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Research on AI-Based Construction of Personalized Learning Paths in Vocational Education

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ABSTRACT: *With the rapid advancement of artificial intelligence (AI) technology, the digital transformation of education has become a global trend. This study explores how AI can drive the construction of personalized learning paths to address the structural contradiction between "mass cultivation" and "individualized needs" in higher education. The research first analyzes the practical challenges faced by traditional educational models under the "impossible trilemma," including difficulties in identifying individual student differences, low precision in matching teaching resources, and the inadequacy of conventional evaluation systems in adapting to diverse needs. Subsequently, the paper systematically reviews the theoretical foundations supporting personalized learning, such as differentiated instruction, cognitive load theory, and metacognition.The core contribution of this study is a multi-level, adaptive framework for constructing personalized learning paths. This framework employs knowledge graphs for semantic modeling, formulates path optimization as a sequential decision-making problem using reinforcement learning, and integrates multi-algorithm fusion strategies to leverage the strengths of different models. The result is a dynamic, precise learning recommendation system. The findings demonstrate that AI, through building learner profiles, optimizing knowledge adaptation models, and embedding personalized service modules, can provide effective technical solutions and practical paradigms for individualized instruction in large-scale education. This research holds significant theoretical value and practical implications for advancing high-quality educational development.*
Keywords: *artificial intelligence; personalized learning path; educational knowledge graph; reinforcement learning; multi-algorithm fusion*

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I. INTRODUCTION

In his congratulatory letter to the International Conference on Artificial Intelligence and Education, President Xi Jinping emphasized: "Artificial intelligence serves as the key driver of the new round of scientific and technological revolution and industrial transformation, profoundly reshaping production, lifestyles, and learning methods, while propelling human society into an intelligent era characterized by human-machine collaboration, cross-boundary integration, and co-creation/sharing" [1]. Within this context, AI has emerged as the core force driving profound transformations in education systems [2].

In April 2025, nine ministries including the Ministry of Education jointly issued the Guidelines on Accelerating Educational Digitalization, explicitly proposing to "advance the digital transformation and upgrading of curricula, teaching materials, and pedagogical practices. Improve knowledge graphs, construct competency frameworks, deepen the application of educational large-scale models, and promote the intelligent development of curriculum systems, textbook systems, and teaching systems. Comprehensively integrate AI technologies throughout the entire teaching-learning process to facilitate the deep convergence of STEM and humanities education" [3].

This policy aligns with the strategic directive outlined in the Education Power Construction Plan (2024-2035) issued by the CPC Central Committee and the State Council in January 2025, which advocates "building a learning society by leveraging educational digitalization to pioneer new development pathways and cultivate competitive advantages" [4]. These developments signify AI's formal recognition as the pivotal solution to resolving higher education's fundamental tension between "mass-scale cultivation" and "personalized needs."

Under the theoretical framework of education's "impossible triangle," conventional models struggle to simultaneously achieve three objectives: high-quality knowledge delivery, large-scale educational coverage, and personalized learning experiences. This stems from inherent limitations in resource allocation mechanisms that perpetuate these structural contradictions. Traditional face-to-face teaching, constrained by instructors' temporal and cognitive capacities, proves inadequate for sustaining individualized learning support [5].

Research demonstrates that generative AI can accurately identify students' learning preferences, recommend diversified learning resources, and comprehensively support teaching objectives, thereby more effectively promoting tailored instruction while reducing cognitive load [6]. AI technologies construct learner competency profiles through multidimensional data acquisition and continuously optimize knowledge adaptation models via intelligent algorithms. Furthermore, they embed personalized service modules within scalable education systems—leveraging digital platforms to extend high-quality educational resources beyond geographical constraints while employing adaptive learning systems to generate individualized pathways aligned with each student's cognitive patterns. This dual approach provides both theoretical foundations and practical paradigms for educational digital transformation..

