Research on Intelligent Construction and Dynamic Optimization of Higher Vocational Education Curriculum Systems Based on Transformers and Knowledge Graphs

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ABSTRACT With the digital transformation of vocational education and the upgrading of industrial demands, the curriculum system of higher vocational education faces core challenges such as lagging industrial alignment, loose knowledge coherence, and insufficient dynamic adjustment. This misalignment is particularly evident in technical fields serving advanced engineering sectors, such as antenna engineering, electromagnetic wave applications, communication equipment manufacturing, and intelligent electronic systems, where graduates are required to master interdisciplinary knowledge and practical engineering skills. To achieve precise alignment between curriculum systems and job requirements, systematic integration of knowledge structures, and dynamic optimization throughout the curriculum lifecycle, this paper proposes an intelligent construction and dynamic optimization method for higher vocational education curricula based on Transformers and knowledge graphs. First, a four-layer knowledge graph linking industry, job, competency, and curriculum is constructed to integrate industrial demands, job standards, and course resources through semantic association. Second, a competency-to-course matching module based on the Transformer model is developed to capture fine-grained correlations between competency requirements and course content through bidirectional attention mechanisms. Third, a multi-objective optimization algorithm is proposed to coordinate the curriculum system's credit structure, prerequisite relationships, and industrial alignment. Finally, a dynamic adjustment mechanism is established to enable real-time iteration of the curriculum system based on evolving industrial demands and learning effectiveness feedback. This mechanism helps maintain curriculum relevance in rapidly developing engineering fields, especially those related to electromagnetic wave propagation, antenna systems, and communication technology.

INDEX TERMS transformer, knowledge graph, curriculum system, antenna engineering, electromagnetic wave propagation

I. INTRODUCTION

A. RESEARCH BACKGROUND

CURRENTLY, digital technologies present new opportunities for reforming vocational education curriculum systems: knowledge graphs can integrate multi-source heterogeneous data to construct semantic association networks among industries, job roles, competencies, and courses. By mapping the specialized digital skill requirements, for instance, these knowledge graphs ensure that course content is precisely aligned with the demands for engineers and production managers proficient in digital workflows and AI-driven quality control [1]; Transformer models, with their robust semantic understanding and feature extraction capabilities, enable deep alignment between competency requirements and curriculum content [2]. Therefore, integrating Transformer and knowledge graph technologies to build an intelligent, dynamic, and precise higher vocational education curriculum system holds significant practical importance for advancing the high-quality development of vocational education and enhancing talent cultivation quality [3].

B. CURRENT RESEARCH STATUS DOMESTICALLY AND INTERNATIONALLY

1) Research on Vocational Education Curriculum System Construction

International research on vocational education curriculum systems focuses on industry alignment and competency orientation: Germany's "dual system" model builds a modular curriculum system based on job competency matrices, achieving collaborative education between schools and enterprises [4]; U.S. community colleges adopt the "Competency-Based Education (CBE)" philosophy, designing course modules centered on job competency requirements [5].

2) Application Research of Knowledge Graphs in Education

Knowledge graphs have become core technologies for educational resource integration and intelligent services: International scholars construct knowledge graphs in education to enable semantic retrieval and related recommendations of curriculum resources [6]; MIT developed a knowledge graph-based curriculum planning system to assist students in designing personalized learning paths [7].

C. RESEARCH QUESTIONS AND INNOVATION POINTS

1) Core Research Questions

1. How to construct a four-layer knowledge graph (industry-Job Role-competency-course) to achieve semantic integration and associative modeling of multi-source heterogeneous data?

2. How to optimize the Transformer model to enhance the granular matching accuracy between position competency requirements and course content?

3. How to design a multi-objective optimization algorithm to maximize the industry adaptability of the curriculum system while satisfying constraints such as credit structure and prerequisite relationships?

4. How can a dynamic adjustment mechanism be established to enable real-time iterative optimization of the curriculum system based on evolving industry demands and learning effectiveness feedback?

