

Design of Intelligent Recommendation System for English Learning Path of Textile Materials Based on Graph Neural Network

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ABSTRACT With the rapid development of intelligent information transmission and semantic communication technologies, personalized knowledge delivery and adaptive learning have become increasingly important in engineering-oriented educational systems. However, most English learning platforms employ unified learning paths that fail to capture learners' individual characteristics, professional backgrounds, and knowledge dependencies, particularly in the specialized domain of textile material terminology. To address this issue, this paper proposes an intelligent recommendation system for textile material English learning paths based on Graph Neural Networks (GNNs). By incorporating the ASTM D123-21 textile terminology standard, a student-knowledge heterogeneous graph is constructed to jointly model learner attributes, professional knowledge, and multidimensional relationships. A Multilevel Graph Attention Aggregation (MGAA) mechanism is further developed to integrate domain semantics with dynamic learning behaviors, while a Heterogeneous Graph Convolutional Network (HGCN) combined with reinforcement learning enables adaptive path optimization according to learner feedback. Experimental results demonstrate that the proposed framework improves path recommendation accuracy, knowledge coherence, and professional adaptability to 96.81%, 0.88, and 0.93, respectively, and achieves a 14.4% improvement in learning efficiency compared with the Knowledge-aware Graph Attention Network (KGAT). The proposed method provides an effective solution for personalized professional education and offers valuable insights into knowledge-driven semantic information transmission, intelligent recommendation, and adaptive communication architectures for future engineering applications.

INDEX TERMS graph neural network, intelligent recommendation, heterogeneous graph, semantic communication, textile english learning

I. INTRODUCTION

DRIVEN by globalization and the construction of “new engineering”, the textile industry increasingly integrates traditional and modern technologies, raising higher demands for professional talent. English proficiency, especially the mastery of textile materials terminology, has become an important indicator of students' comprehensive quality, playing a critical role in understanding international textile technologies, trade, and technical exchanges [1-3]. However, mainstream English learning platforms adopt generalized models that perform poorly in textile terminology learning [4,5]. Traditional collaborative filtering methods achieve accuracy rates of only 65%–85%, while baseline GNN models reach about 85%–90% but still lack professional standards and dynamic behavior modeling. As a result, these methods fail to provide precise, scenario-oriented learning paths tailored to textile students' profes-

sional characteristics, leading to fragmented content and limited learning effectiveness. Given their strong relational modeling capability, GNNs show significant potential for addressing these challenges in educational technology.

Based on this background, this research plan designs a set of intelligent recommendation system for English learning path of textile materials professional terms based on graph neural network. The system will give full play to the technical advantages of GNN, deeply explore the complex relationship between textile materials professional terms, and combine the personalized characteristics of students to build an accurate and efficient learning path recommendation model. It is hoped that through this innovative research, it will break through the limitations of the traditional English learning model, provide textile materials students with more tailored English learning support that is more suitable for actual needs, and enhance their English application ability

and professional literacy, so that they can better adapt to the development of the industry.

II. RELATED WORK

Studies have shown that intelligent recommendation of English learning path is a key means to improve the learning efficiency of students in textile material terminology [6-8]. Existing research has significant limitations in addressing special needs, such as the precise analysis of textile terms such as "warp knitting", technical document translation standards, and international exhibition oral scenarios. Although Guo Jia et al. proposed a recommendation technology based on subject knowledge graphs [9], it did not cover the standard terminology system of the textile industry such as ASTM D123-21; Wang Fang's attention model [10] and Yang Qiujuan's neural network system [11] improved the recommendation accuracy, but it was difficult to handle the ability transition from College English Test Band 4 to Textile Professional English. Xia Yina's data-driven model [12] and Zhou Lina's collaborative filtering method [13] are limited by linear structures and are weak in dynamic scenarios such as textile foreign trade negotiations.

In recent years, GNN has been widely used in fields such as social networks and knowledge graph reasoning due to its excellent graph structure modeling capabilities [14-16]. Some scholars have applied it into educational recommendation systems to improve the accuracy and personalization of recommendations. Zhang Xiaoming proposed a knowledge graph high-order correlation modeling method based on graph convolutional networks [17], Wen Jue's text classification method [18], and Ma Wenjun's contrastive learning model [19], which improved semantic understanding, but did not integrate professional resources such as the Textile Onto textile ontology library. Although Wang Xinhua's hypergraph model [20] can model learner relationships, it still faces the dual bottlenecks of insufficient semantic embedding and lack of dynamic path optimization when dealing with professional knowledge points such as color fastness test standards. This results in low recommendation accuracy of traditional methods in complex tasks such as technical document translation, which is difficult to meet the practical needs of the textile field. This study constructs a student-knowledge point heterogeneous graph and innovatively integrates ASTM D123-21 standard terminology and textile foreign trade negotiation scenarios to break through the limitations of traditional GNN in professional semantic embedding and dynamic path optimization.

III. ENGLISH LEARNING PATH FOR TEXTILE AND MATERIALS PROFESSIONAL TERMS. DESIGN OF INTELLIGENT RECOMMENDATION SYSTEM

A. PROBLEM ANALYSIS AND REQUIREMENTS MODELING

In the process of learning textile English, students often face two major difficulties: one is the high discreteness and complexity of professional terminology, which is seriously

fragmented. Traditional linear teaching makes it difficult to establish effective semantic connections, which can easily lead to understanding gaps when translating professional literature or interpreting industry standards; the other is the high diversity of language application scenarios, which all have different requirements for language proficiency and are difficult to cover in full with traditional teaching content. To meet these challenges, the recommendation system needs to have three capabilities: in terms of personalization, it should combine students' majors and knowledge levels to achieve a smooth transition from general language to professional terminology; in terms of professional adaptability, it is necessary to build a map covering yarn processes, weaving methods, testing standards, etc. to enhance the professional relevance of recommended content; in terms of dynamic optimization, reinforcement learning strategies should be applied to update the recommended path in real time based on students' learning feedback to solve the rigid problem of the one-size-fits-all approach of traditional methods.

