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RESEARCH ARTICLE

The Digital Reform of Japanese Classroom Teaching Modes Under the Graph Convolutional Neural Network

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ABSTRACT This work aims to explore reform methods for Japanese classroom teaching modes in an informationized environment. Addressing issues such as monotonous classroom content and low student engagement in traditional teaching, this work introduces deep learning technology and constructs a personalized recommendation model based on the Bidirectional Encoder Representations from Transformer (BERT) fused with the Graph Convolutional Neural Network (GCNN). Furthermore, this model is applied to Japanese flipped classroom teaching, and a personalized recommendation system-supported Japanese flipped classroom mode is designed. The performance of the constructed model is finally verified. The results show that the personalized recommendation model constructed here has achieved good application effects in Japanese teaching, with a recommendation recognition accuracy of 95.96% and an F1 value of 90.12%. The constructed model exceeds the precision of the baseline algorithm Convolutional Neural Network (CNN) by over 4%. Through questionnaire surveys and empirical analysis of controlled experimental designs, it is found that the Japanese flipped classroom mode supported by the personalized recommendation system demonstrates significant advantages in enhancing student learning abilities and satisfaction. The improvement rates of experimental group students in various indicators all exceed 18%. Therefore, the Japanese teaching mode proposed can significantly improve the teaching effectiveness of Japanese classrooms and provide experimental references for educational mode reforms.

INDEX TERMS Teaching modes, deep learning, personalized recommendation, Japanese classroom, flipped classroom, graph convolutional neural network.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

With the rapid progress and popularization of information technology, the field of education is continuously transforming. Traditional language teaching models typically revolve around the teacher, where students primarily passively receive knowledge in the classroom, lacking interaction and practical opportunities [1], [2], [3], [4]. However, with the widespread application of digital technology, education is undergoing profound changes, and language teaching is no exception [5]. In an informationized environment, teachers and students can conveniently utilize various digital tools and resources for learning and teaching, making classroom instruction more diverse and flexible [6], [7], [8]. In the field of education, the rapid development of information technology provides new possibilities for distance education and mixed learning mode. Blended learning environment combines the advantages of face-to-face teaching and virtual teaching, aiming at providing learners with more flexible and personalized learning experience.

As a foreign language, Japanese learning emphasizes the cultivation of language practice and application abilities. However, traditional Japanese classroom teaching often faces certain issues such as monotonous content and low student engagement [9], [10]. Therefore, leveraging digital tools

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in an informationized environment to reform and innovate Japanese classroom teaching modes has become a focus of attention for scholars in the field.

B. RESEARCH OBJECTIVES

Building upon the aforementioned background and motivation, this work aims to conduct empirical research to gain a deeper understanding of the application of digital technology in Japanese language teaching. It seeks to analyze in depth the Japanese classroom teaching modes in an informationized environment, effectively exploring their potential to improve teaching effectiveness, promote student motivation, and enhance teaching quality. Therefore, this work discusses how to use deep learning technology to improve Japanese classroom teaching mode, especially in personalized learning path and resource recommendation. The work intends to explore the impact of digital reform on enhancing teaching effectiveness and quality, thereby providing valuable insights and recommendations for Japanese language teaching practices and educational technology research.

II. LITERATURE REVIEW

In an informationized environment, language teaching modes are evolving from traditional teacher-centered approaches focused on knowledge delivery towards more interactive, multimedia, and personalized directions, such as video, audio, and interactive games. Many scholars have conducted relevant research. Shahid et al. [11] analyzed students' and teachers' views and practices regarding autonomous learning through questionnaire surveys and interviews. Maharani et al. [12] studied the importance of sound structure in language learning and teaching, providing theoretical foundations and practical guidance for the application of phonetics in language education. Mehdizadeh et al. [13] analyzed teachers' learning and growth experiences in community practices, revealing pathways and mechanisms to promote teachers' professional development in an informationized environment. Vermunt et al. [14] discussed teachers' teaching patterns and influencing factors in classroom research, providing theoretical support and practical guidance for improving classroom teaching quality. Gok et al. [15] analyzed the mechanism of online flipped classrooms on students' anxiety, providing empirical support and theoretical guidance for the reform of foreign language teaching modes in an informationized environment. Tourkmani et al. [16] discussed the diabetes education and nursing mode combining face-to-face and telemedicine, and its mixed education mode was also enlightening in Japanese teaching, showing the potential of mixed mode in improving education effect and patient management. Ab Mahadi et al. [17] systematically summarized the virtual teaching and learning of autistic students during the epidemic, and revealed the application effect of virtual teaching method in special education. These findings were also applicable to Japanese distance teaching, and emphasized the importance of personalized and adaptable teaching methods to improve the learning effect.

