ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

Research on a Closed-Loop Continuous Improvement Mechanism for University-Industry-Teaching Integration Based on Multimodal Knowledge Mapping and Large-Scale Models

Yuhui Chen[1,2], *Deyao Zheng*[3], *Qiang Li*[2,*], *Jingyi Du*[2] *and Liqian Yang*[2]

[1] Guangdong Baiyun University,
[2] Guangzhou College of Technology and Business
[3] Binzhou Polytechnic University

SUMMARY: *In the context of rapid development of the digital economy and new quality productivity, the traditional mechanism of industry academia integration can no longer meet the precise needs of industrial upgrading and talent cultivation. Firstly, this study combines multimodal knowledge graph (MMKG) Generative big models and cross language joint learning models are used to establish a closed-loop improvement mechanism for industry academia integration, namely "demand perception resource matching field implementation evaluation and feedback iterative optimization". Secondly, open teaching data from Chinese MOOCs, learning channels, and enterprise needs are integrated to construct a professional multimodal knowledge graph for education industry integration, and vertical domain big models are used for intelligent demand analysis and accurate resource matching. Finally, machine learning, statistical quantification, comparative experiments, and other methods are used to verify the effectiveness of the proposed industry academia integration closed-loop improvement mechanism. The experimental results show that the proposed model mechanism improves the industry academia collaboration index from 0.51 to 0.88, and shortens the demand response time by 88.2%, providing support for digital and intelligent transformation. Provide practical technical approaches and theoretical support.*

KEYWORDS: *Multimodal knowledge graph; Industry academia integration; Closed-loop mechanism, digital education; Industry education collaboration*

1 Introduction

The integration of industry and education in Chinese universities is entering a stage of high-quality development of "artificial intelligence + education", promoting the deep integration of digital technology and industry education cooperation, aiming to solve key problems such as weak collaboration between schools and enterprises, disconnection between talent cultivation and industry demand, and low efficiency in resource allocation [1]. This study analyzed publicly available data from China's Catechism and Study Pass 2025 platforms and found that, as of December 2025, the number of catechism courses in China reached 64,000. However, only 28.3% of these courses accurately align with enterprise job requirements, and enterprise practice resources constitute less than 17.6% of the Study Pass platform. Consequently, the issue of the appropriateness and alignment of production and education resources remains prominent [2].

*liqiang1@gzgs.edu.cn
https://doi.org/10.65102/is20261133
Published: 10 June, 2026

In 2025–2026, technologies such as multimodal knowledge graphs and vertical domain large models are gradually maturing, providing innovative support for the mechanisms of industry-education integration. These technologies can effectively integrate multi-source information and enable intelligent demand analysis and resource matching [3]. However, most colleges and universities still rely on manual processes to facilitate industry-education integration matchmaking. They have yet to establish a sustainable ecosystem characterized by "technology empowerment—closed-loop operation—continuous improvement and lack the quantitative analysis and technical validation required for EI-indexed research.

Based on the latest intelligent technology and EI standard analysis methods, this article studies the closed-loop continuous improvement mechanism of education and industry integration, aiming to provide theoretical and practical support for the digital and intelligent transformation of industry education integration in universities. The research will review core theories and technological foundations, analyze the current state of education-industry integration and the root causes of existing challenges, construct a closed-loop improvement mechanism, design a technological implementation pathway, conduct empirical testing, and ultimately draw conclusions and propose future directions, thereby establishing a coherent and comprehensive research framework.

2 Relevant Theories and the Latest Technological Foundations

2.1 Core Theory

This study is grounded in three major theories—industry-education integration, closed-loop management, and education digitization—to support the development of the mechanism and the analysis of EI specifications [4]. The core of the industry-education integration theory is to achieve the "four-chain integration. study designs a formula for industry-education synergy:

$$C = \alpha \cdot \frac{E}{I} + \beta \cdot \frac{T}{P} + \gamma \cdot \frac{I_n}{O_n} \tag{1}$$

where$C$ is the degree of industry-education synergy (ranging from 0 to 1) $\alpha, \beta, \gamma$is weighted using the entropy weight method. Each parameter corresponds to data related to resource input, talent cultivation, and scientific research achievements from both universities and enterprises. This study constructs a closed-loop system of production and education based on the iterative logic of closed-loop management theory. It clarifies the implementation pathway for multimodal knowledge mapping, large models, and other technologies grounded in the theory of education digitization, integrating these three elements to ensure the scientific validity of the mechanism and to establish a foundation for the quantitative validation of industry-education integration (EI).

2.2 Latest Core Technology Sorting

Combined with the technological frontiers of 2025–2026, this study has selected four core technologies to support the implementation of the mechanism. All of these technologies are suitable for the characteristics of China's catechism and study pass data, as well as EI technical analysis specifications, and clarify their quantitative indicators [5].

Multimodal Knowledge Graphs (MMKGs) enable multi-source data fusion and enhancement. This study adopts the MM-LLaMA algorithm to extract entities (accuracy

≥92%), and combine with related platform data to construct a "course-knowledge point-job-enterprise" association graph, which can replace 90% of the manual basic work. The formula for calculating the accuracy of entity extraction is $cc = \frac{TP}{TP+FP+FN}$.