II. Theoretical Foundations of Personalized Learning

Differentiated instruction refers to the pedagogical approach wherein teachers adapt instructional strategies based on students' prior knowledge, interests, and learning styles. Carroll's Model of School Learning posits that academic achievement depends on the time a learner requires for mastery, which is closely associated with individual aptitude, quality of instruction, and other factors [7]. This perspective provides a theoretical foundation for optimizing resource allocation in personalized learning. Bloom's Mastery Learning Theory further emphasizes that nearly all students can achieve proficiency when provided with sufficient learning time and appropriate instructional support [8]. Therefore, in personalized learning systems, teaching progression should be flexibly adjusted according to individual differences, and tailored learning support should be provided to enhance each student's learning efficacy.

Human working memory has limited capacity, and learning efficiency declines when the cognitive demands of a task exceed available mental resources. Even when presented with identical instructional materials, different students may experience substantially varying cognitive loads. Thus, it is essential to regulate the presentation, difficulty, and pacing of learning content to maintain students' cognitive load at an optimal level [9]. The Multimedia Learning Theory further explores how multiple representational formats (e.g., text, images, animations) can enhance learning outcomes, noting that learners may exhibit distinct preferences and adaptability to different media modalities.

Learners with well-developed metacognitive abilities are capable of effectively monitoring their own comprehension processes, proactively selecting appropriate learning strategies, evaluating learning outcomes, and dynamically adjusting their learning behaviors. Personalized learning systems can further enhance learners' autonomy and self-regulatory capabilities by cultivating and strengthening their metacognitive skills. At the same time, sociocultural theory emphasizes that personalized learning should not overlook the essential value of social interaction. Even in highly individualized learning environments, students still need to engage in meaningful communication with teachers and peers. Such social interactions play an irreplaceable role in the construction of knowledge and the generation of meaning.

III. Practical Challenges in Building Personalized Learning Pathways in Higher Education

3.1 Challenges in Identifying Individual Differences and Matching Educational Resources

Higher vocational institutions commonly face the contradiction between a large student population and a relative shortage of high-quality teaching resources. Although intelligent monitoring systems can collect data related to students' mastery of theoretical knowledge and practical skills, there are still limitations in the breadth and depth of the data collected. Existing knowledge graphs struggle to accurately identify students' cognitive starting points and specific obstacles encountered during the learning process. Moreover, the resource system in vocational education is vast, frequently updated, and spans multiple disciplines, which leads to insufficient granularity in resource organization and quality assessment in intelligent recommendation algorithms. As a result, the accuracy of matching resources to learners' actual needs remains inadequate.

During the learning phase, students exhibit significant differences in their depth of understanding of core knowledge concepts, yet current intelligent content recommendation systems remain inadequate in adapting to the personalized needs of learners at varying cognitive levels [10]. In practical training sessions, considerable disparities are observed in students' foundational skills and operational performance, while existing teaching resources lack the capability for precise targeting and dynamic adaptation. Furthermore, the overall level of intelligent development of educational resources in vocational education is relatively low. There is a scarcity of high-quality digital resources such as micro-lectures and virtual simulations, and knowledge graphs still fall short in conducting in-depth mining and correlation analysis of vocational knowledge systems. These factors collectively restrict the accurate construction and continuous optimization of learner profiles.

3.2 The Mismatch Between Traditional Teaching Evaluation Systems and Personalized Learning

The current evaluation system in higher vocational education suffers from multiple limitations that hinder its ability to accommodate personalized learning needs, as detailed in Table 1. Although smart learning platforms have accumulated vast amounts of learning behavior data, this data has not yet been systematically integrated or applied effectively within the evaluation process. Existing assessment methods, such as "comprehensive course transcripts," still show room for improvement in their practical effectiveness. The prevailing course evaluation mechanisms are inadequate in stimulating students' innovative thinking and autonomous inquiry awareness, while the assessment of practical skills overemphasizes standardized operational procedures, thereby overlooking students' individualized developmental traits and potential.

Furthermore, there is still a lack of scientific and effective assessment tools and methods for cultivating higher-order competencies such as complex problem-solving skills and critical thinking among vocational students. As a result, evaluation outcomes provide limited support for optimizing personalized learning pathways. The application of intelligent assessment tools remains insufficient, leading to low efficiency in the collection and analysis of learning data. This inefficiency prevents real-time diagnosis of student learning issues and precise feedback, ultimately constraining the continuous improvement of personalized learning outcomes.

