised discovery driven methods to combine behavior with neural data, a consistent latent space was formed to provide kinematic features of the joint behavior. The findings showed that the raised way could decode behaviors with high accuracy and speed. Ibrahim et al. (2024) developed a variable theory model to explore the relationship between social media activity and user engagement. Using data from users and the media, the moderating effect of relationships was examined with structural equation modeling. The experiment findings indicated that the proposed model had good practical value.

However, online user behavior analysis can also be achieved through NLP, and some scholars have conducted research in this area. Khurana et al. (2023) discussed the different levels and components of NLP to analyze its applications across various fields. The results indicated that the available NLP datasets and models were robust. Min et al. (2023) conducted NLP research using large-scale pre-trained language models. They learned potential language expressions from general humanities, investigated the application of pre-training and achieved task sharing. The study findings showed that the raised method performed well. Liu et al. (2023) proposed a prompt-based NLP supervised learning model to accurately perform predictive learning tasks. By modeling text and language, the model probabilistically filled in and modified the text information derived from the template, and learned without sample data. The findings indicated that the proposed model employed an effective optimization strategy. Chen et al. (2023) proposed multi-task learning to address the issues of overfitting and data scarcity when training deep NLP models. Gradient regularization, data sampling, and task scheduling techniques were used to filter useful information. The results indicated that the proposed method had a positive effect on improving task performance. Nath et al. (2022) proposed a human-text language model to address the application of NLP in ophthalmology. Pre-trained transformers were generated through analysis of human language and computer interaction information. The research findings showed that the proposed model significantly reduced the limitations of NLP.

In conclusion, although numerous researchers have conducted studies and analyses of online user behavior, relatively few studies examine the end-to-end deep integration of fine-grained sentiment analysis and deep learning-based recommendation algorithms using NLP technology. Unlike previous work, the core contributions of this study are mainly reflected in three aspects: the first is algorithmic innovation, which proposes a fine-grained sentiment analysis model based on FreeLB adversarial training, effectively enhancing the model's robustness and accuracy in recognizing sentiment elements in complex contexts. The second aspect is model construction. A novel attention-guided recommendation algorithm (AGA) was designed to more accurately capture the dynamic correlation between user and item behaviors via a coordinated attention mechanism, thereby improving recommendation quality. The third aspect is the system framework, which has established a unified NLP-driven user analysis and recommendation framework. It organically combines deep semantic understanding (sentiment analysis) with user behavior preference mining (recommendation algorithms), achieving a closed loop from understanding "why users like" to "recommending what users might like".

3. NLP-Based Analysis and Recommendation of Network User Behavior

3.1. Fine-Grained Sentiment Analysis Algorithm Based on Network User Behavior

The analysis of online user behavior is extremely crucial in the digital age, encompassing the processes of collecting, processing, and interpreting the wide range of data generated by users in online environments. These analyses not only help businesses and organizations better understand their user base but also optimize the user experience, improve operational efficiency, and drive product iteration and innovation. However, in the face of massive behavioral information, human analysis is clearly unable to achieve its goals (Chatterjee et al., 2023). NLP can analyze the opinions and emotions expressed by users on social media, product reviews, forum discussions, and other platforms through sentiment analysis, thereby helping companies understand users' emotional attitudes towards products, services, or brands and improve user satisfaction and loyalty (Hollebeek et al., 2022). Traditional sentiment analysis tasks are unable to handle complex and emotionally diverse behaviors; research has proposed multi-dimensional fine-grained sentiment analysis. When performing NLP, the first step is to preprocess the data and transfer words into vector representations. The study uses Word2vec to represent words as vectors, including two models and an acceleration algorithm. The training methods for Skip-Gram and CBOW models are represented in Eq. (1).

$$y = xW_1W_2 \quad (1)$$

In Eq. (1), y represents the entire model, x represents the input features, W_1 represents the first dimension of the weight matrix, and W_2 represents the second dimension. Both models utilize contextual information of words to predict target words, thereby learning vector representations of words. To calculate the cost of selecting the word with the highest probability, the hierarchical Softmax acceleration algorithm is first applied to reduce the word's probability complexity, as shown in Eq. (2).

$$h_w = x_w W_1 \quad (2)$$

In Eq. (2), h_w represents the intermediate vector of the model, and x_w represents the vector of the word. The calculation used to determine the logic of node vectors is shown in Eq. (3).

$$P(w \in \text{left} | \text{context}) = \frac{1}{1 + e^{-U h_w}} \quad (3)$$

In Eq. (3), $P(w \in \text{left} | \text{context})$ represents the operational logic probability of the vector, U represents the vector of each non-leaf node, and e represents the logarithmic function. Then, the negative sampling acceleration algorithm is applied to update the vectors of positive sample words and a small number of negative sample words. Negative sample selection is shown in Eq. (4).

$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{j=0}^V f(w_j)^{3/4}} \quad (4)$$

In Eq. (4), $P(w_i)$ means the possibility of selecting negative samples, w_i represents negative sample words, w_j represents positive sample words, $f(w_i)$ means the frequency of sample word occurrence, and V means the complexity of the word. This technique trains a neural network model to map each word in the vocabulary to a high-dimensional vector space, so that words with the same sense are positioned closely in the vector space. After vectorizing words, it is necessary to use deep learning modules, such as Convolutional Neural Networks (CNNs), for text feature extraction. The schematic diagram of the CNN structure is represented in Fig. 1.