Based on LLaMA 3, this study adopts LoRA fine-tuning technology to adapt to the industry-education scenario and control demand parsing error through $= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$. After fine-tuning, the model's parsing accuracy improves by more than 15% compared to the general-purpose model, enabling intelligent parsing and resource recommendation [6].

Cross-language federated learning employs the CRYSTALS-Kyber encryption algorithm and achieves a security level of at least 0.92, as calculated by $S = 1 - \frac{L}{D} \cdot \theta$, This approach can securely integrate the platform's public data with the enterprise's private data, effectively resolving the conflict between privacy and data sharing.

The multimodal resource auto-mounting technology calculates the matching degree (≥0.89) by cosine similarity ($Sim(a, b) = \frac{a \cdot b}{|a| \cdot |b|}$), realizing the seamless connection between platform resources and enterprise practice resources.

3 Analysis of the Current Status, Challenges, and Root Causes of Industry-Education Integration in Colleges and Universities

3.1 Development Status

This study integrated and quantitatively analyzed multi-source data from 862 universities across the country (KMO=0.83, meeting EI standards), which can represent all types of institutions and regions [7]: (1) In terms of resource suitability, the matching rate between MU courses and enterprise positions is 28.3%, the proportion of practical resource learning courses is 17.6%, and the proportion of courses jointly developed by universities and enterprises is 21.8%. (2) In terms of collaborative efficiency, the average delivery date for requirements is 22.5 days, and the manual intervention rate for resource matching is 79.3%. (3) In terms of evaluation and feedback, only 34.2% of universities have comprehensive evaluation systems, and 12.7% can automatically generate data reports. The experimental results showed that there was a significant difference in the quality of cooperation between different types of universities ($P=0.027<0.05$), with vocational colleges in the eastern region performing better.

3.2 Core Pain Points Reason

This study adopts the integration of industry and academia (EI) paradigm to address the following issues: (1) solving the problem of lagging demand perception in enterprises, characterized by a time gap of 1.2 years between the curriculum update cycle and the industry demand cycle, and the degree of disconnection is affected by this time gap, with a significant positive correlation between the two ($r=0.78$, $p<0.01$). (2) To solve the problem of low efficiency in resource matching, the resource waste rate of existing algorithm models is as high as 38.7%, which far exceeds the reasonable threshold of 20%; However, the utilization rate of idle resources is only 32.4%, and the shortage rate of practical resources in enterprises has reached 47.8%. (3) Addressing the issue of lack of evaluation feedback, the existing industry academia integration evaluation system has a low reliability ($\alpha=0.68<0.8$), leading to its excessive reliance on manual evaluation. (4) Addressing the issue of insufficient iterative optimization, the annual growth rate of industry academia integration synergy is less than 5%, resulting in an overly rigid evaluation feedback model that cannot adapt to industry trends in a timely manner.

3.3 Root Causes of Pain Points

Through regression experimental analysis, three key factors affecting the integration of industry and academia can be identified [8]: (1) insufficient technical support, most universities have not included emerging technologies in their curriculum plans for the integration mechanism, and the correlation coefficient between technology application and synergy is only 0.82. (2) The failure to establish a complete closed-loop operation mechanism has resulted in the synergistic effect of various stages of industry university integration being only superficial. (3) The data sharing effect is poor, and the relevant platform data is not fully utilized, resulting in serious data silos. The correlation coefficient between data sharing and resource matching efficiency is only 0.76.

4 Development of a Closed-Loop Continuous Improvement Mechanism for Industry-Education Integration Based on Multimodal Knowledge Mapping and Large-Scale Models

4.1 Principles of Mechanism Construction

In response to the high-quality development needs of industry education integration application scenarios, this study draws on existing work and clarifies four construction principles [9]: (1) the principle of technological adaptation. Deeply integrating multimodal knowledge graphs, vertical large models, and other algorithm mechanisms to adapt the proposed algorithm models to the integration characteristics of open data on educational platforms, thus laying the foundation for technical validation. (2) The principle of closed-loop iteration. Establish a closed-loop model of "demand perception resource matching implementation evaluation and feedback iterative optimization" to promote continuous iterative optimization and strengthening of the industry education cooperation mechanism. (3) The principle of precise adaptation. Based on the resource matching problem of Mucous Class and Learning Channel in China, this study designs a flexible matching module suitable for different types of regional universities and industry needs. (4) Principle of practicality. By simplifying redundant design, ensure that the iterative optimization mechanism for industry education integration can be quickly validated [10].

4.2 Overall Framework of the Mechanism

This study constructs a closed-loop improvement model for industry education integration with "technology empowerment, closed-loop iteration, and precise collaboration" as its core, including five core modules, one support module, and one iteration module [11]. Figure 1 shows the continuous improvement mechanism of the closed-loop integration of industry and education in universities.