Significant progress has been made in the application of digital technology in language teaching. For example, Pratama et al. [18] discussed the application of artificial intelligence (AI) in personalized learning, realized the revolutionary change of education through AI technology, provided personalized learning paths and resource recommendations, significantly improved the learning effect and students' participation, and demonstrated the great potential of AI in the field of education. Rahiman and Kodikal [19] studied the application of AI in higher education, and emphasized how AI technology could empower the learning process. Through data-driven personalized learning and intelligent tutoring system, the teaching quality and students' learning experience were improved, and the modern transformation of education mode was promoted. Rintaningrum [20] discussed the integration of technology in English language teaching and learning, along with its benefits and challenges. Moreover, the application of technology in language teaching was analyzed and its impact on the teaching and learning process was discussed. Pikhart and Al-Obaydi [21] revealed the challenges and limitations of online foreign language teaching through investigation and analysis, providing directions for educators to ponder and address. Latha and Rao [22] proposed an enhanced convolutional neural network (CNN) product recommendation system for e-commerce platform. Through the optimized CNN algorithm, the accuracy of product recommendation and user satisfaction were significantly improved, and the application potential of deep learning in personalized recommendation was demonstrated. Hou [23] introduced a personalized music content recommendation system based on CNN, and used CNN to deeply analyze and learn music features, which improved the accuracy and user experience of the recommendation system and verified the effectiveness of CNN in music recommendation. Oraif [24] explored the relationship between natural language processing (NLP) and English as a foreign language (EFL) learning. Chen et al. [25] analyzed the impact of this system on learners through experimental research, particularly discussing it from the perspective of writing feedback. Bekou et al. [26] analyzed the potential application scenarios and limitations of ChatGPT technology in English teaching through questionnaire surveys and discussions, providing relevant reflections and suggestions for educators.

In summary, the content above reveals that previous studies cover various aspects of language teaching in an informationized environment, ranging from teachers and students' attitudes, and the promotion of linguistic sensitivity and expressive abilities, to the relationships between teacher learning modes and influencing factors in classroom research. However, these studies generally tend to focus excessively on describing phenomena and current situations, lacking in-depth theoretical analysis and exploratory research. Therefore, on the basis of previous studies, this work further discusses the application of personalized recommendation system in Japanese teaching. By employing a comprehensive research approach, this work fully explores the implications

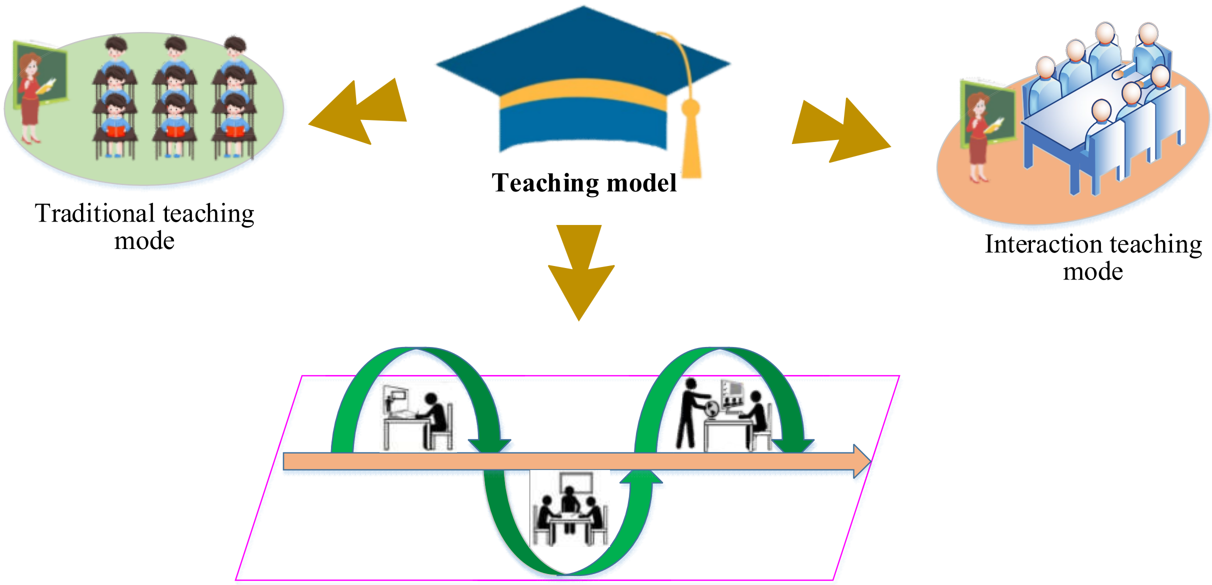

FIGURE 1. Diagram of common teaching modes.

and practical significance of empirical results, providing reliable theoretical and practical support for the reform and optimization of Japanese teaching modes.

