

Research on the Construction and Application of New Business Education Integration Teaching Model Empowered by Artificial Intelligence

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ABSTRACT New business education requires a teaching model capable of dynamically aligning curriculum content, industrial skill demand, project allocation, and practical decision training. To reduce the mismatch between fast-changing industrial requirements and static curriculum revision cycles, this study constructs an AI-empowered industry–education integration model. A dynamic industry-skill knowledge graph is built from 45,600 job postings using BERT and BiLSTM-CRF to extract job-skill entities and relationships. A semantic mapping mechanism calculates the alignment between course syllabi and industry skill nodes, producing curriculum update suggestions. A multi-agent reinforcement learning scheduler then matches students and enterprise projects using ability vectors, project demand vectors, and reward functions considering semantic fit, team complementarity, and resource idleness. Finally, a generative business simulation sandbox based on cGAN and large language models creates dynamic market demand and competitor strategies for decision training. A 16-week controlled experiment shows that AI-driven mapping raises semantic alignment to 0.89, reinforcement learning reduces project-resource idle rate to 5.7%, and generative sandbox training improves students’ strategy innovation and risk-prediction scores by more than 23 points. The model provides an intelligent decision-support framework for adaptive education systems and industry–education resource coordination.

INDEX TERMS knowledge graph, multi-agent reinforcement learning, generative simulation, decision support, industry-education integration

I. INTRODUCTION

CURRENTLY, the digital economy wave is profoundly reshaping global business logic and industrial forms. New business education shoulders the mission of cultivating compound talents with data thinking, cross-border integration and dynamic decision-making capabilities [1]. However, in the process of deepening the integration of industry and education, two structural contradictions have become increasingly prominent: First, the demand iteration cycle for cutting-edge skills such as business data analysis and intelligent operation in the industry has been shortened to the quarterly level, while the revision of university course outlines is usually done on an academic year basis. This “supply and demand time difference” leads to a significant semantic gap between teaching content and actual job requirements; Second, the practical training link of school-enterprise collaborative education has long relied on static case texts and manual coordination, making it difficult to reproduce the nonlinear mutation of supply and demand relationship and the tension of multiparty game in the real business environment, resulting in a clear scene gap between

what students learn and what the industry uses [2,3]. If the above problems are not effectively solved, the integration of industry and education will be difficult to get rid of the practical dilemma of “integration without depth and integration without thoroughness”.

Academia has explored the optimization of teaching models for the integration of industry and education from different perspectives. For example, Crittenden [4] pointed out from the development trend of marketing education that business education is accelerating its transformation towards a paradigm driven by technology and practice-oriented; Guha et al. [5] and Grewal et al. [6] further analyzed the role of AI in the reconstruction of marketing education content system and teaching methods from the perspective of generative artificial intelligence, and believed that AIGC will profoundly change the path of knowledge production and ability cultivation; Kou G [7] proposed a teaching framework based on constructivist theory to achieve deep integration of theory and practice through AI technology. At the same time, in the field of management education, Cook and Cook [8] systematically explored the application

potential and real challenges of artificial intelligence in curriculum design and ability cultivation. In terms of industry-education integration and school-enterprise collaboration, Pujotomo et al. [9] pointed out through a systematic review that the collaborative mechanism between universities and industries in technology development and talent cultivation still faces structural obstacles; Rossoni et al. [10] further analyzed the key promoting factors and constraints in school-enterprise cooperation from the perspective of innovation systems; Vuoriainen et al. [11] summarized the key elements for the successful implementation of higher education and industry collaboration, and provided a theoretical basis for building an efficient collaborative education mechanism. However, existing research still has two limitations: first, most solutions rely on static rule setting based on human experience, lacking the ability to adapt to the dynamic evolution of industry demands; second, the complexity and uncertainty of training environments are far lower than real business decision-making scenarios, making it difficult to effectively assess the transfer effect of students' dynamic cognitive abilities.

The rapid development of artificial intelligence technology provides new methodological support for solving these problems. At the demand perception level, natural language processing and knowledge graph technologies have been used for the automated extraction and structured representation of job competency profiles, enabling real-time capture of industry demand signals; at the resource scheduling level, reinforcement learning and multi-agent systems have been fully validated in areas such as logistics scheduling and cloud computing resource allocation, demonstrating scheduling efficiency surpassing that of manual rules; at the scenario construction level, generative adversarial networks and AIGC technologies have shown unique advantages in simulating non-stationary environments and generating adversarial strategies, opening up new paths for building high-fidelity business decision-making training environments. Nevertheless, current research is mostly a partial application of single technologies and has not yet formed a systematic solution spanning the entire chain of “demand perception—resource matching—scenario training”.

