2025 Volume 3, Issue 9
Lecture Notes in Education, Arts, Management and Social Science
ISSN(Online): 2705-053X

Construction of a "Demand-learning Ability" Double Cycle Education Model for Higher Vocational Colleges Driven by Digital Intelligence

Shuzhen Deng
Quanzhou Engineering Vocational and Technology College, Quanzhou 362000, Fujian, China

Abstract: This paper addresses the prominent issues of "disconnection between posts and curricula, and separation of learning from application" in higher vocational education. It proposes a digital intelligence-driven "Demand-Learning Capacity" dual-cycle educational model. Utilizing AI Agents as the technological engine, this model systematically integrates five key components, including on-campus theoretical instruction and enterprise practical training, through a dual-cycle mechanism. It aims to achieve dynamic alignment between talent cultivation and industrial demands, thereby providing a new framework for the transformation of higher vocational education.

Keywords:demand-learning capacity dual cycle; Agent (AI Agent); five-coordination education model

Online publication: October 26, 2025

1. Introduction

The in-depth development of the new round of technological revolution and industrial transformation marks the advent of the digital and intelligent era, which puts forward higher requirements for the quality structure of technical and skilled personnel. As an educational type closely linked to economic and social development, the high-quality development of vocational education is crucial. However, current higher vocational education still faces prominent challenges such as "disconnect between positions and courses," "separation between learning and application," and insufficient "sustainable development momentum" among students. Specifically, the traditional curriculum system is updated slowly, failing to respond agilely to the technological transformation of the industry, resulting in a gap between talent cultivation and market demand. At the same time, the integration of the teaching process and work practice is insufficient, and the training links are often disconnected from real scenarios, restricting the cultivation of students' practical and innovative abilities. In addition, the existing teaching model does not pay enough attention to students' intrinsic learning motivation, leading to the ineffective cultivation of their autonomous learning and lifelong development capabilities. Although the country advocates "integration of production and education, and school-enterprise cooperation," and implements the comprehensive education of "position-course-competition-certificate," the existing explorations are mostly focused on the linear superposition of elements, lacking an overall framework that systematically and dynamically connects industry demands with learners' abilities. Based on this, this paper aims to propose and construct a new digital-driven higher vocational "demand-learning ability" double-loop education model. The core of this model lies in the introduction of artificial intelligence agents (AI Agent) as a technical engine, constructing a "five-coordinated" education closed loop covering the full process of "on-campus theory—enterprise practice—competition verification—certificate certification—scientific research feedback."

2. Research Status at Home and Abroad

In the field of industry-education integration and comprehensive talent cultivation through "jobs-courses-competitions-certificates," domestic and international scholars have conducted in-depth explorations, providing a significant foundation for this research while also revealing shortcomings in systematic integration. International research, centered on competency-based education (CBE), emphasizes the direct alignment between skill acquisition and job requirements. For instance, MIT's "Open Learning Initiative" in the United States reconstructs vocational curriculum pathways through an adaptive learning system, achieving dynamic matching between personalized learning and skill maps [1]; Germany's "dual system" leverages enterprise demand databases to map industry technology standards in real time to teaching standards, ensuring the precision of talent cultivation [2]. These practices show that the deep integration of digital tools and educational scenarios can effectively improve the agility of vocational education. Domestic research focuses on the construction of the "integration of post, curriculum, competition, and certification" system. Deng Zhixin elaborated on the relationship between "industrial chain, education chain, talent chain, and innovation chain," providing a useful framework for understanding the macro-logic of industry-education integration [3]; Li Qingxiang and colleagues, starting from the "1+X" certificate system, have explored restructuring solutions for the curriculum system [4]. However, existing research and practices often remain at the level of "physical superposition" rather than "chemical integration." Most institutions still adopt linear patchwork models such as "major + certificate" or "course + competition," failing to establish a closed-loop system driven by data and dynamically adjusted among "job competency maps to course knowledge maps to practical training scenario maps to competition certification standards" [5]. Collaboration between enterprises and schools largely relies on unidirectional resource input from enterprises, lacking a long-term, bidirectional "demand-capability" driving mechanism based on data feedback, resulting in insufficient collaborative motivation and depth [6].