III. RESEARCH METHODOLOGY

A. ANALYSIS OF TEACHING MODES IN JAPANESE CLASSROOMS

In current Japanese language teaching, there are various teaching modes, including traditional teaching mode, interactive teaching mode, and flipped classroom teaching mode. The traditional teaching mode typically revolves around the teacher, with the teacher primarily delivering content, and students passively receiving knowledge, resulting in a relatively monotonous learning approach [27]. Conversely, the interactive teaching mode emphasizes student participation and interaction, fostering active dialogue and discussion between teachers and students in the classroom, thereby promoting the development of students' thinking and language abilities [28], [29], [30]. Figure 1 illustrates common teaching modes.

Figure 1 illustrates the flipped classroom teaching mode, which has garnered significant attention in recent years among common teaching modes. In the flipped classroom, teachers prerecord teaching videos or prepare online materials, and students acquire knowledge through self-study before class, engaging in in-depth discussions and practical activities during class. The flipped classroom, with its advantages such as advocating personalized learning recommendations, improving classroom efficiency, enhancing learning depth, and cultivating independent learning abilities, has become an innovative teaching mode of great interest in education [31], [32], [33], [34], [35]. This work considers the special needs of distance education and mixed learning environment, and designs a teaching model that can adapt to these environments. This work also analyzes different teaching modes, including traditional, interactive and flip classroom, and consideres how to integrate personalized recommendation system into these modes to support distance education and mixed learning environment. Finally, taking Japanese classroom as the research object, the online personalized recommendation system is introduced to understand the effect of its application under the flip classroom mode.

B. ANALYSIS OF THE CONSTRUCTION OF A PERSONALIZED RECOMMENDATION SYSTEM FOR JAPANESE LANGUAGE TEACHING BASED ON DEEP LEARNING ALGORITHM

A personalized recommendation system can improve learning efficiency and effectiveness by providing personalized information based on students' learning interests, levels, and learning history. In order to achieve personalized recommendations of Japanese language teaching content, this system utilizes the Bidirectional Encoder Representations from Transformer (BERT) model for text feature recognition [36], [37], [38], and the Graph Convolutional Neural Network (GCNN) model for feature extraction from images or videos [39], [40], [41], [42]. Then, an attention mechanism is employed to fuse and analyze these features. Finally, a model comprising the BERT layer, graph convolutional network layer, attention layer, and classification layer is constructed. It is the personalized recommendation model for Japanese language teaching based on BERT fused with GCNN, as illustrated in Figure 2.

Figure 2 reveals that in this model, the data of Japanese language teaching content are first preprocessed. Then, feature extraction is performed using both the BERT layer and the graph convolutional layer. In the BERT layer,

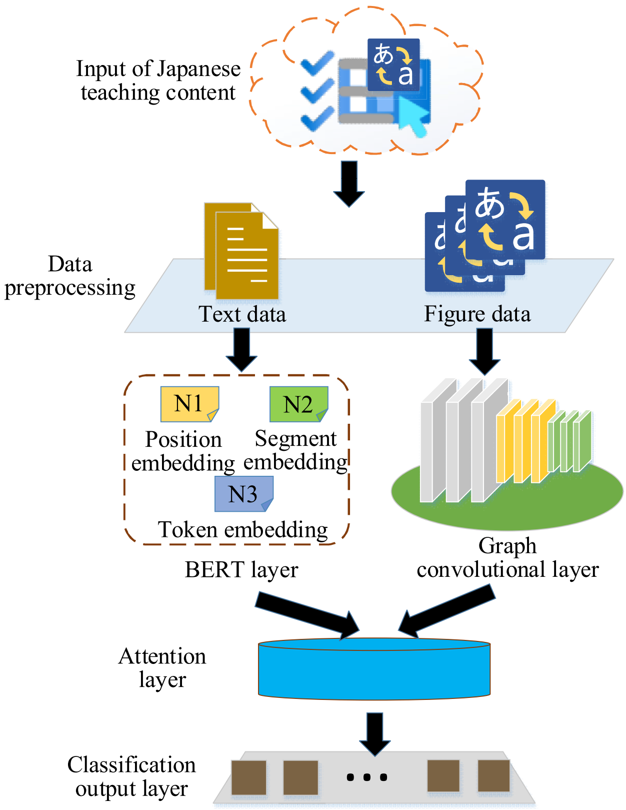

FIGURE 2. Conceptual framework of personalized recommendation model for japanese language teaching based on BERT fused with GCNN.

BERT transforms the input text into real-valued vector representations using a word vector matrix. Assuming that the input Japanese teaching text data sequence x corresponds to a one-hot vector representation $e^t \in R^{N\times|V|}$, its word vector E^t can be represented by Equation (1):

$$E^t = e^t W^t \tag{1}$$

$W^t \in R^{|V|\times e}$ refers to the training word vector matrix, $|V|$ indicates the size of the vocabulary, and e denotes the vector dimension.

Block vectors are typically used to indicate which partition block a word belongs to for encoding. The block vector E^b is represented by Equation (2):

$$E^b = e^b W^b \tag{2}$$

E^b indicates the conversion of block encoding to real-valued vectors through the block vector matrix W^b, $W^b \in R^{|B|\times e}$ represents the block vector matrix, and $|B|$ represents the number of blocks.

