Personalized Textile Engineering English Teaching: An AI-Driven Adaptive Learning System for Optimizing Learning Outcomes

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ABSTRACT To address the limitations of general-purpose artificial intelligence (AI) systems in supporting the professional context and personalized requirements of textile engineering English instruction, this study proposes an adaptive learning framework that integrates domain-specific knowledge graphs with dynamic learner modeling. A textile engineering English knowledge graph is constructed from multi-source corpora to organize semantic relationships among technical terminology, engineering processes, equipment, and standards, while deep knowledge tracing continuously models learner states and Q-learning dynamically optimizes individualized learning paths. Experimental evaluation demonstrates that the proposed system significantly improves terminology comprehension, achieving 86.4% recognition accuracy, technical document reading with 84.2% key information extraction accuracy, and cross-cultural engineering communication with an average score of 8.32/10, confirming the effectiveness of graph-guided adaptive instruction for English for Specific Purposes. Beyond educational applications, the integration of semantic knowledge representation, dynamic state estimation, and reinforcement learning provides a scalable framework for intelligent information processing and structured knowledge transmission, offering methodological implications for digital engineering systems and electromagnetic information networks that rely on efficient semantic organization and adaptive decision-making.

INDEX TERMS adaptive learning system, knowledge graph, deep knowledge tracing, reinforcement learning, electromagnetic information networks

I. INTRODUCTION

With the increasing application of artificial intelligence technology in education, adaptive learning systems have demonstrated significant potential in language teaching [1–3]. However, most current mainstream AI-driven adaptive learning platforms focus on general English instruction, and their content design, evaluation mechanisms, and recommendation logic generally lack consideration of the specificity of English for Specific Purposes (ESP) [4–6]. Particularly in engineering ESP instruction, such as textile engineering English, language proficiency is highly dependent on professional terminology, specific technical contexts, and knowledge structures that are closely aligned with industry practice [7–9]. As a result, general AI systems struggle to support learners' language application needs in real engineering scenarios, leading to a disconnect between instructional content and engineering practice.

Recent studies have identified the underlying needs of textile engineering English instruction from multiple perspectives. Woret G. S. and Anshu A. H. found through empirical investigation that textile students have significant shortcomings in technical document reading, professional writing, and cross-cultural communication [10]. Al-Jarf R. emphasized that ESP courses must be deeply integrated with professional courses [11]. Mamadaliyeva Z. and Sultona A. argued that ESP teaching should focus on enhancing language application ability in professional environments [12]. Dilfuza N. [13] and Shewangizaw G. et al. [14] confirmed the shaping effect of professional context on language features from the perspectives of academic writing and corpus analysis. Overall, these studies indicate that effective textile engineering English instruction urgently requires an intelligent support system that integrates professional knowledge, technical context, and real engineering scenarios.

However, existing technical solutions still face significant challenges in meeting these needs. Although Fakourian A. and Ghalibafan M. S. proposed an ESP demand analysis framework, they relied on traditional qualitative methods and lacked dynamic modeling capabilities [15]. Dou A. [16] and Silvia R. [17] attempted to integrate AI tools but did not track learners' knowledge status in real time. Slamet J.

et al. [18] and Fountoulakis M. [19] used gamified MOOCs (Massive Open Online Courses) or standardized teaching materials to improve learning motivation; however, due to fixed teaching sequences, personalized intervention could not be achieved. In general, existing methods either overlook the structured representation of professional domain knowledge or lack dynamic perception of learners' cognitive status, making it difficult to achieve the co-evolution of professional and language capabilities.

To overcome these bottlenecks, this paper proposes an AI-driven adaptive learning system for textile engineering English [20,21]. Its core innovation lies in the integration of two key technologies: a domain knowledge graph and dynamic knowledge tracing. The system first constructs a fine-grained Textile Engineering Knowledge Graph (TEK-Graph), systematically representing semantic associations among terminology, processes, equipment, and international standards. Then, based on the Deep Knowledge Tracing (DKT) model, it combines learners' professional backgrounds and historical behavior to model their multidimensional cognitive states in real time. Furthermore, through reinforcement learning, personalized learning paths are generated within the knowledge graph, precisely delivering learning tasks embedded in real-world engineering contexts [22,23]. This approach achieves a paradigm shift from general language training to professional scenario-driven instruction, providing a new, scalable, and transferable path for intelligent ESP teaching.