B. CONSTRUCTION OF STUDENT-KNOWLEDGE POINT HETEROGENEOUS GRAPH

In the teaching of professional English terms in textile materials, the traditional unified teaching path often struggles to accommodate the diverse professional backgrounds, language foundations, and cognitive levels of Textile material terminology. Therefore, it is important to construct a student-centered English knowledge heterogeneous graph [21-23]. This paper analyzes the professional terms of textile materials for students. By integrating actual teaching behavior data, this paper constructs a heterogeneous graph of student-knowledge points that accurately reflects students' knowledge mastery and ability structure, and integrates real enterprise business data to enhance scenario relevance. In this graph, student nodes represent individual students of textile majors, and knowledge point nodes cover professional English expressions, common grammar, core vocabulary, and other aspects. The nodes are connected through multi-dimensional relationships such as mastery and ability gap.

The heterogeneous graph data encompass students' learning behaviors in textile English courses, including fabric properties, ASTM D123-21 textile terminology standards, and other relevant topics. To measure students' mastery of a specific knowledge point, the edge weight $M(a,b)$ of the mastery relationship is defined, which represents the cognitive accuracy of student a on knowledge point b through their task completion on this point. The specific model is:

$$M(a,b) = \frac{G_{a,b}}{T_{a,b}} * (1 - e^{-\beta N_{a,b}}) \quad (1)$$

$G_{a,b}$ represents the number of exercises that students have completed correctly on knowledge point b ; $T_{a,b}$ is the total number of attempts; $N_{a,b}$ represents the number of times the knowledge point is learned; and β is the frequency

adjustment factor, which is used to improve the rationality of the edge weight evaluation of high-frequency learners.

To reflect the dynamic changes in students' knowledge mastery, a time-weight factor is applied to express the impact of knowledge memory decay on the learning state. Due to the characteristics of numerous English terms in the textile profession and heavy memory burden, the cognitive retention model with time decay mechanism is used to adjust the edge weight, and the expression is:

$$R_t(a, b) = M \left(a, b * e^{-\lambda(t_{now} - t_{last})} \right) \quad (2)$$

t_{now} is the current time; t_{last} is the time when the student recently learned the knowledge point; λ is the time decay coefficient, and the larger the coefficient, the faster the knowledge point is forgotten. In this study, a systematic method is used to optimize the β and γ parameters in formulas (1) and (2). Among them, the frequency adjustment factor β is determined to be 0.3 in the range of 0.1 to 0.5 through grid search. This value can balance the evaluation weight of high-frequency learners and prevent overfitting accidental high-frequency inefficient behaviors. The time attenuation coefficient γ uses Bayesian optimization to find the optimal value of 0.05 in the exponential attenuation function. This value fits the characteristics of the forgetting curve of textile English terms within two weeks, and the model performance is sensitive to γ . Improper value will affect the reflection of knowledge forgetting and the contribution of historical records. All parameter values, search ranges, and optimization procedures are explicitly described in this section and the subsequent experimental settings, ensuring that the entire experimental process is fully reproducible based solely on the information provided in this manuscript. The heat map of student-knowledge point mastery is shown in Figure 1.

As shown in Figure 1, the mastery of the six textile students on the five core English knowledge points is intuitively displayed through the depth of color. Student C performs well in all knowledge points, especially in professional English expression and core vocabulary, and has a solid foundation and strong learning ability. The heat map in Figure 1 is used to visually present the degree of mastery of each knowledge point by different students. The values of 0.8 and 0.35 in the figure are the real-time mastery scores adjusted by time attenuation, which is the content of equation (2). It synthesizes the accuracy rate of answers, the number of studies, and the attenuation of recent learning time, normalizes it to a score of 0 to 1, and quantifies the current state of students' mastery of knowledge points. Its core value lies in quickly revealing the pattern of mastery relationship between students and knowledge points through matrix visualization.

To study the gap between students' current abilities and target requirements, the ability gap function $G(a, b)$ is applied to measure the degree of deviation between their task performance and curriculum standards, thereby reflecting

the degree of fit between student a and knowledge point b . Its expression is:

$$G(a, b) = \delta_b - S(a, b) \quad (3)$$

δ_b represents the set mastery threshold of the knowledge point in the textile professional English course, and $S(a, b)$ represents the student's actual mastery score of the knowledge point. If $G(a, b) > 0$, it means that the textile college student has not yet achieved the expected mastery level. This edge in the heterogeneous graph is marked as a target weak edge and is strengthened first in the subsequent recommended paths.

C. MGAA MODEL

In the study of intelligent recommendation systems for English learning paths of textile material terminology, traditional GNNs have limitations in modeling multi-granularity heterogeneous relations and in integrating professional semantics with student behavior information [24-26]. In textile professional English learning scenarios, terminology exhibits complex hierarchical dependencies (e.g., between "yarn technology" and "weaving methods"), while traditional GNNs mainly capture shallow relationships, resulting in fragmented semantic representations and incoherent recommendations. In addition, textile students face a heavy terminology memory load, requiring long-term reinforcement, yet traditional methods lack feedback-driven dynamic adjustment mechanisms, leading to poor learning path continuity. These challenges are particularly evident in highly specialized learning contexts that require both local interaction modeling and global structure understanding. To address these issues, this paper proposes an MGAA model based on Graph Attention Networks (GAT) with a two-layer aggregation mechanism to enhance model expressiveness [27-29]. The first layer performs semantic aggregation of English knowledge points and textile terminology, while the second layer aggregates textile students' behavioral states by integrating individual learning trajectories and knowledge mastery.