Position vectors are used to encode the absolute position of each word and can be represented as Equation (3):

$$E^p = e^p W^p \tag{3}$$

$W^p \in R^{N\times e}$ denotes the position vector and N denotes the maximum position length.

In order to enhance the representation power of BERT, the semantic understanding ability of Japanese teaching text data is trained through the masked language model task. The understanding ability between Japanese sentences is trained through the next sentence prediction task, thereby better supporting downstream tasks.

Furthermore, the graph convolutional layer is further analyzed. The image information in Japanese teaching is defined as $G = (V, E)$, with N vertices $v_i \in V$, edge set $e_{ij} \in (v_i, v_j) \in E$, and edge weight w_{ij} in the graph. First, vertex features $X = \{x_i\}_{i=1}^{N}$ for the vertices v in the graph are extracted, where g_i indicates the feature vector of the ith vertex v_i. Then, it is used as input to the GCNN, and g_i is defined as Equation (4) as follows:

$$g_i = concat\left(K_{AB}(v_i), K'_{AB}(v_i)\right) \tag{4}$$

The calculation for GCNN is as follows in Equation (5):

$$H^{(l+1)} = \sigma\left(\bar{D}^{-1/2}\bar{A}\bar{D}^{-1/2}H^{(l)}Q^{(l)}\right) \tag{5}$$

$H^{(l)}$ refers to the hidden layer in the l-th layer, $\bar{A} = I_N + A$ indicates the adjacency matrix of the main interactive graph, I_N denotes the identity matrix, and $\bar{D}_{ii} = \sum_j \bar{A}_{ij}$ represents the degree matrix containing the coefficients of each vertex in the interactive graph. $Q^{(l)}$ represents the parameter matrix learned by the network, and σ denotes the activation function, which adopts the ReLU activation. Finally, it is essential to pool the vector representations of all vertices in the terminal hidden layer into a single vector, it is denoted as K_{AB}. The vector K_{AB} is then fed into a multi-layer perceptron to calculate the final matching score.

In the graph attention layer, a multi-head attention graph network is utilized to enhance the robustness of the model. Concatenating the outputs of multiple heads can be represented as Equation (6):

$$h'_v(T) = \mathop{||}_{t=1}^{T} \sigma\left(\sum_{u\in N_v} \alpha^t_{vu} w^t h_u\right) \tag{6}$$

T denotes the number of attention heads, and N_v is the first-order neighborhoods of vertex v. N_v indicates the normalized correlation coefficients between vertex v in the t-th head and its neighbors. "||" represents the vector concatenation operation. Furthermore, averaging the results of multiple heads can be represented as Equation (7).

$$\overline{h'_v}(T) = \sigma\left(\frac{1}{T}\sum_{t=1}^{T}\sum_{u\in N_v} \alpha^t_{vu} w^t h_u\right) \tag{7}$$

The graph attention mechanism layer is adopted to process the local matching feature vectors $K_{AB}v(i)$ and $\left(K'_{AB}v(i)\right)$, and the calculation for the new feature vector K_{AB} is represented as Equation (8):

$$K_{AB} = GAT\left(K_{AB}v(i)\right)||GAT\left(K'_{AB}v(i)\right) \tag{8}$$

Finally, the prediction layer predicts the final score for personalized recommendations of Japanese teaching content

```
Start
Input: Japanese teaching content data
Output: Personalized recommendation results for Japanese teaching content
class GCNLayer(nn.Module):
  def __init__(self, input_dim, output_dim):
  def forward(self, x, A):
class BERTGCNModel(nn.Module):
  def __init__(self, num_classes, bert_model_name, input_dim, hidden_dim, num_heads):
    super(BERTGCNModel, self).__init__()
    self.bert = BertModel.from_pretrained(bert_model_name)
    self.gcn = GCNLayer(input_dim, hidden_dim)
    self.attention = nn.MultiheadAttention(hidden_dim, num_heads)
    self.output_layer = nn.Linear(hidden_dim, num_classes)
  def forward(self, input_ids, attention_mask, adjacency_matrix):
    bert_output = self.bert(input_ids=input_ids, attention_mask=attention_mask)[0]  # Get BERT output
    gcn_output = self.gcn(bert_output, adjacency_matrix)  # Pass BERT output through GCN layer
    gcn_output = gcn_output.transpose(0, 1)  # Transpose for multihead attention
    attention_output, _ = self.attention(gcn_output, gcn_output, gcn_output)  # Multihead attention
    attention_output = torch.mean(attention_output, dim=1)  # Average multihead attention output
    logits = self.output_layer(attention_output)  # Final classification layer
    return logits
End
```

FIGURE 3. Pseudocode flowchart of the application of BERT fused with GCNN in the personalized recommendation model for Japanese language teaching.

based on the aggregated vector. The vector OUT, which is ultimately fed into the classifier, can be represented as Equation (9):

$$OUT = [gfeat||K_{AB}] \tag{9}$$

The personalized recommendation system can better meet students' individual learning needs, enhance learning efficiency and effectiveness, and promote innovation and development in Japanese language teaching. Figure 3 illustrates the pseudocode of this personalized recommendation model for Japanese language teaching.