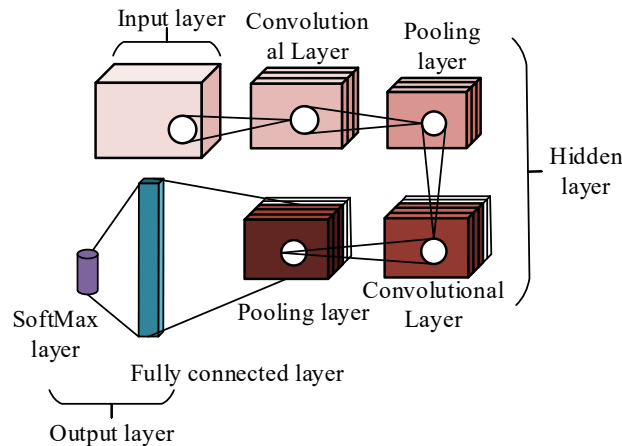


Fig. 1. Schematic diagram of CNN structure

As shown in Fig. 1, the architecture of a CNN is divided into three layers: the input layer, the hidden layer, and the output layer. The input layer is responsible for receiving preprocessed raw behavioral data. The hidden layer contains multiple

functional layers to achieve complex data processing and feature extraction. The output layer is responsible for globally integrating the features extracted by the hidden layer to output the final result (Alimoradi et al., 2022). Next, a paired pre-training algorithm is used to represent the Bidirectional Encoder Representation from Transformers (BERT). The core of the BERT model is grounded on the Transformer encoder architecture, which learns rich representations of language through unsupervised pre-training on large-scale corpora. The structure diagram of the Transformer encoder is represented in Fig. 2.

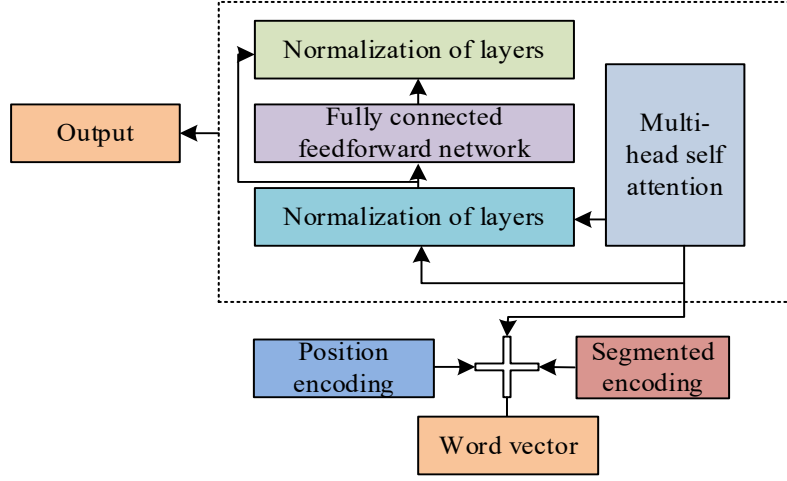


Fig. 2. Transformer encoder structure diagram

Fig. 2 shows the general structure of the Transformer encoder, the core component of the dual-tower BERT model we proposed. However, in the specific implementation of the research, it was subject to crucial customization and application. The study constructed two Transformer encoder stacks with the same structure, which were respectively used as the main tower and the adversarial tower of the model. These two towers share parameters, ensuring that they learn a unified feature representation space. The word embedding vector in the input layer is not only the representation of the words themselves, but also the perturbation object for subsequent adversarial training. The encoder is composed of multiple identical layers stacked together, each containing two key sublayers: the self-attention layer and the feedforward neural network layer. Because the Transformer model does not contain cyclic or convolutional structures, it cannot directly capture sequential information. Therefore, positional encoding is required to add positional information to each element in the sequence. Positional encoding can be obtained either through supervised learning or by random initialization, as shown in Eq. (5).

$$PE_{2i} = \sin(pos / 10000^{2i/d_{model}}) \quad (5)$$

In Eq. (5), PE represents the vector encoding the location of the word, i means one of the dimensions of the position vector, pos represents the position, and d_{model} represents the dimension of segmented encoding. The positional encoding of words can also be obtained through trigonometric function initialization, as shown in Eq. (6).

$$PE_{2i+1} = \cos(pos / 10000^{2i/d_{model}}) \quad (6)$$

In Eq. (6), $2i$ means the dimension of even numbers, and $2i+1$ means the dimension of odd numbers. After obtaining the positional encoding of the words, the word vector representation of the text is added to the segmented encoding and input into each sub-layer of the fully connected layer in the Transformer model. Then, normalization is applied to all connected layers, as shown in Eq. (7).

$$y = LayerNorm(x + SubLayer(x)) \quad (7)$$

In Eq. (7), y represents the normalization result, $LayerNorm$ represents the hierarchical specification, and $SubLayer$ represents the sub layers. The attention mechanism calculation in the multi-head self attention mechanism layer is shown in Eq. (8).

$$Attention(Q, K, V) = \text{soft max}(\frac{QK^T}{\sqrt{d_k}})V \quad (8)$$

In Eq. (8), Q, K, V represent the three inputs of the Transformer, T means the number of fully connected layers, and d_k means the hidden layer dimension. The multi-head self attention mechanism layer captures various contextual information in the input sequence by using multiple self attention heads in parallel, concatenates the outputs of all heads, and obtains the final output representation through a linear transformation. Then, the main model is used for adversarial training on triplet samples to enhance the network's robustness. The final fine-grained sentiment analysis algorithm, grounded in network user behavior, is shown in Fig. 3.