2) Research Innovations

1. Proposes a "four-layer knowledge graph-driven, Transformer-based fine-grained matching, multi-objective collaborative optimization, dynamic feedback iteration" framework for curriculum system construction, integrating multi-dimensional semantic associations across industry, job roles, competencies, and courses to achieve end-to-end alignment from demand to curriculum;

2. Constructs a four-layer knowledge graph (industry-job-competency-course), designs multi-source data fusion strategies and semantic association inference rules to uncover latent competency-course and job-course relationships;

3. Optimizes the Transformer model's attention mechanism by incorporating job competency weights and course knowledge weights, enabling fine-grained matching between competency requirements and course content to enhance curriculum precision;

4. Propose a multi-objective curriculum optimization algorithm integrating three goals: industry alignment, knowledge coherence, and credit rationality, while satisfying constraints like prerequisite relationships and class hour limitations;

5. Establish a dynamic adjustment mechanism combining industry demand monitoring and learning effectiveness evaluation to achieve full-lifecycle iterative optimization of the curriculum system.

Each technical component in the framework is based on existing mature theories (e.g., Competency-Based Education Theory, Knowledge Graph Theory, Multi-Objective Optimization Theory). The core innovation of this study lies in organically integrating these dispersed technologies and customizing optimization for the special needs of higher vocational education curriculum system construction (such as industry adaptability, knowledge coherence, and dynamic adjustment), rather than inventing independent new technologies.

D. RESEARCH SIGNIFICANCE

1) Theoretical Significance

1. Enriches the theoretical framework for constructing vocational education curricula, reveals the integration mechanism between digital technologies and curriculum reform, and provides theoretical support for the digital transformation of vocational education;

2. Establishes an educational intelligent modeling method integrating knowledge graphs and Transformers, advancing semantic association modeling and intelligent optimization theories in vocational education.

2) Practical Significance

1. Provides intelligent curriculum system construction tools for higher vocational colleges, shortening curriculum update cycles and enhancing alignment with industry demands;

2. Optimizes students' knowledge structures and competency development pathways, improving job readiness and promoting high-quality employment;

3. Offers decision support for education administrators, driving optimized allocation and precise provision of vocational education resources;

4. Advances digital reform in vocational education, providing technical support for implementing the integrated "job-course-competition-certification" education model. This reform is crucial for modernizing traditional fields, enabling the rapid development of specialized training modules tailored to the high-tech requirements of industries, particularly in areas such as intelligent machinery operation and sustainable material management.

II. THEORETICAL AND TECHNOLOGICAL FOUNDATIONS

A. CORE THEORETICAL SUPPORT

1) Competency-Based Education Theory

Competency-Based Education (CBE) centers on job competency requirements, emphasizing precise alignment between educational objectives and workplace demands [8]. Its core tenets include:

1. Competency Orientation: Designing educational content around knowledge, skills, and competencies required for actual job roles;

2. Modular Construction: Decomposing competency requirements into distinct modules, each corresponding to a course unit;

3. Dynamic Adaptability: Continuously optimizing course modules and content based on evolving job competency demands [9].

This theory provides core guidance for modeling the industry-job-competency-course relationship, clarifying the objectives and logic for constructing curriculum systems [10].

2) Knowledge Graph Theory

Knowledge graph theory focuses on constructing and reasoning about structured semantic relationships, with core elements including [11]:

1. Entities and Relationships: Entities encompass core elements such as industries, positions, competencies, and courses; relationships include "industry contains positions," "positions require competencies," and "competencies correspond to courses";

2. Semantic Inference: Utilizes rule-based reasoning and machine learning to uncover latent relationships and refine semantic networks;

3. Multi-source Integration: Combines structured (e.g., job descriptions), semi-structured (e.g., course outlines), and unstructured (e.g., industry reports) data [12].

This theory provides methodological support for integrating multidimensional semantic associations, facilitating the construction of a complete semantic chain linking industry-job-competency-curriculum [13].

3) Multi-Objective Optimization Theory

Multi-objective optimization theory addresses decision problems involving multiple conflicting goals. Its core principles include [14]:

1. goal coordination: Seeking optimal balance among multiple objectives (e.g., industry alignment, knowledge coherence);

2. Constraint Satisfaction: Achieving objective optimization while satisfying constraints like credit requirements and prerequisite relationships;

3. Pareto Optimality: Recognizing no absolute optimal solution exists, instead seeking the best solution within the set of non-dominated solutions [15].

This theory provides core guidance for multi-objective collaborative optimization of curriculum systems, ensuring comprehensive optimality across multidimensional demands [16].

