Adaptive Recommendation and Learning Behavior Prediction of Textile English Teaching Resources Based on Transformer and Emotion Recognition Algorithms

Yanghui Zhong

International Business School, Hainan College of Foreign Studies, Wenchang 571300, Hainan,China

Corresponding author: Yanghui Zhong (e-mail: coffee4125@126.com)

ABSTRACT To address the insufficient real-time perception of learners' emotional states and learning behavior trajectories in textile English teaching, which limits the accuracy and dynamic adaptability of resource recommendation, this study develops a collaborative framework for adaptive recommendation and learning behavior prediction. A Transformer variant equipped with a multi-head emotional attention mechanism is employed to process learner interaction text and generate emotionally enhanced semantic representations. These representations are subsequently integrated with a lightweight Gated Recurrent Unit (GRU) predictor to infer learning behavior trajectories. By dynamically evaluating the semantic consistency between emotionally enhanced representations and predicted behavioral patterns, a personalized recommendation list is generated through a differentiable ranking optimization mechanism. Experimental results demonstrate that the proposed approach achieves recommendation matching accuracies of 77.2% in the fiber materials domain, 81.5% in the weaving technology domain, and 78.3% in the fashion design domain, confirming the effectiveness of collaborative optimization between resource recommendation and behavior prediction. Furthermore, the proposed framework provides a data-driven paradigm for multimodal cognitive state perception and intelligent information processing, offering potential methodological support for adaptive signal interpretation and intelligent sensing applications in advanced engineering systems.

INDEX TERMS transformer, emotion recognition, learning behavior prediction, multimodal information processing, intelligent sensing

I. INTRODUCTION

THE globalization of the textile industry places higher demands on the English proficiency of its employees. Textile English, as a professional communication tool, encompasses terminology related to specific fields such as fiber materials and weaving processes, and its learning efficiency directly impacts international business expansion [1-3]. Traditional teaching resource delivery models lack personalized adaptation, failing to meet the diverse needs of learners and resulting in low knowledge absorption rates [4-6]. Intelligent teaching systems, through real-time data analysis to optimize learning paths, can effectively improve the quality of professional talent training and provide core support for textile enterprises [7,8]. This research, combining artificial intelligence with language education, promotes the evolution of textile English teaching towards precision and dynamism, possessing significant industry application value. Existing systems face significant challenges in textile English learning scenarios. Learners' emotional states, such as frustration or interest, when faced with dense professional terminology lack effective means of quantification, and cognitive overload is common [9,10]. Behavioral data, including interaction duration and error patterns, is not deeply analyzed, and resource recommendation mechanisms cannot dynamically respond to changes in individual needs [11,12]. General recommendation algorithms are not adaptable to textile professional contexts, and sentiment recognition technologies focus on surface text analysis while ignoring industry characteristics [13]. Temporal behavior prediction models fail to integrate sentiment variables, resulting in a disconnect between resource matching and learners' actual states, which affects the improvement of teaching effectiveness [14]. Researchers have used collaborative filtering algorithms to optimize resource recommendations, but this method relies on user rating data and has limited accuracy in matching resources to new learners. LSTM (Long Short-Term Memory)-based behavioral prediction models capture temporal dependencies but struggle to handle the coupling between emotional factors and specialized terminology [15,16]. In the field of emotion recognition, BERT (Bidirectional Encoder Representations from Transformers) fine-tuning models are used to classify learner emotions, but these have not been domain-adapted to textile English corpora [17,18]. These methods handle emotional or behavioral dimensions independently, failing to establish a joint modeling mechanism between emotional states and learning trajectories, resulting in a lack of real-time dynamic adjustment capabilities in the recommendation system. Existing work has not yet solved the problem of deep integration between real-time capture of emotional variables and behavioral prediction. To address the issue of insufficient accuracy in resource recommendation caused by the lack of real-time capture of emotional states and learning behavior predictions, this paper constructs a variant Transformer model based on a multi-head emotional attention mechanism. After learner interactive text input is encoded, a multi-head self-attention layer generates contextual semantic embeddings. In the decoder stage, the attention distribution is dynamically adjusted using an emotional polarity weight matrix to focus on the emotional features of textile terms, generating an emotional enhancement vector. This vector, along with behavioral sequence data, is input into a lightweight GRU predictor, which uses temporal dependencies to infer future learning trajectories. Finally, combined with the semantic embeddings from a textile English resource database, the recommendation list generation is iteratively optimized using a differentiable ranking loss function, aiming to construct a collaborative modeling framework that integrates emotional and behavioral aspects.