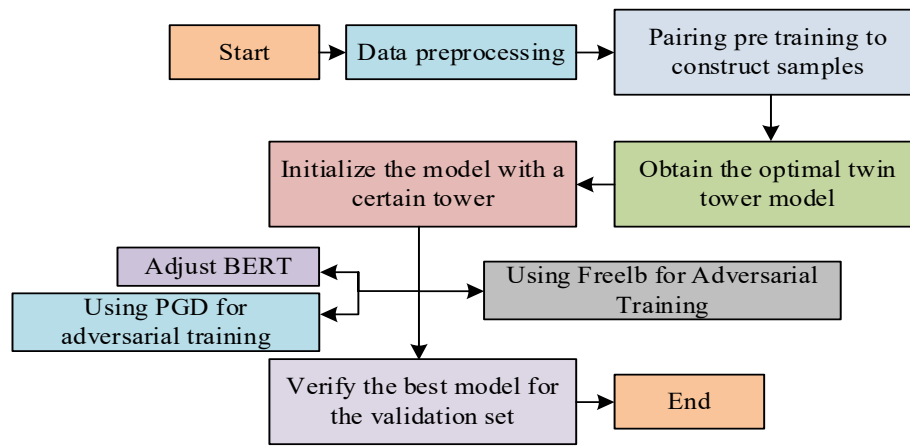


Fig. 3. Fine-grained sentiment analysis algorithm flow based on network user behavior

Fig. 3 summarizes the overall process of the fine-grained sentiment analysis algorithm proposed in the research. Compared with the general process, the specific innovations and implementation details of this work are reflected in the following key links: First, the targeted nature of data preprocessing. During the "data preprocessing" stage, we not only carried out conventional word segmentation and stop word filtering, but also constructed domain-specific aspect word dictionaries based on the characteristics of e-commerce reviews and social media texts, and designed rules to initially identify candidate aspect objects in the reviews, laying the foundation for subsequent fine-grained analysis. Second, the collaborative training mechanism of the dual-tower model. Third, the specific implementation of adversarial training. The "adversarial training" step does not use the standard PGD or FGM methods but instead employs the FreeLB strategy. This strategy generates more powerful perturbations by conducting multi-step, degree-of-freedom adversarial searches in the embedding space, thereby more effectively simulating real-world noise and attacks and guiding the model to learn smoother decision boundaries.

3.2. Recommendation Algorithm Based on Network User Behavior

Adversarial-enhanced emotional representation is trained by introducing controlled perturbations into the embedding space, enabling the model to learn smoother, more robust semantic representations that surpass empirical correlations based solely on surface word frequency or explicit ratings. This enhanced representation can more accurately capture users' stable preferences and core intentions in complex texts (such as conflicting evaluations or implicit emotions), providing a deeper, noise-resistant user profile for downstream recommendations and thereby improving the accuracy and generalization of those recommendations. However, merely analyzing online user behavior cannot achieve the desired application results. The next step is to build a recommendation system based on user-preference features derived from NLP analysis. The recommendation system is an indispensable part of modern Internet enterprises, and text recommendation is a recommendation method based on text content. NLP plays a core role in feature engineering here: it helps recommendation systems extract key semantic and emotional features from unstructured text behaviors such as comments and descriptions. Specifically, the structured sentiment information we obtained through fine-grained sentiment analysis in Section 2.1 (for example, user U has positive sentiment towards attribute A of item I) can serve as a powerful feature in the recommendation model. The recommendation system's modeling method is shown in Fig. 4.

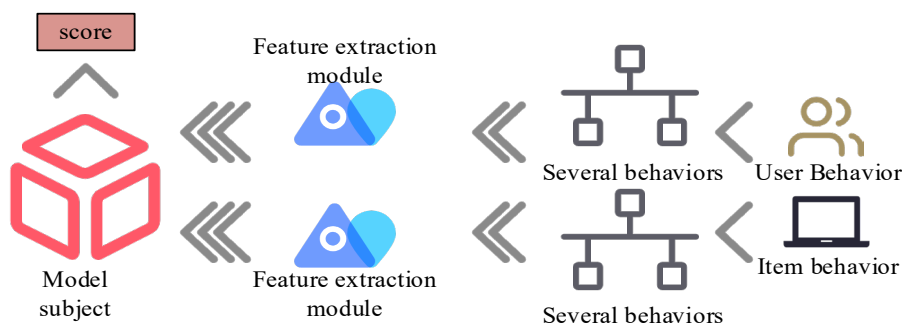


Fig. 4. Modeling methods for recommendation systems

From Fig. 4, it can be seen that the recommendation system simultaneously concatenates various behaviors the user has previously performed and various behaviors the material has been subjected to. Then, by converting word vectors and applying max pooling in a CNN, features are extracted. After passing through various feature extraction modules, the main body of the model is simultaneously fed in. Finally, the recommendation system's rating is obtained. The study proposes the AGA by introducing attention mechanisms to guide information transmission in the network, enabling key information to reach target nodes more efficiently. The core components of the AGA algorithm include attention distribution calculation, information transmission optimization, and information reception and processing modules. The attention distribution

calculation module utilizes model parameters and data streams to extract user behavior features (Bayer et al., 2023). The structure of the characteristic extraction module is represented in Fig. 5.

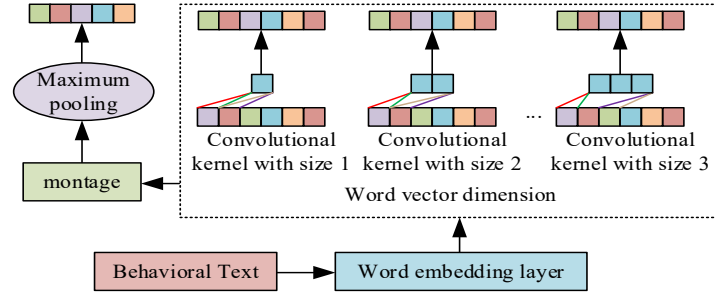


Fig. 5. Structure of feature extraction module

As shown in Fig. 5, the text string input to the feature extraction module must first be split into a sequence of identifiers, typically words, punctuation, or subword units. Then these identifiers will be fed into the word embedding layer, which represents them as word vectors, enabling the computer to understand their meanings and the relationships between them. Finally, the output features are concatenated and then max-pooled to produce the extracted features. After processing, verify and validate the actual application structure as shown in Fig. 6.