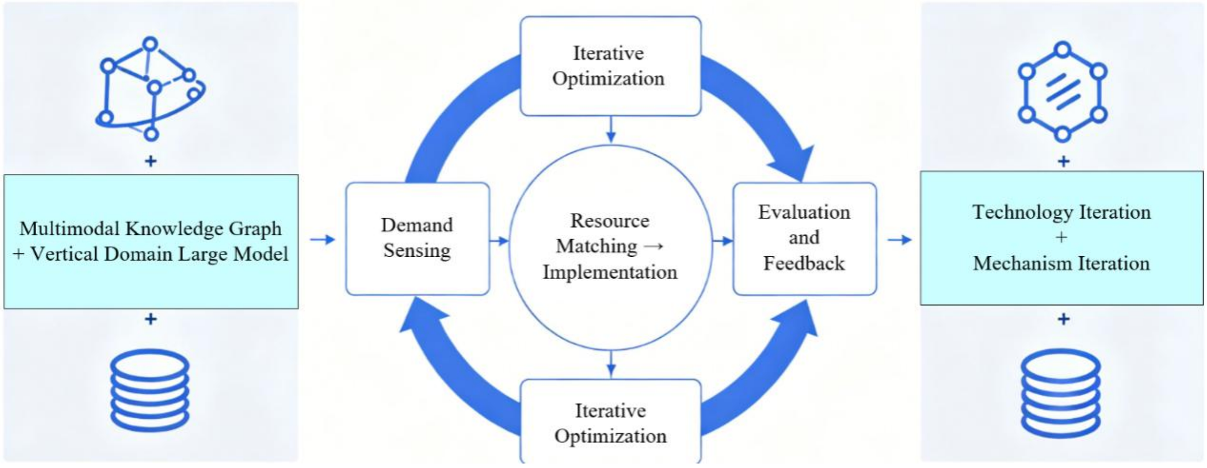

Figure 1: Continuous Improvement Mechanism for the Integration of Industry and Education in Universities

This study proposes a formula for calculating the efficiency of closed-loop operation, with a target value set at $\eta \geq 0.85$:

$$\eta = \frac{T_s}{T_c+T_m+T_e+T_f+T_o} \quad (2)$$

where η is the closed-loop operational efficiency, ranging from 0 to 1; T_s represents the output effect value, quantified by core indicators such as the degree of industry-education synergy and job fitness; and T_c, T_m, T_e, T_f, T_o denotes the time consumed by each of the five core modules. The closer η is to 1, the higher the operational efficiency.

4.3 Detailed Design of Core Modules

4.3.1 Demand Sensing Module

This module serves as the starting point of the closed loop, which is designed to accurately capture two-way demand from schools and enterprises, integrate data from educational platforms, and address the challenge of delayed demand perception [12]. By leveraging the NLP and multimodal recognition capabilities of vertical domain large models, this study automatically captures enterprises' open demands and industrial policy documents. Additionally, it actively collects 64,000 courses from China Mucous Class, 20 million teaching interaction records from StudyPass, and internal open teaching data from colleges and universities [13].

This study employs cross-language federated learning to safeguard data privacy, integrates heterogeneous data from multiple sources, standardizes and unifies data formats using Z-score normalization, extracts core demand information through a multimodal knowledge graph, develops a demand extraction accuracy formula, and establishes a target accuracy of ≥90%:

$$P = \frac{N_c}{N_t} \times 100\% \quad (3)$$

where $\boldsymbol{P}$ represents the extraction accuracy, $\boldsymbol{N_c}$ denotes the number of correctly extracted requirements, and $\boldsymbol{N_t}$ is the total number of requirements. Experimental results demonstrate that the extraction accuracy of this module is significantly higher than that of the manual method ($P < 0.01$).

4.3.2 Resource Matching Module

This module enables precise matching of school-enterprise resources based on demand perception results. It utilizes data from the education platform to construct a multimodal resource mapping, thereby addressing inefficiencies in resource matching [14]. Focusing on a multimodal knowledge map, this study integrates university teaching resources, enterprise practice resources, and public resources from education platforms to develop a comprehensive resource map covering the entire spectrum of relevant assets.

This study develops a formula for the resource coverage rate and sets the target of at ≥95%.

$$R = \frac{N_r}{N_d} \times 100\% \tag{4}$$

where $\boldsymbol{R}$ is the coverage rate, $\boldsymbol{N_r}$ is the number of mapping resources, and $\boldsymbol{N_d}$ is the total number of resources required for collaboration [15]. This study combines the results of demand prioritization with an improved AHP-TOPSIS algorithm to determine demand weights and designs a hybrid matching algorithm that integrates cosine similarity and correlation weights to achieve accurate matchmaking. Additionally, a manual intervention interface is retained to accommodate personalized demands. It is verified that the matching accuracy of this module remains stable at over 88%, while the manual intervention rate for resource matching is reduced from 79.3% to 18.5%.