Table 1. Comparative Analysis of Traditional Evaluation Systems in Higher Vocational Education and the Requirements of Personalized Learning

Evaluation Dimension	Characteristics of Traditional Evaluation System	Actual Needs of Personalized Learning
Evaluation Content	Focuses on final exams and skill-based assessments; emphasizes knowledge point testing.	Requires holistic and multi-dimensional assessment that values knowledge construction and competency development.
Evaluation Method	Uniform standards; primarily manual evaluation; relies on singular quantitative metrics.	Calls for differentiated criteria, diversified intelligent evaluation tools, and a multi-dimensional indicator system.
Evaluation Timeliness	Dominated by summative assessment; feedback is often delayed.	Emphasizes process evaluation and real-time feedback with guidance.
Evaluation Indicators	Measures subject knowledge mastery and standardized skill performance.	Requires multi-dimensional indicators including learning behaviors, cognitive traits, and ability improvement.
Use of Evaluation Results	Used for semester grading and graduation qualification.	Should guide the optimization of personalized learning paths and the recommendation of learning resources.
Data Analysis	Relies mainly on total and average scores; lacks in-depth analysis.	Requires big data-based analysis of learning trajectories and predictive analytics.
Evaluation Participants	Teacher-centered evaluation; lacks diverse involvement.	Needs the integration of intelligent tools to facilitate teacher-student mutual evaluation and self-assessment.

IV. Construction of AI-Powered Personalized Learning Pathways

An AI-driven personalized learning pathway refers to a dynamically adapted knowledge acquisition sequence tailored to individual learners through intelligent algorithms. The system leverages machine learning techniques to construct accurate learner models, analyzing in real-time multidimensional characteristics such as knowledge mastery, cognitive style, and learning pace. Integrated with the semantic relationships of educational knowledge graphs, it generates highly customized learning plans.

Compared to traditional fixed pathways, its core advantage lies in a "dynamic adjustment" mechanism: by continuously collecting data on exercise performance, time investment, and interactive behaviors, and employing algorithms such as reinforcement learning and collaborative filtering to iteratively optimize path planning, it ensures both the logical coherence of the knowledge structure and alignment with individual learner adaptability. This approach effectively mitigates issues of cognitive load imbalance, thereby enhancing learning efficiency and personalization (see Fig. 1).

4.1Knowledge Graph Representation and Modeling

Constructing a comprehensive educational knowledge graph requires the deep integration of domain expertise, textbook content structure, and practical teaching experience. The graph represents knowledge or skill points as nodes and various semantic relationships as edges. In addition to common relationships such as prerequisite, part–whole, and similarity, several education-specific relationship types should be defined, including common misconception associations, cross-domain application associations, and thinking mode associations. This facilitates theoretical support for multidimensional collaborative decision-making in complex environments.

The granularity design of the knowledge graph is critical: excessively coarse granularity may reduce the accuracy of learning path planning, while overly fine granularity can significantly increase the complexity of the graph, posing challenges for maintenance and management [11]. Therefore, a multi-level representation mechanism should be adopted while maintaining consistency across hierarchies. This involves macroscopically partitioning knowledge domains and microscopically refining knowledge points. When classifying knowledge points, it is essential to consider both the diversity of teaching objectives and students' cognitive characteristics.