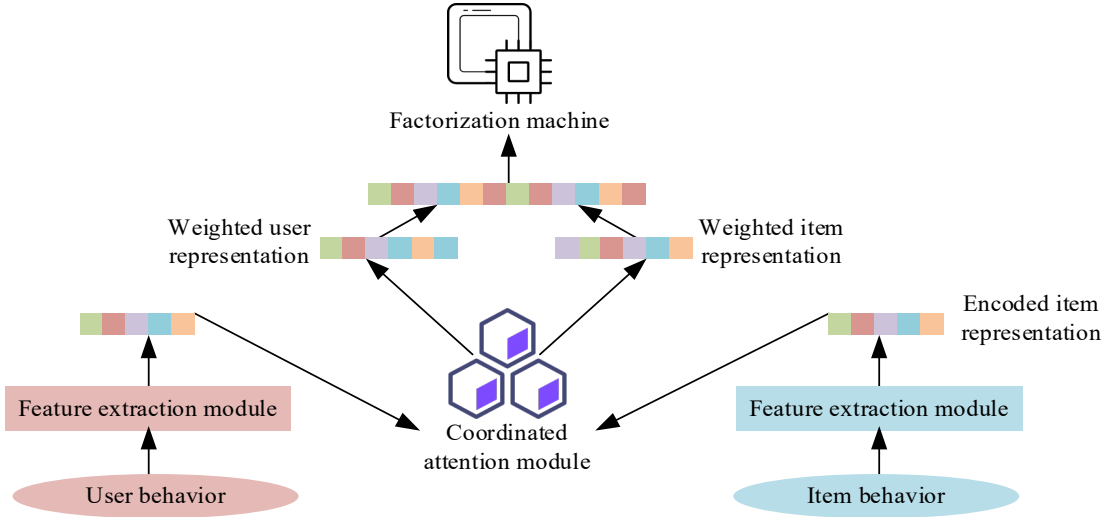


Fig. 6. Validate and test on actual application structure

In Fig. 6, the first step in verifying and validating the actual application structure is to pass the behavior identification of users and items through the characteristic extraction module, extract the characteristics, represent the encoded users and items, and input them into the coordinated attention module. The coordinated attention module weights the encoded users and items separately, then concatenates feature information from different channels and puts them together into the factorization machine output. Among them, the coordinated attention layer can coordinate attention allocation among multiple attention units to optimize the overall information processing flow. The encoded user behavior is represented by Eq. (9).

$$\hat{E}_u = E_u * W + \hat{b} \quad (9)$$

In Eq. (9), $\hat{E}_u$ represents the encoded representation of user behavior, E_u represents user behavior, W represents the trainable parameter matrix in the convolution kernel, and $\hat{b}$ means the bias term. The behavior of the encoded item is represented by Eq. (10).

$$\hat{E}_i = E_i * W + \hat{b} \quad (10)$$

In Eq. (10), $\hat{E}_i$ represents the behavior representation of the encoded item. By multiplying the two representations through a fully connected layer, the correlation matrix can be obtained as shown in Eq. (11).

$$M = \hat{E}_u * \hat{E}_i^T \quad (11)$$

In Eq. (11), M represents the correlation matrix between each user behavior and each passive behavior of the item. The maximum value of each column in the matrix is extracted as represented in Eq. (12).

$$A_u = \max_{col}(M) \quad (12)$$

In Eq. (12), A_u represents the maximum value of each column in the matrix. Extract the maximum value of each row is extracted as shown in Eq. (13).

$$A_i = \max_{col}(M) \quad (13)$$

In Eq. (13), A_i means the maximum value of each row in the matrix. By identifying behaviors with high similarity between users and items, the AGA recommendation algorithm can better help users filter out the most relevant and interesting content or products from massive data, enhance user experience, and promote content consumption and product sales. The pseudocode for the proposed method in this research is shown in Table 1.

Table 1. Attention-guided recommendation algorithm pseudocode

Attention-Guided Recommendation Algorithm	
Input: User behavior sequence B_u , Item behavior sequence B_i	
Output: Predicted click-through rate $\hat{y}_{ui}$	
// Feature Extraction	
$V_u \leftarrow \text{CNN-Encoder}(B_u)$	// $V_u \in \mathbb{R}^{m \times d}$
$V_i \leftarrow \text{CNN-Encoder}(B_i)$	// $V_i \in \mathbb{R}^{n \times d}$
// Compute Coordinated Attention	
$C \leftarrow V_u \odot V_i^{\text{top}}$	// Correlation matrix, Eq. (11)
$M \leftarrow \text{MaxPooling}_{\text{column}}(C)$	// User behavior weights, Eq. (12)
$N \leftarrow \text{MaxPooling}_{\text{row}}(C)$	// Item behavior weights, Eq. (13)
// Generate Weighted Representations	
$\tilde{V}_u \leftarrow \sum_{j=1}^m M_j \odot V_u^j$	// Weighted user representation
$\tilde{V}_i \leftarrow \sum_{k=1}^n N_k \odot V_i^k$	// Weighted item representation
// Final Prediction	
$z \leftarrow \text{Concat}(\tilde{V}_u, \tilde{V}_i)$	
$\hat{y}_{ui} \leftarrow \sigma(\text{MLP}(z))$	// σ is Sigmoid function
return $\hat{y}_{ui}$	

4. Validity Verification of NLP-Based Network User Behavior Analysis and Recommendation

4.1. Experimental Analysis of Network User Behavior Based on Fine grained Emotions

To testify to the validity of NLP-based network user behavior analysis and recommendation, the study first conducted experiments on fine-grained sentiment-based network user behavior analysis. The experiment used the Multi-Aspect Multi-Sentiment (MAMS) dataset and the Adam optimizer for comparative validation in Python 3.6. The MAMS dataset included two tasks, Atsa and Acsa, so internal comparative experiments were conducted separately on each. Firstly, it was necessary to validate the performance of the BERT twin-tower model by verifying the accuracy of the left and right towers of BERT with 20 control rounds. The performance comparison of the BERT model initialization is shown in Fig. 7.