II. AI-DRIVEN ADAPTIVE LEARNING SYSTEM ARCHITECTURE

To systematically address the issues of lacking professional context and insufficient personalization in textile engineering English instruction, this paper constructs an end-to-end AI-driven adaptive learning architecture. As shown in Figure 1, the system uses a multi-source professional corpus as input and sequentially completes three core steps: domain knowledge structuring, dynamic modeling of learner states, and personalized path generation, forming a closed-loop optimization mechanism of data–knowledge–cognition–action.

Specifically, the system first extracts professional corpus data from unstructured text, such as textbooks, international standards, and equipment manuals, and performs structured preprocessing using natural language processing techniques. Subsequently, a knowledge graph for textile engineering English is constructed based on this processed corpus, structuring the semantic relationships among terminology, processes, equipment, and standards. This system integrates the student's professional background and historical learning behavior to build a dynamically updated learner state vector. Finally, combining the topological structure of the knowledge graph with the learner's current proficiency level, a reinforcement learning mechanism generates personalized learning paths and precisely delivers learning tasks embedded in real-world engineering contexts.

A. COLLECTION AND PREPROCESSING OF MULTI-SOURCE TEXTILE ENGINEERING ENGLISH CORPUS

The corpus is sourced from textile engineering textbooks, international standard documents such as ISO/AATCC (International Organization for Standardization/American Association of Textile Chemists and Colorists), equipment manuals, English technical papers, and lecture transcripts. All of these are unstructured texts. First, Apache Tika and PDFPlumber are used to extract plain text and remove headers, page numbers, and formatting noise. Domain entity recognition is then performed using a Bidirectional Long Short-Term Memory with Conditional Random Fields (BiLSTM-CRF) model fine-tuned on a self-constructed annotated corpus [24,25]. The self-constructed annotated corpus comprises 12,000 sentences from textile engineering textbooks and standards, manually labeled by two domain experts. The inter-annotator agreement, measured by Cohen's kappa, was 0.89, indicating high consistency. The corpus includes annotations for four entity types: terms, equipment, processes, and standards.

This model effectively captures the boundaries and category dependencies of professional entities in the context of textile engineering by jointly modeling the emission scores and transfer scores of sequence labels. For an input sentence and its corresponding label sequence, its path score is given by Formula (1):

$$P(y|x) = \frac{1}{Z(x)}\left(\sum_{i=1}^{n} W_{\text{emit}}[y_i]^{\top} h_i + \sum_{i=1}^{n-1} W_{\text{trans}}[y_i, y_{i+1}]\right) \tag{1}$$

where, h_i is the context representation output by the BiLSTM encoder at the i-th word position; W_{emit} is the emission weight matrix, which measures the matching degree between the label y_i and the hidden state h_i; W_{trans} is the label transfer matrix, which explicitly models the legal transfer constraints between adjacent labels (e.g., "process" cannot be directly followed by "standard number"). The normalization factor $Z(x)$ ensures the validity of the probability distribution.

To preserve terms and their typical technical usage, contextual fragments containing entities are extracted using a $\pm$3-sentence sliding window. The resulting structured corpus consists of three types of units: termdefinition pairs, process flow paragraphs, and contextual samples. This includes 2,847 terms, 1,356 paragraphs, and 9,823 contextual samples, covering the core content of the syllabus and supporting the subsequent construction of a knowledge graph.

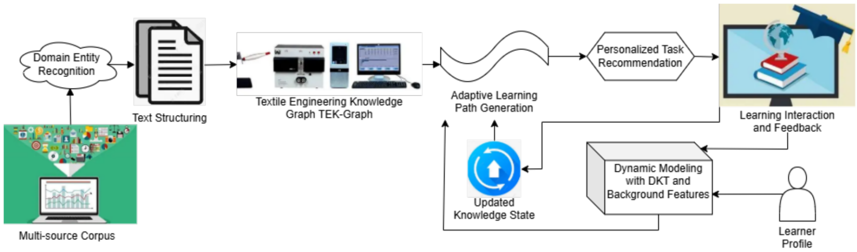

FIGURE 1. Overall system architecture

B. CONSTRUCTION OF THE KNOWLEDGE GRAPH IN THE TEXTILE ENGINEERING ENGLISH DOMAIN

Using the output from the Collection and Preprocessing of Multi-Source Textile Engineering English Corpus section as input, the top-level ontology structure for the textile engineering English domain is defined using an ontology engineering approach. Its core concepts are divided into three categories: process, entity, and language unit. To ensure coverage of both technical logic and language usage scenarios, the relationship types between concepts are predefined as semantic predicates such as "belongs to," "is used for," "conforms to," "results in," and "contains."