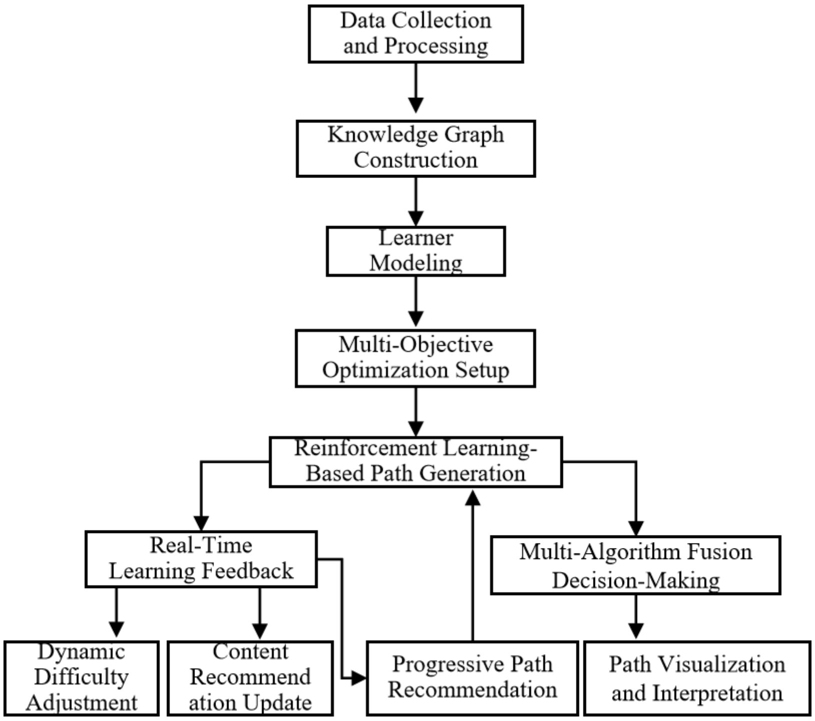

Fig. 1 Research Workflow Diagram

Item Response Theory provides a method for quantifying the difficulty of knowledge points, enabling an objective comparison between the difficulty of knowledge points and learners' abilities on a unified scale. Furthermore, the temporal dynamics of knowledge cannot be overlooked, as the importance or accuracy of certain knowledge may change over time and should be dynamically reflected in the graph.

Traditional static knowledge graphs struggle to capture the dynamic nature of knowledge, such as its timeliness, popularity, and other time-sensitive attributes. By incorporating a temporal dimension for analyzing instructional content over time, it becomes possible to trace the evolution of knowledge and predict its developmental trends. Through a crowdsourcing mechanism, teachers and learners can collaboratively participate in the refinement of the knowledge graph, leveraging collective intelligence to identify new connections or correct existing relationships.

The weights assigned to knowledge associations must be dynamically adjusted according to different learning objectives and application scenarios. For example, in interest-driven learning contexts, greater weight should be given to interest-oriented associations. The interaction between the knowledge graph and the learner model constitutes the core mechanism for enabling personalized recommendations: the system must continuously compare the learner’s current state with the competency requirements specified in the knowledge graph to identify the most suitable subsequent learning targets. This comparison process encompasses not only knowledge mastery, but also multiple factors such as cognitive load balance and learning style alignment.

In the design of knowledge graph traversal algorithms, it is essential to balance efficiency and recommendation quality, avoiding both local optima and excessive computational complexity. As learning progresses, the system should be capable of dynamically adjusting the graph structure by strengthening important associations, weakening less critical ones, and even uncovering entirely new and more effective learning paths.

4.2 Learning Path Optimization Objective Setting

Learning path optimization is inherently a multi-criteria decision-making problem that requires finding an optimal balance among multiple competing objectives. Maximizing learning effectiveness constitutes the primary goal, which can be measured through multidimensional indicators such as the breadth and depth of knowledge mastery, as well as transfer ability: breadth reflects the scope of knowledge covered by the learner, depth evaluates the understanding of core concepts, and transfer ability indicates the learner’s capacity to apply acquired knowledge to new contexts [12]. The weight assignments for each objective in learning path optimization are presented in Table 2.

Table 2. Weight Allocation of Learning Path Optimization Objectives

Optimization Objective	Short-Term Weight (0–1)	Medium-Term Weight (0–1)	Long-Term Weight (0–1)	Dynamic Adjustment Threshold
Breadth of Knowledge Mastery	0.35	0.28	0.20	0.15
Depth of Understanding	0.40	0.35	0.30	0.20
Knowledge Transfer Ability	0.25	0.37	0.50	0.25

Long-term memory retention represents another critical dimension of optimization. Based on the Ebbinghaus forgetting curve, scientifically scheduling review intervals is essential for knowledge consolidation. The system should be capable of predicting individual learners' forgetting patterns and initiating reinforcement exercises at optimal times to facilitate long-term knowledge retention.