C. ANALYSIS OF THE APPLICATION OF FLIPPED CLASSROOM SUPPORTED BY PERSONALIZED RECOMMENDATION SYSTEM IN JAPANESE LANGUAGE TEACHING

With the advancement of educational technology and the rise of personalized education concepts, the flipped classroom has overturned traditional teaching modes. It utilizes classroom time for in-depth discussions and practical activities, while dedicating pre-class time to self-learning and previewing. Personalized recommendation system is based on deep learning technology to analyze and extract multimedia features in teaching materials, such as images and video content. Through the attention mechanism, the system can integrate features from different sources and generate comprehensive student portraits and resource recommendations, thus providing customized learning resources and paths for Japanese classroom teaching. The introduction of personalized recommendation systems further enhances the effectiveness and practicality of the flipped classroom in Japanese language teaching, as shown in Figure 4.

Figure 4 illustrates how the personalized recommendation system can provide customized Japanese learning content and learning paths for each student based on their individual learning interests, levels, and history. In the flipped classroom, students can access personalized learning materials and video tutorials tailored to their needs through the recommendation system before class, enabling them to prepare for classroom discussions and practical activities more effectively and efficiently. Through the personalized recommendation system, teachers can track each student's pre-class preparation. It allows them to adjust classroom content and teaching methods according to individual student's learning progress and needs, thereby enhancing the effectiveness and targeting of teaching.

Moreover, in the flipped classroom, students can engage in cooperative learning and discussions based on the learning materials and tasks provided by the personalized recommendation system. This collaborative approach enables students to work together to solve problems and complete tasks, thereby facilitating communication and collaboration among students and enhancing learning outcomes and teamwork skills.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

In order to evaluate the performance of the personalized recommendation model built based on BERT fused

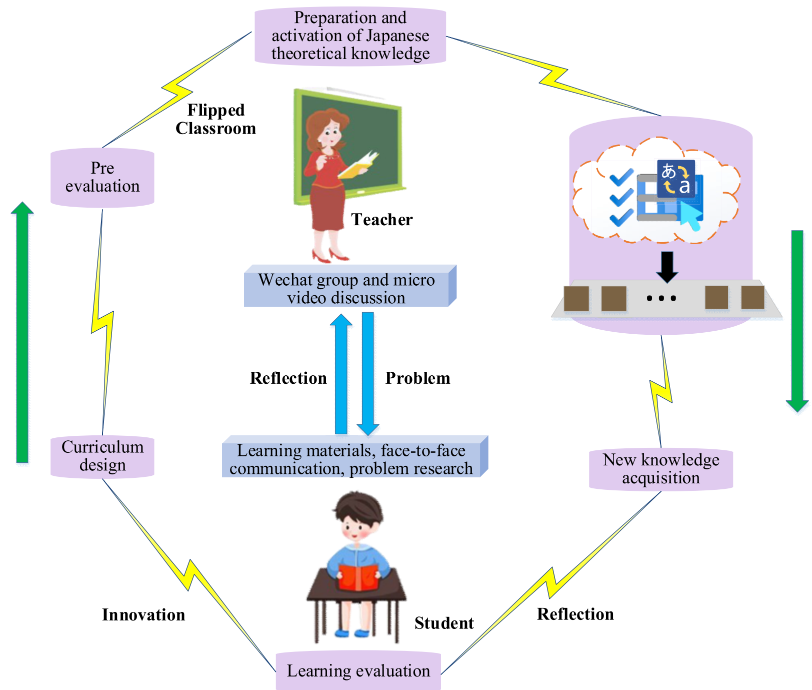

FIGURE 4. Schematic diagram of flipped classroom supported by personalized recommendation system in Japanese language teaching.

with GCNN for Japanese language teaching, data are sourced from https://huggingface.co/datasets/izumi-lab/llm-japanese-dataset. The Japanese-related texts in this dataset have been desensitized, cleaned, and tokenized to reduce noise and maintain lexical consistency. The dataset includes various types of text such as news articles, Wikipedia entries, and novels, ensuring that the model can learn diverse language features.

Furthermore, in order to validate the performance of the personalized recommendation system-supported Japanese flipped classroom mode, a controlled experimental design is adopted. Control and experimental groups are set up, and dimensions such as students' autonomous learning ability, learning satisfaction, participation, problem-solving ability, and classroom time utilization efficiency are investigated and analyzed for both groups. Japanese language teaching serves as an example. Among them, the quantification of student participation can be measured by the frequency of classroom interaction, the timeliness of homework submission and the activity of online discussion. The quantification of problem-solving ability can be evaluated by the strategies students adopt when facing complex problems, the speed and quality of completing tasks. Table 1 presents the specific experimental design.