II. ADAPTIVE RECOMMENDATION METHOD BASED ON SENTIMENT-BEHAVIOR COLLABORATIVE MODELING

Emotional Enhancement Attention Mechanisms for Textile English

The multi-head sentiment attention mechanism applies a sentiment polarity weight matrix in the Transformer decoder [19,20]. This matrix dynamically modulates the attention distribution through learnable parameters, enabling the model to focus on the sentiment features of textile English terminology. The sentiment polarity weight matrix is generated jointly by the text sentiment features and the semantic features of the professional domain, and its calculation process is expressed as [21]:

$$W_{\text{sent}} = \sigma(W_p \cdot [h_{\text{text}}; h_{\text{domain}}] + b_p) \tag{1}$$

W_{sent} represents the sentiment polarity weight matrix; σ is the sigmoid activation function; W_p is the learnable weight parameter matrix; b_p is the bias term; h_{text} is the text sentiment feature vector; h_{domain} is the semantic feature vector of the textile professional domain; [;] represents the vector concatenation operation. This weight matrix is used in the self-attention mechanism through element-wise multiplication with the regular attention weights to form the sentiment-modulated attention distribution. The sentiment enhancement representation vector is obtained by integrating the outputs of multi-head sentiment attention, and its calculation formula is [22,23]:

$$Z_{\text{sent}} = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h)W^O \tag{2}$$

Z_{sent} is the sentiment enhancement representation vector; $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K \odot W_{\text{sent}}, VW_i^V)$ represents the output of the i-th sentiment attention head; Q, K, and V are the query, key, and value matrices, respectively; W_i^Q, W_i^K, and W_i^V are the linear transformation weights corresponding to each head; $\odot$ represents element-wise multiplication; W^O is the output layer weight matrix; h is the number of attention heads. W_{sent} dynamically modulates the attention distribution of key vectors, enabling the model to capture emotional features when processing textile English terminology. The model optimizes the learnable parameters of the sentiment polarity weight matrix through backpropagation, enabling the attention distribution to dynamically respond to changes in sentiment features within the textile professional context, thus providing a sentiment-enhanced semantic representation for subsequent learning behavior prediction.

Temporal Prediction of Learning Behavior Based on GRU

The system architecture is shown in Figure 1. The core process includes that: semantic embeddings from learner interaction text are generated via a Transformer encoder; the attention distribution is dynamically adjusted using a sentiment polarity weight matrix to generate sentiment enhancement vectors; these vectors with standardized behavioral features are fused and input into a lightweight GRU predictor to infer future learning trajectories; the semantic embeddings finely tuned by BERT from the textile English resource database are combined with the optimization of the recommendation list, using a differentiable ranking loss function to achieve collaborative modeling of sentiment states and learning behaviors, thereby improving recommendation accuracy and dynamic adaptability.

The sentiment enhancement representation vector and the learning behavior sequence are fused temporally through a timestamp alignment mechanism to construct a multimodal input feature matrix [24-26]. The learning behavior sequence consists of temporal features, including interaction duration, click frequency, and error rate, which are standardized using Z-score normalization by subtracting the feature mean and dividing by the standard deviation calculated from the training set, forming a multi-dimensional vector where each element represents a specific behavioral metric; the actual behavioral trajectory value yi in the prediction loss function denotes this multi-dimensional vector containing future values of these behavioral features across the prediction horizon. The feature matrix is divided into fixed-length

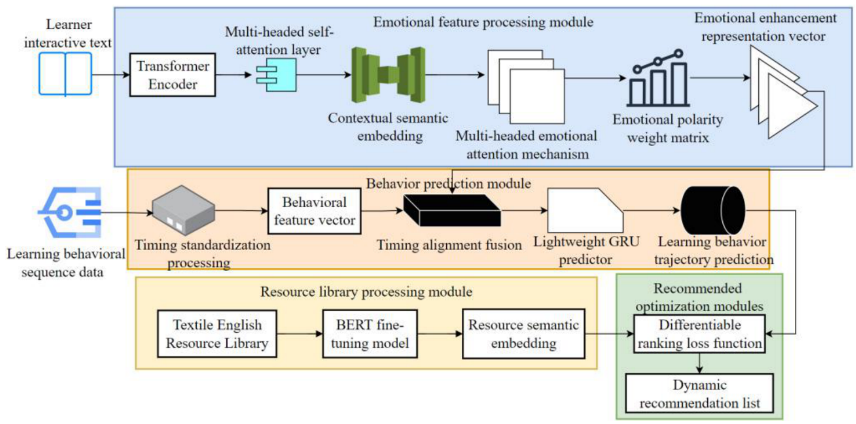

FIGURE 1. Architecture of the adaptive recommendation and behavior prediction system for textile English teaching resources based on multi-head sentiment attention mechanism

sliding windows in the time dimension to ensure temporal consistency between sentiment state and learning behavior prediction [27,28]. The GRU predictor adopts a single-layer structure design with a hidden layer dimension of 128, and controls the flow of information through update gates and reset gates [29,30]. The internal state calculation process of the GRU cell is described by the following formula:

$$\begin{aligned} r_t &= \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \\ z_t &= \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \\ \tilde{h}_t &= \tanh(W_{xh}x_t + r_t \odot (W_{hh}h_{t-1}) + b_h) \\ h_t &= (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \end{aligned} \tag{3}$$

x_t represents the input feature vector at time step t; h_t is the hidden state at time step t; r_t and z_t are the reset gate and update gate, respectively; $\tilde{h}_t$ represents the candidate hidden states. W_{xr}, W_{hr}, W_{xz}, W_{hz}, W_{xh}, and W_{hh} are the learnable weight matrices; b_r, b_z, and b_h are the bias terms; σ is the sigmoid activation function; $\odot$ represents the element-wise multiplication operation. The time series prediction loss is measured by the MSE (Mean Squared Error) function, defined as [31]:

$$L_{\text{seq}} = \frac{1}{N}\sum_{i=1}^{N} \|\hat{y}_i - y_i\|^2 \tag{4}$$

N is the predicted sequence length; y_i is the actual behavioral trajectory value; $\hat{y}_i$ is the predicted value. This loss function optimizes the GRU predictor parameters through backpropagation, enabling the model to capture the temporal dependencies in learning behavior prediction during the textile English learning process. The prediction results are directly input into the recommendation optimization module, providing dynamic behavioral trajectory data for resource recommendation.

Sentiment-Behavior Driven Adaptive Recommendation of Teaching Resources

A dimension harmonization process ensures consistent representation across all modalities prior to feature fusion. The sentiment enhancement representation vectors from the Transformer decoder undergo linear projection to 512 dimensions through a trainable weight matrix. Behavioral features, initially comprising 32 temporal metrics after Z-score normalization, are expanded to 512 dimensions using a fully connected layer with ReLU (Rectified Linear Unit) activation. The GRU predictor output, with a hidden dimension of 128, is projected to 512 dimensions via a linear transformation layer. This uniform 512-dimensional representation enables coherent semantic alignment between emotional states, behavioral trajectories, and resource embeddings. The semantic representation of the textile English teaching resource database is constructed using a pretrained BERT model, which generates resource feature vectors after fine-tuning with a textile professional corpus [32-34]. After the resource text is input into the BERT model, context-related representations are extracted through a multi-layer bidirectional Transformer encoder. The text content of each teaching resource in the resource database is processed by word segmentation and then input into the model, outputting a standardized 512-dimensional vector space representation. The similarity between the predicted learning behavior trajectory and the semantic embeddings of the textile English teaching resource database is calculated to form a candidate recommendation set. The recommendation system employs a differentiable ranking optimization mechanism, transforming the recommendation problem into a ranking learning task to ensure that the recommendation list matches the learner's real-time needs. The core of the recommendation process lies in designing a differentiable ranking loss function. This function dynamically adjusts the recommendation weights through gradient backpropagation, enabling the model to iteratively optimize the recommendation list. The ranking loss function is defined as:

$$L_{\text{rank}} = -\frac{1}{N'}\sum_{i=1}^{N'} \log \frac{\exp(\text{sim}(p_i, v_{r_i}^{+}))}{\exp(\text{sim}(p_i, v_{r_i}^{+})) + \sum_{j=1}^{K}\exp(\text{sim}(p_i, v_{r_i}^{(j)}))} \tag{5}$$

N' represents the training batch size; p_i is the predicted behavioral trajectory vector for the i-th learner; $v_{r_i}^{+}$ is the semantic embedding of the corresponding positive sample resource; $v_{r_i}^{-(j)}$ is the semantic embedding of the j-th negative sample resource corresponding to the i-th learner; $\mathrm{sim}(\cdot,\cdot)$ represents the cosine similarity function. This loss function continuously optimizes recommendation quality by minimizing the similarity difference between positive samples and the predicted results while maximizing the similarity difference between negative samples. A dynamic threshold control strategy is implemented during the recommendation process, adjusting the number of resources pushed based on the confidence level of the predicted learning behavior trajectory. The system calculates the similarity score between each resource in the candidate recommendation set and the predicted learning behavior trajectory; only resources with scores exceeding a preset dynamic threshold are included in the final recommendation list. The dynamic threshold is jointly determined by the confidence level of the behavior trajectory prediction result and the cognitive load parameter set by the system, ensuring that the number of resources pushed is appropriate for the learner's current learning status.

III. EXPERIMENTS AND RESULTS

Experimental Environment and Dataset Configuration

The experimental environment is configured on a workstation equipped with an Intel Xeon Gold 6248 processor and an NVIDIA Tesla V100 graphics processor, running Ubuntu 20.04. The deep learning framework used is PyTorch version 1.9.0. The textile English learning dataset is divided into training, validation, and test sets to ensure the reliability of model training and evaluation. To quantify model performance, recommendation matching accuracy is defined as the proportion of the intersection between recommended resources and the resources actually chosen by the learner, while behavior prediction error is measured by the mean squared error between the predicted trajectory and the actual trajectory.