In the knowledge point semantic layer, considering the large number of professional terms in textile professional English, they not only share semantic proximity but also exhibit a hierarchical relationship. Therefore, the term GAT mechanism is applied to connect professional terms with English knowledge points in the subgraph, and the information value of adjacent nodes is measured by GAT weight [30-32]. Supposing a node in the English knowledge point graph is represented by h_i , and its adjacent node is N_i , then the GAT weight is calculated as follows:

$$\alpha_{i,j} = \frac{\exp(\text{LeakyReLU}(\bar{x}[Wh_i || Wh_j]))}{\sum_{b \in N(i)} \exp(\text{LeakyReLU}(\bar{x}[Wh_i || Wh_j]))} \quad (4)$$

W is the linear transformation matrix; $\bar{x}$ is the learned attention vector; and $||$ represents the vector concatenation operation.

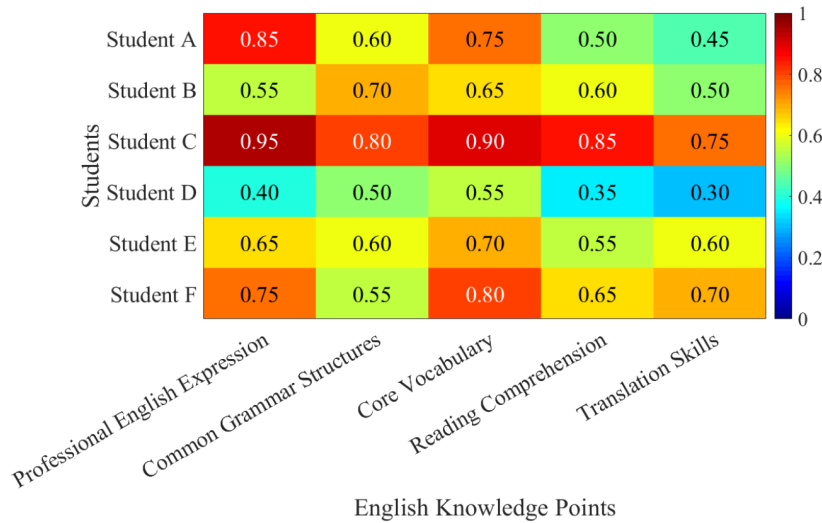


FIGURE 1. Heat map of student-knowledge mastery

In the second textile college student aggregation layer, the model focuses on integrating the students' behavioral data during the learning process with their knowledge point mastery status to construct cognitive representation at the current time. The student node is initialized as a multi-dimensional feature vector, covering static attributes and dynamic learning behaviors, and its embedding results in the knowledge point graph. For the student node a , its final representation is obtained by aggregating the knowledge point nodes connected to it. Considering the regulatory role of edge weight $r_{a,b}$ in attention allocation, the edge weight regulation attention mechanism is applied as follows:

$$\beta_{ab} = \frac{\exp(r(a,b) * \text{LeakyReLU}(\vec{y}[W_s h_a \| W_b h_b]))}{\sum_{b' \in N(a)} \exp(r(a,b') * \text{LeakyReLU}(\vec{y}[W_s h_a \| W_b h_{b'}]))} \quad (5)$$

W_s and W_b are the linear transformation matrices of students and knowledge points, and $\vec{y}$ is the attention vector parameter. In this way, the model can dynamically adjust the aggregation strength according to the students' mastery of different knowledge points, and strengthen the weight of their strong or weak knowledge points in the cognitive vector representation. The aggregation of English knowledge points and student features based on GAT is shown in Figure 2.

As shown in Figure 2, the GAT model is used to aggregate English knowledge points and student features, and the node color represents the feature value. Initially, the mastery of knowledge points K1, K2, and K3 is 0.4, 0.7, and 0.5, respectively, and the feature values of students S1 and S2 are 0.28 and 0.63. Through adjacent edges and attention weights, knowledge point information is transmitted to students to achieve feature aggregation.

To enhance the adaptability of the model to heterogeneous graph structures and help it deal with the heterogeneity problem in the semantic interaction between

college students' behaviors and knowledge points in textile professional English learning, this paper applies a gating mechanism (GM) in the MGAA structure to adjust the information transmission ratio between the knowledge point layer and the student layer. GM can dynamically adjust the degree of feature fusion between different semantic levels, ensuring the effective extraction of local semantics while retaining the characteristics of students' personalized cognitive paths.

The intermediate representation $h_b^{(i)}$ generated by knowledge point layer aggregation is not directly input into the student node $h_a^{(i)}$, but is reconciled through the gating function. A fusion gate function, g_{ab} , is designed to determine the information transmission intensity based on the joint features of the student node and the knowledge point node. The gating value is jointly determined by the node features and is defined as follows:

$$g_{ab} = \sigma \left(W_g \left[h_a^{(i)} \| h_b^{(i)} \right] + b_g \right) \quad (6)$$

σ is the Sigmoid activation function; $\|$ represents the feature concatenation operation. W_g and b_g are the learnable parameter matrix and bias term. The function output scalar $g_{ab} \in (0, 1)$ reflects the degree of students' acceptance of knowledge point information.