TABLE 1. Design for teaching experiment.

	Control Group	Experimental Group
Teaching Experiment Subjects	50 students in Japanese Department of S University, B University and K University	50 students in Japanese Department of S University, B University and K University
Teaching Implementation Environment	School classrooms in S University, B University and K University	School classrooms in S University, B University and K University
Teaching Experiment Arrangement	Traditional teaching mode	Japanese flipped classroom teaching mode supported by personalized recommendation system
Teaching Experiment Variables	Control Variable: Whether the control group and experimental group adopt a Japanese flipped classroom supported by the personalized recommendation system	

Note: 50 students from Japanese Department of S University, B University and K University in the control group and the experimental group are allocated by random experiment, and S University, B University and K University belonged to famous universities in different cities to ensure the representativeness of the samples. In addition, a double-blind design is adopted to ensure that neither experimenters nor participants know who belongs to which group, thus reducing prejudice. Meanwhile, the variables in the experiment should be clearly controlled, and other conditions such as teachers and teaching time should be consistent except the teaching mode.

B. EXPERIMENTAL ENVIRONMENT

This experiment is built using the TensorFlow framework software and implemented using the Python language for data preprocessing and algorithm details. The software and hardware involved are as follows: Windows 10 64-bit operating system, TensorFlow 2.3.0, Python 3.7, Nvidia 2080 Ti GPU, and 16GB of memory.

C. PARAMETERS SETTING

In the personalized recommendation model, the number of iterations is set to 100. The optimizer is Adma, which combines the advantages of AdaGrad and RMSProp to adjust the learning rate adaptively. The stochastic gradient descent algorithm [43] is adopted to optimize the loss function. The initial learning rate is set to 0.001. The discarding rate in the graph attention mechanism is also fixed at 0.2, and a certain proportion of network connections is randomly discarded in the training process to prevent the model from over-fitting. In BERT network, the size of word vector matrix is V×d, where V is the size of word list, and the value is 5. D is the word vector dimension, with a value of 4. The size of the block vector matrix is S×d, where s is the number of blocks and the value is 2. The size of the position vector matrix is N×d, where N is the maximum position length and the value is 5.

D. PERFORMANCE EVALUATION

1) PERFORMANCE EVALUATION AND ANALYSIS OF THE PERSONALIZED RECOMMENDATION SYSTEM

The performance of the model proposed is evaluated by comparing it with GCN [44], CNN [45], AlexNet [46], and a collaborative filtering recommendation algorithm designed by Yang et al. [47] on two indicators: Accuracy and F1 score. Accuracy and F1 score are shown in equations (10) and (11):

$$Acc = \frac{TP + TN}{TP + FP + TN + FN} \tag{10}$$

$$F1 = \frac{2\,\mathrm{Pr}\,ecision \cdot \mathrm{Recall}}{\mathrm{Pr}\,ecision + \mathrm{Recall}} \tag{11}$$

TP is the number of positive samples with positive prediction. *FP* is the number of negative samples predicted to be positive. *FN* is the number of positive samples predicted to be negative. *TN* is the number of negative samples predicted to be negative. Accuracy (ACC) is used to measure the overall classification accuracy, that is, the proportion of samples predicted correct. *Recall* stands for recall rate, which is used to measure the coverage rate of positive samples, that is, the proportion of correctly classified positive samples to the total number of positive samples. *Precision* means the ratio of the examples classified as positive examples to the actual positive examples. *F1* value is the weighted harmonic average of precision and recall.

The comparison results of Accuracy and F1 values of each algorithm are shown in Figure 5 and Figure 6.

Figures 5 and 6 demonstrate that the recommendation recognition accuracy of the model algorithm proposed reaches 95.96%, with an F1 score of 90.12%. Compared to other model algorithms (GCN, CNN, AlexNet, and the model proposed by Yang et al. (2023)), the accuracy has been improved by at least around 4%. Furthermore, the recommendation accuracy of each algorithm, from highest to lowest, is as follows: the model algorithm constructed > the algorithm proposed by Yang et al. > GCN > AlexNet > CNN. Therefore, the personalized recommendation model constructed exhibits superior quality, ensuring that the Japanese knowledge learned and understood by users is accurate, reliable, and valuable.

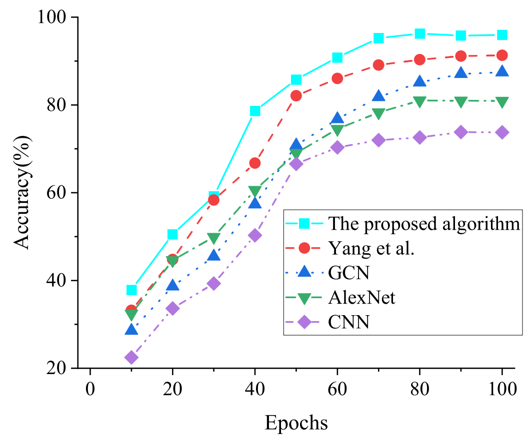

FIGURE 5. The accuracy results chart for recommendation recognition under different algorithms.

