Intelligent Assessment and Improvement System for Teachers' AI Literacy in Higher Vocational Education: Architecture, Algorithms and Applications

Shijian Gao[a,*], Hui Liu[b], Junhong Yuan[c]

Yunnan Forestry Technological College, Kunming, Yunnan 650051, China

[a]2022010011@ynftc.edu.cn, [b]2021020468@ynftc.edu.cn, [c]yjhmagic@aliyun.com

Abstract. The rapid development of artificial intelligence technology is profoundly reshaping the ecology of vocational education, and the artificial intelligence literacy of teachers in higher vocational colleges has become a key factor driving the integrated innovation of "Artificial Intelligence + Vocational Education". However, the current AI literacy of teachers in higher vocational colleges generally presents the status of "advanced awareness, insufficient knowledge, weak skills and vague ethics", and there is a lack of a scientific, dynamic and personalized assessment and training system. Based on a systematic combing of the connotation and framework of AI literacy, and in view of the characteristics of "industry-education integration and practice orientation" of higher vocational education, this paper proposes a system framework integrating intelligent assessment, accurate diagnosis and personalized improvement. The core algorithms integrate behavior analysis based on multi-source data, a fuzzy comprehensive evaluation model based on the competency framework, and a personalized learning path planning algorithm combining collaborative filtering and knowledge graph. Finally, the typical application scenarios of the system in the professional development of teachers in higher vocational colleges, curriculum teaching reform and industry-education collaborative innovation are discussed, which provides a set of feasible technical solutions and practical paths for higher vocational colleges to systematically improve teachers' AI literacy and empower the digital transformation of education.

Keywords: AI Literacy, Higher Vocational Colleges, Intelligent Assessment, Personalized Recommendation, System Architecture.

1 Introduction

With the advancement of policies such as the Three-Year Action Plan for Teaching and Research Work in Vocational Education (2025-2027) and the continuous emergence of typical application scenarios of "Artificial Intelligence + Higher Education", empowering the high-quality development of vocational education with artificial intelligence has become a clear direction[1]. As the key subject of cultivating technical and skilled

I. A. Khan et al. (eds.), *Proceedings of the 2026 5th International Conference on Educational Innovation and Multimedia Technology (EIMT 2026)*, Atlantis Highlights in Social Sciences, Education and Humanities 51,
https://doi.org/10.2991/978-94-6239-691-3_57

talents, teachers in higher vocational colleges directly determine the depth and effect of the integration of artificial intelligence and vocational education with their AI literacy level[2]. Studies have shown that the overall level of AI literacy of teachers in higher vocational colleges is currently low, with an existing "digital divide", and the training system is facing challenges such as vague goals, imbalance between supply and demand, and ethical risks[3,4].

Existing researches mostly focus on the definition of connotation, framework construction and current situation investigation of AI literacy[5,6]. Although many improvement strategies have been proposed[7,8], there is a general lack of operable and intelligent technical system support that connects the closed loop of "assessment" and "improvement".

Traditional non-intelligent or semi-intelligent methods represented by conventional Learning Management Systems (LMS) and offline training modes have inherent limitations in the cultivation of teachers' AI literacy: First, the assessment function is single, mostly limited to the result evaluation of course completion and simple test scores, unable to realize multi-dimensional dynamic evaluation of literacy connotation, and lack of in-depth diagnostic function for competency weaknesses; Second, the resource supply adopts a unified "top-down" push mode, which cannot match the personalized needs of teachers with different foundations, different disciplines and different development goals, resulting in the prominent "one-size-fits-all" problem; Third, the learning process is isolated, lacking the mechanism to associate assessment results with subsequent improvement paths, and failing to form a closed loop of "assessment-diagnosis-improvement-feedback", with serious disconnection between evaluation and training; Fourth, it is difficult to realize continuous tracking and iterative optimization of teachers' professional development process, and the feedback of training effect is seriously lagging. Therefore, it is of important theoretical value and practical urgency to construct a system that can dynamically assess, accurately diagnose and intelligently recommend improvement resources.

2 Core Concepts and Framework Foundation

In this paper, the AI literacy of teachers in higher vocational colleges is defined as: a comprehensive set of competencies for teachers in higher vocational colleges to understand, apply, evaluate and manage artificial intelligence technologies and resources effectively, responsibly and in order to adapt to the reform of vocational education in the intelligent era, so as to promote teaching, scientific research, social services and professional self-development. Its core elements shows in Table 1:

Table 1. Core elements of AI Literacy.

Elements	Connotation
AI Awareness and Cognition	Understanding of the value and limitations of AI technology and its impact on vocational education.
AI Knowledge and Skills	Mastery of basic AI principles and tools, as well as application skills in professional teaching (e.g., prompt engineering).