D. HGCN-BASED REINFORCEMENT LEARNING OPTIMIZER

In the intelligent recommendation of English learning path for textile material professional terms, traditional methods mostly rely on collaborative filtering and content recommendation, which are difficult to effectively deal with the heterogeneity and complex dependencies of professional knowledge, resulting in a lack of accuracy and coherence in the recommended paths, and unable to meet the individual needs of Textile material terminology. There are significant differences in individual students, and there are differences in the speed and needs of learners from

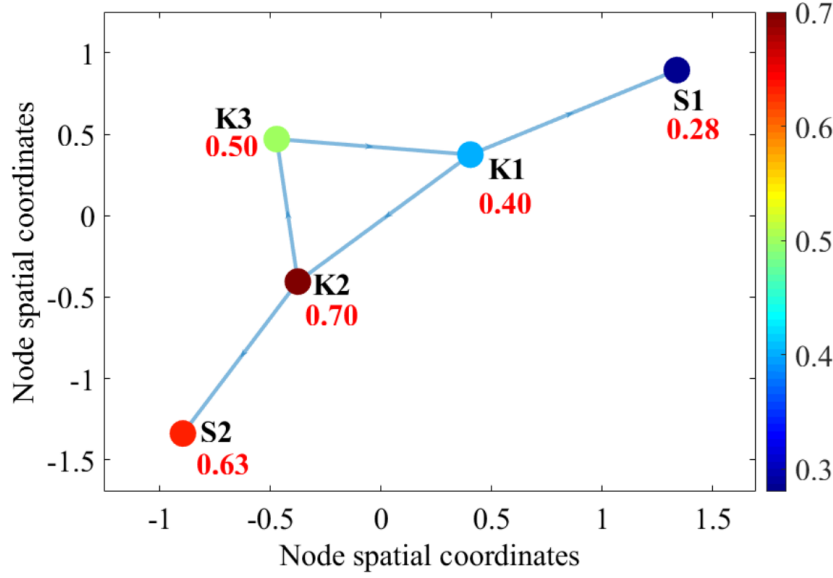


FIGURE 2. GAT-based aggregation of English knowledge points and student characteristics

different professional backgrounds to master terminology, but traditional methods do not integrate student behavior data and knowledge mastery status, and the recommended path lacks personalized adaptation. To this end, this paper studies a dynamic path optimization model based on a heterogeneous graph convolutional network (HGCN). By constructing a heterogeneous graph that integrates textile professional terminology, English knowledge points, and student behavior data, it deeply mines the semantic information in different node types and their complex relationships to achieve efficient transfer and fusion of knowledge. HGCN effectively solves the shortcomings of traditional methods in heterogeneity modeling, personalized recommendation, and long-term knowledge retention, thereby improving the accuracy and practicality of the recommendation path. The structure diagram of the dynamic path optimization model based on HGCN is shown in Figure 3.

Based on the constructed student-knowledge point heterogeneous graph, the model divides nodes and edges into multiple types. The heterogeneous graph convolutional network is used to achieve cross-type feature fusion through the message passing mechanism [33-35]. Assuming that the heterogeneous graph is $G = (V, E, \eta, R)$; V represents the set of all nodes; η is the set of node types; and R is the set of edge types. The node features are initialized to $X = \{x_v | v \in V\}$, and each node contains corresponding semantic and behavioral features. For edge type $r \in R$, the update formula of HGCN is:

$$h_v^{(l+1)} = \sigma \left(\sum_{r \in R} \sum_{a \in N_r(v)} \frac{1}{c_{v,r}} W_r^{(l)} h_a^{(l+1)} + W_0^{(l)} h_v^{(l)} \right) \quad (7)$$

$h_v^{(l)}$ represents the feature vector of the l -th layer node

v ; $N_r(v)$ represents the set of neighbor nodes connected to the node v through the relationship r ; $W_r^{(l)}$ is the weight matrix of the corresponding edge type; $W_0^{(l)}$ is the self-loop weight; $c_{v,r}$ is the normalization coefficient; σ is the nonlinear activation function.

In this study, MGAA and HGCN constructed a joint modeling framework with a hierarchical and clear division of labor. MGAA acts as the underlying feature extractor, focusing on the fusion of node-level semantics and behavioral information. The first layer aggregates knowledge points and professional semantic relationships, and the second layer aggregates students' personalized behavioral characteristics to output high-quality node embedding. These embedded input HGCN modules, which serve as the upper-level heterogeneous relational inference engine, use a multi-type messaging mechanism to mine cross-type complex interactions and generate a global representation of path recommendations. MGAA and HGCN are a synergistic relationship with cascading and complementary functions before and after, which jointly support the subsequent enhanced learning-driven path generation and dynamic adjustment.

Based on the point embedding vector, dynamic path generation uses path search combined with reinforcement learning to maximize the comprehensive reward function. The reward function consists of two parts: one is the professional demand satisfaction R_{pro} , which is used to measure the matching degree between the knowledge points in the path and the core skills and tasks of the textile major; the other is the knowledge coherence R_{coh} . R_{pro} is specifically defined as follows:

$$R_{pro}(P) = \frac{1}{|P|} \sum_{v \in P} 1(v \in V_p^{core}) \quad (8)$$

Path $P = \{v_1, v_2, \dots, v_n\}$ is the recommended sequence;