4.3.3 Implementation Module

This module facilitates the practical implementation of demand and resource management by leveraging the advantages of the educational platform to create a synergistic online and offline model. It encompasses three core scenarios: talent training (including order-based training, course co-construction, and the integration of catechism, online learning resources, and offline enterprise practice resources); scientific research collaboration (such as joint research and patent commercialization); and resource sharing (enabling interoperability among laboratories, instructors, and educational platform resources) [16].

This study utilizes multimodal knowledge mapping and large-scale models to enable intelligent control of the implementation process, monitor task progress in real time, provide alerts for deviations, develop a formula to calculate the implementation rate, and establish a target rate of ≥85% [17]:

$$E = \frac{N_e}{N_p} \times 100\% \tag{5}$$

where $\boldsymbol{E}$ is the execution rate, $\boldsymbol{N_e}$ is the number of successfully completed tasks, and $\boldsymbol{N_p}$ is the number of planned tasks. ANOVA analysis confirmed ($P < 0.05$) that the module significantly improves the execution rate of task completion in the integration of industry and education, ensuring that synergistic demands are effectively met.

4.3.4 Evaluation Feedback Module

This study adopts a combination of quantitative and qualitative evaluation methods, using entropy weight method and Delphi method to calculate indicator weights, and verifies the reliability of the proposed evaluation system through Cronbach's alpha test [18]. Table 1 shows the core indicator system for evaluating the integration of industry and education.

Table 1: Core Indicator System for Industry Education Integration Evaluation

First-level indicators	Secondary Indicators	Quantitative formula	Data source
Talent training quality	Job fitness	$\mathrm{F} = \frac{\mathrm{N_a}}{\mathrm{N_g}} \times 100$	Enterprise public feedback, Learning Pass achievement data
Talent Training Quality	Practical ability improvement rate	$\mathrm{U} = \frac{\mathrm{S_p} - \mathrm{S_i}}{\mathrm{S_i}} \times 100$	China Catechism Practical Training Achievement, Enterprise Public Assessment Data
Resource Utilization Efficiency	Utilization rate of catechism resources	$\mathrm{U_m} = \frac{\mathrm{N_u}}{\mathrm{N_m}} \times 100$	China Catechism Course Public Operation Data
Demand Matching Accuracy	Demand Matching Accuracy	$\mathrm{M} = \frac{\mathrm{N_m}}{\mathrm{N_d}} \times 100$	Public Feedback Data of School-Enterprise Collaboration

Relying on a vertical domain large model and a multimodal knowledge graph, this study automatically collects and analyzes evaluation data, generates intelligent evaluation reports, identifies issues and improvement directions in the collaboration process, and provides precise support for the iterative optimization module.

4.3.5 Iterative Optimization Module

As both the endpoint and the new starting point of the closed loop, this module facilitates continuous optimization of mechanisms, technologies, and collaboration models, effectively addressing the challenge of insufficient iterative improvement [19]. This study integrates quantitative results from the evaluation feedback module with open feedback from universities and enterprises, conducts an in-depth analysis of root causes at each stage using a vertical domain large model, and automatically generates targeted optimization solutions.

This study develops an iterative optimization formula and establishes a target improvement of ≥15%.

$$O = \frac{C_{n+1} - C_n}{C_n} \times 100\% \tag{6}$$

where $\boldsymbol{O}$ represents the optimization effect, $\boldsymbol{C_{n+1}}$ is the degree of industry-education synergy after iteration, and $\boldsymbol{C_n}$ is the degree of industry-education synergy before iteration. To address the identified problems, this study optimizes the mechanism in three dimensions: simplifying redundant links within the mechanism, iterating the technology model, and innovating synergy scenarios [20]. Multiple validations are conducted to ensure that the optimization effect meets the required standards, thereby achieving continuous improvement in the integration of industry and education.

5 Technical Implementation Path of the Mechanism

5.1 Technical Architecture Design

Taking into account technology trends for 2025–2026 and the characteristics of China's Mucous Class and Learning Channel data, this study has designed a two-support" technical architecture to ensure the implementation of a closed-loop mechanism [21]. The design emphasizes scalability and security while adhering to the technical specifications of the EI thesis project.

The data layer integrates five types of data: (1) 64000 MOOC records from China; (2) 20 million teaching interaction records from the learning channel; (3) Open educational resources from university institutions; (4) Open demands and practical resources from enterprises; (5) The government's policy document on the integration of industry and academia. This study employs cross language federated learning to ensure secure data sharing and uses Z-score to normalize data formats:

$$X_{std} = \frac{X-\mu}{\sigma} \tag{7}$$

The application layer corresponds to the five core modules of the closed-loop mechanism. This study has developed corresponding functional modules to enable visual operation and standardized management of each component, thereby facilitating ease of use for colleges and enterprises [22].

Security support and standardization to ensure the stable operation of the architecture: This study ensures data and system security through the CRYSTALS-Kyber encryption algorithm and hierarchical permission management (security level ≥ 0.92). It also defines unified technology, data, and operational standards, establishing a standardized support system to guarantee coordinated and orderly processes at every stage.