Elements	Connotation
AI Thinking and Innovation	The ability to solve problems in teaching and professional fields by using computational thinking and critical thinking.
AI Ethics and Security	The ability to abide by ethical norms, protect data privacy and security, and identify and avoid biases when applying AI.
AI Industrial Application Literacy	The ability to combine AI technology with the cutting-edge of industrial development to cultivate students' post adaptability and transfer innovation ability.

3 System Architecture

The system adopts the design concept of layering and microservices to ensure scalability, flexibility and reliability. The overall architecture is shown in Figure 1, which is divided into four layers: Data Perception Layer, Intelligent Assessment Layer, Personalized Recommendation Layer and Feedback and Optimization Layer.

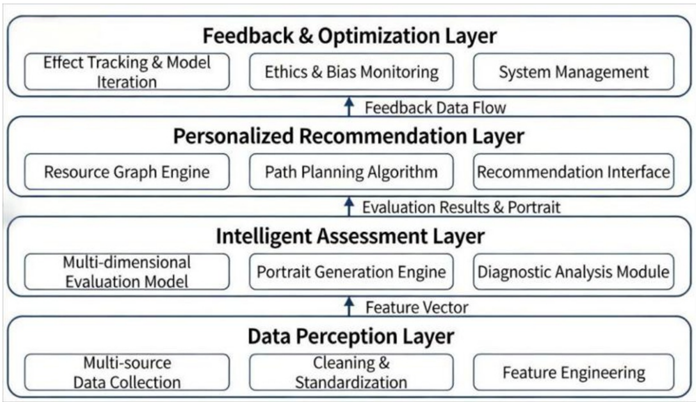

Fig. 1. System Architecture.

3.1 Data Perception Layer

This layer is responsible for collecting original data related to teachers' AI literacy from multiple dimensions and sources, and conducting preprocessing on the data. The data includes: behavioral data (e.g., login data of teachers on online learning platforms, course learning records, tool usage data, interactive discussion records); achievement data (e.g., instructional design schemes, teaching videos, developed AI teaching resources, scientific research papers, patents, enterprise practice reports); self-assessment and peer assessment data (e.g., periodic self-assessment questionnaires based on scales, peer review results); and contextual data (e.g., affiliated major, course nature, school-enterprise cooperation project information).

The data processing workflow is: Data Cleaning -> Missing Value Treatment -> Standardization -> Feature Engineering. Key features include: tool usage frequency, prompt complexity, alignment of generated content with teaching objectives, depth of AI integration in teaching cases, and frequency of participation in AI-related teaching and research activities.

3.2 Intelligent Assessment Layer

This layer is the core of the system, responsible for transforming raw features into interpretable literacy assessment results. It includes the following three modules:

1.Multi-dimensional Assessment Model: Constructs an assessment indicator system based on the five dimensions defined in Section 2. Each dimension comprises several secondary and tertiary observable indicators.

2.Profile Generation Engine: Synthesizes quantitative scoring and qualitative analysis to generate a "Digital AI Literacy Profile" for each teacher, visualized in forms like radar charts and competency maps.

3.Diagnostic Analysis Module: Compares individual teacher profiles against group benchmarks or development goals for their major/institution, identifying strengths and areas for improvement, and generating preliminary diagnostic reports.

3.3 Personalized Recommendation Layer

Based on the diagnostic results from the assessment layer, this layer dynamically plans personalized development paths for teachers. It contains the following three modules:

1.Resource Graph Engine: Constructs an "AI Literacy Knowledge-Skill-Resource" graph. Nodes include: knowledge points (e.g., Machine Learning Basics), skill points (e.g., Data Visualization), micro-courses, case libraries, tool tutorials, academic literature, industry reports, etc. Edges represent prerequisite, correlational, or similarity relationships between nodes.

2.Path Planning Algorithm: Taking the teacher's current "profile" as the starting point and the target competency model as the endpoint, it searches for the optimal or near-optimal learning and practice path on the resource graph.

3.Recommendation Interface: Transforms the planned path into a concrete, sequenced list of recommended learning tasks, practical projects, and community activities, pushed to the teacher through the front end.

3.4 Feedback Optimization Layer

This layer enables the system's self-evolution and closed-loop management. It performs the following three functions:

1.Effect Tracking: Monitors changes in teacher behavior after accepting recommendations (e.g., completion rates, score improvements, new outcome production) to evaluate recommendation effectiveness.

2.Model Iteration: Uses feedback data to optimize the weights of the assessment model and the parameters of the recommendation algorithm.