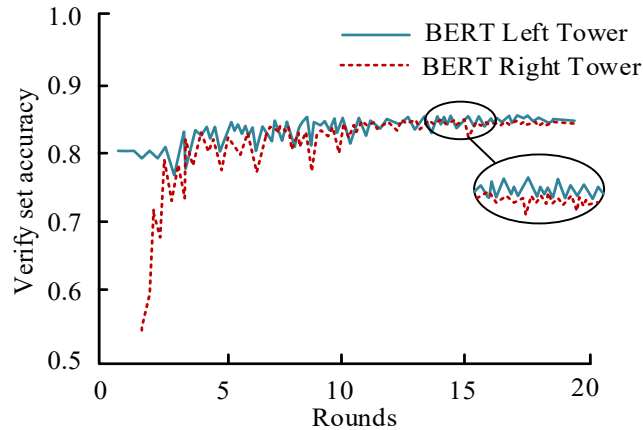


Fig. 7. Comparison of initialization performance of BERT models

As shown in Fig. 7, an increase in the number of training epochs occurred, the accuracy of the validation set initialized with left and right BERT towers first increased and then stabilized. Within 5 turns, the initial BERT value of the left tower was higher, and the increased value of the right tower was greater. But in the later training rounds, the convergence of the left tower BERT was faster, and the accuracy was always higher than that of the right tower. The results indicate that, compared to the right tower, the left tower BERT had better accuracy and convergence speed. Then, internal comparative

experiments were conducted under both Atsa and Acsa tasks, using different optional plugins to evaluate the global accuracy under different plugins. The plugins used in the experiment included Projected Gradient Descent (PGD) adversarial training, which simulated potential adversarial attacks during the training process and optimized the model to resist these attacks. FreeLB adversarial training improved the generalization of the model through adversarial training. Dtdata data augmentation, increasing available data during paired training. Capsule Network (CapsNet) used capsules instead of traditional neurons to achieve higher-level understanding and expression of complex data. The recall accuracy of these four types of models was observed. The internal comparison experiment results of the plugin are shown in Fig. 8.

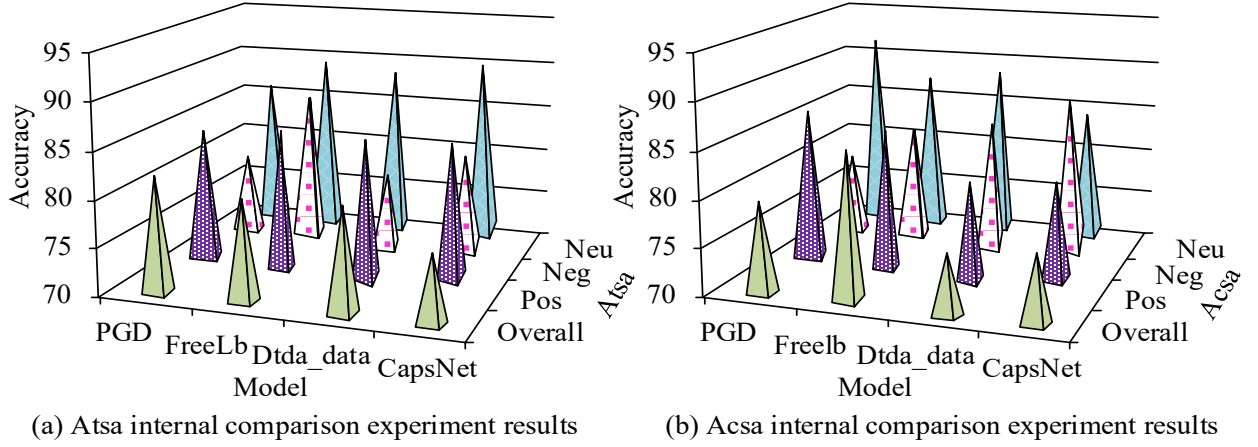


Fig. 8. Internal comparison experiment of plugins

In Fig. 8, the FreeLB model achieved higher average accuracy than the other models across both tasks. In Fig. 8 (a), in the Asta task, CapsNet had the highest positive sample recall rate globally, but its negative sample recall rate was lower than that of FreeLB. Different models might have accounted for the handling of neutral samples during construction. Although the specific implementation methods might vary, the goal was to divide the decision boundary as accurately as possible, resulting in little difference in the recall rate for neutral samples across models. In Fig. 8(b), in the Acsa task, PGD achieved the highest positive sample recall rate because it was robust to small changes in the input data, enabling it to accurately identify positive samples even in the presence of noise or slight deformation. The results showed that using the FreeLB model could make fine-grained sentiment analysis more accurate while improving its recall for positive and negative samples. The FreeLB model was compared with several existing models, including BERT-pt, trained unsupervised on non-domain data; Domain-adapt, trained with the same type of information adjustment; and the BERT-pair benchmark model for constructing auxiliary sentences. The comparative experimental results obtained are shown in Fig. 9.