B. KEY TECHNOLOGICAL SUPPORT

1) Knowledge Graph Construction Technology

Knowledge graph construction technology encompasses the entire process of data processing, ontology design, association extraction, and reasoning:

1. Ontology Design: Utilizes OWL (Web Ontology Language) to define core concepts and relationship types for industries, positions, competencies, and courses;

2. Association Extraction: Combines rule extraction with BERT models to extract entity association relationships from multi-source data [17];

3. Semantic Reasoning: Implements hidden relationship inference based on Markov Logic Networks (MLN) to refine the knowledge graph [18];

4. Knowledge Update: Designs an incremental update mechanism to enable dynamic iteration of the knowledge graph [19-21].

2) Core Technologies of the Transformer Model

The core technologies of the Transformer model focus on semantic understanding and feature matching:

1. Self-Attention Mechanism: Calculates association weights among elements in the input sequence to capture global semantic relationships [22];

2. Bidirectional Encoding: Achieves deep semantic understanding of competency requirements and course content through bidirectional attention calculations in the encoder [23-25];

3. Pre-training and Fine-tuning: Pre-trains models on educational domain corpora, then fine-tunes them for competency-course matching tasks to enhance matching accuracy [26];

4. Attention Weight Optimization: Incorporates domain knowledge weights to strengthen semantic features relevant to job competencies [27].

3) Multi-Objective Optimization Algorithms

Multi-objective optimization algorithms enable collaborative optimization of the curriculum system:

1. Non-Dominated Sorting Genetic Algorithm (NSGA-III): Seeks multi-objective optimal solutions through non-dominated sorting and crowding degree calculations [28];

2. Objective Function Construction: Design three core objective functions: industry adaptability, knowledge coherence, and credit rationality;

3. Constraint Handling: Integrate constraints including prerequisite relationships, class hour limitations, and total credit requirements [29];

4. Algorithm Optimization: Improve selection operators by incorporating simulated annealing techniques to accelerate algorithm convergence [30].

4) Dynamic Adjustment Technology

Dynamic adjustment technology supports real-time iteration of the curriculum system:

1. Industry demand monitoring: Utilizes web crawling and text mining technologies to collect real-time data on

industrial policies, job postings, and other indicators to identify demand shifts;

2. Learning effectiveness evaluation: Constructs a multi-dimensional learning effectiveness evaluation system, integrating student grades, skill certifications, and job feedback data to assess course outcomes;

3. Iterative Optimization Mechanism: Design trigger-based adjustment rules to initiate curriculum system optimization when demand shifts or learning outcomes fall below standards.

5) Evaluation Indicator System Construction

Aligned with core requirements of higher vocational education curricula, construct a four-dimensional evaluation system using the Analytic Hierarchy Process (AHP) to determine indicator weights:

TABLE 1. Evaluation indicator system

First-level Indicator	Weight	Second-level Indicator	Weight	Evaluation Method
Industry Adaptability	0.35	Job Competency Matching Rate (%)	0.45	Proportion of the curriculum system covering core job competencies
		Technology Update Responsiveness (%)	0.35	Proportion of curriculum content covering new technologies
		Industry Demand Response Speed (days)	0.20	Adjustment cycle of the curriculum system in response to industrial changes
Knowledge Structure Quality	0.25	Knowledge Coherence (%)	0.50	Proportion of rationality in prerequisite-follow-up relationships between courses
		Knowledge Coverage Completeness (%)	0.30	Proportion of the curriculum system covering knowledge required for the job
		Module Relevance (%)	0.20	Degree of tightness of knowledge coherence between curriculum modules
Talent Cultivation Effect	0.25	Job Competency Score (points)	0.50	Enterprise's score for graduates' job performance (full score: 100)
		Skill Certification Pass Rate (%)	0.30	Pass rate of students' vocational skill level certificates
		Employment Matching Rate (%)	0.20	Proportion of graduates' jobs matching their major
System Optimization Performance	0.15	Dynamic Adjustment Response Time (hours)	0.50	Time from initiation to completion of curriculum system adjustment

III. INTELLIGENT CONSTRUCTION AND DYNAMIC OPTIMIZATION METHODOLOGY FOR CURRICULUM SYSTEMS BASED ON TRANSFORMERS AND KNOWLEDGE GRAPHS

A. OVERALL CONSTRUCTION FRAMEWORK

This paper proposes a four-stage construction framework: "Knowledge Graph Construction—Competency-Curriculum Matching—Multi-Objective Optimization—Dynamic Adjustment Iteration." Inputting multi-source data including industry demands, job standards, and course resources, it first constructs a four-layer knowledge graph spanning industry-job-competency-course. Then, leveraging an optimized Transformer model, it achieves fine-grained competency-course matching. Subsequently, a multi-objective optimization algorithm generates the optimal curriculum system. Finally, a dynamic adjustment mechanism is established to enable continuous iteration of the curriculum system based on evolving industry demands and learning effectiveness feedback.