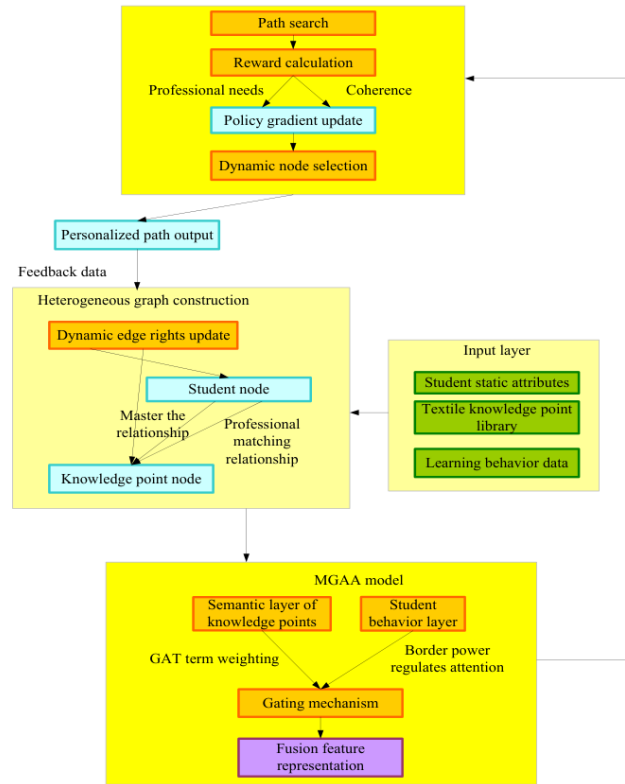


FIGURE 3. Structure diagram of the dynamic path optimization model based on HGCM

$V_p^{core} \subset V_p$ is the core terminology set of textile majors; and the indicator function $1(\cdot)$ marks whether the node belongs to the core set. Knowledge coherence is defined as:

$$R_{coh}(P) = \frac{1}{n-1} \sum_{i=1}^{n-1} 1((v_i, v_{i+1}) \in E_{pre}) \quad (9)$$

E_{pre} represents the set of pre-dependent edges of the knowledge point, and rewards whether the adjacent nodes in the path meet the prerequisite knowledge relationship to ensure the logical progression of the learning path. The overall reward function is the weighted sum of the two:

$$R(P) = \lambda R_{pro}(P) + (1 - \lambda) R_{coh}(P) \quad (10)$$

Parameter $\lambda \in [0, 1]$ controls the importance weight of professional requirements and coherence. For offline evaluation and stable policy learning, both components of the reward function were computed from fixed annotation protocols. Professional demand satisfaction was evaluated by mapping each recommended path to a predefined textile professional competency matrix derived from curriculum standards and industry task descriptions. Each knowledge point in the path was assigned a binary relevance label based on its alignment with mandatory professional terminology and task requirements, and the final score was obtained by normalizing the cumulative relevance over the path length. Knowledge coherence was computed deterministically using

the prerequisite dependency graph of textile English knowledge points, where a positive contribution was assigned only when the sequential order of the path strictly followed the predefined prerequisite relations. All prerequisite relations were extracted from standardized teaching outlines and domain expert-reviewed terminology dependency graphs, ensuring objectivity and consistency of the coherence evaluation. These definitions allowed the reward function to be fully computed offline without subjective intervention during reinforcement learning training.

The path generation process adopts a policy gradient-based reinforcement learning method. Assuming the policy function is $\pi_\theta(P|G, a)$, which represents the probability of generating path P under the conditions of heterogeneous graph G and student node a , and the parameter is θ . The goal is to maximize the expected reward:

$$J(\theta) = E_{P \sim \pi_\theta} [R(P)] \quad (11)$$

E. SYSTEM ARCHITECTURE AND INTERACTION DESIGN

This system adopts a front-end/back-end separation and microservice architecture, combining a contextualized interactive interface and an intelligent recommendation engine to build an immersive textile English learning environment. Through VR(Virtual Reality) virtual exhibitions, students can engage in English conversations with virtual buyers, with the system recognizing terminology accuracy in real

time and providing personalized feedback. The lab report module provides standardized templates to enhance professional English writing skills. Foreign trade simulation scenarios revolve around typical tasks such as product disputes, with multiple rounds of interaction to improve practical communication and language adaptability. The back-end is powered by a feedback-driven dynamic path optimization engine, which, based on behavioral data collection and reinforcement learning strategies, adjusts the learning path in real time and accurately pushes supplementary content to achieve continuous intervention and personalized learning.

IV. EXPERIMENTAL PROCESS AND RESULT ANALYSIS

A. EXPERIMENTAL PROCEDURES

This experiment is based on a multi-source heterogeneous dataset. The core data comes from the actual learning logs of 1,283 students from the Textile College of a university from 2019 to 2022, totaling 4,562,371 records, comprehensively reflecting their English learning behavior. The data is divided into three categories according to textile major characteristics: basic English learning trajectory, professional English interaction information, and feedback from practical application scenarios. The model comparison adopts a two-layer benchmark system: the base layer is a traditional recommendation method (such as collaborative filtering CF), and the higher layer is a graph neural network model (such as GCN, KGAT). To ensure fairness, all comparison models use the same feature input and optimization objective.

For MGAA and HGCN, all model hyperparameters and training configurations were fixed across experiments. The node embedding dimension was set to 128, and both MGAA and HGCN adopted a two-layer architecture to balance representation capacity and computational cost. The Adam optimizer was used with an initial learning rate of 0.001, and L2 regularization with a coefficient of $1e-4$ was applied to prevent overfitting. A dropout rate of 0.3 was employed on intermediate representations during training. The batch size was set to 256 student-knowledge subgraphs sampled from the heterogeneous graph, and negative sampling was conducted uniformly over unobserved student-knowledge interactions. All models were trained for a maximum of 200 epochs, and early stopping was triggered when the validation loss did not decrease for 15 consecutive epochs. These settings were consistently applied to MGAA, HGCN, and all GNN-based baselines to ensure comparability of experimental results.