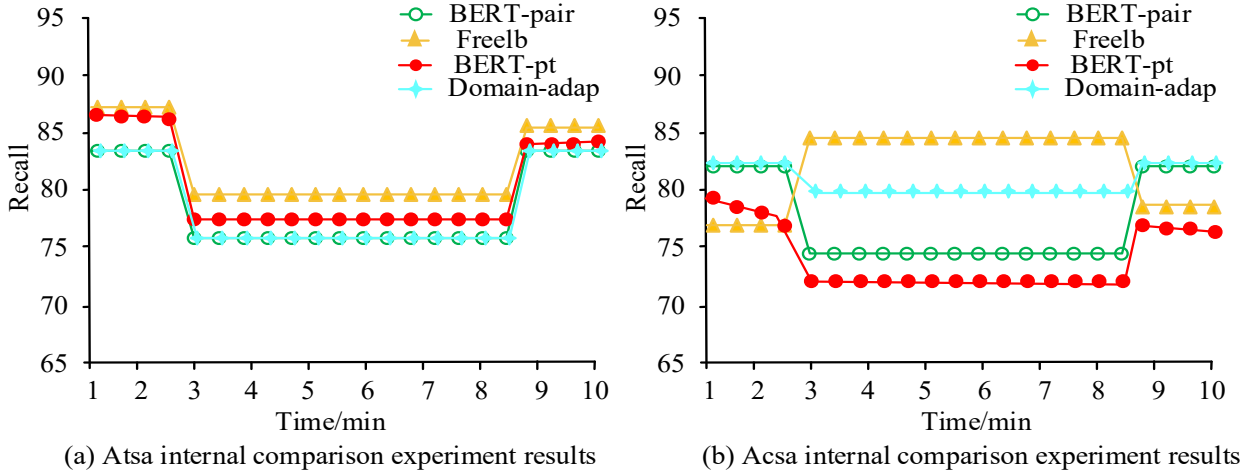


Fig. 9. Comparative experimental results

In Fig. 9, the original FreeLB model outperformed other benchmark models across various recall metrics over time. In Fig. 9(a) for the Atsa task, the recall rates of each model first decreased and then increased over time, with the average recall rate of the FreeLB model increasing by 3.6%, 4.2%, and 4.3%, respectively, compared to BERT-pt, Domain-adapt, and BERT-pair. In Fig. 9(b), in the Acsa task, the recall rate of the FreeLB model changed in the opposite direction to the other models, showing a decreasing-then-increasing trend, yet its average recall rate remained higher than that of the other models. They increased by 7.9%, 5.4%, and 3.5%, respectively, compared to BERT-pt, Domain-adapt, and BERT-pair. Compared to Acsa, the FreeLB model had a smoother recall curve in Atsa tasks and improved algorithm performance.

4.2. Performance Experiment of Network User Recommendation Based on Recommendation Algorithm

The study compared the AGA model with other deep learning models and used Mean Squared Error (MSE) as an evaluation metric to assess the model's accuracy. Other deep models included Deep Cooperating Neural Networks (DeepCoNN), which extracted features via concatenation, and Dual Attention Convolutional Models (D-ATT), which included two types of attention layers. The study used Yelp 19 and Electronics datasets, with an initial learning rate and weight decay of 0.001 and a maximum user and item behavior length of 50. The performance comparison results for each model during training are shown in Fig. 10.

In Fig. 10, the MSE loss trend during model training varied across datasets, with the AGA model showing a slightly lower MSE than the other models. In Fig. 10(a) for the Yelp 19 dataset, when the number of rounds reached 1, the MSE values of all models increased; as the number of rounds increased further, the MSE values of each model showed an overall downward trend. Among them, the MSE value of the AGA model was always lower than those of the other models, converging at 6.52% and 7.48%, respectively, compared to D-ATT and DeepCoNN. In Fig. 10(b) for the Electronics dataset, when the number of rounds reached 2, the MSE values of all models decreased significantly, but there was no significant trend of change thereafter. At this time, the average MSE of the AGA model was the smallest, at 7.26% and 9.45% lower than those of D-ATT and DeepCoNN, respectively. The results indicated that during the training phase, the AGA model performed better and had higher prediction accuracy for user recommendations. The performance comparison of each model during the validation phase is shown in Fig. 11.