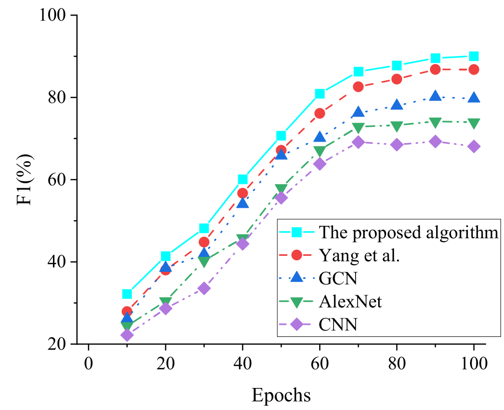

FIGURE 6. The F1 score results chart for recommendation recognition under different algorithms.

2) COMPARATIVE EXPERIMENT EVALUATION AND ANALYSIS

Further comparison of the results between the control group and the experimental group in this survey questionnaire is conducted using SPSS 26.0 software, as shown in Figures 7-9. P<0.05 indicates statistical differences.

Figures 7 and 8 demonstrate that the Cronbach's α values for each variable in this questionnaire are all greater than 0.800, the KMO values are all greater than 0.700, and the Sig. values are all 0.000, less than 0.050. This indicates that the survey questionnaire designed exhibits significant internal consistency and stability, possesses high reliability, and meets the specific standards of validity and reliability analysis.

Figure 9 illustrates that before the experiment, students in both the experimental and control groups show similar performance in terms of autonomous learning ability, learning satisfaction, participation, problem-solving ability, and classroom time utilization efficiency in Japanese classes, with no statistical differences. The proportion of agreement in each dimension between the experimental and control groups after the experiment is further analyzed. The results reveal that in the experimental group, the proportion of students who agree that the adoption of the Japanese flipped classroom model

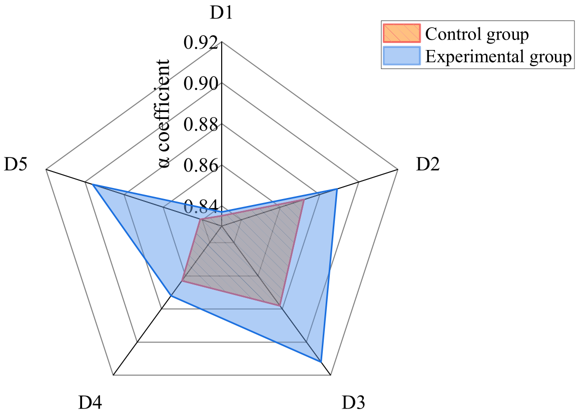

FIGURE 7. Chart for questionnaire survey reliability results (D1 represents the dimension of autonomous learning ability, D2 represents the dimension of learning satisfaction, D3 represents the dimension of participation, D4 represents the dimension of problem-solving ability, and D5 represents the dimension of classroom time utilization efficiency).

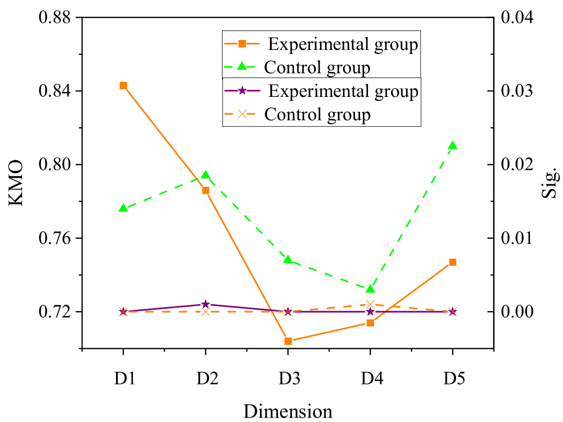

FIGURE 8. Chart for questionnaire survey validity results (D1-D5 have the same meanings as in Figure 7).

designed significantly improves their autonomous learning ability, learning satisfaction, participation, problem-solving ability, and classroom time utilization efficiency all exceeds 50%; however, the proportion of agreement in the control group is all below 50%, indicating significant statistical differences. Additionally, in terms of improvement in abilities, it is observed that the agreement rate of improvement in each dimension in the experimental group exceeds 18%, while in the control group, the improvement rate in each dimension is below 15%. Therefore, by applying the personalized recommendation system-supported Japanese flipped classroom model designed, students' abilities can be significantly enhanced. It provides strong guidance for the optimization and improvement of the Japanese classroom model.