The framework's core logic:

- Knowledge graphs integrate semantic associations across the entire chain
- Transformer models enhance matching precision
- Multi-objective optimization ensures comprehensive curriculum quality
- Dynamic adjustments enable full lifecycle adaptation

B. CONSTRUCTION OF THE FOUR-LAYER KNOWLEDGE GRAPH (INDUSTRY-POSITION-COMPETENCY-CURRICULUM)

1) Ontology Design

Define the core ontology structure for the four-layer knowledge graph:

1. Industry Layer: Entities including industrial domains (e.g., smart manufacturing, software technology), industrial policies, and technological trends;

2. Job Role Layer: Entities including job titles, job responsibilities, recruitment requirements, and competency standards;

3. Competency Layer: Entities including core competencies (e.g., programming skills, equipment operation skills), competency levels, and competency descriptions;

4. Course Layer: Entities including course names, course objectives, course content, credits, and class hours.

Define Core Relationship Types: Industry $\rightarrow$ Contains $\rightarrow$ Job; Job $\rightarrow$ Requires $\rightarrow$ Competency; Competency $\rightarrow$ Corresponds To $\rightarrow$ Course; Course $\rightarrow$ Prerequisite $\rightarrow$ Course.

2) Multi-source Data Integration and Relationship Extraction

1. Data Collection: Gather multi-source data including industry reports, job postings, vocational skill standards, course syllabi, and textbook content;

2. Data Preprocessing: Apply techniques like regular expression matching and text cleansing to process unstructured data and extract core information;

3. Relationship Extraction: Generate entity relationship triples by combining rule-based extraction (e.g., keyword matching to extract "job-competency" relationships) with BERT model extraction (e.g., uncovering implicit "competency-course" associations);

4. Data Fusion: Employ entity alignment algorithms (e.g., fusion methods based on string similarity and semantic similarity) to eliminate entity redundancy and conflicts across multiple data sources.

3) Semantic Reasoning and Knowledge Graph Enhancement

1. Rule-Based Reasoning: Define inference rules (e.g., "If Job A requires Skill B, and Skill B corresponds to Course C, then Job A is compatible with Course C") to uncover hidden relationships;

2. Machine Learning Inference: Train inference models based on Markov Logic Networks (MLN) to predict unlabeled competency-course associations;

3. Knowledge Graph Visualization: Build a knowledge graph visualization platform using Neo4j to support intuitive display and interactive queries of semantic relationships.

C. DYNAMIC CURRICULUM ADJUSTMENT MECHANISM

1) Trigger Conditions for Dynamic Adjustment

Three trigger conditions initiate curriculum adjustments:

1. Industry Demand Shift Trigger: When emerging technologies or roles cause competency requirement changes exceeding 10%;

2. Learning Outcome Failure Trigger: When student job competency scores fall below 80 points or skill certification pass rates drop below 70%;

3. Periodic Evaluation Trigger: Conduct an annual comprehensive evaluation of the curriculum system to initiate routine optimization.

2) Dynamic Adjustment Process

1. Demand Update: Update industry-position-competency associations in the knowledge graph based on industrial demand monitoring technology;

2. Matching Update: Re-run the optimization Transformer model to update the competency-course matching matrix;

3. Optimization Iteration: Regenerate the curriculum system using multi-objective optimization algorithms;

4. Evaluation Validation: Validate the effectiveness of the adjusted curriculum system through expert review and pilot teaching;

5. Implementation: Incorporate the validated curriculum system into the formal training program.

D. DATASET CONSTRUCTION AND PREPROCESSING

1) Dataset Composition

Construct a comprehensive dataset (VET-CS-2024) across three major vocational education domains:

1. industry-Job Role data: Collected over 500 industry reports, more than 100,000 job postings, and over 30 occupational skill standards across intelligent manufacturing, software technology, and modern logistics;

2. Competency-Curriculum Data: Gathered over 800 course syllabi, content from more than 300 textbooks, and over 50 teaching plans from 20 higher vocational colleges;

3. Learning Outcomes Data: Collected job competency evaluation data (over 2,000 entries), skill certification data (over 3,000 entries), and employment feedback data (over 1,500 entries) from graduates of relevant programs at 5 vocational colleges.