This study systematically processed multi-source heterogeneous data during the data preprocessing and graph construction stages. The original data came from over 4.56 million learning behavior logs of 1,283 textile students, covering basic English, professional terminology learning, and practical scenario feedback. Preprocessing included removing invalid and duplicate data, text segmentation and vectorization, numerical standardization, and time series sliding window modeling. The quantitative integration of professional English interaction information was completed

in three steps: constructing a textile terminology knowledge subgraph based on the ASTM D123-21 standard; mapping students' terminology learning behaviors to edge weights and calculating mastery; and introducing a time decay factor to dynamically adjust edge weights to reflect knowledge retention. Practical feedback was mapped to corresponding nodes or edge weights, such as the number of virtual exhibition dialogues corresponding to the scenario ability node weights. The dataset was divided by time: 2019-2021 as the training set (70%), the first half of 2022 as the validation set (15%), and the second half of 2022 as the test set (15%), to simulate real-world application scenarios that predict future behavior based on historical data, ensuring the timeliness and generalization of the evaluation.

This study places strong emphasis on data privacy and research ethics, complying with China's Personal Information Protection Law, Data Security Law, and relevant educational data regulations. Student data are anonymized, sensitive attributes removed, and only non-sensitive behavioral features are used. Analyses are conducted at an aggregated level without individual identification, ensuring both regulatory compliance and the protection of student privacy.

The study did not involve any intervention beyond routine teaching activities. All data were derived from existing educational records generated during normal learning processes and were fully anonymized prior to analysis. The research used only non-identifiable learning behavior data and did not collect sensitive personal information. Data usage complied with relevant data protection regulations and institutional teaching management policies, and students were informed that their anonymized learning data might be used for educational research purposes. No individual-level identification or profiling was conducted at any stage of the study.

B. RESULTS ANALYSIS

To evaluate the effectiveness of MGAA in recommending personalized English learning paths for Textile material terminology, a comparative experiment is designed to compare and analyze the MGAA model with CF, GCN, GAT, HAN (Hierarchical Attention Network), and KGAT. The evaluation indicators include different dimensions such as accuracy, recall, knowledge coherence, NDCG (Normalized Discounted Cumulative Gain), etc. The specific research results are shown in Table 1.

The response time reported in Table 1 was measured under a unified experimental environment. All models were evaluated on a single NVIDIA RTX 3090 GPU with 24 GB VRAM and an Intel Xeon CPU operating at 3.0 GHz. The batch size was fixed to 256, and all measurements were conducted under a warm-start setting with model parameters fully loaded into memory and caching enabled. The reported values represent the average inference latency per recommendation request over 1,000 repeated runs, ensuring stable and comparable response time measurements across different models.

TABLE 1. Performance comparison of multiple models in textile English learning path recommendation

Model	Accuracy (%)	Recall (%)	Knowledge coherence (0-1)	Professional adaptability (0-1)	NDCG (0-1)	Response time (ms)
MGAA	96.81	95.63	0.88	0.93	0.91	156
CF	84.46	83.79	0.62	0.68	0.64	93
GNN	90.63	89.71	0.70	0.73	0.71	105
GCN	91.07	90.18	0.75	0.77	0.76	125
GAT	92.93	92.04	0.78	0.81	0.79	145
HAN	91.48	90.43	0.76	0.83	0.8	178
KGAT	93.87	92.88	0.77	0.85	0.82	195

As shown in Table 1, the MGAA model achieves the best overall performance, with 96.81% accuracy and 95.63% recall, significantly outperforming CF and other baselines. It also shows strong knowledge coherence (0.88) and professional adaptability (0.93), ensuring alignment with textile terminology systems and knowledge dependencies. The NDCG of 0.91 confirms high-quality ranking of recommendations. Although its response time is 156 ms, slightly higher than CF, it remains well within practical limits. Overall, MGAA effectively integrates student behavior, knowledge dependencies, and professional semantics, delivering accurate, coherent, and personalized learning path recommendations.

To evaluate the performance of each algorithm, the reward value and accuracy are selected as the core indicators. The reward value reflects the performance of the recommended path in terms of personalized fit and rationality of knowledge structure, and the accuracy measures the hit ratio of recommended knowledge points. By comparing HGCN with DGCF (Dynamic Graph Convolutional Filter), KGAT, NCF (Neural Collaborative Filtering), GNN, and GCN common recommendation models, the overall effect is presented in Figure 4.

As shown in Figure 4, HGCN achieves the highest and most stable reward value, indicating its ability to generate learning paths that balance individual needs and knowledge structure. While other models show improvement, their convergence levels remain lower. HGCN also demonstrates superior accuracy, increasing from about 0.64 to nearly 0.95, significantly outperforming the baselines, which confirms its robustness and effectiveness in dynamic and personalized recommendation.

To verify the performance of HGCN in personalized English learning path recommendation, a comparative experiment is constructed to compare it with models such as DGCF, KGAT, NCF, GNN, and GCN. The evaluation indicators cover multiple dimensions such as mean absolute error (MAE) and root mean square error (RMSE), personalization degree, and professional adaptation. The experimental results are detailed in Table 2. In Table 2, the best performance value under each evaluation index is highlighted in bold to indicate the optimal result among all compared models.