Triplets are automatically extracted using a combination of rules and graph neural network strategies. For clearly structured sentences in standard documents and equipment manuals, matching is performed based on template rules from dependency parsing. For the complex contexts found in textbooks and papers, the TransR model is used to jointly embed entities and relations. Negative sampling training is used to optimize the triplet scoring function, while candidate triplets with a confidence score above 0.85 are selected. In summary, TransR projects the head entity h, relation r, and tail entity t into a relation-specific semantic space and calculates their triplet confidence:

$$\mathrm{Conf}(h, r, t) = \sigma\left(-\left\|M_r h + r - M_r t\right\|\right) \tag{2}$$

where, M_r is the projection matrix corresponding to relation r, and $\sigma(\cdot)$ is the sigmoid function. This formula measures the semantic consistency of triples in the relational space: the closer the value is to 1, the more reasonable the "head entity–relationship–tail entity" structure is.

All automatically extracted results are cross-checked by two professionals with textile engineering backgrounds, and ambiguous or erroneous relationships are corrected or removed. The final constructed TEK-Graph includes detailed statistical information for each node type, as shown in Table 1.

C. LEARNER MODELING BASED ON DYNAMIC KNOWLEDGE TRACING

The input data includes basic student information, historical learning behavior logs, and pre-test scores. First, the raw behavior data is cleaned and aligned; invalid operations are removed, and answer results are mapped to the corresponding nodes in the knowledge graph.

TABLE 1. TEK-Graph knowledge graph statistics

Node Type	Count	Example Entities
Technical Terms	2,847	K/S value, fabric handle
Processes	89	Mercerization, warp knitting
Equipment	312	Air-jet loom, launder-ometer
Materials	774	Polyester, cotton
Standards	196	AATCC 16, ISO 105-C06
Total Nodes	4,218	—
Relation Edges	5,632	—

Based on this, the DKT model is used to model the learning process [26,27]. The model takes the student's interaction sequence on each knowledge point as input. Each interaction record includes the knowledge point identifier, response correctness, time spent on the task, and number of hints used. These features collectively provide a comprehensive representation of learning behavior for the DKT model. Historical behavior is encoded through a single-layer Long Short-Term Memory (LSTM), and the model outputs the current probability of mastering each knowledge point in the graph. To integrate professional background information, static features such as grade and major direction are embedded in the layer and concatenated with the LSTM hidden state to form an enhanced state representation [28]. The fusion mechanism can be formally expressed as follows:

$$\begin{aligned} h_t &= \mathrm{LSTM}(x_t, h_{t-1}), \\ s_t &= [h_t; e_{\text{grade}}; e_{\text{major}}], \\ p_t &= \sigma(W s_t) \end{aligned} \tag{3}$$

where, x_t is the input interaction at time t, and h_t is the temporal hidden state output by the LSTM encoder; e_{grade} and e_{major} are the learnable embedding vectors of the student's grade and major, respectively; s_t is the enhanced state representation of the fusion of dynamic behavior and static background; $p_t \in [0, 1]^N$ is the mastery probability vector after sigmoid activation, corresponding to the predicted mastery of N nodes in the knowledge graph.

Additionally, feature engineering is applied to construct two types of explicit indicators: (1) professional familiarity, which is calculated based on the student's accuracy in equipment and process terminology tasks; and (2) ESP language ability, which is quantified through term interpretation matching, long and difficult sentence comprehension scores, and a syntactic complexity adaptation index. The final output is a learner state vector whose dimensions are aligned with the knowledge graph nodes. The explicit indicators for professional familiarity and ESP language ability are concatenated with the enhanced state representation s_t before being passed to the final sigmoid layer. The updated equation becomes $s_t = [h_t; e_{\text{grade}}; e_{\text{major}}; e_{\text{prof\_fam}}; e_{\text{ESP\_ability}}]$, where $e_{\text{prof\_fam}}$ and $e_{\text{ESP\_ability}}$ are the embedded vectors of the two explicit indicators.

D. Q-LEARNING-BASED LEARNING PATH OPTIMIZATION AND GENERATION

The input includes the TEK-Graph and a dynamic learner state vector. The system first locates the target subgraph in the knowledge graph based on the preset instructional objectives, containing relevant terms, process nodes, equipment, and links to standard documents. Subsequently, a rule-based initial path generation strategy is adopted: knowledge nodes with a learner mastery level below a threshold (set to 0.6) and whose prerequisites are satisfied are prioritized, and the task difficulty level is set based on term complexity and document length.