Learning efficiency optimization aims to help learners achieve the best possible outcomes within limited time, with its core lying in the scientific sequencing of learning activities. An effective learning sequence should align with principles of cognitive development, establishing foundational concepts before progressing to more advanced content. Cognitive load management serves as a key aspect of efficiency optimization; the system must ensure that the difficulty of learning tasks matches the learner's current ability level, avoiding loss of interest due to tasks that are too simple or frustration caused by excessive challenge.

The allocation of attentional resources also significantly influences learning efficiency. Research indicates that learners' sustained attention is limited; thus, it is essential to scientifically structure intervals between focused learning and rest. In multi-task learning scenarios, the cognitive cost associated with attention switching must also be taken into account. According to the challenge-skill balance theory, a flow state is most likely to be achieved when task difficulty slightly exceeds the learner's current ability level [13]. Therefore, personalized systems should dynamically adjust difficulty progression to provide each learner with an appropriate level of challenge.

Interest maintenance constitutes another critical aspect. By analyzing learners' emotional feedback and behavioral data, the system can identify individual interest patterns and recommend relevant learning materials. Furthermore, the sense of autonomy also markedly influences the learning experience: studies show that intrinsic motivation tends to be stronger when learners possess a degree of control over the learning process. Hence, the system should provide adequate opportunities for choice and self-regulation to enhance learner autonomy and engagement.

4.3 Reinforcement Learning-Based Pathway Generation

Within the reinforcement learning (RL) framework, the problem of learning path optimization can be naturally modeled as a sequential decision-making process. In this framework, an agent (i.e., the recommendation system) continuously interacts with the environment (the learner and their learning context) to progressively optimize its recommendation policy. The design of the state space is particularly critical and must incorporate sufficient information to characterize the learning context, typically including the learner's current knowledge state, cognitive traits, and historical behaviors [14].

To address the complexity arising from high-dimensional state representations, deep reinforcement learning (DRL) often employs neural networks as function approximators to autonomously learn efficient state representations. In practical applications, partial observability is a common challenge: since the system cannot directly access the learner's full internal state (such as emotional status or cognitive load), it often relies on observation histories to perform probabilistic inference.

In reinforcement learning-driven learning path recommendation, the design of the action space plays a critical role in system performance. A discrete action space treats each knowledge point or learning activity as an independent action, which is simple and intuitive but limited in scalability. A continuous action space can express richer recommendation strategies, such as using continuous values to control the mixing ratio of different knowledge points. A hierarchical action space combines the advantages of both: a high-level policy selects macro-learning goals, while a low-level policy determines specific learning activities or resources. Composite actions enable the system to recommend multiple learning elements simultaneously, such as combinations of content type, difficulty level, and media format. A well-designed action space can significantly improve the precision and adaptability of recommendations.

The sparse reward problem is prevalent in educational settings, as learning outcomes often take considerable time to manifest. To address this issue, dense intermediate reward signals can be designed based on short-term feedback such as learners' interaction engagement or quiz performance. In the context of multi-objective optimization, reward signals from different objectives must be carefully combined. Since these objectives may vary in scale, normalization is typically required. Furthermore, incorporating intrinsically motivated reward mechanisms based on psychological principles can encourage exploratory behaviors and prevent the system from converging prematurely to local optima. Inverse reinforcement learning techniques can infer latent reward functions from exemplary teaching practices, enabling the system to imitate the decision-making patterns of expert educators.

In personalized learning scenarios, excessive exploration may lead to unstable learning experiences, while over-exploitation can cause recommendations to become rigid. To ensure stable policy updates, trust region methods constrain the magnitude of policy changes, preventing significant deviations from the currently effective strategy. Model-based reinforcement learning improves sample efficiency by first learning a model of environmental dynamics and then performing policy planning based on this model. In a multi-agent framework, instructors can also be modeled as agents, enabling human-AI collaborative teaching decisions. Furthermore, meta-reinforcement learning techniques can extract shared patterns across multiple learners, allowing the system to adapt quickly to new users and thereby enhancing the efficiency and adaptability of the personalization process.

4.4 Optimization Through Multi-Algorithm Fusion

A single algorithm often struggles to fully address the complex challenges involved in learning path optimization, whereas a multi-algorithm fusion framework can effectively integrate the complementary strengths of diverse methods. The concept of ensemble learning can be introduced into this domain, combining outputs from multiple base recommenders to form more reliable final decisions [15]. Weighted averaging represents the simplest fusion strategy, while more refined approaches such as stacked generalization can learn the relative reliability of different algorithms in specific contexts, enabling more adaptive integration.