Table 1 records the sample size and key parameters at each stage of dataset processing. The dataset contains 9,875 samples, with 512 feature dimensions, 6 sentiment label classes, and a behavior sequence length of

120. The training set contains 6,913 samples; the validation set contains 1,481 samples; the test set contains 1,481 samples. Each subset maintains the same feature dimensions, sentiment label classes, and behavior sequence length parameters to ensure consistency of experimental conditions and reproducibility of results. The dataset size of 9,875 samples represents a comprehensive collection of domain-specific interactions for textile English learning. The model architecture incorporates regularization techniques, including dropout layers with 0.3 probability, L2 weight decay with coefficient 0.01, and gradient clipping with threshold 1.0 to prevent overfitting. Domain-specific pretraining on a larger general English corpus followed by fine-tuning on the textile dataset leverages transfer learning to enhance model generalization. Cross-validation across multiple random splits confirms consistent performance metrics, indicating sufficient data representation for the model complexity. The specialized nature of textile English learning context reduces the required sample size compared to general language models due to the constrained professional vocabulary and structured learning patterns.

TABLE 1. Statistics of textile English learning dataset

Dataset types	Sample size	Feature dimension	Emotional tag categories	Behavior sequence length
Dataset	9,875	512	6	120
Training set	6,913	512	6	120
Validation set	1,481	512	6	120
Test set	1,481	512	6	120

Comparison of Recommendation Performance Across Different Professional Fields

To evaluate the impact of sentiment feature fusion on the accuracy of recommendations for textile English teaching resources, this study compares the proposed method with BERT4Rec, Self-Attentive Sequential Recommendation (SASRec), Deep Collaborative Filtering (CF), and a Transformer-based baseline method across five major professional fields: fiber materials, weaving technology, dyeing and printing technology, fashion design, and textile machinery. Fiber materials and weaving technology, as the core of basic textile English content, form the foundation of the knowledge system; dyeing and printing technology and fashion design exhibit significant sentiment features due to their extensive use of descriptive terminology; the textile machinery field is predominantly characterized by objective technical parameters. Figure 2(a) presents the comparative results of recommendation matching accuracy across professional fields, reflecting the alignment between teaching resources and learner needs; Figure 2(b) quantifies the accuracy improvement resulting from sentiment feature fusion, visually demonstrating the optimization value of the multi-head sentiment attention mechanism.

Figure 2 demonstrates that BERT4Rec achieves recommendation matching accuracy rates of 64.5%, 68.2%, 59.7%, 61.8%, and 63.9% in the fiber materials, weaving technology, dyeing and printing technology, fashion design, and textile machinery fields, respectively. SASRec attains accuracy rates of 65.8%, 69.5%, 60.9%, 63.2%, and 65.1%, while Deep CF reaches 66.4%, 70.1%, 61.5%, 64.1%, and 65.7%. The Transformer baseline method achieves 68.5%, 72.8%, 63.2%, 65.7%, and 67.9% accuracy. After applying the proposed multi-head sentiment attention mechanism, the accuracy rates improve to 77.2%, 81.5%, 74.1%, 78.3%, and 73.8%, representing improvements of 8.7% to 19.2%. The highest improvement occurs in the fashion design field at 19.2%, followed by the dyeing and printing technology field at 17.2%, consistent with the industry characteristics of these fields, which contain emotionally rich descriptive terminology. Fiber materials and weaving technology as foundational fields show improvements of 12.7% and

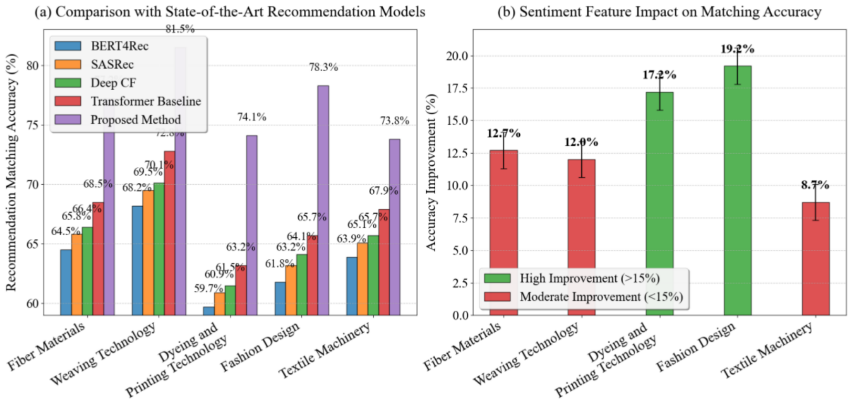

FIGURE 2. Comparison of matching accuracy and emotional feature fusion gains with the most advanced recommendation models in the field of textile expertise: (a) Comparison with state-of-the-art recommendation models; (b) Sentiment feature impact on matching accuracy