3.Ethical Monitoring: Continuously detects potential biases in the assessment process to ensure fairness.

4 Core Algorithm Models

4.1 Intelligent Assessment Algorithm Based on Multi-dimensional Weighting and Fuzzy Comprehensive Evaluation

The assessment problem has the characteristics of multi-indicator and fuzziness. Let the set of assessment dimensions be $D=\{d_1,d_2,\ldots,d_5\}$., corresponding to the five dimensions in Section 2 respectively. The indicator set under each dimension d_i is $I_i=\{i_{i1},i_{i2},\ldots\}$.

Step 1: Indicator quantification and normalization. For quantitative indicators (e.g., learning duration), normalization is performed directly; for qualitative indicators (e.g., instructional design scores), normalization is conducted after expert scoring or text sentiment analysis/topic matching degree calculation, resulting in indicator values $v_{ij}\in[0,1]$.

Step 2: Weight Determination. Using the Analytic Hierarchy Process (AHP) combined with the Delphi method, experts in vocational education and AI education determine the weights for each dimension and indicator. Let the dimension weight vector be $W_D=(w_1,w_2,w_3,w_4,w_5)$, satisfying $\sum w_i=1$. The weight vector for indicators under dimension d_i is W_{I_i}.

Step 3: Dimension score calculation. For each dimension d_i, its score S_i is the weighted sum of its subordinate indicators:

$$S_i=\sum_j (w_{ij}\cdot v_{ij}) \tag{1}$$

where w_{ij} is the component of W_{I_i}.

Step 4: Fuzzy comprehensive evaluation. Define the comment set V = {Excellent, Good, Medium, To be improved}. Convert each dimension score S_i into a membership vector for the comment set through a membership function (e.g., trapezoidal membership function):

$$R_i=(r_{i1},r_{i2},r_{i3},r_{i4}) \tag{2}$$

Then the fuzzy evaluation matrix is:

$$R=\begin{bmatrix}R_1\\R_2\\R_3\\R_4\\R_5\end{bmatrix} \tag{3}$$

The comprehensive assessment result vector B is:

$$B=W_D\circ R \tag{4}$$

The intelligence assessment algorithm shown in Algorithm 1:

Algorithm 1: Intelligent assessment algorithm

```
comprehensive_assessment (teacher_data, weight_dim, weight_indicators):
    dimension_scores = []
    for dim_idx, dim in ENUMERATE(DIMENSIONS):
        indicator_values = extract_indicators(teacher_data, dim)
        # Calculate the raw score for the dimension
        raw_score = 0
        for  each pair in zip(weight_indicators[dim_idx], indicator_values):
            w = first element of pair
            v = second element of pair
            raw_score = raw_score + (w * v)
        append raw_score to dimension_scores
    # Fuzzification
    evaluation_matrix = []
    for score in dimension_scores:
        membership_vector = calculate_membership(score)  # Returns the membership degree of
score
        append membership_vector to evaluation_matrix
    # Comprehensive Evaluation
    B = fuzzy_synthesis(weight_dim, evaluation_matrix)
    final_level = determine_level(B)
    return dimension_scores, final_level, B
```

4.2 Personalized Path Recommendation Algorithm Integrating Collaborative Filtering and Knowledge Graph

The goal of this algorithm is to recommend a learning path sequence *Path = {resource$_1$, resource$_2$, ..., resource$_n$}* for teacher *T*, leading from their current state to the target state.

Step 1: Construct Teacher-Resource Interaction Matrix and Identify Similar Groups. Build a matrix *M* based on historical data, with rows representing teachers and columns representing learning resources. Values indicate interaction strength (e.g., completion rate, rating). For target teacher *T*, use User-based Collaborative Filtering (User-CF) to find a group *G* of teachers most similar to *T* based on their AI literacy dimension score vectors.

Step 2: Initial Resource Rating Prediction. For a resource *r* in the resource graph that teacher *T* has not accessed, the potential interest score $\hat{r}_{T,r}$ is predicted by using the interaction of the similar group *G* with the resource:

$$\hat{r}_{T,r}=\bar{r}_T+\frac{\sum_{U\in G} sim(T,U)\cdot(r_U-\bar{r}_U)}{\sum_{U\in G}|sim(T,U)|} \tag{5}$$

where *sim(T, U)* is the cosine similarity based on literacy dimension scores, $v_{U,r}$ is the interaction value of teacher *U* for resource *r*, $\bar{v}$ *is* interaction average value.