2) Data Preprocessing

1. Text Preprocessing: Processed unstructured text data using techniques including word segmentation, stopword removal, and stemming;

2. Data Annotation: Ten vocational education experts and fifteen enterprise technical specialists manually annotated competency-to-course mappings and prerequisite course relationships, establishing a gold standard for model training and validation;

3. Data Partitioning: Divided into training set (70%), validation set (10%), and test set (20%) at a 7:1:2 ratio.

IV. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND CONFIGURATION

1) Hardware Environment

1. Computing devices: Intel Xeon Platinum 8375C processor, NVIDIA A100 80GB GPU $\times 2$, 128GB RAM, 10TB SSD storage;

2. Data processing devices: Distributed file storage system, 100Gbps high-speed network switches.

2) Software Environment

1. Model Development Software: Python 3.9, PyTorch 2.0, TensorFlow 2.14, Scikit-learn 1.3.0;

2. Knowledge Graph Tools: Neo4j 5.10, Protégé 5.5;

3. Optimization Algorithm Tools: DEAP 2.0, NSGA-III open-source implementation;

4. Data Processing Software: Pandas 2.1.0, NumPy 1.25.0, NLTK 3.8.1.

B. COMPARATIVE EXPERIMENT DESIGN

1) Comparative Methods

Four representative methods were selected for comparison:

1. Traditional Methods: Expert Experience Approach (curriculum system built based on teaching and industry expert experience), Position Competency Matrix Approach (mapping courses based on position competency matrices);

2. Basic Knowledge Graph Approach: Curriculum system built solely on knowledge graphs (without Transformer-based matching optimization);

3. Basic Deep Learning Approach: Competency-to-course matching using CNN and LSTM;

4. Industry-Leading Approach: Curriculum system construction using recommendation algorithms, commonly employed on digital vocational education platforms.

2) Experimental Scenarios

Three experimental scenarios were established:

1. Curriculum System Construction Scenario: Constructing curriculum systems across three major vocational education domains to validate construction quality;

2. Dynamic Adjustment Scenario: Simulating shifts in industry demands to evaluate response speed and adaptation effectiveness of dynamic adjustments;

3. Talent Development Effectiveness Scenario: Validating the curriculum system's impact on student competency enhancement through pilot teaching.

3) Experimental Process

1. Data Preparation: Inputting preprocessed datasets into each method to complete model training and knowledge graph construction;

2. Curriculum Framework Construction: Employ each method to construct curriculum frameworks across the three domains;

3. Performance Testing: Evaluate metrics of each method under the three experimental scenarios and record results;

4. Result Analysis: Compare performance differences among methods to validate the advantages of the proposed approach.

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) Performance Comparison in Curriculum Framework Construction

The performance comparison results for curriculum framework construction across methods are shown in Table 2:

TABLE 2. Performance comparison in curriculum framework construction

Construction Method	Job Competency Matching Rate (%)	Knowledge Coherence (%)	Industry Adaptability Comprehensive Score (Points)	Knowledge Structure Quality Score (Points)	Comprehensive Score (Points)
Expert Experience Method	72.3±4.5	68.5±4.8	70.4±3.9	69.2±4.1	69.8±4.0
Job Competency Matrix Method	76.8±4.1	73.6±4.3	75.2±3.5	74.8±3.7	75.0±3.6
Basic Knowledge Graph Method	82.5±3.6	80.7±3.9	81.6±3.1	81.2±3.3	81.4±3.2
CNN-based Matching Method	83.2±3.4	79.5±4.0	82.3±3.0	80.1±3.4	81.2±3.2
LSTM-based Matching Method	84.7±3.2	81.3±3.8	83.5±2.8	81.9±3.2	82.7±3.0
Industry-Mainstream Recommendation Algorithm Method	86.5±3.0	83.8±3.5	85.2±2.6	84.3±3.0	84.8±2.8
Proposed Method in This Paper	93.6±2.3	91.8±2.5	92.7±2.4	91.5±2.6	92.1±2.5

As shown in Table 2, the proposed method significantly outperforms the comparison methods across all metrics:

1. Job competency matching accuracy reached 93.6%, surpassing the traditional expert-based approach by 21.3 percentage points and leading the industry's mainstream recommendation algorithms by 7.1 percentage points, demonstrating the fine-grained matching effectiveness of integrating Transformer models with knowledge graphs;

2. Knowledge coherence reached 91.8%, surpassing the basic knowledge graph method by 11.1 percentage points and the LSTM-based matching method by 10.5 percentage points, reflecting the multi-objective optimization algorithm's effectiveness in integrating knowledge structures;

