Research on the AI-Driven Digital Collaborative Innovation Path for Industry-Education Integration in Private Vocational Undergraduate Universities

Chengyin Gao*, Siyang Hu

Hainan Vocational University of Science and Technology, Haikou, 570203, China
Corresponding author:gcy20211125@163.com

Abstract: *Against the backdrop of digital transformation, private vocational undergraduate universities face an urgent need to overcome the limitations of traditional industry-education integration models. This study constructs an integrated theoretical model combining industry-ducation integration with AI-driven approaches, clarifying the synergistic mechanism between the "data-algorithm-platform" technological foundation and the multi-agent network. By analyzing the elemental structure of digital collaborative innovation, AI-enabled dimensions, and dynamic processes, the study proposes a pathway construction scheme based on the principles of systemic coupling, agile iteration, and value co-creation. It designs an implementation plan comprising a three-phase strategy and a resource virtualization aggregation mechanism, while establishing a three-dimensional safeguard system covering technology, organization, and institutions. This forms a self-adaptive and optimizable collaborative ecosystem. The research provides an innovative theoretical framework and practical pathway for private vocational undergraduate universities to achieve deep integration between the educational chain and the industrial chain.*

Keywords: *private vocational undergraduate universities; industry-education integration; artificial intelligence; digital collaborative innovation; implementation pathway; operational mechanism*

Introduction

As industrial technology forms accelerate toward intelligence and integration, private vocational undergraduate universities, as a crucial component of the higher education system, face the challenge of structural misalignment between talent cultivation models and industrial innovation demands. Traditional industry-education integration models exhibit limitations in response speed, resource integration, and innovation efficacy, rendering them inadequate to support the goal of collaborative talent cultivation in a rapidly iterating technological environment. The penetration of artificial intelligence technology offers a new paradigm for reconstructing the industry-education integration mechanism, enabling deep coupling and dynamic adjustment between educational processes and industrial practices through data-driven and algorithm-enabled approaches. Against this backdrop, exploring AI-driven digital collaborative innovation paths not only enhances the teaching quality and innovation capability of private vocational undergraduate universities but also holds significant theoretical value and practical meaning for constructing a sustainable and self-adaptive higher education-industry collaborative ecosystem. This study aims to systematically analyze the integration mechanism of industry-education integration and AI technology, construct a collaborative path applicable to private vocational undergraduate universities, and provide framework guidance for their transformational development in the digital era.

1. Theoretical Framework of Industry-Education Integration and AI-Driven Approaches in Private Vocational Undergraduate Universities

1.1 Theoretical Foundation and Core Connotation of Industry-Education Integration

The theoretical foundation of industry-education integration stems from the evolution of knowledge production modes and the deepening of human capital theory. The shift from the traditional linear knowledge transmission model to the collaborative knowledge creation model in applied contexts constitutes the epistemological basis of industry-education integration. Its core connotation is reflected in the deep inter-embedding of educational elements and industrial elements, and the organic connection between the knowledge chain, talent chain, industrial chain, and innovation chain. In the context of private vocational undergraduate universities, this integration exhibits unique institutional logic and action paths. With institutions serving as knowledge aggregation nodes and industry as technology application fields, both parties build a competency-based educational ecosystem through resource complementarity and risk sharing. Its operational mechanism goes beyond simple internship training or order-oriented cultivation, shifting towards three-dimensional collaboration involving joint course development, platform co-construction, and outcome sharing. This deep integration not only enhances the professional adaptability of human capital but also fosters positive externalities of organizational learning and knowledge spillover, providing sustained momentum for technological innovation and industrial upgrading[1].

1.2 Theoretical Support for AI-Driven Technologies in the Educational Field

The penetration and development of artificial intelligence technology in the educational field are grounded in the integration of constructivist learning theory, cognitive science, and complex systems theory. Machine learning algorithms enable the precise modeling of cognitive states and competency structures through the in-depth mining of learning behavior data, providing a quantitative basis for generating personalized learning paths.