Step 3: Path Planning Based on Knowledge Graph. Treat the resource graph as a directed graph G_{kg} = (*V*, *E*). Map the teacher's current state to a set of mastered nodes

V_{known} in the graph. The target state, determined by assessment weaknesses, is mapped to a set of target nodes V_{target} . this step includes two parts:

1. Sub-goal Prioritization: Prioritize targets in V_{target} based on the diagnostic report.
2. Path Search: For each high-priority target node $t \in V_{target}$, use an improved A* algorithm on G_{kg} to find the least-cost path from any node in V_{known} to t. The path cost *cost* integrates the estimated learning duration of resources (from metadata), the gap between resource difficulty and the teacher's current level, $(1\text{-}\hat{p}_{T,r})$as an interest cost (lower interest leads to higher cost), and ensures the path satisfies prerequisite constraints (defined by graph edges).

Step 4: Path Integration and Sequencing. Integrate the multiple paths found for different sub-goals, remove duplicates, and sort/schedule them according to learning logic (basic before applied, theory before practice) and estimated total workload, forming the final personalized learning plan.

Pseudocode for the path search algorithm shown in Algorithm 2:

Algorithm 2: path search algorithm

```
Function recommend_path(teacher_profile, target_skills, resource_graph, predicted_ratings):
    # Map the teacher's current skills to nodes in the graph
    known_nodes = map_to_nodes(teacher_profile.current_skills)
    # Map the target skills to nodes in the graph
    target_nodes = map_to_nodes(target_skills)
    # Initialize an empty list to store the planned paths
    planned_path = []
   # For each target node, find the best path from known nodes
    for each target in prioritize(target_nodes):
        #Initialize variables to store the best path and its cost
        best_path = None
        min_cost = infinity
        # For each known node, find the path to the target node
        for each start in known_nodes:
            (path, cost) = a_star_search(start, target, resource_graph, cost_function, predict-
ed_ratings)
            # If the found path has a lower cost, update the best path
            if cost < min_cost:
                min_cost = cost
                best_path = path
        # If a best path is found, add it to the planned path
        if best_path is not None:
            planned_path.append(best_path)
    # Integrate and schedule all the best paths to generate the final sequence
    final_sequence = integrate_and_schedule(planned_path)
    # Return the final sequence
    return final_sequence
```

5 System Implement and Application

5.1 System Implement

The system's development and runtime environment encompasses a comprehensive technology stack across multiple domains. For front-end development, the framework combines Vue3 with TypeScript, enhanced by Element Plus UI components and ECharts for data visualization. The back-end infrastructure leverages Spring Boot and Spring Cloud for microservices architecture, integrated with MyBatis-Plus for efficient database operations. Algorithm implementation is conducted in Python, utilizing PyTorch for deep learning, Scikit-learn for traditional machine learning, and Hugging Face Transformers for natural language processing tasks. The database ecosystem includes MySQL 8.0 for structured data management, MongoDB 6.0 for unstructured data storage, and Neo4j 5.0 for knowledge graph representation. Deployment is standardized on CentOS 7.9 servers, with Docker containerization for application isolation and Kubernetes clusters for container orchestration and management.

5.2 System Application

This system can be deeply integrated into the whole process of professional development of teachers in higher vocational colleges, with specific applications including:

1. Precise management of on-the-job training: Replacing the traditional "one-size-fits-all" training with precise "one plan per person" training. School managers can grasp the overall situation of teachers' AI literacy and scientifically formulate training plans.

2. Intelligent support for teaching practice: When teachers design lesson plans for "Artificial Intelligence + Professional Courses", the system can recommend successful cases based on dual-dimensional similarity matching model, prompt engineering skills and assessment tools. Among them, the similarity definition of the cases includes two dimensions: explicit discipline label matching and deep teaching feature matching . This model can not only provide accurate reference for the teaching innovation of the same discipline, but also realize high-value cross-disciplinary case recommendation, helping teachers break the discipline barrier and draw on the innovative experience of different fields.

3. Construction of an industry-education integration bridge: The system can introduce industrial AI application cases and technical standards as special resource nodes to help teachers update their industrial AI cognition, feed back into teaching, and assist in cultivating students meeting the requirements of "digital craftsmen".

4. Incubation of teaching and research innovation communities: Discover teachers with similar improvement goals or complementary skills through the system, intelligently form cross-professional teaching and research teams, and jointly solve difficult problems in the application of AI in teaching.

6 Conclusion and Prospect

Aiming at the practical pain points in the development of AI literacy of teachers in higher vocational colleges, this paper proposes a complete architecture of an intelligent assessment and improvement system, and designs its core assessment and recommendation algorithms in detail. The system integrates key technologies such as multi-source data analysis, fuzzy mathematics, collaborative filtering and knowledge graph, aiming to realize the accuracy of assessment, personalization of recommendation and sustainability of development.