Currently, the application of AI technology in education is predominantly focused on optimizing micro-teaching processes such as personalized learning resource recommendations, intelligent tutoring systems, and academic early warning, with its role more inclined towards being a "teaching tool" rather than an "engine for reshaping the educational ecosystem"[7]. For instance, Lin Mengcheng et al. utilized recommendation algorithms to enhance robot path planning, reflecting the value of technology in specific stages[8]. However, most of such research confines the application of technology to the "point" in the teaching process, failing to form a comprehensive framework covering the entire "teaching design-implementation-evaluation-feedback" process and integrating the systematic AI Agent framework of both "school-enterprise" subjects. The empowering role of artificial intelligence has yet to permeate the top-level design and core operational mechanisms of the educational model, making it difficult to address the aforementioned structural issues such as the dynamic disconnection between positions and courses, and the separation of learning and application[9]. Learning ability, as a comprehensive quality encompassing learning motivation, ability, perseverance, and transformation power, is a core indicator for measuring the quality of education and the sustainable development potential of students[10]. Existing research has fully demonstrated the importance of enhancing learning ability, but most of it originates from the perspectives of pedagogy or psychology, discussing its connotation or influencing factors. In the context of the digital transformation of vocational education, how to transform the cultivation of learning ability from an educational concept into an operational, assessable, and feedback-oriented routine educational practice through technologically empowered teaching process reconstruction and resource optimization allocation remains weak in related mechanism research. In summary, existing research has made significant progress in their respective fields. However, in response to the needs of systematic transformation in higher vocational education in the digital age, there are obvious limitations: the research on "production-education integration" lacks an intelligent architecture with a full chain connection, the research on "education artificial intelligence" lacks a macro perspective on empowering the reconstruction of the overall model, and the research on "learning ability" lacks an implementation path deeply integrated with the digital educational ecosystem. There is a gap between the three, and they have not formed a synergy.

3. The "Demand-Learning Ability" Dual-Cycle Education Model

The core of this research is to construct a numerically intelligent vocational education and training model. This architecture takes AI Agent[11] as the core technical engine, integrating and reengineering the five key processes—"on-campus theory, enterprise practice, competition verification, certificate certification, and scientific research feedback"—through two interrelated driving mechanisms: the "job demand-driven cycle" and the "learning ability development-driven cycle." Ultimately, it forms a dynamic and adaptive new ecological system of vocational education with the fundamental goal of continuously enhancing students' comprehensive learning abilities.

3.1. The Job Demand-Driven Cycle

The external cycle is a critical mechanism ensuring the synchronization of talent cultivation with industrial needs. It begins with the extensive collection and intelligent analysis of industrial data. AI continuously acquires structured and unstructured data from sources such as recruitment platforms and technical documents through various technological means and uses natural language processing and other technologies to deeply analyze and accurately identify emerging skills, technological trends, and changes in job competencies. Subsequently, these demand information is transformed into teaching optimization instructions: the system compares new skill points with the existing curriculum knowledge graph to automatically generate content update recommendations, driving the dynamic iteration of courses; it converts real enterprise technical challenges into training projects, enabling students to apply what they have learned in practical situations. At the same time, the system calibrates the skill competition questions and the assessment standards of professional skill certificates to ensure consistency with the cutting edge of the industry. The cycle ends with the optimized teaching and training effectiveness being fed back to the industry through indicators such as employment quality, verifying effectiveness and enhancing the willingness of enterprises to cooperate, forming a closed loop from "perception of industrial needs" to "teaching adjustment" and finally to "quality feedback of cultivation." The core lies in enabling the educational system to be sensitive to, even predict, changes in the industry, ensuring the forefront and adaptability of educational supply.

3.2. The Learning Ability Development-Driven Cycle

The internal cycle focuses on the individual student, aiming to stimulate intrinsic learning motivation and achieve personalized growth. The foundation of this cycle is the comprehensive perception of students' learning process data. AI Agent, akin to an intelligent study companion, collects multi-dimensional data such as cognitive engagement, skill operation, innovative attempts, and collaborative performance in activities such as online learning, virtual training, project collaboration, and competition participation. In the stage of personalized intervention and support, the system provides precise support based on the "learning ability portrait" [12]. Moreover, the internal cycle also drives the transformation of the evaluation system, shifting from a single result evaluation to a developmental evaluation that focuses on the learning process and the increase in capabilities. It assesses the growth and progress of students by comparing their portraits at different stages.

3.3. The "Five Synergies" Ecosystem under the Empowerment of AI Agent

The effective operation of the aforementioned dual circulation mechanism is highly reliant on the technical support provided by AI Agent, an intelligent hub. AI Agent is not a single tool but a complex system integrating multiple functional modules, akin to the brain and neural network, which tightly connects the five relatively independent phases into an organic living entity.

Under the AI Agent framework, the "Five Collaborations" no longer exist as isolated entities but rather constitute a closed-loop system driven by data flow and continuously enhancing value streams. For instance, real-world problems encountered by students during corporate internships can be transformed into research topics for competition validation; innovative solutions generated in competitions, after refinement, can serve as cases for research-driven academic support, thereby enriching the content of on-campus theoretical instruction. Furthermore, the competencies validated through certification provide students with credentials to secure higher-quality corporate internship opportunities. In this manner, the output of each stage becomes the input for the next, fostering a mutually reinforcing and cyclically advancing ecosystem.