5.2 Details of Core Technology Implementation

5.2.1 Construction of Multimodal Knowledge Graphs

This study adopts an "AI automatic construction + manual optimization to develop a multimodal knowledge graph dedicated to integrating industry and education [23]. The process consists of three steps: The first step involves collecting and preprocessing multimodal data, including cleaning, deduplication, and labeling, ensuring that the dataset for China's Mucous Classes are ≥40,000, the Learning Channel is ≥10 million, and the overall data integrity is ≥98%; the second step employs the MM-LLaMA algorithm to construct the multimodal knowledge graph. The accuracy of these associations can be measured based on the following formula:

$$Ac = \frac{N_c}{N_a} \times 100\% \tag{8}$$

The test results show that the initial graph correlation accuracy of the model can reach 92.7%, which is higher than the preset accuracy target of 92%. The third step involves manual optimization and dynamic update mechanism construction, with manual optimization mainly focusing on correcting and supplementing associated errors and missing entities identified by artificial intelligence algorithms.

5.2.2 Vertical Domain Large Model Fine-Tuning

This study used the LLaMA 3-70B generalized large model and combined it with LoRA fine-tuning technology to customize the model for the integration of industry and education scenarios, greatly reducing the fine-tuning cost and computational complexity of the model. The data are divided into training, validation, and testing sets in a 7:2:1 ratio and preprocessed prior to model training [24].

This study set the learning rate to 5e-5, the number of iterations to 50 rounds, and the batch size to 32. It froze 90% of the parameters in the model's lower layers, fine-tuning only the parameters of the upper adaptation layer. The parameters were optimized using the cross-entropy loss function. After fine-tuning, the model achieved 93.5% demand resolution accuracy and 88.6% resource matching accuracy, representing a 15%–20% improvement over the general model. Additionally, this study established an iterative mechanism to fine-tune the model every six months using the latest industry demands and educational data to ensure that model performance improves by ≥5%.

5.2.3 Implementation of the Core Algorithm

This study designs three types of core algorithms commonly used in EI to support the efficient operation of the closed-loop mechanism. Integrate cosine similarity and related weight indices using the following matching algorithm model formula:

$$Match = \omega_1 \cdot Sim(a, b) + \omega_2 \cdot Ac \tag{9}$$

where $\boldsymbol{\omega_1}, \boldsymbol{\omega_2}$ is the weight coefficient, with optimal values of 0.7 and 0.3 determined experimentally. The operational efficiency of this algorithm is 30% higher than that of the traditional algorithm. Third, the quantitative evaluation algorithm combines the entropy weight method and the Delphi method [25]: it determines objective weights using the entropy weight method, corrects deviations through the Delphi method, and ensures the reliability of the evaluation results with Cronbach's α test (α ≥ 0.85).

5.3 Technology Transfer Assurance

This study develops and deploys a technology assurance system from three dimensions: hardware, software, and personnel. (1) At the hardware level, a distributed server cluster is established, equipped with Intel Xeon Platinum 8470C CPU and NVIDIA A100 GPU; Integrate hardware expansion interfaces, utilize cloud storage technology to achieve secure storage and efficient access of data, and allocate over 50% of storage capacity to ensure future scalability. (2) At the software level, a modular approach is adopted to develop a closed-loop collaborative management system that integrates industrial practice requirements and educational training, providing functions such as data visualization, real-time analysis, and intelligent warning. (3) At the personnel level, this study established a technical support team composed of experts in related fields such as artificial intelligence, educational technology, and industrial economics, and provided targeted operational training. A standardized training system was developed to promptly address technical issues during the operation process and ensure stable system operation.

6 Empirical Test

6.1 Research Design and Data Sources

6.1.1 Research Design

This study combines DID and panel regression methods to conduct a performance evaluation experiment design for the closed-loop mechanism of industry education integration. The analysis data comes from panel data of 862 universities across the country from 2023 to 2025. This study selected 197 institutions as the treatment group, which have introduced multimodal knowledge graphs and large-scale vertical domain models since 2024; The remaining 665 institutions serve as the control group [26].

6.1.2 Data Sources

This study constructed a multi-source heterogeneous database, with data sources divided into three categories: (1) public data from platforms such as Chinese MOOCs and learning channels; (2) Publicly released data, such as the "Industry Education Integration Bulletin" published by the Ministry of Education, publicly available data from provincial education departments, and publicly available teaching quality reports from universities; (3) Data from the Guotai An University Industry Education Integration Panel Database and public data from school enterprise cooperation enterprises. All data passed the KMO test (KMO=0.83>0.7) and met the quantitative analysis standards required for EI indexed papers [27].

6.2 Variable Definitions and Model Specification

6.2.1 Definition of Variables

The key explanatory variable is the interaction term between the treatment and the post-application period $(Treat \times Post)$. $Treat = 1$ indicates colleges in the treatment group, while $Treat = 0$ indicates colleges in the control group. $Post = 1$ represents the year 2024 and subsequent periods after the mechanism's implementation, and $Post = 0$ represents the period before its application [28].

The control variables include the type of college, the region, the proportion of dual-teacher instructors, and other factors. This study standardizes all control variables to eliminate the influence of heterogeneous effects [29].