12.0%, respectively, reflecting the relatively secondary role of sentiment features in basic knowledge learning. The textile machinery field shows only an 8.7% improvement, confirming that the objectivity of technical terminology in this field diminishes sentiment feature contributions. This differential distribution indicates that the multi-head sentiment attention mechanism effectively identifies and utilizes sentiment features within professional contexts. The impact of sentiment feature fusion on recommendation accuracy depends on the sentiment richness of domain-specific terminology. The substantial gains in sentiment-intensive domains such as fashion design and dyeing and printing technology validate the optimization value of sentiment cognition modeling for textile English teaching resource recommendations.

Temporal Dynamics of Behavioral Prediction Errors Across Textile Domains

To systematically examine the dynamic evolution of prediction errors in textile English learning behavior across different professional fields, this study comprehensively compares the prediction performance of the proposed method with the Temporal Fusion Transformer (TFT) and Transformer-XL across multiple domains. Mean Squared Error (MSE), as a key parameter for evaluating prediction accuracy, objectively reflects the deviation between model output and actual behavioral trajectory, with its value directly determining prediction reliability. To measure the model's ability to infer short-term and medium-term behavioral trajectories, the experiment establishes prediction time steps of 1, 3, and 5 steps, corresponding to three typical learning scenarios: immediate feedback, short-term planning, and medium-term goals. By examining the evolution trend of prediction errors across different time spans, critical points for learning trajectory inference can be identified, providing empirical evidence for evaluating the model's capacity to capture long-term temporal dependencies. Figure 3 presents the spatial distribution characteristics of behavioral prediction errors in textile professional fields and their temporal evolution patterns. Figure 3(a) shows the model comparison analysis, while Figure 3(b) illustrates the temporal dependency characteristics.

Figure 3 demonstrates that the prediction results for textile English learning behavior show higher accuracy in sentiment-intensive domains (fashion design and dyeing and printing technology) compared to technically objective domains (textile machinery). The Mean Squared Error (MSE) values for fashion design and dyeing and printing technology are 0.059 and 0.068, respectively, which are 0.032 and 0.023 lower than those for textile machinery, confirming the enhancing effect of sentiment feature fusion on behavior modeling. In terms of temporal dimension, the MSE difference between 5-step and 1-step predictions ranges from 0.068 to 0.124. The difference in fashion design is 0.068, lower than the 0.124 observed in textile machinery, indicating stronger temporal stability in sentiment-rich domains. Stability boundary is defined as the prediction step where mean squared error exceeds 0.1; analysis reveals this boundary for sentiment-intensive domains occurs at 5-step prediction, while textile machinery reaches this threshold at 3-step prediction. This difference stems from the lack of sentiment buffering mechanisms for objective technical terms in textile machinery, leading to rapid error accumulation over time. In fashion design, the MSE difference between 3-step and 1-step predictions is 0.026, while in textile machinery, the corresponding difference is 0.044, demonstrating that sentiment features provide additional stability support for learning trajectory inference. The Temporal Fusion Transformer and Transformer-XL, as modern sequence modeling approaches, show improved performance over traditional methods across all domains, but the proposed method demonstrates superior prediction accuracy and temporal stability in sentiment-intensive domains, validating the effectiveness of joint sentiment-behavior modeling.

Influence of Emotional State on Recommendation Effectiveness

This paper selects several domains as analysis objects to explore the influence mechanism of emotional state on the accuracy of textile English teaching resource recom-

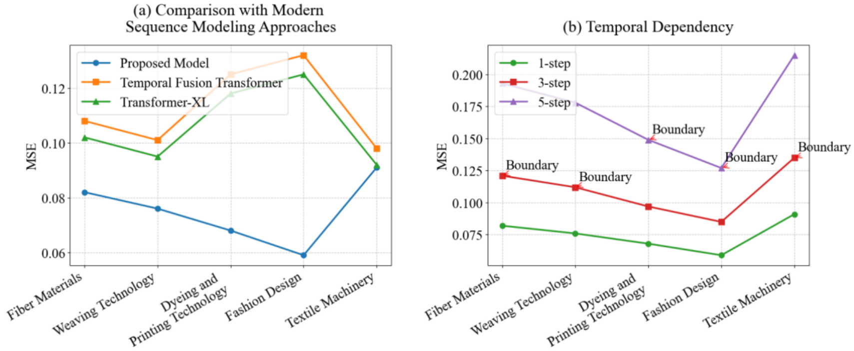

FIGURE 3. Time distribution characteristics and stability boundary analysis of prediction errors in textile English learning behavior: (a) Comparison with modern sequence modeling approaches; (b) Temporal dependency

mendations, and examines the correlation strength between three core emotional dimensions—frustration, interest, and anxiety—and recommendation effectiveness. Pearson correlation coefficients are calculated using cross-validation to quantify the correlation between emotional enhancement vectors and recommendation results. The paper focuses on comparing the differences in emotional-recommendation correlation between the activated and deactivated states of multihead emotional attention mechanisms, revealing the intrinsic mechanism of emotional variables in dynamically adjusting resource difficulty, as shown in Figure 4.