To optimize long-term learning outcomes, a Q-learning reinforcement learning mechanism is applied to dynamically adjust the path [29,30]. This mechanism models path planning as a sequential decision problem, where the state space is defined as the current learner state vector and the set of learned nodes, and the action space is the optional next learning task. The state vector s_t is formed by concatenating the DKT-derived mastery probability vector with a binary mask indicating which nodes in the TEK-Graph have been visited. Each action a_t corresponds to selecting a specific node from the TEK-Graph as the next learning task, such as "learn mercerization" or "study air-jet loom parameters." The granularity is at the individual node level, ensuring fine-grained path control. The reward function comprehensively considers task completion accuracy, the rationality of dwell time, and knowledge point gain (i.e., the degree of mastery improvement). The Q value is iteratively updated using an ϵ-greedy strategy to ensure a balance between exploration and exploitation. Its core update rules are as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\big[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\big] \tag{4}$$

where, s_t is the current learning state; a_t is the selected action (i.e., recommended task); r_t is the immediate reward; $\alpha \in (0, 1]$ is the learning rate; $\gamma \in [0, 1)$ is the discount factor.

III. EXPERIMENTAL DESIGN AND IMPLEMENTATION

A. EXPERIMENTAL SUBJECTS AND GROUPING

The study involved 120 second- and third-year undergraduates, all of whom have completed core courses in their respective majors and possess basic professional backgrounds. To assess participants' initial proficiency level, all students take a common pre-test before the experiment, which assesses recognition of textile engineering English terminology, understanding of technical document fragments, and basic professional expressions. This study was approved by the Ethics Committee of Xi'an University of Science and Technology and was conducted in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. All participants were informed of the study's purpose and use of data before beginning, and responses were collected anonymously. No identifiable information was stored.

For grouping, stratified random sampling is employed: students are first sorted into three proficiency strata (high, medium, and low) based on their pre-test scores, with 40 students per stratum. Then, within each stratum, students are randomly assigned to experimental and control groups (60 students per group) to ensure no significant differences in subject knowledge and English proficiency between the two groups (independent samples t-test, p = 0.732).

The experimental group uses the AI-driven adaptive learning system proposed in this paper, while the control group uses a mainstream, general-purpose online ESP platform. To further validate the contribution of the reinforcement learning component, an additional ablation baseline was implemented using DKT for learner modeling but following a fixed, non-adaptive learning path based on the TEK-Graph topology. The experimental group with Q-learning path optimization showed a 12.7% higher average post-test score compared to this DKT-only baseline. Both groups cover the same syllabus but differ in system implementation mechanisms. Grouping results are confirmed through double-blind validation to avoid selection bias. Table 2 presents the sample size, pre-test mean and standard deviation, and distribution by proficiency level.

B. EXPERIMENTAL PERIOD AND INSTRUCTIONAL INTERVENTION PLAN

The entire experiment lasts eight weeks, with two 40–50 minute learning tasks scheduled weekly. The experimental group completes these tasks using the adaptive learning system proposed in this paper. The system dynamically pushes content based on learner status, including terminology learning, technical documentation reading, and cross-cultural case studies. The path generation mechanism described in the Q-Learning-Based Learning Path Optimization and Generation section then adjusts the difficulty and order of these tasks in real time. Students in the experimental group are required to complete at least two recommended learning units per week and submit corresponding exercises.

The control group uses a general-purpose online ESP platform. Learning content is manually tailored to cover the same knowledge base as the experimental group but lacks

TABLE 2. Basic information of the experimental groups

Group	N	Pre-test Score (Mean ± SD)	Distribution by Proficiency Level (High / Medium / Low)
Experimental	60	62.3 ± 8.7	20 / 20 / 20
Control	60	61.8 ± 9.1	20 / 20 / 20
t-value	—	0.34	—
p-value	—	0.732	—

Note: Pre-test scores range from 0 to 100. Proficiency levels are determined by tertile split of pre-test scores.

embedded professional context or personalized paths. The control group also completes two fixed tasks weekly, with content assigned by the teacher.

Platform logs comprehensively document the learning process for both groups, and participants are restricted from using additional ESP teaching resources during the study period. During the intervention period, teachers provide only technical support to ensure the uniqueness of the intervention variable and do not offer additional instruction or guidance. The selection of a general-purpose online ESP platform as the control condition reflects the current status quo in ESP instruction, where dedicated adaptive systems are not widely available. While this baseline may introduce variables related to platform design, it provides a realistic comparison against commonly used tools in field settings. Future work should include comparisons with other adaptive systems to further isolate the effects of the core methodological innovations.