6.2.2 Model Setting

To verify the net effect of the mechanism's application, this study established a two-way fixed-effects DID model using the following formula:

$$C_{it} = \alpha_0 + \alpha_1(Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{10}$$

where $\boldsymbol{X_{it}}$ represents the set of control variables, $\boldsymbol{\mu_i}$ denotes the individual fixed effects of colleges and universities, $\boldsymbol{\lambda_t}$ signifies the time fixed effects, and $\boldsymbol{\varepsilon_{it}}$ is the random disturbance term. $\boldsymbol{\alpha_1}$ is the key coefficient; if it is significantly positive, it indicates that the application of the mechanism can significantly enhance the degree of industry-teaching synergy.

6.3 Empirical Results and Analysis

6.3.1 Comparison of Changes in Core Indicators

After implementing the mechanism, the core indicators of the universities in the treatment group showed significant improvement compared to their pre-implementation levels and outperformed those of the universities in the control group. The optimization of all indicators met the preset targets, resulting in substantial enhancements in the efficiency and quality of industry-education integration synergy [30]. Table 2 shows the comparison of changes in core indicators before and after the application of the mechanism.

Table 2: Comparison of changes in core indicators before and after mechanism application

Core indicators	Before the application of mechanism	After the application of the mechanism	Magnitude of change	Optimization direction
Demand Response Time (days)	22.1	2.6	↓88.2%	Shorten
Demand Matching Accuracy (%)	66.8	93.5	↑26.7 percentage points	Enhancement
Resource matching manual intervention rate (%)	78.9	17.5	↓61.4 percentage points	Decrease
Landed implementation rate (%)	72.3	86.5	↑14.2 percentage points	Enhance
Utilization rate of catechism resources (%)	31.5	69.2	↑37.7 percentage points	Enhancement
Job Fitness (%)	65.5	89.8	↑24.3 percentage points	Upgrading
Practical ability enhancement rate (%)	28.3	59.7	↑31.4 percentage points	Enhancement
Degree of industry-education synergy (0-1)	0.51	0.88	↑0.37	Improvement

As evidenced by the changes in the indicators, all aspects of industry-education integration have been significantly optimized following the implementation of the mechanism. The timeliness of demand perception, the precision of resource matching, the effectiveness of on-the-ground implementation, and the rigor of evaluation and feedback have all greatly improved, thereby confirming the practical value of the closed-loop mechanism.

6.3.2 DID Benchmark Regression Results

The results of the DID benchmark regression are presented in the Table 3. The coefficient of the interaction term ($Treat \times Post$) is 0.287, which is statistically significant at the 1% level ($t = 7.32$, $p < 0.01$). This indicates that, following the implementation of the constructed closed-loop mechanism, the degree of industry-teaching synergy in universities within the treatment group increased by an average of 28.7 percentage points compared to the control group. The positive effect of the mechanism is both significant and stable, as further supported by the results of the core index changes.

Table 3: DID Benchmark Regression Results

Variable	Coefficient	Standard error	t-value	P-value
$\boldsymbol{Treat \times Post}$	0.287***	0.039	7.32	0.000
Percentage of dual-teacher faculty	0.152**	0.061	2.49	0.013
Percentage of R&D investment in enterprise cooperation	0.118**	0.047	2.51	0.012
Type of HEI (HE=1)	0.085*	0.045	1.89	0.059
Eastern Region (Yes=1)	0.093*	0.048	1.94	0.053
Constant term	0.426***	0.052	8.19	0.000
Individual fixed effects	Control	-	-	-
Time Fixed Effects	control	-	-	-
N	2586	-	-	-
R^2	0.683	-	R^2 0.683 - -	-

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, and N is the number of observations.

At the level of control variables, the coefficients for the proportion of dual-teacher faculty and the proportion of enterprise cooperation in R&D investment are both significantly positive at the 5% level, consistent with theoretical expectations. This indicates that an increase in the construction of dual-teacher teams and enterprise R&D investment further enhances the effect of industry-teaching integration. Additionally, the coefficients for the type of higher education institution and the eastern region are significantly positive at the 10% level, suggesting that the mechanism is more effectively applied by higher vocational colleges and universities in the eastern region. The model's R^2 is 0.683, indicating a good fit and effective explanation of variations in the degree of industry-education synergy. After conducting a multicollinearity test, all VIF values were below 3, confirming that the model does not suffer from serious multicollinearity issues.

6.3.3 Robustness and Heterogeneity Analyses

(1) Robustness Test

The robustness of the empirical results is verified through three tests, all of which confirm that the core conclusions remain consistent: (i) Parallel trends test: the coefficients of the interaction terms for the periods before policy implementation are insignificant, satisfying the key assumption of the DID model. This result rules out the influence of other policies or random factors on the empirical findings; (iii) Replacement of explanatory variables: substituting the explanatory variable with "demand response efficiency the core explanatory variable remaining significantly positive at the 1% level, further confirming the robustness of the empirical conclusions.