From the perspective of theoretical connotation, this study is rooted in the core principles of teacher professional development theory, personalized learning theory and constructivist learning theory, and constructs a technical logic system that is coupled with the growth law of vocational education teachers. The system breaks the traditional "top-down" teacher training mode, and reconstructs the internal mechanism of teachers' professional development ecosystem from three aspects: First, it establishes a dynamic perception mechanism of teachers' literacy development, which changes the static and result-oriented evaluation mode in the past, and realizes the full-cycle tracking and dynamic diagnosis of teachers' literacy growth process; Second, it constructs a supply and demand matching mechanism of educational resources centered on teachers' individual needs, which realizes the accurate connection between literacy weaknesses and improvement resources, and provides technical support for the personalized professional development of teachers; Third, it forms a collaborative innovation mechanism of teacher development with complementary advantages, which breaks the isolated learning state of individual teachers, and promotes the ecological aggregation of teacher groups from individual growth to collaborative development.

From the perspective of practical value, the application of this system will promote profound changes in teaching methods and teacher roles in higher vocational education under the background of intelligence. In terms of teaching method reform, the system will promote the transformation of vocational education teaching from "knowledge and skill transfer" to "intelligent enabling and collaborative innovation", and promote the deep integration of AI technology and professional course teaching from sporadic application to systematic reform; it will also drive the teaching evaluation mode to change from the traditional result evaluation to the process evaluation, value-added evaluation and developmental evaluation, and establish a more scientific and comprehensive teacher teaching ability evaluation system. In terms of teacher role transformation, with the support of the system, teachers will be transformed from the traditional "knowledge imparter" to the designer of intelligent teaching scenes, the organizer of collaborative learning, the innovator of industry-education integrated teaching, and the practitioner of AI ethical norms, which is more in line with the core requirements of vocational education reform in the intelligent era for teachers' abilities and roles.

Future work will focus on algorithm optimization,Introducing deep learning models to conduct more refined feature extraction and prediction on teachers' complex behavior patterns; and will explore privacy protection further, studying model training methods based on technologies such as federated learning under the premise of protecting teachers' data privacy; and consider empirical research, deploying the system in pilot colleges, verifying its actual effectiveness through longitudinal follow-up research, and conducting continuous iterative optimization.

Acknowledgments

This work was supported by the institutional project of Yunnan Forestry Technological College "Digital Intelligence Era: Cultivating AI Literacy for Higher Vocational College Teachers and Empowering Teaching Practice" and the second phase of the "Shuang Gao Plan" project of Yunnan Forestry Technological College, under Grant No. YY-YNLZSGJH-SZJX-2025093.

References

1. General Office of the Ministry of Education. Notice on the Action of Empowering Teachers' Development with Digitalization, http://www.moe.gov.cn/srcsite/A10/s7034/202507/t20250704_1196586.html, (2025).
2. Thomas K.F. Chiu, Ismaila T. Sanusi. Define, foster, and assess student and teacher AI literacy and competency for all: Current status and future research direction.Computers and Education Open, https://doi.org/10.1016/j.caeo.2024. 100182, (2024)
3. Nils Knoth, Antonia Tolzin,Andreas Janson, Jan Marco Leimeister. AI literacy and its implications for prompt engineering strategies.Computers and Education: Artificial Intelligence, https://doi.org/10.1016/j.caeai.2024.100225, (2024)
4. Zhao Yimin, Peng Xueqin, Cun Guomei. Artificial Intelligence Literacy: Connotation, Framework, and Evaluation System. Library and Information Service, 2025, 69(13): 83-93. DOI: 10.13266/j.issn.0252-3116.2025.13.007
5. Ravinithesh Annapureddy, Alessandro Fornaroli, and Daniel Gatica-Perez. Generative AI Literacy: Twelve Defining Competencies. https://doi.org/10.1145/3685680 (2025).
6. Zhong B C. What is AI Literacy: Essence, Composition and Evaluation System. Journal of East China Normal University (Educational Sciences), 2024, 42(1): 71-84. DOI:10.16382/j.cnki.1000-5560.2024.01.005
7. Al-Abdullatif, A.M. Modeling Teachers' Acceptance of Generative Artificial Intelligence Use in Higher Education: The Role of AI Literacy, Intelligent TPACK, and Perceived Trust[J]. education science, https://doi.org/10.3390/educsci14111209, (2024)
8. Lérias E, Guerra C, Ferreira P. Literacy in Artificial Intelligence as a Challenge for Teaching in Higher Education: A Case Study at Portalegre Polytechnic University. Information, https://doi.org/10.3390/info15040205, (2024)