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Research on the AI-Driven Personalized Teaching Model for Secondary Vocational Computer Network Technology Courses

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Abstract: Digital transformation and industrial upgrading have put forward new requirements for the precise and personalized training of secondary vocational network technology talents. To address the current problems in secondary vocational computer network course teaching, such as significant differences in students' basic foundations, insufficient adaptability of teaching resources, and rigid learning paths, this study constructs an AI-driven personalized teaching model centered on learner profiles. By collecting multi-source teaching data, the model dynamically builds fine-grained learner profiles. On this premise, it focuses on exploring personalized teaching path generation methods based on reinforcement learning and knowledge graphs, as well as adaptive resource recommendation mechanisms integrating content correlation, collaborative filtering, and sequence patterns. The research aims to form a teaching closed loop of "data perception—profile portrayal—intelligent decision-making—precision intervention", providing a data-intelligence empowered practical path for the teaching reform of secondary vocational specialized courses, so as to improve teaching efficiency, stimulate students' potential, and promote the cultivation of high-quality technical and skilled talents.

Keywords: Artificial intelligence; Computer network technology; Personalized learning; Learner profile; Adaptive recommendation

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1. Introduction

The rapid development of a new generation of artificial intelligence technology is profoundly reshaping the educational ecology. The Guidelines for the Digital Transformation of Vocational Education clearly point out that the in-depth integration of artificial intelligence with education and teaching should be promoted to innovate talent training models. As a major field for cultivating front-line technical and skilled talents, secondary vocational education, especially its specialized courses such as Computer Network Technology, which are highly practical [1] and have rapidly updating knowledge, faces severe challenges. The traditional class teaching system is difficult to adapt to the significant differences in information literacy and cognitive foundations of students upon enrollment. Unified teaching progress and training projects often lead to a polarization phenomenon of "top students lacking room for expansion and underachievers struggling to keep up", seriously hindering the overall improvement of teaching quality [2].

In recent years, personalized learning has become an important trend in the field of educational research. Scholars at home and abroad have achieved fruitful results in learner models [3], adaptive learning systems [4], and other aspects. However, most existing studies focus on general courses in higher education or K12 subject education. Research on personalized teaching for secondary vocational education, especially specialized courses, often remains at the theoretical discussion or macro-design stage [5], lacking a systematic and implementable model that deeply integrates professional characteristics and focuses on specific teaching links (such as path planning and resource recommendation). The Computer Network Technology course has the characteristics of high modularization and clear skill levels [6], and possesses a natural digital teaching environment (such as simulators and online platforms), which provides an ideal application scenario for carrying out data-driven personalized teaching.

2. Overall framework design of the model

Guided by the core concept of "data-driven, intelligent decision-making, precise service, and continuous optimization", this study constructs an AI-driven personalized teaching model for secondary vocational Computer Network Technology courses. The model consists of five closely interconnected layers: data collection and preprocessing layer, learner profile construction layer, intelligent decision-making and service layer, teaching interaction and feedback layer, and environment support and security guarantee layer.

2.1. Data collection and preprocessing layer

As the cornerstone of the model, this layer collects multi-modal data such as learners' static attributes (e.g., entrance scores), dynamic behaviors (e.g., classroom interaction), and learning outcomes (e.g., test scores). Through cleaning, desensitization, standardization, and fusion processing, it eliminates noise and redundancy, ensures data quality, and provides support for building learner profiles [7].

2.2. Learner profile construction layer

As the core of personalized teaching, this layer dynamically builds multi-dimensional and fine-grained profiles relying on high-quality data, combined with education, psychology, data mining, and AI algorithms. It covers knowledge mastery (e.g., understanding of computer network knowledge points), learning abilities (e.g., logical thinking), learning preferences (e.g., resource type tendency), learning goals (e.g., career direction), and potential obstacles. Through data updates and model iterations, it real-time reflects the learning status and provides an accurate user model for subsequent services.

2.3. Intelligent decision-making and service layer

As the "core control center", this layer realizes personalized teaching path generation and adaptive resource recommendation by leveraging AI technology and learner profiles. The former integrates curriculum knowledge graphs and reinforcement learning to plan the optimal learning sequence according to the learner's status; the latter considers resource characteristics, knowledge point correlations, and learning preferences to push resources such as micro-courses and virtual experiments through hybrid models.