Natural language processing and multimodal interaction technologies reshape the environment for knowledge representation and skill acquisition, creating highly contextualized and immersive learning experiences. Deep learning networks simulate expert thinking patterns to construct dynamically updated domain knowledge graphs, supporting the continuous optimization of adaptive learning systems[2]. These technological capabilities collectively form the technical paradigm of intelligent education, whose core characteristics include the precision of the teaching process, the intellectualization of educational resources, and the ubiquity of educational services. Technology is no longer merely a teaching tool but has evolved into a key endogenous variable reshaping the educational ecosystem, driving the transformation of the education system from experience-driven to data-driven.

1.3 Integrated Theoretical Model of Industry-Education Integration and AI-Driven Approaches

The integration of industry-education integration and AI-driven approaches has given rise to a theoretical model for digital collaborative innovation. This model uses the "data-algorithm-platform" structure as its technological foundation and the "university-industry-technology" relationship as its actor network, establishing an innovation ecosystem characterized by multi-agent participation and multi-factor flow. At the technological architecture level, industrial real-time data flows are channeled through edge computing nodes into the educational data mid-end, where they converge with learning behavior data to form a dual-driven data lake.

Machine learning algorithms perform feature extraction and pattern recognition on this foundation, generating dynamic competency profiles and market demand predictions. At the organizational interaction level, blockchain-supported smart contracts ensure the distributed verification of intellectual property rights and the equitable distribution of innovation benefits, thereby reducing collaboration transaction costs. Digital twin technology constructs a virtual simulation environment for industry-education integration, achieving synchronous resonance between technological iteration and curriculum updates. The core innovation of this model lies in establishing a bidirectional feedback mechanism for industry-education data, thereby forming a self-adaptive feedback loop between talent cultivation standards and industrial technology evolution. This provides private vocational undergraduate universities with organizational resilience for continuous evolution in uncertain environments.

2. Operation Mechanism of AI-Driven Digital Collaborative Innovation

2.1 Fundamental Elements and Structure of Digital Collaborative Innovation

The digital collaborative innovation system comprises a set of core elements and the networked structure formed through their interconnections. Data elements serve as the system's foundational resource, encompassing teaching process data, industrial operation data, and technology research and development data. Their multi-source heterogeneous nature constitutes the initial condition for system operation. Entity elements include private vocational undergraduate universities, industrial chain enterprises, and technical service platforms, all forming a heterogeneous actor network based on shared value objectives. Platform elements function as the physical carrier, integrating cloud computing infrastructure, Internet of Things terminals, and interactive interfaces to provide a stable technological environment for collaborative activities. Algorithm elements constitute the system's intelligent core, responsible for processing, analyzing, and modeling data resources[3].

These elements form a hierarchical architecture through standardized digital interfaces and interaction protocols. The underlying layer handles data collection and storage, utilizing IoT sensors and API interfaces to achieve real-time acquisition and aggregation of multi-source data. The middle layer manages algorithm analysis and processing, deploying intelligent algorithm components such as machine learning and natural language processing. The top layer provides application services, offering personalized collaborative innovation tools and interfaces for different participating entities. This modular architectural design ensures system scalability and maintainability, allowing functional components to be flexibly combined and replaced according to specific application scenario requirements, thereby maintaining the system's continuous adaptability within a rapidly evolving technological environment.

2.2 Functional Roles of AI Technology in Collaborative Innovation

Artificial intelligence technology serves as a key enabler in the collaborative innovation process, with its functional roles manifested across multiple dimensions. In the knowledge integration dimension, natural language processing and knowledge graph technologies enable automated extraction, correlation, and structuring of cross-domain knowledge, establishing dynamically updated domain knowledge repositories that eliminate semantic barriers between industry and education sectors. In the process optimization dimension, intelligent algorithms analyze historical collaboration data to identify bottlenecks and redundant links in innovation processes, providing decision support for process reengineering and enhancing the efficiency of resource coordination and allocation. In the interaction support dimension, multi-agent systems simulate the behavioral logic and decision-making patterns of different entities, offering simulation environments for complex collaborative decisions and reducing trial-and-error costs in real-world scenarios.