As shown in Table 2, HGCN outperforms all baseline models across key metrics. It achieves a click-through rate of

0.326, higher than NCF (0.241) and GCN (0.253), indicating stronger alignment with student interests, and an NDCG of 0.438, reflecting superior ranking quality. HGCN also attains the lowest prediction errors (MAE 0.213, RMSE 0.327). In terms of learning path quality, it reaches 0.89 professional adaptability and 0.91 knowledge coherence, demonstrating well-structured paths aligned with textile terminology systems. Additionally, HGCN shows strong long-tail knowledge coverage (0.64) and personalization (0.78). Although its average recommendation time is 1.32 s, slightly higher than NCF (1.18 s), it remains well within the acceptable 2–3 s threshold, ensuring real-time interaction and smooth learning experiences.

To study the actual effect of the personalized recommendation model for English learning paths in Textile material terminology based on HGCN in improving students' learning efficiency, this experiment selects HGCN as the core model and compared it with five commonly used recommendation systems: DGCF, KGAT, NCF, GNN, and GCN. The details are shown in Figure 5.

As shown in Figure 5, HGCN shows superior path recommendation performance in most experimental samples. Its improvement in college students' English learning efficiency is mostly distributed in the range of 30% to 45%, reflecting that HGCN has advantages in knowledge continuity, personalization, and professional knowledge coverage, and can more accurately meet the differentiated needs of students. The average learning efficiency improvement of HGCN is 35.3%, which is better than DGCF's 27.2%, KGAT's 20.9%, NCF's 23%, GNN's 22.2% and GCN's 25.6%. The core advantage of HGCN is that it applies a multi-layer graph attention mechanism, which gives flexible weight adjustment capabilities to different types of nodes and edge relationships, thereby effectively extracting students' learning behavior characteristics and knowledge mastery depth, and enhancing the model's adaptability and generalization capabilities.

In the context of textile foreign trade negotiations, this paper conducts an in-depth comparative analysis of the performance of six mainstream recommendation models, namely HGCN, DGCF, KGAT, NCF, GNN, and GCN, from five dimensions: personalization, professional relevance, knowledge coherence, response speed, and student satisfaction, as shown in Figure 6.

As shown in Figure 6, HGCN outperforms other algo-

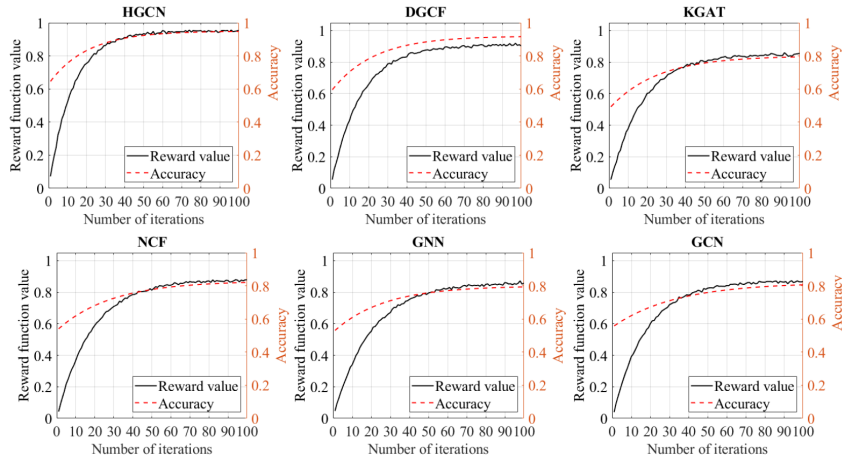


FIGURE 4. Comparison of reward value and accuracy of different models in the recommended learning path of English for textile material terminology

TABLE 2. Comparison of performance of different model algorithms in English learning path recommendation for textile terms

Evaluation index	HGCN	DGCF	KGAT	NCF	GNN	GCN
Click-through rate	0.326	0.295	0.287	0.241	0.265	0.253
NDCG	0.438	0.401	0.392	0.351	0.367	0.359
MAE	0.213	0.248	0.237	0.274	0.259	0.266
RMSE	0.327	0.361	0.354	0.398	0.374	0.386
Professional adaptability	0.89	0.81	0.83	0.75	0.78	0.76
Knowledge coherence	0.91	0.84	0.82	0.73	0.77	0.74
Long tail knowledge point coverage rate	0.64	0.56	0.59	0.42	0.47	0.45
Average recommended time (seconds)	1.32	1.25	1.43	1.18	1.36	1.29
Degree of personalization (recommended differences)	0.78	0.69	0.66	0.58	0.63	0.61

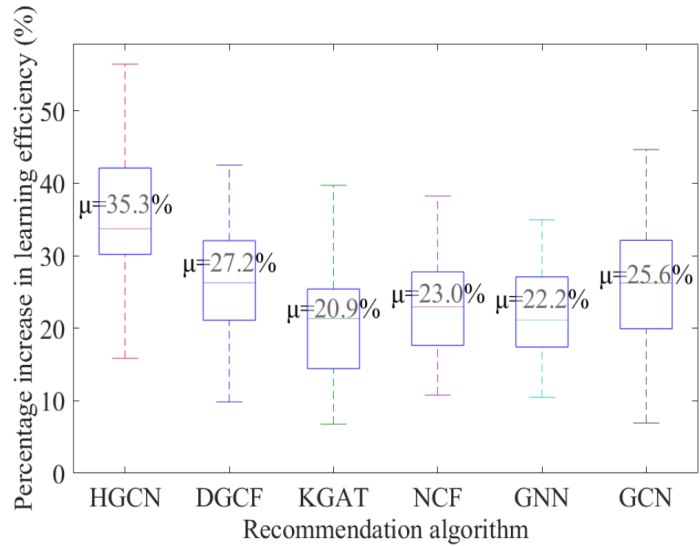


FIGURE 5. Comparison of different models to improve the efficiency of English learning of textile terms for students

gorithms across all metrics, demonstrating strong overall performance. It achieves 0.94 personalization, 0.95 professional relevance (well above KGAT at 0.67 and GNN at 0.71), 0.91 knowledge coherence, and 0.93 student satisfaction,

indicating highly customized, coherent, and well-recognized recommendations aligned with textile terminology systems. By integrating reinforcement learning, HGCN continuously optimizes learning paths via policy gradients, enhancing