In summary, the overall architecture of this model is driven by a "dual-cycle" engine, anchored by an "AI Agent" as the intelligent foundation, and operationalized through the "five synergies" as a practical carrier, all converging toward the ultimate goal of continuously enhancing students' comprehensive learning capabilities. It explores a feasible pathway to achieve a dynamic balance between educational supply and industrial demand, as well as between large-scale cultivation and personalized development.

4. System Architecture and Key Technologies

The "Demand-Learning Ability" double-loop educational system constructed in this study employs a three-tiered architecture of "Platform-Engine-Module." It is centered around the AI Agent as the core control hub, which provides intelligent support for the entire educational process through data collection, knowledge organization, intelligent reasoning, and dynamic regulation. The system architecture diagram of this study is depicted in **Figure 1**.

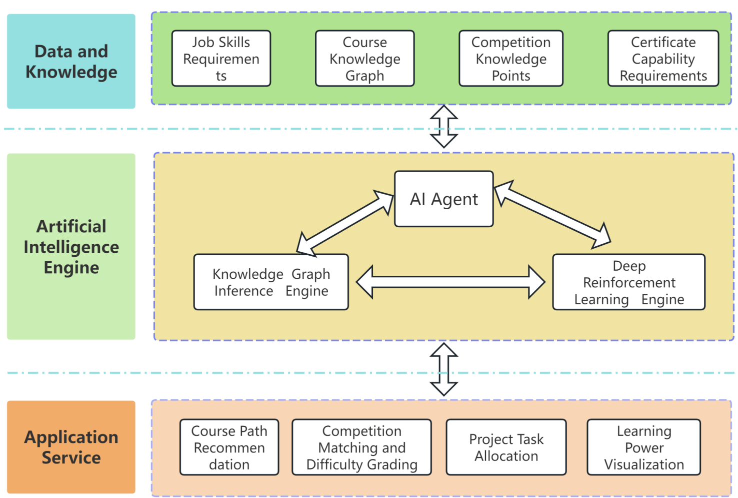

Figure 1. System Architecture Diagram

The foundational layer of the system is the data and knowledge layer, primarily integrating the skill requirements of industry positions, the structure of course knowledge, the knowledge systems of competitions and certifications, as well as student learning behavior data. The core function of this layer is to construct a comprehensive knowledge foundation and behavioral data base, encompassing a repository of industry position skill requirements, a course knowledge graph, and a database of competition knowledge points, among others. Through the structured processing of position data, the extraction of knowledge points from course texts, and the in-depth recording of behavioral data, a unified data foundation and knowledge representation are provided for subsequent intelligent engines.

The intelligent engine layer at the core of the system is composed of the AI Agent engine, the knowledge graph reasoning engine, and the deep reinforcement learning engine [13]. The AI Agent engine undertakes the critical tasks of demand analysis and task chain management, capable of automatically identifying competency items based on job requirements, mapping relevant knowledge points, and generating learning task paths; the knowledge graph reasoning engine, based on the curriculum knowledge graph, achieves associative analysis of learning content, inference of skill paths, and mapping of competition and certificate difficulty levels through graph-structured relational reasoning, thereby endowing the learning path with features of interpretability and structuralization [14].

At the system's upper layer, the application service layer is oriented towards diverse subjects such as students, teachers, and enterprises, providing a variety of intelligent educational services. These services encompass personalized pathway recommendations for courses and projects, matching and difficulty grading of competitions and certifications, task allocation and progress management, visual analysis of learning capabilities, and teaching diagnostics for teachers. This layer presents the decision outcomes of the intelligent engine in an understandable manner, enabling students to clearly define their learning stages and objectives, teachers to accurately grasp the progress of learning, and enterprises to comprehend the structure of talent capabilities, thereby realizing multi-party collaboration under the integration of industry and education.

In the realm of key technologies, the AI Agent task chain control technology stands as the core of system intelligence. By means of semantic parsing of job requirements, it converts job competency items into specific knowledge points and learning tasks, thereby realizing the automatic chaining inference from "demand to learning" [15]. The technology for constructing curriculum knowledge graphs, through NLP and knowledge representation methods, associates curriculum knowledge points, vocational skill requirements, and learning resources, forming a knowledge network that is amenable to reasoning, which serves as a basis for path generation. The competition and certification recommendation algorithm performs multi-level matching based on skill sets, difficulty levels, and the adaptability of learning abilities, providing students with the optimal participation opportunities and preparation strategies.