The Bayesian framework offers a principled approach to multi-algorithm fusion by treating different algorithms as distinct information sources and combining them organically through probabilistic inference. A key advantage of this method lies in its ability to explicitly handle uncertainty: when the confidence in an algorithm's output is low, the system can automatically reduce its decision weight, thereby enhancing the robustness and accuracy of recommendations.

At the base level, multiple specialized submodules handle distinct tasks: the cognitive diagnosis module assesses the learner's knowledge mastery, the interest prediction module analyzes content preferences, and the affect recognition module monitors learning-related emotions in real time. A coordinator in the middle layer integrates outputs from these modules and resolves potential decision conflicts. For example, when the cognitive module suggests advancing to more complex topics while the affect module detects learner anxiety, the coordinator may adjust the recommendation strategy to balance cognitive and emotional needs. At the top level, a meta-controller monitors long-term learning progress and triggers strategy adjustments or signals the need for human intervention when necessary. This hierarchical architecture maintains the independence of specialized modules while ensuring effective global coordination.

A multi-stage processing mechanism facilitates optimized allocation of computational resources. During the cold-start phase, when data are scarce, content-based recommendation or transfer learning techniques can be employed to leverage experiences from similar learners. As data accumulate, the system can gradually transition to more sophisticated methods such as collaborative filtering and knowledge tracing. In the real-time interaction phase, lightweight models are used to ensure responsiveness, while during offline periods, computationally intensive algorithms are executed for in-depth analysis and large-scale optimization. This phased approach enables efficient use of backend resources without compromising user experience. Furthermore, the incorporation of incremental learning allows models to be updated continuously without complete retraining, significantly enhancing the system's adaptability and scalability.

V. Conclusion

This study addresses the core question of how artificial intelligence can enable the construction of personalized learning pathways through systematic discussion and framework design. The main conclusions are as follows:

First, AI technologies are key to resolving the traditional "impossible triangle" dilemma in education. It has been demonstrated that through generative AI, learning analytics, and other techniques, multi-dimensional perception of learners' cognitive states, interest preferences, and emotional states can be achieved. This makes it feasible to provide personalized services in large-scale educational settings, effectively compensating for the limitations of traditional face-to-face instruction in terms of scalability and depth of support.

Second, a successful personalized learning system must be grounded in solid educational theoretical foundations. This study integrates theories such as differentiated instruction, cognitive load, and metacognition, ensuring that technological applications not only pursue efficiency but also align with the principles of human cognitive development and the essence of social learning. This approach mitigates the potential risks of over-reliance on technology at the expense of fundamental educational values.

Third, the artificial intelligence-based framework proposed in this study demonstrates significant systemic advantages. By integrating dynamic semantic representation through knowledge graphs, sequential decision optimization via reinforcement learning, and collaborative computation from multi-algorithm fusion, the framework forms a coherent system that effectively balances knowledge structure, individual adaptability, and operational efficiency. Its hierarchical architecture and multi-stage processing mechanism successfully reconcile computational complexity with real-time responsiveness, providing strong feasibility for practical implementation.

Fourth, the deep application of artificial intelligence is reshaping instructional assessment and intervention models. Intelligent evaluation tools not only facilitate a shift from "summative assessment" to "formative assessment," but also provide precise feedback for dynamic learning path adjustments through the evaluation of higher-order thinking skills. This establishes a closed loop of "assessment–diagnosis–optimization," continuously enhancing personalized learning outcomes.

Looking forward, AI-driven personalized learning still faces multiple challenges, such as data privacy and ethics, the delineation of authority and responsibility in human–AI collaboration, and the quality and equity of digital resources. Future research should further explore the deep integration of multimodal data, the application of explainable artificial intelligence (XAI) in educational decision-making, and the effective embedding of teachers' experiential wisdom into intelligent systems. Ultimately, these efforts will contribute to building a new future educational ecosystem characterized by human–AI symbiosis and collaborative evolution.

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