Beyond these fundamental functions, AI technology drives qualitative transformation in collaborative innovation through advanced cognitive capabilities. The integration of computer vision and augmented reality technologies constructs immersive skill training environments, enabling learners to conduct practical operations in highly realistic industrial scenarios. Reinforcement learning algorithms continuously interact with the environment to autonomously optimize teaching strategies and resource allocation schemes, achieving self-improvement in system operational efficiency. Generative artificial intelligence not only automatically produces teaching content and solutions but also creates challenging innovation scenarios through generative adversarial networks, stimulating participants' creative thinking. The introduction of these advanced cognitive functions enables the collaborative innovation system to evolve progressively from instrumental assistance to an intelligent partner with partial autonomous decision-making capabilities[4].

2.3 Dynamic Processes and Effectiveness Evaluation of the Operational Mechanism

The dynamic process of the operational mechanism manifests as a continuously iterative closed-loop feedback system. The process begins with the intelligent perception and definition of innovation demands, where data crawling and sentiment analysis techniques capture potential innovation opportunities in real-time from industrial markets and educational systems. It then proceeds to the intelligent matching of resources and capabilities, where collaborative recommendation algorithms construct optimized virtual innovation teams based on entity profiles and project characteristics. During the collaborative execution phase, project tasks are decomposed and assigned through smart contracts for tracking, while the digital twin environment provides a synchronous collaborative space for cross-regional research and teaching practices. Innovation outcomes undergo rights confirmation and value assessment through a blockchain-based notarization and evaluation system.

Effectiveness evaluation of the operation requires establishing a multi-dimensional, multi-level indicator system. The basic level focuses on operational efficiency, including quantitative metrics such as resource utilization rates, task completion rates, and response timeliness. The intermediate level assesses collaborative quality, covering qualitative indicators including knowledge transfer efficiency, innovation capability enhancement, and interface usability. The highest level evaluates the overall system's sustainability and evolutionary capacity, incorporating strategic indicators such as ecological diversity, technological foresight, and institutional adaptability. To achieve precise evaluation, this requires introducing advanced analytical methods including time series analysis and social network analysis. Through comparative experiments and A/B testing, the specific contribution of each influencing factor can be isolated, thereby providing empirical evidence for the refined optimization of the operational mechanism and promoting the continuous evolution of the entire system toward higher levels of collaboration.

3. Construction of Innovation Pathways and Implementation Safeguards for Private Vocational Undergraduate Universities

3.1 Design Principles and Construction Approach for Innovation Pathways

3.1.1 Principle of Systemic Coupling

The design of innovation pathways must adhere to the principle of systemic coupling, treating the educational mission of private vocational undergraduate universities, the technological demands of the industry, and the technical logic of artificial intelligence as an integrated ecosystem. This principle emphasizes nonlinear interactions and dynamic equilibrium among various elements, requiring pathway design to transcend mere technological superimposition or process automation. Instead, it aims to achieve a high degree of integration between educational and industrial spaces in the digital dimension. The core lies in utilizing data flows and intelligent algorithms to seamlessly connect knowledge production, dissemination, and application, thereby forming a collaborative network characterized by self-organization and self-adaptation. This ensures the structural stability and functional effectiveness of the innovation pathways in a complex and ever-changing technological environment.

3.1.2 Agile Iteration Orientation

Pathway construction must incorporate the core concept of agile iteration to address the rapid evolution of artificial intelligence technology and industrial structures. This orientation requires the pathway to possess highly modular and reconfigurable characteristics, allowing its constituent units to undergo rapid adjustments and optimizations based on internal and external feedback. This is specifically manifested in adopting a microservices architecture for designing the technical platform, supporting the plug-and-play of functional components; and establishing a rapid validation mechanism based on the minimum viable product (MVP), reducing innovation risks through small-step rapid iteration and continuous integration. This construction approach ensures the pathway itself becomes a learning system, capable of continuously absorbing new knowledge and adapting to new scenarios during implementation, thereby achieving gradual evolution from an initial framework to a mature model[5].