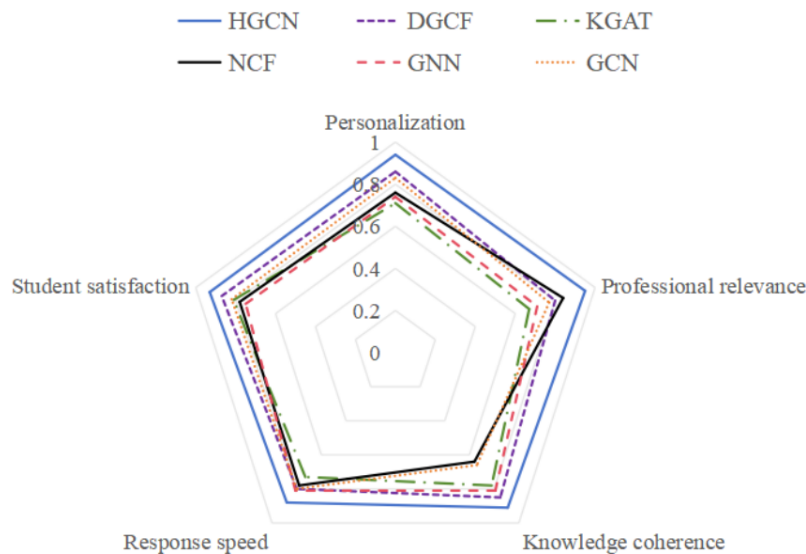


FIGURE 6. Multi-dimensional performance comparison of different models in the recommendation of English learning path for textile professional terms

adaptability and robustness in complex learning tasks.

To evaluate the generalization of HGCN across professional backgrounds, experiments were conducted in textile engineering, clothing design, textile materials, and international trade, comparing recommendation accuracy with other models. The results, shown in Figure 7, demonstrate HGCN's advantages in relational modeling and semantic representation.

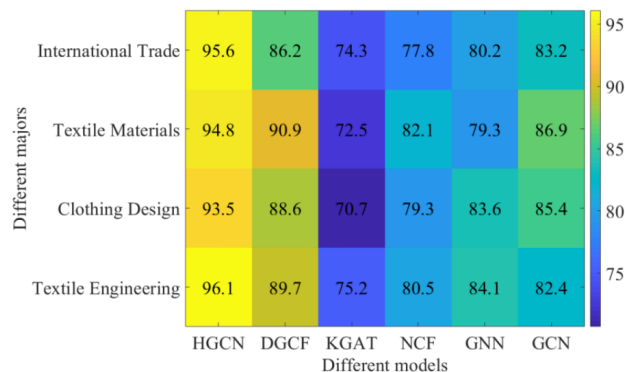


FIGURE 7. Accuracy analysis of different methods in recommending English learning paths for college students in different textile majors

As shown in Figure 7, HGCN achieves the highest accuracy in textile engineering, clothing design, textile materials, and international trade, reaching 96.1%, 93.5%, 94.8%, and 95.6%, respectively, demonstrating strong generalization and personalized modeling ability. Other models perform less effectively due to limited structural representation or insufficient heterogeneous information fusion, especially in terminology-intensive majors. HGCN's superior performance is attributed to its heterogeneous graph architecture, which integrates student behavior, knowledge structures,

and professional semantic information to enhance contextual relevance across different professional domains.

Experimental results show that the proposed framework effectively improves real teaching outcomes, increasing click-through rate, learning efficiency, student satisfaction, and knowledge retention. Students follow the recommended paths more willingly, learn with greater continuity and less cognitive interruption, and acquire professional terminology in a more coherent and efficient manner, demonstrating clear practical value in textile English instruction.

V. CONCLUSION

This study proposes a GNN-based intelligent recommendation system to address insufficient personalization and low professional adaptability in textile English learning paths. By constructing a student–knowledge heterogeneous graph and designing the MGAA model with dual-layer attention, the system effectively integrates ASTM standard terminology with student learning behaviors, improving semantic understanding and personalized recommendation accuracy. Combined with an HGCN-based dynamic optimization strategy, the system enables real-time, adaptive learning path adjustment. Experiments show superior performance over baseline models, achieving 96.81% accuracy and significantly enhanced professional adaptability. The study offers both a practical solution for textile English learning and a generalizable technical framework for personalized recommendation in professional education.

Beyond technical contributions, the system supports industry–education collaboration by aligning textile English instruction with industrial competency requirements through standardized terminology and task-oriented scenarios, providing a scalable foundation for outcome-oriented curriculum reform and integration of enterprise standards into

university teaching. This study demonstrates strong performance in personalized path recommendation for textile English, but has several limitations: scalability issues of the HGCN messaging mechanism on ultra-large heterogeneous graphs, cold-start problems for freshmen or new knowledge points due to insufficient behavioral data, and limited interpretability of recommendation results. Future work will focus on improving large-scale graph efficiency, addressing cold-start scenarios, and enhancing interpretability through attention mechanisms and rule-based reasoning.

AUTHOR CONTRIBUTIONS

All work in this study was independently completed by Yanjun Guan.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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