E. DISCUSSION

Through the performance evaluation of the personalized recommendation model constructed, it is found that compared to other models (GCN, CNN, AlexNet, and the model proposed by Yang et al. (2023)), the recognition accuracy of the proposed model reaches 95.96%, with an F1 score of 90.12%. This represents an improvement in

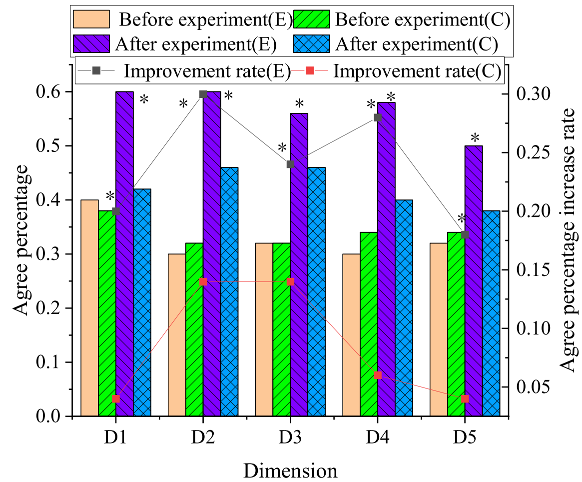

FIGURE 9. Comparison of the improvement rate of agreement in experimental and control groups before and after the experiment (D1-D5 have the same meanings as in Figure 7) (*P<0.05).

accuracy of at least around 4% compared to other model algorithms, indicating precise recommendation effectiveness. This finding is consistent with the views of Wang et al. and Liu et al. [48], [49].

Furthermore, through empirical analysis, it is found that in the controlled experiment, after applying the Japanese flipped classroom model supported by the personalized recommendation system designed to the Japanese classroom, the autonomous learning ability, learning satisfaction, participation, problem-solving ability, and classroom time utilization efficiency of the experimental group students are significantly improved. In contrast, the proportion of agreement in the control group is relatively low after the experiment, showing significant statistical differences. This finding aligns with the views of Ustun et al. [50].

Therefore, through in-depth analysis of how personalized recommendation system adapts to distance education and mixed learning environment, its positive influence on students' learning motivation and teaching effect can be found. By providing customized learning resources and paths, these systems can meet the individual needs of students, thus stimulating their interest and motivation in learning. As the experimental results show, the students in the experimental group have significantly improved their autonomous learning ability, learning satisfaction and participation, which shows that the personalized recommendation system can promote students' active learning and deep participation. In addition, personalized recommendation system can also improve the teaching effect. Teachers can better understand students' learning situation according to the data and feedback provided by the system to adjust teaching strategies and contents and realize more targeted teaching. This data-driven teaching method is helpful to improve the quality and efficiency of teaching.

However, the implementation of personalized recommendation system also faces some challenges and limitations. Firstly, the integration and implementation of technology requires time and resources, including teacher training, platform development and maintenance. Secondly, students' and teachers' acceptance of new technology and usage habits may affect the effectiveness of the system. In addition, data privacy and security issues are also important factors that must be considered, especially when dealing with students' personal information and study data. Therefore, through this work, not only the effect of Japanese teaching is improved, but also the reform of education mode is promoted.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

This study successfully constructs a personalized recommendation model based on BERT fused with GCNN and designs a Japanese flipped classroom model supported by the personalized recommendation system. Through validation analysis, it is found that the recommendation recognition accuracy exceeds 90%. Moreover, in empirical analysis, the improvement rates of the experimental group students in dimensions such as autonomous learning ability, learning satisfaction, participation, problem-solving ability, and classroom time utilization efficiency all exceed 18%. This model can provide innovative teaching methods for Japanese language instruction. Therefore, this work summarizes the potential and influence of personalized recommendation system in distance education and mixed learning environment. By using these technologies, the personalization and interactivity of Japanese classroom teaching can be significantly improved, which provides valuable insights for the future reform of educational model.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

However, this work has certain limitations. Firstly, due to the small sample size and the specificity of the experimental environment, the universality of the research results may be limited. In addition, the subjectivity of the evaluation method may affect the objectivity of the results, and the generalization ability of the model has not been verified in other languages or fields. In view of these limitations, in the follow-up study, people can further expand the sample size, including a wider group of students, and conduct experiments in different educational environments to enhance the adaptability and stability of the model. Meanwhile, more objective evaluation tools and techniques, such as behavior data analysis in learning management system, are adopted to improve the accuracy of evaluation. In the potential future research direction, people can further optimize the existing model, explore its application in different language teaching and other disciplines, and study how to integrate with existing educational technology tools and platforms. Future research will further explore the application of personalized recommendation system in wider distance education and mixed learning environment. It will study how to optimize these systems to meet the needs of different learners, and consider how to extend these technologies to other languages and disciplines. In addition, in-depth analysis of students' learning process, research on the influence of personalized recommendation system on students' long-term learning achievements, and consideration of ethical and privacy issues will be important areas for future research. Through these efforts, it is expected to promote the innovation of educational technology and provide learners with a more personalized and effective educational experience.

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