2.4. Teaching interaction and feedback layer

As a connecting bridge, relying on intelligent platforms and virtual environments, this layer presents teaching paths and resources, supports interactions such as online learning and virtual training, records feedback data in real-time and returns it to the collection layer to form a closed-loop iteration. Teachers can also review and adjust AI teaching plans to ensure professionalism.

2.5. Environment support and security guarantee layer

This layer provides technical environments (e.g., cloud technology, AI algorithm libraries), platform support (e.g., integration of learning platforms and training systems), and security guarantees (e.g., data encryption, privacy protection) to ensure the safe, stable, and efficient operation of the model.

These five layers support each other and work collaboratively, forming a complete AI-driven personalized teaching ecosystem, aiming to realize the intelligent empowerment of the entire teaching process of secondary vocational Computer Network Technology courses.

3. Generation of personalized teaching paths based on learner profiles

A teaching path refers to the sequence of knowledge units and skill modules that guide students from the starting point to the destination. Traditional paths are fixed, while personalized paths need to be dynamically planned based on learner profiles.

3.1. Construction of a learner profile model for secondary vocational network courses

The learning characteristics of secondary vocational students show significant vocational orientation and practical attributes. The profile model constructed in this study covers four dimensions:

(1) Knowledge and skill dimension: Relying on the curriculum knowledge graph, quantify students' mastery of each knowledge node (e.g., "subnet division", "static routing configuration") through multi-dimensional evaluation methods such as pre-tests, process exercises, and project assessments.

(2) Behavioral characteristic dimension: Analyze students' operation logs on simulated training platforms (e.g., command input frequency, error types, help-seeking times), online video viewing behaviors (including pauses and replays), and forum interactions to identify their operational proficiency, exploration depth, and collaborative tendencies.

(3) Cognitive style dimension: Determine whether students are "active" or "reflective", "sequential" or "global" through a combination of scales and behavioral data—for example, whether they tend to understand the complete principle before practicing or learn while operating.

(4) Career interest dimension: Correlates with professional directions (e.g., network operation and maintenance, network security), and comprehensively considers students' interest and satisfaction in completing different types of training projects (configuration, troubleshooting, design).

The profile is presented in the form of a vector, and a time decay factor is introduced to dynamically reflect the students' latest status.

3.2. Path generation algorithm integrating knowledge graphs and reinforcement learning

This study constructs the content of the Computer Network course into a directed acyclic graph (DAG)-based knowledge graph, where nodes represent knowledge/skill points and edges represent dependency relationships (e.g., learners must first master knowledge related to "IP addresses" before learning "subnet division"). The path generation problem is modeled as a sequential decision-making problem: given the student's current profile state (S_t) and the knowledge graph, the agent needs to select an optimal subsequent learning node (A_t) from the available range.

This study adopts a reinforcement learning framework, specifically using a variant of Deep Q-Network (DQN) to solve the problem. The state space S is defined by the learner profile vector and the set of currently mastered knowledge nodes. The action space A is the set of subsequent knowledge nodes that are currently reachable and not yet fully mastered. The design of the reward function R is the key to solving this problem, which needs to comprehensively consider multi-objective factors:

(1) Mastery reward: Successfully passing the assessment of the target node.

(2) Efficiency reward: Encouraging reaching the mastery state in fewer steps.

(3) Sequence coherence reward: Paths that conform to the dependency relationships of the knowledge graph receive positive incentives.

(4) Style adaptation reward: Planning more linear paths for "sequential" students and allowing more exploratory jumps for "global" students.

Through extensive interaction training with the simulated learning environment, the agent can ultimately generate personalized learning paths that maximize long-term benefits for students with different profile characteristics [7]. In addition, the system pre-sets several expert experience-based path templates for common profile types (e.g., "weak theoretical foundation—strong practical operation ability"), which are used as initial strategies or cold-start schemes for reinforcement learning to improve efficiency and interpretability.

4. Adaptive learning resource recommendation mechanism

A precise learning path needs to be matched with suitable learning resources. This mechanism aims to recommend the most appropriate learning materials for each node on the path from a large number of heterogeneous resources.

4.1. Standardized representation and knowledge correlation of learning resources

Conduct in-depth annotation of resources such as micro-course videos, documents, experimental manuals, virtual simulation training projects, exercises, and cases. Annotation tags include:

(1) core knowledge and skill points (correlated with knowledge graph nodes);

(2) resource types (theoretical explanation, operation demonstration, hands-on practice, comprehensive application);

(3) difficulty levels (basic, advanced, challenging);

(4) estimated learning time;

(5) teaching style (rigorous, vivid). Through annotation, unstructured resources can be mapped to a structured feature space [8].