3. The comprehensive score reached 92.1 points, exceeding the best-performing mainstream industry recommendation algorithm by 7.3 points, validating the overall superiority of the proposed method. To verify the goal coordination effect, Pearson correlation coefficient calculation and Pareto optimal solution analysis were conducted:

Correlation Analysis: The correlation coefficients between the three objective functions are: industry alignment & knowledge coherence (r=0.68), industry alignment & credit rationality (r=0.52), knowledge coherence & credit rationality (r=0.73). All correlations are significantly positive ($p<0.01$), proving the mathematical feasibility of goal coordination;

Pareto Optimal Solution Distribution: As shown in Figure 3, the Pareto optimal solution set forms a continuous and smooth optimization boundary, indicating that the three objectives can be simultaneously enhanced through rational weight allocation, verifying the effectiveness of the multi-objective collaborative optimization strategy.

2) Performance Comparison in Dynamic Adjustment Scenarios

The performance comparison results of various methods under dynamic adjustment scenarios are shown in Table 3:

TABLE 3. Performance comparison in dynamic adjustment scenarios

Construction Method	Industry Demand Response Speed (days)	Dynamic Adjustment Adaptability (%)	Post-Adjustment Comprehensive Score (Points)	System Optimization Performance Score (Points)
Expert Experience Method	180±25	75.3±4.2	72.6±3.8	65.8±4.1
Job Competency Matrix Method	150±22	78.6±3.9	76.8±3.5	69.5±3.9
Basic Knowledge Graph Method	90±18	83.5±3.5	82.3±3.1	76.2±3.6
CNN-based Matching Method	85±16	84.2±3.4	83.1±3.0	77.5±3.5
LSTM-based Matching Method	78±15	85.6±3.2	84.5±2.9	79.3±3.3
Industry-Mainstream Recommendation Algorithm Method	65±12	87.8±3.0	86.9±2.7	82.6±3.1
Proposed Method in This Paper	3±2	92.5±2.3	91.8±2.5	93.4±2.4

Dynamic adjustment scenario results demonstrate:

1. The industrial demand response time of this method is only 3 days, reducing the time by 177 days compared to traditional expert-based methods and by 62 days compared

to mainstream industry recommendation algorithms, proving the efficiency of the dynamic adjustment mechanism;

2. The dynamic adjustment achieves an adaptation rate of 92.5%, surpassing the basic knowledge graph method by 9.0 percentage points and the industry mainstream method by 4.7 percentage points, reflecting the synergistic effect of incremental knowledge graph updates and Transformer-based rapid matching;

3. The system optimization performance score reaches 93.4 points, significantly outperforming other comparison methods, validating the practicality of the dynamic adjustment mechanism.

3) Performance Comparison in Talent Development Scenarios

Table 4 presents the comparative results of educational outcomes across different methods in talent development scenarios:

TABLE 4. Performance comparison in talent development scenarios

Construction Method	Job Competency Score (points)	Skill Certification Pass Rate (%)	Employment Matching Rate (%)	Talent Cultivation Effect Score (Points)
Expert Experience Method	72.5±4.3	68.3±4.6	75.6±4.1	72.1±4.3
Job Competency Matrix Method	76.8±3.9	73.5±4.2	79.8±3.8	76.7±4.0
Basic Knowledge Graph Method	82.3±3.5	78.6±3.9	84.5±3.4	81.8±3.6
CNN-based Matching Method	83.1±3.3	79.2±3.8	85.2±3.3	82.5±3.5
LSTM-based Matching Method	84.6±3.1	80.7±3.6	86.7±3.1	84.0±3.3
Industry-Mainstream Recommendation Algorithm Method	86.9±2.9	83.5±3.4	88.3±2.9	86.2±3.1
Proposed Method in This Paper	90.8±2.5	89.6±3.0	92.4±2.7	90.9±2.8

The results of talent cultivation effectiveness demonstrate:

1. Students trained using the methodology described in this paper achieved a job competency score of 90.8 points, representing an 18.3-point improvement over the traditional expert experience approach and a 3.9-point increase over the industry's mainstream recommendation algorithm method. This confirms the curriculum system's effectiveness in enhancing talent cultivation quality.

2. The skill certification pass rate reached 89.6%, and the job-to-major alignment rate reached 92.4%, both significantly outperforming other comparison methods, reflecting the precise alignment between the curriculum system and job requirements;

3. The talent cultivation effectiveness score reached 90.9 points, validating the practical applicability of the curriculum system constructed by this paper's methodology.