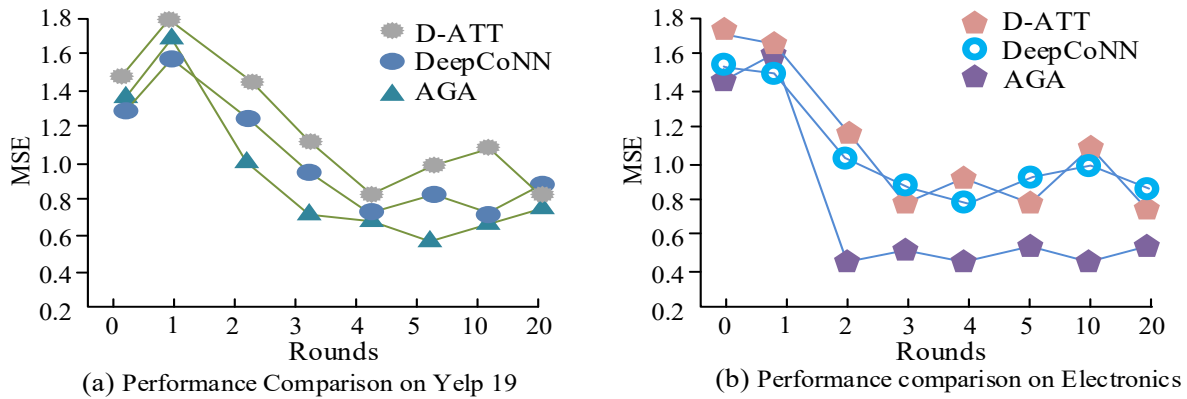


Fig. 10. Performance comparison of various models during the training phase

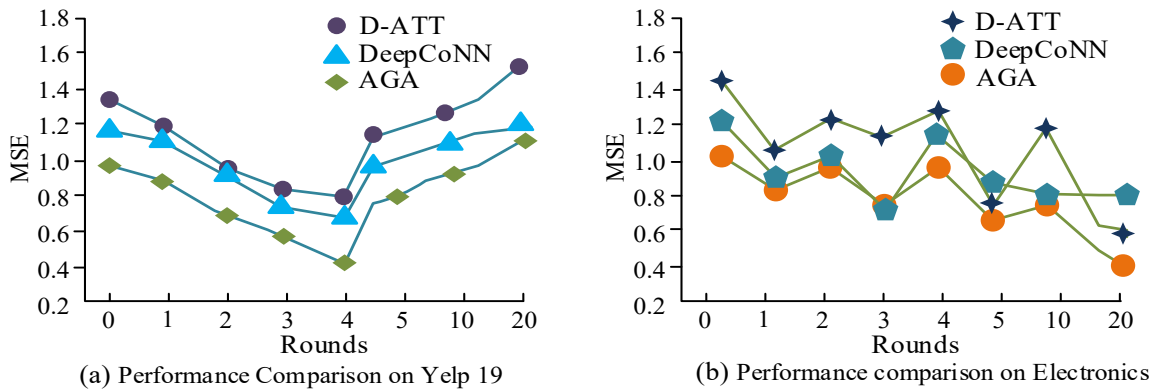


Fig. 11. Performance comparison of various models during the validation phase

In Fig. 11, the MSE loss during model validation differed between the two datasets, with the AGA model's loss clearly smaller. In Fig. 11(a), on the Yelp 19 dataset, the model loss decreased initially and then increased as the number of validation rounds increased. When the validation round was 4, the loss function values of all models were the smallest. The MSE values of the AGA model decreased by 12.1% and 8.6% compared to other models. According to Fig. 11(b), on the Electronics dataset, the MSE of the three models showed irregular fluctuations. On average, the loss function value of the AGA model decreased by 6.2% and 7.5%, respectively, compared to the other two models. The performance comparison of each model during the testing phase is shown in Fig. 12.

In Fig. 12, the MSE loss trend during model testing was similar across both datasets, and the AGA model's loss value remained the smallest. From Fig. 12(a), it can be seen that on the Yelp 19 dataset, as the number of test epochs increased, the overall trend in MSE for all three models showed a decreasing-then-increasing pattern, reaching its minimum at 3 test epochs. The MSE values of the AGA model decreased by 3.6% and 5.2% compared to other models. In Fig. 12(b), the models' trends on the Electronics dataset were similar to those on the Yelp 19 dataset. When the test round was 4, the MSE values of all models reached their minimum. The loss function values of the AGA model decreased by 4.9% and 5.8%, respectively, compared to the other two models. The experimental results showed that these models exhibited stability and

consistency across different datasets, and the AGA model maintained high prediction accuracy when processing data from different fields, making it effective and superior for network user recommendation. Table 2 presents the quantitative results for each model in detail, including prediction accuracy, ranking quality and classification performance on the Yelp 19 and electronic product datasets.

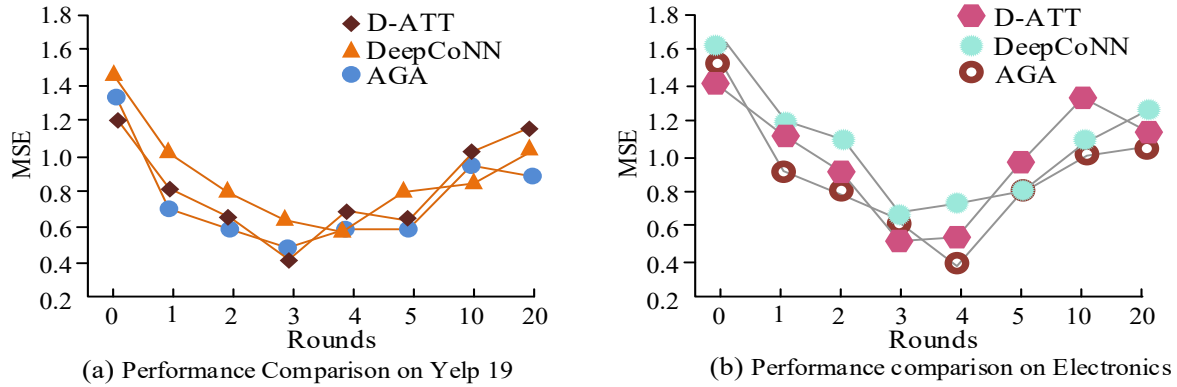


Fig. 12. Performance comparison of various models during the testing phase

Table 2. Comparison of comprehensive performance of different recommendation algorithms

Method	Indicator	Yelp 19 dataset	Electronic product dataset
Luo et al. (2022)	MSE	1.248	0.945
	<u>NDCG@10</u>	0.681	0.723
	AUC	0.812	0.834
Schneider et al. (2023)	MSE	1.152	0.892
	<u>NDCG@10</u>	0.715	0.758
	AUC	0.845	0.861
Ibrahim et al. (2024)	MSE	1.105	0.865
	<u>NDCG@10</u>	0.734	0.781
	AUC	0.863	0.879
Research methods	MSE	1.035	0.812
	<u>NDCG@10</u>	0.783	0.821
	AUC	0.895	0.912

In Table 2, for the two datasets, Yelp 19 and Electronic products, the method proposed in this study achieved the best performance across all evaluation metrics. Specifically, in terms of prediction accuracy, the mean square error values for this method are the lowest, at 1.035 and 0.812, respectively, demonstrating more precise scoring prediction. In terms of ranking quality, the NDCG@10 indicators were 0.783 and 0.821, respectively, indicating that it effectively ranks the items users are most interested in at the top. In terms of classification performance, the AUC values reached 0.895 and 0.912, respectively, demonstrating that the model has stronger discriminative power in distinguishing positive and negative samples. Compared with the methods described in Luo et al. (2022), Schneider et al. (2023), and Ibrahim et al. (2024), this method demonstrates significant and consistent superiority across all indicators. To quantitatively evaluate the management decision value and business impact that the AGA recommendation algorithm proposed in this study may deliver in real business scenarios, additional business-effect simulation experiments were designed. The experiment aims to simulate an online engineering knowledge base or project management tool platform, where users engage in core behaviors such as retrieving technical documents, learning and training materials, using design tool templates, and participating in problem discussions. The goal of the platform is to improve resource utilization, user engagement, and service conversion rates. The research simulates user access flow in chronological order from the test set, and when users engage in interactive behavior, the model generates a Top-K recommendation list in real time. If the recommended list includes items that the user actually interacts with, it is recorded as a successful recommendation hit. Based on this framework, the impact of the AGA model on click-through rate (CTR), conversion rate, user retention rate, and potential revenue was compared with DeepCoNN and D-ATT. The specific results are shown in Table 3.