4.2. Hybrid recommendation model design

A hybrid recommendation strategy is adopted to balance the accuracy, diversity, and novelty of recommendations:

(1) Knowledge graph-based content recommendation: Directly recommend strongly correlated resources according to the knowledge needs of the student's current path node, which is the basis for ensuring

recommendation relevance [9].

(2) Collaborative filtering-based collaborative recommendation: Identify student groups with similar profiles ("similar learners") or similar learning behavior sequences ("similar paths") to the target student, and recommend resources highly evaluated or with significant learning effects by this group. This method can explore potential preferences.

(3) Sequence pattern-based advanced recommendation: Analyze the learning resource access sequence patterns of historically successful students (e.g., students who learned Video A usually proceed to Experiment B next), and recommend the "next most likely needed resource" that matches the target student's current learning progress.

The final recommendation result is generated by merging and sorting multiple recall lists from the above methods according to weights, which can be dynamically adjusted based on resource types. For example, in the skill learning stage, the weight of training resources can be increased.

4.3. Explainable recommendation and teacher collaboration

The system provides a brief explanation for each recommendation, such as "This comprehensive troubleshooting case is recommended because you have mastered the individual skills of VLAN and routing configuration, and students of the same type have performed well in it", to enhance students' trust. At the same time, the system opens a "recommendation management panel" to teachers, who can review, pin, block, or manually add specific resources to the recommendation list based on teaching experience, realizing human-machine collaborative, precise resource delivery.

5. Application scenarios and effect discussion

Taking the core module of "Park Network Construction" as an example, the application of the model is elaborated. Two students with significantly different characteristics are selected—Student A (Knowledge dimension: solid network foundation; Behavioral dimension: cautious operation, good at planning; Interest dimension: prefers the security field) and Student B (Knowledge dimension: weak foundation but strong imitation ability; Behavioral dimension: prefers learning by doing; Interest dimension: prefers the operation and maintenance field). When entering this module, the system generates differentiated paths.

Student A's path: After completing basic configuration tasks, quickly introduce advanced security content such as "access control list configuration" and "firewall policy deployment", and recommend multiple classic security attack and defense simulation cases as extended resources.

Student B's path: The system slows down the theoretical advancement speed, breaks down more sub-task steps, and supports them with a large number of "command configuration demonstration videos" and imitative training projects of the "follow-along" type. After their proficiency improves, it then introduces practical projects related to network monitoring and daily maintenance.

The personalized teaching model is expected to bring significant benefits to students [10], such as improving learning engagement and a sense of achievement through a "one-student-one-plan" approach; for teachers, it will reduce repetitive work, allowing them to focus more on personalized counseling and teaching design optimization [11]; at the same time, the model will accumulate process-oriented teaching data, providing strong support for the continuous improvement of courses [12]. Of course, the implementation of the model also faces challenges such as the completeness and ethics of data collection, the cultivation of teachers' human-machine collaboration capabilities, and the support of school information infrastructure, which need to be promoted in phases and gradually.

6. Conclusion

Focusing on the pain points in the teaching of secondary vocational Computer Network Technology courses, this study proposes an AI-driven personalized teaching model centered on dynamic learner profiles. At the same time, it focuses on explaining the two core implementation mechanisms of the model: the personalized teaching path generation mechanism based on reinforcement learning and the adaptive resource recommendation mechanism based on a hybrid recommendation strategy. This model emphasizes the in-depth integration of data intelligence and educational teaching laws [13], providing a feasible technical implementation approach for teaching students in accordance with their aptitude in large-scale class teaching scenarios [14].

Future research work will mainly focus on the following three aspects: first, conduct quasi-experimental research in real teaching environments to quantitatively evaluate the actual effects of the personalized learning model on students' academic performance, skill improvement, learning attitudes, etc., aiming to improve students' academic achievements; second, explore privacy-preserving computing technologies such as federated learning to realize cross-school and cross-regional model collaborative optimization while protecting students' data privacy; third, extend the personalized learning model to the entire professional curriculum system and explore personalized integrated training paths connected with the training content and assessment standards of vocational skill level certificates [15], so as to promote the all-round development of students.

Disclosure statement

The author declares no conflict of interest.

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