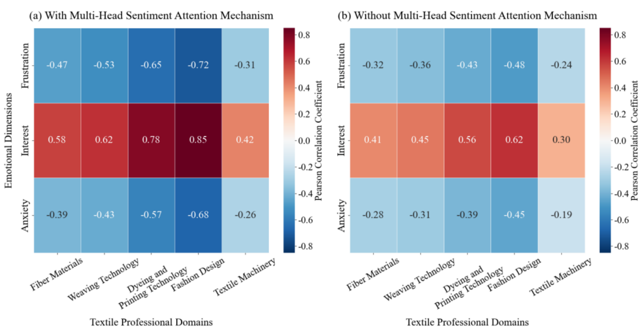

FIGURE 4. Comparison of sentiment-recommendation correlation under multi-head sentiment attention mechanism activation: (a) With multi-head sentiment attention mechanism; (b) Without multi-head sentiment attention mechanism

In Figure 4(a), the correlation coefficient between interest and recommendation results in the fashion design field reaches 0.85 under the activated mechanism state, while the correlation coefficient for frustration in the dyeing and printing technology field is -0.65, confirming the correlation between learners' emotional state and recommendation accuracy in emotion-intensive fields. Before and after mechanism activation {Figure 4(b)-Figure 4(a)}, the correlation coefficient of interest in the fashion design field increases from 0.62 to 0.85, and in the dyeing and printing technology field from 0.56 to 0.78, while in the textile machinery field it only increases from 0.30 to 0.42. This differentiated improvement stems from the fact that the fashion design and dyeing and printing technology fields contain a large number of descriptive emotional terms, and the multiheaded emotional attention mechanism can effectively capture and utilize these emotional features to optimize the recommendation strategy. The correlation coefficient of the fiber materials and weaving technology field increases moderately, reflecting that although the emotional features of basic fields are not as prominent as those of emotion-intensive fields, they still have an important impact on the recommendation effect. In Figures 4(a) and (b), the absolute value of the correlation coefficient of the textile machinery field is the lowest, verifying that the contribution of emotional features to the recommendation system is limited in technology-objective fields. The strong correlation between emotional state and recommendation results provides a theoretical basis for constructing an adaptive teaching resource recommendation system, and proves that the fusion of emotional features is an effective way to improve recommendation accuracy.

IV. CONCLUSION

This paper constructs a Transformer variant model based on a multi-head sentiment attention mechanism. After the learner's interactive text is encoded into contextual semantic embeddings by the encoder, the attention distribution is dynamically modulated using an sentiment polarity weight matrix in the decoder stage to generate an enhanced sentiment representation vector. This vector is then input into a lightweight GRU predictor along with the behavior sequence. The recommendation list is optimized using a differentiable ranking loss function, combined with resource repository semantic embeddings. Experiments show that the multi-head sentiment attention mechanism achieves a recommendation matching accuracy of 78.3% in the fashion design field. In terms of behavior prediction, the MSE in the fashion design field is 0.059, verifying the role of sentiment feature fusion in improving prediction accuracy. This method effectively solves the problem of not capturing learners' sentiment states and learning behavior predictions in real time in textile English teaching. It achieves dynamic synergy between resource recommendation and learning trajectory prediction, providing a precise and personalized intelligent support system for textile professional English teaching, and promoting the transformation of the international talent training model in the textile industry towards a data-driven approach and a deep integration of sentiment cognition and behavior prediction.

AUTHOR CONTRIBUTIONS

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

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] G. Shewangizaw, A. Hailu, and W. Haile, "A COMPARATIVE ANALYSIS OF LANGUAGE FEATURES ACROSS COMMUNICATIVE ENGLISH SKILLS AND GARMENT VOCATIONAL TEXTS," Celtic: A Journal of Culture, English Language Teaching, Literature and Linguistics, vol. 11, no. 2, pp. 353-376, 2024, doi: 10.22219/celtic.v11i2.35885.

[2] G. Sratdinova, "STRUCTURAL-SEMANTIC FEATURES OF LIGHT INDUSTRY AND TEXTILE TERMS IN ENGLISH," Mental Enlightenment Scientific-Methodological Journal, vol. 5, no. 08, pp. 335-341, 2024, doi: 10.37547/mesmj-V5-I8-44.