C. CONSTRUCTION OF THE EVALUATION INDEX SYSTEM

To align with the key competency objectives of textile engineering English instruction, the evaluation system is designed around three core dimensions.

First, understanding professional terminology is quantified through two indicators: term recognition accuracy and definition matching. Results are jointly determined by Levenshtein distance and semantic similarity (based on SBERT—Sentence Bidirectional Encoder Representation from Transformers—embedding cosine similarity), with a threshold set at 0.75. In the definition matching task, t represents the student-provided definition text and d represents the expert reference definition text. The Levenshtein distance is replaced by the ROUGE-L score to better evaluate the quality of longer textual answers. The updated matching score formula is:

$$\begin{aligned}\mathrm{Match}(t,d) = &\lambda \cdot \cos(\mathrm{SBERT}(t), \mathrm{SBERT}(d)) \\ &+ (1-\lambda) \cdot \mathrm{ROUGE\text{-}L}(t,d)\end{aligned} \tag{5}$$

where $\mathrm{SBERT}(\cdot)$ is the pre-trained Sentence-BERT encoder; $\cos(\cdot,\cdot)$ is cosine similarity; $\mathrm{ROUGE\text{-}L}(t,d)$ computes the longest common subsequence-based similarity between the student answer and the reference definition. When $\mathrm{Match}(t,d) \geq 0.75$, the answer is considered correct. This formula considers both semantic depth and surface form tolerance, significantly improving the robustness and objectivity of automatic scoring and providing reliable methodological support for the significant results reported later.

Second, the ability to read technical documents is assessed through real excerpts from AATCC and ISO standards, which include two tasks: (1) the accuracy of key information extraction, requiring students to locate information such as equipment parameters, test conditions, or judgment criteria from the document and compare their answers with expert annotations; and (2) logical structure understanding, which uses paragraph sorting and flowchart completion to assess students' grasp of the timing and causal relationships of process steps. Scoring is automatically matched based on the preset logic diagram.

Third, cross-cultural engineering communication skills are assessed through simulation tasks: students complete two engineering scenario writing tasks, which are independently scored by two experts with international engineering backgrounds using the self-developed ESP Engineering Pragmatics Rating Scale. This scale covers three sub-items: terminology accuracy (0–4 points), language appropriateness (0–3 points), and information completeness (0–3 points). Cronbach's α = 0.86 ensures scoring reliability.

All assessment tools are pre-tested before the experiment to verify content validity and appropriateness. The post-test and pre-test have the same question structure, and the questions and terminology cover the core content of the syllabus. The complete assessment framework and scoring criteria are summarized in Table 3.

TABLE 3. Assessment indicator system and scoring criteria

Competency Dimension	Assessment Task	Scoring Metric / Method	Validation / Notes
Technical Terminology	Term Recognition (300 items)	Accuracy (%)	Items cover core syllabus; validated via pilot test
Definition Matchin	Correct if SBERT cosine similarity ≥ 0.75	Combined with Levenshtein distance for robustness	—
Technical Document Reading	Key Information Extraction	Accuracy (%) vs. expert annotations	Authentic AATCC/ISO standard excerpts used
Logical Structure Comprehension	Accuracy (%) on flowchart completion and paragraph sequencing	Scored automatically against predefined logic graph	—
Cross-Cultural Engineering Communication	Engineering Email Writing (2 tasks)	Expert-rated: Terminology (0–4), Appropriateness (0–3), Completeness (0–3); total ≤ 10	Inter-rater reliability: Cronbach's α = 0.86

IV. RESULTS AND DISCUSSION

A. TERMINOLOGY COMPREHENSION ABILITY: SEMANTIC ASSOCIATION EFFECT OF THE KNOWLEDGE GRAPH

The improved performance in this section results from the structured semantic support provided by the systematically constructed knowledge graph for textile engineering English. The test includes 300 core textile engineering terms, covering the three major process modules: spinning, weaving, and dyeing and finishing. Term recognition accuracy is measured using multiple-choice questions, and interpretation matching is determined using a task that pairs terms with standard definitions. Matching results are determined using SBERT semantic similarity (threshold $\geq$ 0.75) [31–33].