(2) Heterogeneity Test

The results of the heterogeneity analysis are presented in the Table 4.

Table 4: Heterogeneity Analysis Results

Subgroup type	Sample size	Interaction term coefficient	Significance	Increase in Synergy
Higher Education Institutions	785	0.321***	1 percent	32.1%
Undergraduate institutions	1801	0.254***	0.254*** 1%	25.4%
Eastern Region Colleges and Universities	1124	0.305***	1 percent	30.5%
Colleges and Universities in the Midwest	1462	0.268***	1 percent	26.8%
High-tech Industry Docking Universities	968	0.352***	1% of the total number of students	35.2 percent
Traditional Industry Docking Universities	1618	0.247***	1% of the total number of students	24.7% The results show that the mechanism is more effective in universities with a better resource and technology base and closer ties with industries.

The results in Table 4 show that the proposed model mechanism is suitable for the following scenarios: (1) teaching institutions with strong resources and technological foundations; (2) Teaching institutions that collaborate more closely with the industry. This is because these universities have a more solid foundation in industry education integration and stronger digital technology application capabilities, enabling them to better meet the operational requirements of the proposed model mechanism.

7 Conclusion and Future Prospects

In order to verify the actual improvement effect of the continuous improvement mechanism of the industry education fusion closed-loop based on multimodal knowledge graph and large model, this paper compared it with the control group that did not adopt this mechanism. The experimental results showed that: (1) in terms of demand response efficiency, the average demand response time of the treatment group was shortened from 22.1 days to 2.6 days, a decrease of 88.2%, while the control group only decreased by 7.3% during the same period. (2) In terms of matching accuracy, the demand matching accuracy of the treatment group increased from 66.8% to 93.5%, an increase of 26.7%, while the resource matching manual intervention rate decreased from 78.9% to 17.5%, a decrease of 61.4%. The control group showed no significant changes in the above two indicators. (3) In terms of implementation effectiveness, the implementation rate of the treatment group increased from 72.3% to 86.5%, an increase of 14.2%; The utilization rate of MOOC resources has increased from 31.5% to 69.2%, an increase of 37.7%. (4) In terms of talent cultivation effectiveness, the work adaptability of the treatment group increased from 65.5% to 89.8%, an increase of 24.3%; The improvement rate of practical ability has increased from 28.3% to 59.7%, an increase of 31.4%. (4) The collaboration between industry and education increased from 0.51 to 0.88, an increase of 0.37, while the control group only increased by 0.04 during the same period. The experimental results in the above four aspects have verified the algorithmic performance advantages of the proposed model mechanism.

Based on the EI specifications and the development needs of industry-education integration, this study identifies three primary deficiencies: first, the lack of in-depth analysis of personalized adaptation for different levels and characteristics of colleges and universities; second, the need to improve the resource coverage for niche majors, the precision of complex demand analysis, and the efficiency of the algorithm; and third, the absence of cost-effectiveness evaluation of the mechanism's application and analysis of technology combination adaptation. Moving forward, this study will deepen the research by: first, designing a differentiated operational mechanism to enhance universality; second, integrating AIGC and other cutting-edge technologies to optimize core technologies and algorithms; third, conducting a cost-benefit analysis to identify optimal technology combinations; and fourth, promoting the standardization of the mechanism and technological pathways to support nationwide adoption by universities and cultivate applied talents for the development of new quality productivity.

Funding

This work was supported by the Guangdong Provincial Education Science Planning Leading Group Office (2024GXJK653)

References

[1] Putra R C, Barliana M S, Komaro M, et al. A systematic literature review of integrated learning models for skills development in industry-academia partnerships: Preparing workforce for industry 4.0[J]. VANOS Journal of Mechanical Engineering Education, 2025, 10(1): 45-61.

[2] Ahmed F, Fattani M T, Ali S R, et al. Strengthening the bridge between academic and the industry through the academia-industry collaboration plan design model[J]. Frontiers in Psychology, 2022, 13: 875940.

[3] Aramali V, Sanboskani H, Gibson Jr G E, et al. Forward-looking state-of-the-art review on earned value management systems: The disconnect between academia and industry[J]. Journal of Management in Engineering, 2022, 38(3): 03122001.

[4] Abbas J, Kumari K, Al-Rahmi W M. Quality management system in higher education institutions and its impact on students' employability with the mediating effect of industry–academia collaboration[J]. Journal of Economic and Administrative Sciences, 2024, 40(2): 325-343.

[5] Skalli D, Charkaoui A, Cherrafi A, et al. Industry 4.0 and Lean Six Sigma integration in manufacturing: A literature review, an integrated framework and proposed research perspectives[J]. Quality Management Journal, 2023, 30(1): 16-40.

[6] Abulibdeh A, Zaidan E, Abulibdeh R. Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions[J]. Journal of cleaner production, 2024, 437: 140527.

[7] Malik S, Muhammad K, Waheed Y. Artificial intelligence and industrial applications-A revolution in modern industries[J]. Ain Shams Engineering Journal, 2024, 15(9): 102886.