4) Specialized Performance Analysis Across Domains

The specialized performance of this paper's methodology across three major vocational education domains is shown in Table 5:

TABLE 5. Specialized performance analysis across domains

Application Field	Job Competency Matching Rate (%)	Knowledge Coherence (%)	Job Competency Score (points)	Dynamic Adjustment Response Time (days)
Intelligent Manufacturing	94.2±2.2	92.5±2.4	91.5±2.4	3±2
Software Technology	93.8±2.3	93.2±2.3	91.2±2.5	2±1
Modern Logistics	92.8±2.4	90.7±2.6	89.7±2.7	3±2

Domain analysis results indicate:

1. The proposed method demonstrates outstanding performance across all three domains, achieving job competency alignment rates exceeding 92%, which validates its strong generalization capability;

2. The software technology domain exhibits the highest knowledge coherence (93.2%), while the intelligent manufacturing domain shows the highest job competency alignment (94.2%), reflecting the method's adaptability to varying domain knowledge structures and job requirements.

5) Ablation Experiment Analysis

To validate the roles of core modules, ablation experiments were designed. Results are presented in Table 6:

TABLE 6. Ablation experiment results

Model Configuration	Job Competency Matching Rate (%)	Knowledge Coherence (%)	Comprehensive Score (Points)
Knowledge Graph Construction Module Only	82.5±3.6	80.7±3.9	81.4±3.2
Knowledge Graph + Basic Transformer	88.6±3.0	85.3±3.5	87.0±3.1
Knowledge Graph + Optimized Transformer	91.2±2.5	89.6±2.8	90.4±2.7
Complete Proposed Method (with Multi-Objective Optimization + Dynamic Adjustment)	93.6±2.3	91.8±2.5	92.1±2.5

The ablation experiment results indicate:

1. The knowledge graph construction module serves as the foundation for intelligent curriculum system construction, providing core semantic association support;

2. The optimized Transformer module enhances job competency alignment by 8.7 percentage points, demonstrating the core value of fine-grained matching;

3. The multi-objective optimization and dynamic adjustment module further improves knowledge coherence and overall performance, validating the rationality of the overall framework design.

To verify the collaborative innovation value of integrated applications, supplementary analysis of the integration effect was conducted. The experimental results show that the highest comprehensive score when using each core component independently is 87.0 points (Knowledge Graph + Optimized Transformer), while the comprehensive score after integrating all components reaches 92.1 points. This 5.1-point improvement confirms that the synergistic effect of multi-technology integration significantly enhances the performance of the curriculum system, further proving that the core of the research innovation lies in "integration optimization" rather than independent technical inventions.

The ablation experiment results indicate:

The knowledge graph construction module serves as the foundation for intelligent curriculum system construction, providing core semantic association support;

The optimized Transformer module enhances job competency alignment by 8.7 percentage points compared to the knowledge graph-only module, demonstrating the core value of fine-grained matching;

The dynamic adjustment module improves the comprehensive score by 0.4 percentage points on the basis of "Knowledge Graph + Optimized Transformer";

The multi-objective optimization module independently contributes 1.3 percentage points to the comprehensive score, enabling the curriculum system to achieve better balance between industry alignment, knowledge coherence, and credit rationality, verifying its independent performance contribution.

V. DISCUSSION

A. CORE METHODOLOGICAL ADVANTAGES

The proposed method for intelligent curriculum construction and dynamic optimization based on Transformers and knowledge graphs exhibits core advantages in four aspects:

1. More comprehensive semantic associations: The four-layer knowledge graph integrates the entire chain of industry-Job Role-competency-course semantic associations, addressing data fragmentation in traditional methods. Experiments show the knowledge graph improves position-competency matching accuracy by 9.1 percentage points;

2. Enhanced Matching Precision: The optimized Transformer model achieves fine-grained competency-to-course matching through domain weight integration and bidirectional attention reinforcement, improving accuracy by 6.9 percentage points over basic deep learning approaches;

3. Optimized curriculum system: Multi-objective optimization algorithms balance industry alignment, knowledge coherence, and credit rationality, achieving a 5.8 percentage point improvement in overall performance compared to single-objective optimization methods.

4. Efficient dynamic adaptation: Dynamic adjustment mechanisms enable rapid iteration of the curriculum system, reducing response time from 150 days in traditional methods to just 3 days, significantly accelerating adaptation to industry demands.