The results of the business simulation experiment designed in this study show that the proposed AGA model exhibits significant advantages in multiple key performance indicators. Specifically, compared to the benchmark model DeepCoNN, AGA increased the absolute click-through rate by 4.3 percentage points, representing a 34.4% relative increase. This growth directly reflects a substantial leap in the model's accuracy in capturing users' immediate interests and intentions. More importantly, the conversion rate increased by 40.6%, indicating not only a significant improvement in the efficiency of converting user behavior from browsing to deeper interaction, but also the model's effectiveness in understanding users' underlying needs and aligning with the core value of items. This is crucial for improving the value of platform services and

resource utilization. At the same time, the 30 day user retention rate increased to 48.9%, an increase of 7.6 percentage points from the baseline, indicating that the model effectively enhances user stickiness and long-term engagement by continuously providing accurate recommendations, which helps to build a healthy and sustainable user ecosystem. The overall improvement in these operational indicators translates into an estimated 22.1% increase in per capita income contribution, strongly demonstrating the commercial value of integrating fine-grained semantic understanding into recommendation systems. These quantitative results provide a clear basis for management decisions: operators can rely on the high-potential resources and user preference patterns identified by the AGA model to optimize content investment, personalized marketing strategies, and product feature design, achieving data-driven, refined management and resource allocation.

Table 3. Business impact assessment of different recommendation models

Evaluation metrics	DeepCoNN	D-ATT	AGA	The improvement brought by AGA (compared to DeepCoNN)
CTR	0.125	0.141	0.168	0.344
Conversion rate	0.032	0.037	0.045	0.406
30 day user retention rate	0.413	0.447	0.489	0.184
Estimated increase in per capita income contribution (ARPU)	/	/	/	0.221

5. Conclusion

The research conducted fine-grained sentiment analysis and NLP-based recommendation algorithms to analyze and recommend based on online user behavior. Firstly, Word2vec was used to convert words into vector form and preprocess the data. Then, the deep learning module CNN was used for text feature extraction, followed by a pre-trained language representation model, BERT, for pairing with the pre-training algorithm. Element position information was encoded using supervised learning to obtain a fine-grained sentiment analysis algorithm. Finally, the recommendation system was integrated with the AGA algorithm to analyze the actual application structure and obtain a recommendation algorithm that accounts for user and item behavior. The research results indicated that NLP-based fine-grained sentiment analysis methods could ensure accuracy even with higher recall rates, while AGA recommendation models could effectively provide accurate recommendations to users. The method proposed by the research institute employs a modular architecture and a distributed training strategy, effectively handling industrial-scale data through parallel processing. Meanwhile, the model supports online learning and incremental update mechanisms, enabling real-time adaptation and expansion of dynamically growing user behavior data. The technical framework proposed in this study combines fine-grained emotional semantic understanding with dynamic behavior modeling, providing a quantifiable analytical tool for examining the social technology system underlying "human technology task" interactions in engineering environments. Its modeling approach can provide a new empirical research path for understanding patterns of personnel decision-making behavior in complex project environments. The framework proposed in the study will shift engineering managers' decision-making from relying on empirical intuition to a model that integrates fine-grained emotional insights and real-time behavioral data, enabling more accurate demand perception and risk prediction. Specifically, managers can dynamically allocate resources to high-potential areas, high-feedback teams, or urgent process links identified by the AGA recommendation system, based on the model's analysis, thereby systematically improving project management efficiency and the return on investment of resources.

However, the framework proposed in this study still has limitations in practical engineering scenarios, such as performance being constrained by the scarcity and quality fluctuations of domain-specific text data, and its universality in complex project management environments across cultures and languages, which requires further validation. In addition, the model's in-depth analysis of user behavior and emotions has raised ethical considerations regarding data privacy, algorithmic transparency, and the balance between human judgment and machine suggestions in management decisions. Future research will explore the transferability of this model in cross-language and cross-domain engineering project environments and develop data augmentation and domain adaptation methods for small-sample and low-quality text data to enhance its universality and robustness. At the same time, efforts should be made to develop algorithm modules with greater interpretability and to establish AI ethical governance frameworks and usage guidelines suitable for engineering management scenarios, to achieve responsible decision-making through human-machine collaboration.

6. Policy impact

The model framework of this study will inevitably involve important policy and governance issues in practical deployment and application. First, at the level of data governance, text data collected in engineering and project management environments (such as communication records and reports) often contain sensitive information; strict standards for data ownership, access permissions, and anonymization must be established. Second, the ethical use of user behavior analysis requires us to be vigilant about the bias and discrimination that algorithms may bring, such as ensuring that the analysis results are not used for unfair monitoring or decision-making in resource recommendations or performance evaluations. Finally, as a decision aid tool, the transparency and interpretability of AI-based recommendation systems should be given attention, and regulatory frameworks should encourage algorithmic accountability to ensure that their recommendations comply with project management ethics and organizational social responsibility. Therefore, promoting responsible

innovation and incorporating ethical and governance considerations in the early stages of technology development is crucial for the healthy application of this technology in the field of engineering management.

Author Contributions

Bing Zhang contributed to conceptualization, methodology, software, validation, analysis, investigation, and data collection. Chenhe Yang contributed to draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition.

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Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no AI tools were used in the preparation of this manuscript.

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Bing Zhang obtained his Master of Arts in Foreign Language Studies (2014) from Northeastern University, China. He is currently working as a Lecturer in the School of Foreign Languages at Guangdong University of Science and Technology, China. His areas of interest include comparative media studies, East Asian communication ecology and regional and national communication.



Chenhe Yang obtained her Master of Science in TESOL (2016) from the University of Edinburgh. She is currently working as a Lecturer in the School of Foreign Languages at Guangdong University of Science and Technology, China. Her research interests include cross-cultural communication, new media discourse analysis and business communication.