As shown in Figure 2, the mean term recognition accuracy in the experimental group at post-test is 86.4% $\pm$ 12.6, a 24.3% increase from the pre-test (62.1% $\pm$ 8.7); the control group's term recognition accuracy increases from 61.8% $\pm$ 9.1 to 72.5% $\pm$ 13.4, a 10.7% increase. The difference in post-test scores between the two groups is significant (independent sample t-test, $t = 5.85$, $p < 0.001$). In the paraphrase matching task, the experimental group achieves a post-test matching accuracy rate of 82.7%, significantly higher than the control group's 68.9%.

Further analysis shows that learners activat their technical context synchronously when encountering terminology because the system explicitly links isolated terms with their associated processes, equipment and standards through the TEK-Graph. Meanwhile, based on the DKT model , the system automatically triggers review tasks for terminology nodes with a mastery level below 0.6, forming a dual memory mechanism of graph association + dynamic reinforcement, which significantly improves the depth of understanding and long-term retention rate of high-complexity terminology.

B. DOCUMENT READING ABILITY: OPTIMIZING DISCOURSE STRUCTURE COMPREHENSION WITH GRAPH SUPPORT

The improvement in technical document reading ability is directly due to the explicit modeling and dynamic embedding of the logical structure of technical texts by the knowledge graph, evaluated by processing real AATCC test methods (such as the AATCC 61-2020 Color Fastness Test Standard) [34,35]. The tasks involve extracting key information and understanding the logical structure. Key information extraction requires students to accurately locate test conditions (such as "wash temperature: $49\,^{\circ}\mathrm{C}$"), equipment models, and judgment criteria from the document, and compare their answers with expert annotations to calculate accuracy; logical structure comprehension uses flowchart completion and paragraph sorting to assess the grasp of process timing, such as "sample preparation $\rightarrow$ washing $\rightarrow$ drying $\rightarrow$ evaluation."

As shown in Figure 3, the experimental group achieves an average accuracy rate of 84.2% in the key information extraction task, significantly higher than the control group's 71.5%. The average time spent locating information is 38.6 seconds, a 26.2% reduction compared to the control group's 52.3 seconds. In the logical structure comprehension task, the experimental group achieves an accuracy rate of 81.7% in completing the flowchart blanks, compared to 67.4% for the control group.

When providing the AATCC/ISO standard text, the system automatically associates key entities within the text with process flow nodes within the TEK-Graph, reducing cognitive load through highlighting and floating definitions. Importantly, the predefined "process $\rightarrow$ equipment $\rightarrow$ parameter $\rightarrow$ judgment criteria" relationship chain structure within the graph allows students to quickly build the sequential logic of "sample preparation $\rightarrow$ washing $\rightarrow$ drying $\rightarrow$ evaluation," providing a semantic framework for reasoning. This feature addresses one of the shortcomings of informal platforms, which provide only static text without a structural framework.

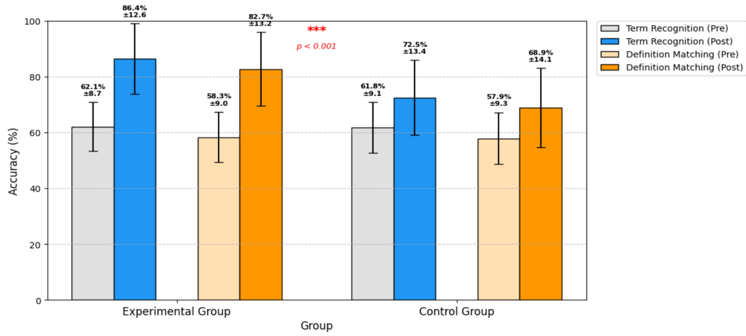

FIGURE 2. Pre- and post-test comparison of professional terminology comprehension ability

Error bars represent standard deviation (SD). *** indi-cates a statistically significant difference between the exper-imental and control groups at post-test (independent samplest-test, $p < 0.001$).