5. Discussion and Conclusion

This study addresses the core challenges faced by vocational education in the digital-intelligent era, such as the disconnect between job roles and courses, the separation of learning and application, and insufficient motivation for student development. It systematically constructs a novel talent cultivation model driven by an artificial intelligence agent (AI Agent) as the technological engine, a "demand-learning capability" dual-cycle mechanism, and a "five-cooperation" practical framework. The key contribution of this model lies in its non-trivial technological overlay of the existing "job-courses-competitions-certificates" concept, but rather represents a systematic reshaping from both theoretical frameworks to practical pathways. Looking ahead, further research on this model can be advanced in the following directions: First, the refinement and quantification of the dual-cycle mechanism. Future studies could employ system dynamics models to simulate and optimize parameters such as feedback intensity and delay effects within the "demand-learning capability" dual cycle, thereby enhancing the precision and controllability of the model's operation. Second, strengthening integration with emerging technologies. For instance, leveraging large language models (LLMs) to enhance the AI Agent's capabilities in natural language interaction and content generation, or utilizing blockchain technology to construct a trustworthy competency certificate system. Third, conducting pilot empirical studies at the level of specific disciplines and regions. Action research across various types of vocational education programs can validate and refine the applicability and effectiveness of the model, summarize replicable and scalable practical examples, and explore its compatibility with the existing educational management system.

Funding

Research on the transformation of the "Five Synergies and Double Cycles" education model driven by digital intelligence - a practical path based on AI Agent, Fujian Provincial Education Science Planning Project (Project No.: FJJKB25219).

Disclosure statement

The author declares no conflict of interest.

References

[1] Watters A, 2023, Teaching machines: The history of personalized learning. mit Press.

[2] Rakhimovna B N, 2024, Integration of theory and practice of the dual education system in the field of light industry education. European International Journal of Multidisciplinary Research and Management Studies, 4(02): 336-341.

[3] Deng Z X, 2023, Research on the Operation Mechanism of Modern Vocational Colleges under the Context of Adaptability: On the Relationship among Industrial Chain, Educational Chain, Talent Chain, and Innovation Chain. China Vocational and Technical Education, (31): 47-53.

[4] Li Q X, 2025, A Study on the Mechanisms and Paths of Development of the "Five Synergies and Five Integrations" Subject System for Higher Vocational Digital Media Majors under the "1+X" Certification System. Cai Zhi, (13): 89-92.

[5] Yan C, Huang G C, 2025, "An Exploration of Teaching Reform in Preschool Literature Courses in Vocational Colleges under the Integrated 'Job, Course, Competition, Certificate, Training, and Innovation' Educational Model". Modern Vocational Education, (22): 129-132.

[6] Li X, He J B, 2025, A Study on the Conditional Configuration Paths of Poor Effectiveness in Industry-Education Integration in Vocational Colleges: A Clear Set Qualitative Comparative Analysis Based on 40 Industry-Education Integration Projects. Vocational and Technical Education, 46(32): 74-80.

[7] Li X, 2024, A Comparative Study and Inspiration on the Application of Artificial Intelligence Technology in Digital Humanities Education for Archives in China and Foreign Countries. Shanxi Archives, (11): 147-149.

[8] Lin M C, Xue B, Liu X Y, 2025, Welding Robot Path Planning Method Based on Improved Ant Colony Algorithm. Sensors and Microsystems, 44(07): 24-27+31.

[9] Yu J B, Sun L, Lan Y Q, 2025, Research on the Realistic Dilemmas and Countermeasures of Integrating Artificial Intelligence into Higher Vocational Teaching Work. Journal of Yunnan Open University, 27(04): 59-64.

[10] Liu J H, Huang R H, 2025, What exactly is learning ability - from daily language, academic perspectives to integrated conceptual genealogy. Audio-visual Education Research, 46(03): 28-34+94.

[11] Masterman T, Besen S, Sawtell M, 2024, The landscape of emerging AI agent architectures for reasoning, planning, and tool calling: A survey. arXiv preprint arXiv: 2404.11584.

[12] Ayeni O O, Al Hamad N M, Chisom O N, 2024, AI in education: A review of personalized learning and educational technology. GSC Advanced Research and Reviews, 18(2): 261-271.

[13] Abu-Salih B, Alotaibi S, 2024, A systematic literature review of knowledge graph construction and application in education. Heliyon, 10(3): e25383.

[14] Chen L, Tong P, Jin Z, 2024, Plan-on-graph: Self-correcting adaptive planning of large language model on knowledge graphs. Advances in Neural Information Processing Systems, 37: 37665-37691.

[15] Zhao Z, Lu B, Gan X, 2025, CHAINSFORMER: Numerical Reasoning on Knowledge Graphs from a Chain Perspective. arXiv preprint arXiv: 2504.14282.