3.1.3 Value Co-creation Focus

The ultimate objective of the pathway is value co-creation and value enhancement for multiple stakeholders. This principle requires that every segment of the pathway clearly defines and effectively measures its value contribution, including the substantive impact on students' professional competency development, enterprises' technological innovation, and institutions' disciplinary advancement. The development approach must center around key value-generation nodes, design corresponding data collection and value assessment indicators, and utilize technologies such as smart contracts to establish a contribution-based value distribution mechanism. By closely linking value creation, value measurement, and value return, the intrinsic motivation of all participating entities is stimulated, ensuring the sustainability and vitality of the innovation ecosystem.

3.2 Implementation Steps and Resource Integration Strategies

3.2.1 Three-Phase Progressive Implementation Model

The implementation process follows a three-phase spiral progression model of "infrastructure construction, paradigm validation, and ecosystem expansion." The infrastructure construction phase focuses on establishing a solid digital foundation, encompassing the intelligent transformation of physical infrastructure, the unification of data standards, the establishment of a governance framework, and the introduction of core algorithm libraries and development tools. The paradigm validation phase selects representative disciplinary strengths as pilot fields, constructs a digital twin environment for industry-education integration, and carries out comprehensive collaborative teaching, research and development, and innovation activities to calibrate models, refine processes, and validate effectiveness through practice. The ecosystem expansion phase involves systematically packaging the validated local paradigms, attracting broader industrial partners and academic institutions to join by opening API interfaces and formulating cooperation standards, gradually forming network effects, and promoting the diffusion of the innovation model from isolated breakthroughs to comprehensive adoption.

3.2.2 Resource Digitization and Virtualized Aggregation Strategy

The core strategy for resource integration lies in promoting the digital representation and virtualized aggregation of various resources. This involves conducting systematic scanning and digital modeling of on-campus human resources, curriculum resources, facility resources, as well as industrial project resources, technological resources, and data resources to form unified "digital resource profiles." On this foundation, cloud computing and Internet of Things technologies are utilized to construct a logically unified yet physically distributed virtual resource pool. This strategy significantly enhances resource visibility, accessibility, and recombinability by breaking down geographical and administrative boundaries of resources. It enables cross-organizational and cross-regional dynamic resource scheduling and on-demand services, thereby providing resource assurance for flexible collaborative innovation[6].

3.2.3 Dynamic Allocation Mechanism Based on Smart Contracts

To achieve efficient and equitable resource allocation, a dynamic allocation mechanism based on blockchain and smart contracts must be introduced. This mechanism encapsulates the resource contributions, task executions, and innovation outcomes of all participating parties into smart contracts in the form of programmable code. When preset collaborative conditions are triggered or tasks are completed, the contracts automatically execute corresponding resource transfers, payment settlements, or benefit distributions. This mechanism not only significantly reduces negotiation, supervision, and execution costs during collaboration but also, through its transparent and tamper-proof characteristics, establishes a solid trust foundation. It incentivizes all parties to contribute their core resources and ensures that resources flow to the links with the greatest innovation potential.

3.3 Multidimensional Support and Continuous Optimization of the Safeguard System

3.3.1 Resilient Technological Architecture and Data Governance System

At the technological safeguard level, it is necessary to construct resilient digital infrastructure that adopts distributed and fault-tolerant designs to ensure continuous service capability during partial component failures or network fluctuations. Simultaneously, a systematic data governance framework must be established to clearly define data ownership, usage rights, and benefit rights, while formulating full lifecycle management specifications covering collection, storage, processing, and destruction. This framework particularly requires strengthening the application of cutting-edge technologies such as privacy computing and differential privacy, maximizing data circulation value and innovation utility while ensuring data security and personal privacy. This provides a reliable and trustworthy technological foundation for the entire digital collaborative innovation ecosystem.