[3] S. Ashraf, K. Jahan, T. Abbas, A. Shahbaz, M. Zaidi, and N. Fatima, "ESP COURSE FOR FASHION DESIGNERS," Journal of Applied Linguistics and TESOL (JALT), vol. 8, no. 3, pp. 01-95, 2025, doi: 10.63878/jalt946.

[4] L. E. Sigalla and H. F. Kimario, "Customizing Classrooms: How Teachers Can Adapt Education to Fit Student Needs," European Journal of Contemporary Education and E-Learning, vol. 3, no. 3, pp. 38-59, 2025, doi: 10.59324/ejceel.2025.3(3).04.

[5] K. Rathnasekara, K. Yatigammana, and N. Suraweera, "Innovative pedagogical framework in K12 education: enhancing productivity and engagement of digital natives within resource-constrained environments," Quality Education for All, vol. 2, no. 1, pp. 413-438, 2025, doi: 10.1108/QEA-11-2024-0129.

[6] R. Mulenga and H. Shilongo, "Hybrid and blended learning models: Innovations, challenges, and future directions in education," Acta Pedagogia Asiana, vol. 4, no. 1, pp. 1-13, 2025, doi: 10.53623/apga.v4i1.495.

[7] S. Wang, J. Meng, Y. Xie, L. Jiang, H. Ding, and X. Shao, "Reference training system for intelligent manufacturing talent education: platform construction and curriculum development," Journal of Intelligent Manufacturing, vol. 34, no. 3, pp. 1125-1164, 2023, doi: 10.1007/s10845-021-01838-4.

[8] A. Adel, "The convergence of intelligent tutoring, robotics, and IoT in smart education for the transition from industry 4.0 to 5.0," Smart Cities, vol. 7, no. 1, pp. 325-369, 2024, doi: 10.3390/smartcities7010014.

[9] T. D. Pham Thi and N. T. Duong, "Investigating learning burnout and academic performance among management students: a longitudinal study in English courses," BMC Psychology, vol. 12, no. 1, pp. 219-233, 2024, doi: 10.1186/s40359-024-01725-6.

[10] M. Nizamani, F. Ramzan, M. Fatima, and M. Asif, "Investigating How Frequent Interactions with AI Technologies Impact Cognitive and Emotional Processes," Bulletin of Business and Economics (BBE), vol. 13, no. 3, pp. 316-325, 2024.

[11] T. Ruan, Q. Liu, and Y. Chang, "Digital media recommendation system design based on user behavior analysis and emotional feature extraction," PLoS One, vol. 20, no. 5, Art. no. e0322768-e0322782, 2025, doi: 10.1371/journal.pone.0322768.

[12] L. Wang, J. Zhang, H. Yang, Z. Chen, J. Tang, and Z. Zhang, "User behavior simulation with large language modelbased agents," ACM Transactions on Information Systems, vol. 43, no. 2, pp. 1-37, 2025, doi: 10.1145/3708985.

[13] N. Ingle and W. J. Jasper, "A review of the evolution and concepts of deep learning and AI in the textile industry," Textile Research Journal, vol. 95, no. 13-14, pp. 1709-1737, 2025, doi: 10.1177/00405175241310632.

[14] Y. Zhang and J. Li, "Deep learning-based model for predicting student learning behavior: A pathway to early intervention and enhanced outcomes," Journal of Computational Methods in Sciences and Engineering, vol. 25, no. 3, pp. 2822-2835, 2025, doi: 10.1177/14727978251322332.

[15] F. Li, "A Multi-Component Deep Learning Framework for Psychological Profiling of College Students Using Behavioral and Sentiment Data," Informatica, vol. 49, no. 32, pp. 175-194, 2025, doi: 10.31449/inf.v49i32.8648.

[16] E. Kalita, H. El Aouifi, A. Kukkar, S. Hussain, T. Ali, and S. Gaftandzhieva, "LSTM-SHAP based academic performance prediction for disabled learners in virtual learning environments: a statistical analysis approach," Social Network Analysis and Mining, vol. 15, no. 1, pp. 1-23, 2025, doi: 10.1007/s13278-025-01484-1.

[17] A. Areshey and H. Mathkour, "Transfer learning for sentiment classification using bidirectional encoder representations from transformers (BERT) model," Sensors, vol. 23, no. 11, pp. 5232-5249, 2023, doi: 10.3390/s23115232.

[18] F. Mohammad, M. Khan, S. N. K. Marwat, N. Jan, N. Gohar, M. Bilal, et al., "Text augmentation-based model for emotion recognition using transformers," Computers, Materials & Continua, vol. 76, no. 3, pp. 3523-3547, 2023, doi: 10.32604/cmc.2023.040202.