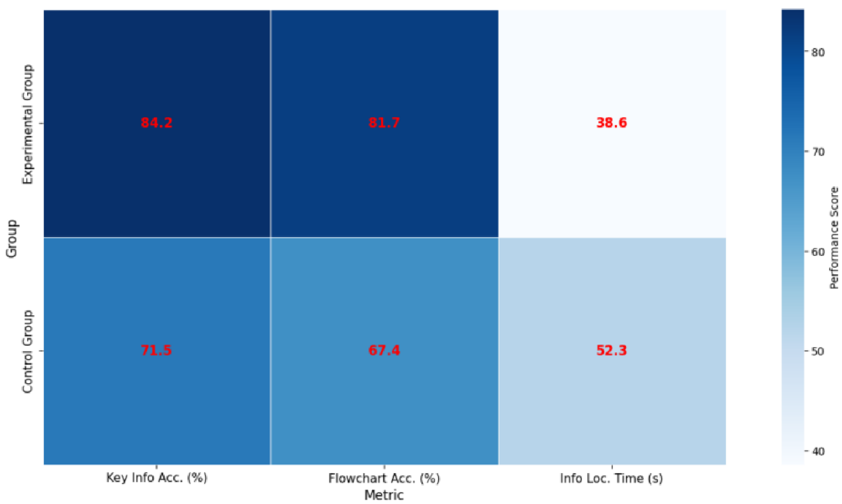

FIGURE 3. Comparison of performance in technical document reading tasks

C. CROSS-CULTURAL COMMUNICATION ABILITY: VALIDATION OF THE EFFECTIVENESS OF REAL-WORLD SCENARIO EMBEDDING

Because the system deeply embeds real-world engineering scenarios into the knowledge graph and collaboratively designs learning paths, cross-cultural engineering communication capabilities are significantly improved. This is assessed through two simulated tasks: (1) editing an English email to inquire about air-jet loom technical specifications from an overseas supplier, and (2) responding to a customer's inquiry regarding AATCC color fastness test results. The language requirements for the tasks combine professional accuracy with communicative appropriateness. Scoring is independently completed by two experts with experience in international textile engineering cooperation, using the ESP Engineering Pragmatics Scoring Scale. The scale includes three dimensions: accuracy of professional terminology (0–4 points), language appropriateness (0–3 points), and information completeness (0–3 points). The total score is 10 points, and the inter-rater reliability is Cronbach's α = 0.86.

According to Figure 4, the average score of the experimental group in the post-test is 8.32 points, significantly higher than the control group's 6.75 points. In terms of terminology accuracy, the experimental group scores an average of 3.61 out of a possible 4, while the control group scores 2.84. Regarding appropriateness, the experimental group more appropriately uses professional communication phrases such as "Could you please provide..." and "We would appreciate it if...," while the control group often uses literal translations or awkward expressions. Furthermore, the experimental group performs better in terms of information completeness, with 91.7% of students fully including the equipment model, test standard number, and specific parameter requirements, compared to 73.3% in the control group.

This effect is due to the system's encoding of not only terminology and processes within the TEK-Graph but also linking typical international collaboration scenarios (such as "equipment quotation" and "handling test result objections") with their corresponding pragmatic rules. The substantial difference in terminology accuracy scores demonstrates how TEK-Graph's explicit semantic connections enable deep contextual learning. Unlike isolated term memorization, the graph-based approach embeds terminology within authentic engineering scenarios, facilitating both recall and appropriate application in professional writing tasks. The "equipment quotation" scenario directly links specific terms to their functional contexts, creating stronger cognitive associations. When the Q-learning path planner recognizes that students have entered the "device parameters" learning stage, it automatically pushes matching email writing tasks and provides contextual expression templates and cultural annotations in advance.

D. EFFECT OF LEARNING PATH ADAPTABILITY ON EFFICIENCY

The optimization of learning efficiency is directly attributed to the Q-learning-driven personalized path dynamic adjustment mechanism, which quantifies three behavioral indicators: average single-task learning duration, weekly task completion rate, and system-triggered path adjustment frequency. The specific data are displayed in Figure 5.