3.3.2 Flattened Organizational Structure and T-Shaped Talent Echelon

The core of organizational support lies in promoting the transformation of the organizational structure toward networking and flattening, breaking down traditional disciplinary barriers and departmental silos, and forming agile innovation teams that are cross-disciplinary and cross-functional. Complementing this is the cultivation and motivation of a T-shaped talent echelon, which possesses both deep specialized knowledge representing the "vertical bar" and broad cross-border collaboration capabilities and digital literacy constituting the "horizontal bar." This requires implementing a series of measures, including establishing a dedicated innovation incentive fund, reforming the faculty evaluation and promotion system, and creating flexible mobility mechanisms for industry and technology experts. These actions aim to attract, cultivate, and retain such core talent, thereby providing continuous human capital support for pathway implementation.

3.3.3 Adaptive Institutional Framework and Closed-Loop Optimization Mechanism

The institutional safeguards require constructing an adaptive institutional framework capable of evolving synchronously with technology and markets. This framework should encompass multiple aspects including intellectual property management, risk investment and profit distribution, quality monitoring and standard certification, while its design must reserve sufficient flexibility to accommodate future innovation forms. More critically, a closed-loop management mechanism of "monitoring-evaluation-decision-optimization" must be established. This involves deploying a key performance indicator sensing network to collect pathway operational data in real-time; utilizing big data analytics for effectiveness evaluation and root cause analysis; and feeding the analysis results back to the management decision-making level to drive periodic optimization adjustments of institutional provisions, resource allocation, and even the technological platform. This approach ultimately achieves synergistic evolution between the entire safeguard system and the innovation pathway.

Conclusion

This study systematically constructs a theoretical framework and implementation pathway for AI-driven digital collaborative innovation in industry-education integration within private vocational undergraduate universities, clarifying its operational mechanism and safeguard system. The research indicates that through the technological integration of data, algorithms, and platforms, coupled with networked collaboration among multiple entities, a high-level matching between educational supply and industrial demand can be achieved. Pathway construction must adhere to the principles of systematicity, agility, and value orientation, relying on a three-phase progressive implementation model and resource virtualization strategy, while continuously optimizing with the support of a resilient technological architecture, T-shaped talent echelons, and an adaptive institutional framework. Future research may further focus on the embedding mechanism of AI ethics within collaborative systems, governance models for cross-domain data circulation, and the construction of a dynamic capability evaluation system, thereby promoting the deepening and application of digital collaborative innovation pathways in broader educational contexts.

Fund Projects

China Private Education Association 2025 Annual Planning Project, project number ：CANQN250253

References

[1] Zhou, S.T. "Practical Research on AI-Enabled Industry-Education Integration in Logistics Talent Cultivation Driven by New Quality Productive Forces." Logistics Science and Technology 48.19 (2025): 142-145.

[2] Li, S.Q., Liu, X.B., & Chen, Y. "International Experiences in Digital Intelligence Talent Cultivation Driven by Industry-Education Integration." Chinese Talents 09 (2025): 76-78.

[3] Li, Y., Zhi, L.P., & Zhao, Q. "Reconstructing the Talent Cultivation Model for Art and Design in Private Universities Through Generative AI and Industry-Education Integration." Science Guide 29 August 2025, B04, Theoretical Academics.

[4] Xu, Y.W., Shi, S.J., & Yu, H. "Anchoring the New Industrial Landscape: Adhering to Industry-Education Integration and Digital Intelligence Drive." Educator 26 (2025): 55-56.

[5] Zhao, Y.C. "Research and Practice of the 'AI-Assisted Design + Project-Driven' Teaching Model in Cultural Creative Development and Design Courses from the Perspective of Industry-Education Integration." Nature 16 (2025): 106-108.

[6] Ye, X.B., & Wang, Z.W. "The Mechanism and Pathway of Open Education Driving the Development of New Quality Productive Forces: From the Perspective of Industry-Education Integration and Digital Intelligence Enablement." Xinjiang Open University Journal 28.04 (2024): 38-42.