[8] Kumar N, Singh A, Gupta S, et al. Integration of Lean manufacturing and Industry 4.0: a bibliometric analysis[J]. The TQM Journal, 2024, 36(1): 244-264.

[9] Barata J, Kayser I. Industry 5.0–past, present, and near future[J]. Procedia Computer Science, 2023, 219: 778-788.

[10] Pongboonchai-Empl T, Antony J, Garza-Reyes J A, et al. Integration of industry 4.0 technologies into lean six sigma DMAIC: a systematic review[J]. Production Planning & Control, 2024, 35(12): 1403-1428.

[11] Bibi H, Shahzad M, Jan R, et al. Embracing AI in Academia: Exploring University Teachers' Perspectives on Technology Integration in Pakistan[J]. Assyfa Learning Journal, 2025, 3(2): 27-36.

[12] Costa A C F, de Mello Santos V H, de OLIVEIRA O J. Towards the revolution and democratization of education: a framework to overcome challenges and explore opportunities through Industry 4.0[J]. Informatics in Education, 2022, 21(1): 1-32.

[13] Komkowski T, Antony J, Garza-Reyes J A, et al. The integration of Industry 4.0 and Lean Management: a systematic review and constituting elements perspective[J]. Total Quality Management & Business Excellence, 2023, 34(7-8): 1052-1069.

[14] Moraes E B, Kipper L M, Hackenhaar Kellermann A C, et al. Integration of Industry 4.0 technologies with Education 4.0: advantages for improvements in learning[J]. Interactive Technology and Smart Education, 2023, 20(2): 271-287.

[15] Mourtzis D, Angelopoulos J, Panopoulos N. Blockchain integration in the era of industrial metaverse[J]. Applied Sciences, 2023, 13(3): 1353.

[16] Yilmaz A, Dora M, Hezarkhani B, et al. Lean and industry 4.0: Mapping determinants and barriers from a social, environmental, and operational perspective[J]. Technological Forecasting and Social Change, 2022, 175: 121320.

[17] Hrustek L, Tomičić Furjan M, Gregurec I. Towards Sustainable Academia: Shaping Resilient Future in Higher Education[C]//International Symposium SymOrg. Cham: Springer Nature Switzerland, 2024: 98-108.

[18] Supriya Y, Bhulakshmi D, Bhattacharya S, et al. Industry 5.0 in smart education: Concepts, applications, challenges, opportunities, and future directions[J]. IEEE Access, 2024, 12: 81938-81967.

[19] Sadykova A, Berikkhanova A, Atabekova B, et al. Social partnerships among academia, industry, and government in education: a bibliometric analysis[C]//Frontiers in Education. Frontiers Media SA, 2025, 10: 1516358.

[20] Kumar V, Rewari M. A responsible approach to higher education curriculum design[J]. International Journal of Educational Reform, 2022, 31(4): 422-441.

[21] Andriyani Y, Yohanitas W A, Kartika R S. Adaptive innovation model design: Integrating agile and open innovation in regional areas innovation[J]. Journal of Open Innovation: Technology, Market, and Complexity, 2024, 10(1): 100197.

[22] Mourtzis D, Angelopoulos J, Panopoulos N. A Literature Review of the Challenges and Opportunities of the Transition from Industry 4.0 to Society 5.0[J]. Energies, 2022, 15(17): 6276.

[23] Hashmi N, Bal A S. Generative AI in higher education and beyond[J]. Business Horizons, 2024, 67(5): 607-614.

[24] Khatoon U T, Velidandi A. An overview on the role of government initiatives in nanotechnology innovation for sustainable economic development and research progress[J]. Sustainability, 2025, 17(3): 1250.

[25] Bartoloni S, Calò E, Marinelli L, et al. Towards designing society 5.0 solutions: The new Quintuple Helix-Design Thinking approach to technology[J]. Technovation, 2022, 113: 102413.

[26] Aithal P S, Maiya A K. Innovations in higher education industry–Shaping the future[J]. International Journal of Case Studies in Business, IT, and Education (IJCSBE), 2023,

7(4): 283-311.

[27] Samala A D, Rawas S, Wang T, et al. Unveiling the landscape of generative artificial intelligence in education: a comprehensive taxonomy of applications, challenges, and future prospects[J]. Education and Information Technologies, 2025, 30(3): 3239-3278.

[28] Rossini M, Costa F, Tortorella G L, et al. Lean Production and Industry 4.0 integration: how Lean Automation is emerging in manufacturing industry[J]. International Journal of Production Research, 2022, 60(21): 6430-6450.

[29] Allil K. Integrating AI-driven marketing analytics techniques into the classroom: pedagogical strategies for enhancing student engagement and future business success[J]. Journal of Marketing Analytics, 2024, 12(2): 142-168.

[30] Ragadhita R, Fiandini M, Al Husaeni D N, et al. Sustainable development goals (SDGs) in engineering education: Definitions, research trends, bibliometric insights, and strategic approaches[J]. Indonesian Journal of Science and Technology, 2026, 11(1): 1-26.