[19] C. Liu, Y. Wang, and J. Yang, "A transformer-encoder-based multimodal multi-attention fusion network for sentiment analysis," Applied Intelligence, vol. 54, no. 17-18, pp. 8415-8441, 2024, doi: 10.1007/s10489-024-05623-7.

[20] H. Luo, T. Shao, S. Li, and T. Kishi, "An innovative 3D attention mechanism for multi-label emotion classification: H," Luo et al. Scientific Reports, vol. 15, no. 1, pp. 35951-35963, 2025, doi: 10.1038/s41598-025-95804-2.

[21] F. Zhang, J. Chen, Q. Tang, and Y. Tian, "Evaluation of emotion classification schemes in social media text: an annotation-based approach," BMC Psychology, vol. 12, no. 1, pp. 503-521, 2024, doi: 10.1186/s40359-024-02008-w.

[22] R. Ullah, M. Asif, W. A. Shah, F. Anjam, I. Ullah, T. Khurshaid, et al., "Speech emotion recognition using convolution neural networks and multi-head convolutional transformer," Sensors, vol. 23, no. 13, pp. 6212-6231, 2023, doi: 10.3390/s23136212.

[23] F. H. Labib, M. Elagamy, and S. N. Saleh, "Emoberta-x: Advanced emotion classifier with multi-head attention and des for multilabel emotion classification," Big Data and Cognitive Computing, vol. 9, no. 2, pp. 48-70, 2025, doi: 10.3390/bdcc9020048.

[24] M. Hou, Z. Zhang, C. Liu, and G. Lu, "Semantic alignment network for multi-modal emotion recognition," IEEE Transactions on Circuits and Systems for Video Technology, vol. 33, no. 9, pp. 5318-5329, 2023, doi: 10.1109/TCSVT.2023.3247822.

[25] S. Yoon and B. Kim, "Multi-Scale Temporal Fusion Network for Real-Time Multimodal Emotion Recognition in IoT Environments," Sensors, pp. 25(16)5066-5091, 2025, doi: 10.3390/s25165066.

[26] H. Cheng, Z. Yang, X. Zhang, and Y. Yang, "Multimodal sentiment analysis based on attentional temporal convolutional network and multi-layer feature fusion," IEEE Transactions on Affective Computing, vol. 14, no. 4, pp. 3149-3163, 2023, doi: 10.1109/TAFFC.2023.3265653.

[27] Z. Wang, W. Wu, C. Zeng, and J. Shen, "Physioformer: Integrating multimodal physiological signals and symbolic regression for explainable affective state prediction," PloS One, vol. 20, no. 10, Art. no. e0335221-e0335258, 2025, doi: 10.1371/journal.pone.0335221.

[28] F. Harby, M. Alohali, A. Thaljaoui, and A. Talaat, "Exploring Sequential Feature Selection in Deep Bi-LSTM Models for Speech Emotion Recognition," Computers, Materials & Continua, vol. 78, no. 2, pp. 2689-2719, 2024, doi: 10.32604/cmc.2024.046623.

[29] Q. Hua, Z. Fan, W. Mu, J. Cui, R. Xing, H. Liu, et al., "A short-term power load forecasting method using CNN-GRU with an attention mechanism," Energies, vol. 18, no. 1, pp. 106-122, 2024, doi: 10.3390/en18010106.

[30] X. Zhou, Q. Wang, Y. Zhang, B. Li, and X. Zhao, "Short-Term Bus Passenger Flow Prediction Based on BiLSTM Neural Network," Journal of Transportation Engineering, Part A: Systems, vol. 151, no. 1, Art. no. 04024090, 2025, doi: 10.1061/JTEPBS.TEENG-8703.
[31] Y. Huang and R. Ren, "A GARCH model selection and estimation method based on neural network with the loss function of mean square error and model confidence set," Journal of Forecasting, vol. 43, no. 8, pp. 3177-3193, 2024, doi: 10.1002/for.3175.
[32] X. Zunlan and N. Xiaohong, "Dynamic bert-svm hybrid model for enhanced semantic similarity evaluation in english teaching texts," Journal of English Language Teaching and Applied Linguistics, vol. 7, no. 1, pp. 01-11, 2025, doi: 10.32996/jeltal.2025.7.1.1.
[33] X. Yuan, "Evaluation of rural tourism development level using BERT-enhanced deep learning model and BP algorithm," Scientific Reports, vol. 14, no. 1, pp. 25748-25761, 2024, doi: 10.1038/s41598-024-77444-0.
[34] K. Li, C. Qian, and X. Yang, "Evaluating the quality of student-generated content in learnersourcing: A large language model based approach," Education and Information Technologies, vol. 30, no. 2, pp. 2331-2360, 2025, doi: 10.1007/s10639-024-12851-4.