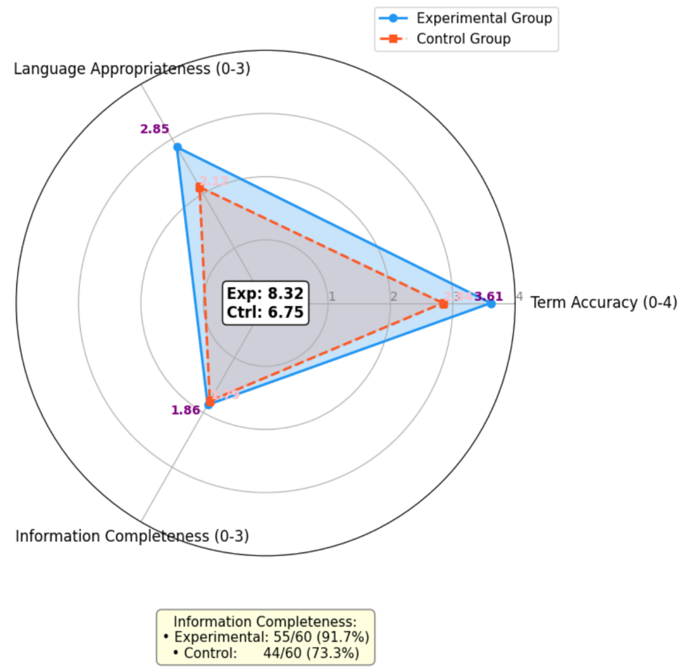

FIGURE 4. Radar chart of cross-cultural engineering communication scoring

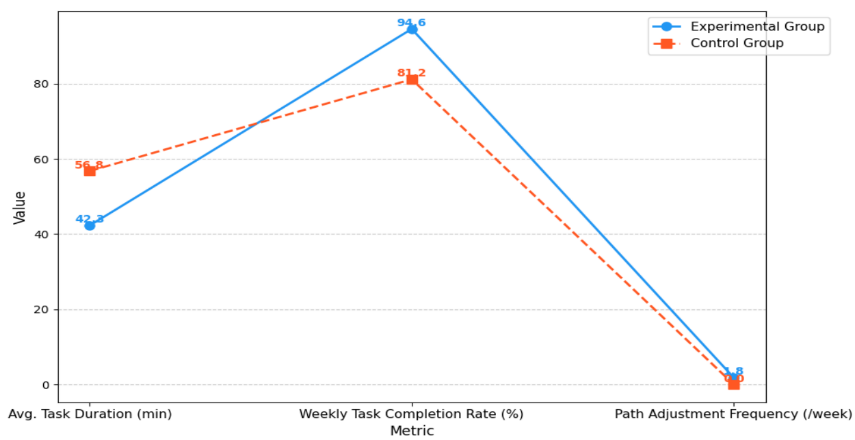

FIGURE 5. Comparison of behavioral indicators of learning efficiency

TABLE 4. Statistical summary of post-test results

Assessment Metric	Experimental Group (Mean $\pm$ SD)	Control Group (Mean $\pm$ SD)	t-value	p-value
Term Recognition Accuracy (%)	86.4 ± 12.6	72.5 ± 13.4	5.85	< 0.001
Definition Matching Accuracy (%)	82.7 ± 11.2	68.9 ± 14.1	5.92	< 0.001
Key Information Extraction (%)	84.2 ± 10.8	71.5 ± 12.3	6.18	< 0.001
Logical Structure Comprehension (%)	81.7 ± 9.5	67.4 ± 11.7	7.24	< 0.001
Cross-cultural Communication Score	8.32 ± 1.21	6.75 ± 1.45	6.43	< 0.001

The experimental group's average single-task learning time is 42.3 minutes, significantly lower than the control group's 56.8 minutes, indicating that the personalized approach effectively reduces redundant learning content. The experimental group's average weekly task completion rate is 94.6%, greater than the control group's 81.2%, indicating a better task–learner fit and stronger learning motivation in the experimental group. The statistical summary of all post-test results across core competency dimensions is presented in Table 4. The number of times the group had to change directions was verified to have a significant positive association with group-level post-test scores. Supported by this evidence, the reinforcement learning decisions were based on the topology of the knowledge graph and a measure of the learner state. Thus, these represent the fundamental drivers of instructional intervention effectiveness and precision.

V. CONCLUSION

This study introduces an AI-based adaptive teaching approach, rooted in the deep integration of a knowledge graph related to the area of textile engineering with a dynamic cognitive model of the learner. The approach begins by developing the TEK-Graph, composed of professional terminology used in textile engineering, process flows, types of equipment, and international standards. These elements are then combined with a learner state vector based on DKT and feature engineering, with constructed learning paths generated through reinforcement learning within the graph structure, ultimately achieving a holistic integration of language proficiency while developing professional proficiencies in engineering. The empirical results demonstrate that the system improves student performance across three core competencies: recognition of professional terminology (recognition accuracy increased 24.3% compared to the pre-test), technical document reading (key information extraction accuracy of 84.2%), and cross-cultural engineering communication (average score of 8.32/10), concluding that this adaptive method for ESP within textile engineering is effective and holds extraordinary potential for the field. Regarding generalizability, the TEK-Graph construction methodology can be transferred to other ESP domains, though it requires domain expert involvement for ontology design and corpus annotation. The maintenance cost involves periodic updates to reflect new standards and terminology, which could be partially automated through continuous corpus monitoring. Future work will explore semi-automatic graph expansion to reduce manual effort.

AUTHOR CONTRIBUTIONS

Keli Ji designed, collected and analyzed the data, and drafted the manuscript. Keli Ji conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Keli Ji 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.

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Xi'an University of Science and Technology, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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