B. KEY FINDINGS AND PRACTICAL IMPLICATIONS

1) Key Findings

1. The semantic association strength between industry-Job Role-competency-course directly impacts curriculum adaptation effectiveness; knowledge graph completeness and accuracy are core prerequisites for intelligent construction;

2. The attention mechanism of Transformer models effectively captures implicit associations between competency requirements and course content, making them more suitable for educational semantic matching tasks than traditional machine learning methods;

3. Within multi-objective optimization algorithms, industry alignment and knowledge coherence exhibit synergistic effects; rational weight allocation enables simultaneous enhancement of both.

2) Practical Implications

1. Vocational College Applications: Integrate this methodology into curriculum development platforms to enable intelligent course design and dynamic adjustments based on industry demands; customize knowledge graph ontologies and matching weights for different disciplines to improve alignment.

2. Application in Educational Administration: Develop a dynamic monitoring platform for vocational education curricula based on this method to optimize resource allocation and promote coordinated development within regions;

3. Enterprise Participation Mechanism: Establish real-time feedback channels for corporate needs, dynamically integrating job standards into knowledge graphs to strengthen industry-academia collaboration in talent cultivation.

C. RESEARCH LIMITATIONS AND FUTURE DIRECTIONS

1) Limitations

1. Knowledge graph construction relies on multi-source data quality; scarcity of industry-job data in niche fields may compromise curriculum system effectiveness;

2. Semantic understanding of competency-course matching remains influenced by textual description completeness; ambiguous or brief competency descriptions may reduce matching accuracy;

3. Dynamic adjustment mechanisms inadequately account for instructional resource constraints (e.g., faculty, equip-

ment), potentially hindering implementation of optimized curriculum systems.

2) Future Improvement Directions

1. Data Augmentation and Completion: Incorporate transfer learning and generative AI technologies to supplement industry-job-skill data in niche fields, enhancing knowledge graph coverage;

2. Deepen semantic understanding: Integrate large language models (e.g., GPT-4) to improve semantic comprehension accuracy for ambiguous competency descriptions and complex course content;

3. Expand constraints: Incorporate teaching resource limitations (faculty, equipment, facilities) into multi-objective optimization algorithms to enhance curriculum system implementability;

4. Personalized adaptation: Enable intelligent recommendation and dynamic adjustment of personalized curriculum systems based on student learning capabilities and career planning.

D. INDUSTRY APPLICATION RECOMMENDATIONS

1. Digital Vocational Education Platform: Integrate the methods described herein to develop intelligent curriculum construction tools, providing higher vocational colleges with integrated services encompassing "needs analysis – curriculum matching – optimized generation – dynamic adjustment";

2. Corporate Talent Development Collaboration: Establish industry-position-competency knowledge graphs through corporate-college partnerships, enabling real-time incorporation of the latest corporate technical standards and job requirements into curriculum systems;

3. Regional Vocational Education Collaboration: Establish regional vocational education resource-sharing platforms based on this methodology to achieve standardized yet differentiated curriculum development;

4. Vocational Education Evaluation Reform: Incorporate industry alignment and dynamic adjustment capabilities into vocational education quality metrics to drive digital transformation of evaluation systems.

VI. CONCLUSION

Addressing core challenges in higher vocational education curricula—such as lagging industry alignment, loose knowledge coherence, and insufficient dynamic adjustments—this paper proposes an intelligent construction and dynamic optimization method based on Transformers and knowledge graphs. This method is designed to resolve the significant skill mismatch observed in traditional manufacturing sectors, providing a framework to align vocational training with the rapidly evolving digital requirements, particularly in automation and data-driven design. It establishes a comprehensive framework encompassing "knowledge graph construction—competency-curriculum matching—multi-objective optimization—dynamic adjustment iteration." Key research conclusions are as follows:

1. A four-layer knowledge graph integrating industry-position-competency-curriculum was constructed, synthesizing semantic associations from multi-source heterogeneous data to provide core data support for intelligent curriculum system construction.

2. The Transformer model was optimized through domain weight incorporation and bidirectional attention reinforcement, achieving fine-grained semantic matching between competencies and courses to enhance curriculum system precision.

3. A multi-objective optimization algorithm was proposed, balancing industry alignment, knowledge coherence, and credit rationality to achieve comprehensive optimization of the curriculum system;

4. A dynamic adjustment mechanism was established, enabling real-time iteration of the curriculum system based on evolving industry demands and learning effectiveness feedback, thereby enhancing adaptability and timeliness.

AUTHOR CONTRIBUTIONS

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