Taking the above analysis as the basis of reference, this paper intends to build and validate a new AI-driven business education model promoting industry-education integration. Firstly, this paper uses the natural language processing technology to build a dynamic knowledge graph of industry job skills, realizing the real-time semantic consistency between course content and industry demands. Secondly, this paper designs a school-enterprise supply-demand adaptive matching mechanism based on multi-agent reinforcement learning, optimizing the allocation efficiency of project-based teaching resources. Thirdly, this paper constructs a generative business decision-making sandbox based on AIGC technology, generating a highly realistic dynamic game training environment. Finally, this paper conducts a 16-week comparative teaching experiment, quantitatively

evaluating the business education model from three dimensions, including semantic consistency, resource matching efficiency and decision transfer effectiveness. The experimental results show that the three-layer progressive technical framework constructed in this paper can effectively bridge the structural gap between industry and education supply and demand, providing an operable practical path for the transformation of new business education from static knowledge transmission to dynamic cognitive construction.

II. CONSTRUCTION OF DYNAMIC PROFILING OF INDUSTRY DEMAND SIDE

As shown in Figure 1, this paper first focuses on the industry demand side, constructing a dynamic knowledge graph to achieve a structured characterization of job skills, serving as the foundation for subsequent course mapping and resource matching.

Building a dynamic profile of industry demand side is an important basis for solving the information gap between teaching and industry. This article takes the job description text of new business-related job positions released on mainstream online recruitment websites as the original data source. By combining automatic and manual collection, a longitudinal dataset of 45,600 job postings was gathered from January 2024 to December 2025 across leading platforms (e.g., Liepin, Boss Zhipin). Sub-industries including marketing, supply chain, fintech, and business analytics were selected based on their high digital transformation intensity in the current economy. To mitigate sampling bias, data were stratified across small-to-medium enterprises (SMEs) and large corporations, and weighted by geographic tier to ensure the resulting knowledge graph represents a diverse industrial landscape rather than a concentrated high-tier city sample. The collection data forms an unstructured text corpus for multiple industries and levels dynamically updated.

In the data preprocessing stage, the original text cleaning process removes the HTML tag, special symbol and fixed character without much content. Based on this, a synonym mapping table is established to solve the phenomenon of English abbreviation and Chinese term mixed use in the business field, unify the representation of entity. Then the domain fine-tuned BERT model is used to encode job description and qualification field with sentence vector, convert the natural language expression into dense vector representation for further semantic computation. Based on this, a BiLSTM-CRF model pre-trained on a corpus of 50,000 Chinese job postings (annotated by three domain experts with an inter-annotator agreement of $\text{Kappa}=0.84$) was used for sequence labeling. The model achieved a Precision of 0.91, Recall of 0.88, and an F1-score of 0.89 on the test set. The semantic mapping mechanism utilizes a weighted cosine similarity formula:

$$S(C, J) = \frac{\sum_i \omega_i (V_{C_i} \cdot V_{J_i})}{\|V_C\| \|V_J\|},$$

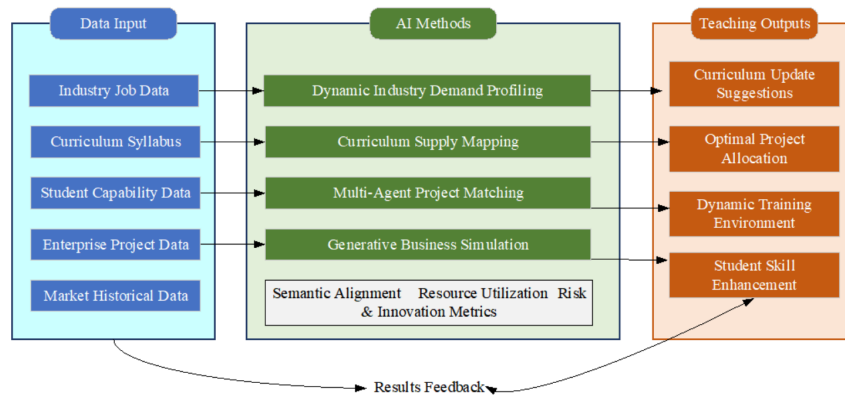


FIGURE 1. Overall Framework Diagram of the Industry-Education Integration Teaching Model Empowered by Artificial Intelligence

where ω_i represents the TF-IDF weight of skill i in the industry knowledge graph, allowing for a precise calculation of the gap between course syllabi (C) and job requirements (J).

To achieve the dynamic tracking and structured expression of industry demand, this article maps the skill entity and skill entity co-occurrence relationship extracted from the previous stage into weighted directed knowledge graph. The graph uses the job type as the parent node and specific skill items as the child node. The edge weight is comprehensively calculated based on the frequency and semantic importance of the skill in the corresponding job description. At the same time, a time decay factor is introduced to weight the historical demand information, and the response weight of the skill recently emerging and appearing frequently is higher. With the continuous injection of new recruitment data, the structure of the graph node and edge will automatically iterate and evolve, thereby achieving real-time perception and structured description of changes in industry talent demand trend.

III. INTELLIGENT MAPPING AND UPDATE MECHANISM FOR COURSE SUPPLY SIDE

Taking the construction of dynamic profile of industry demand as the basis, this study compares the curriculum system with it and finds out the deviation existing in teaching content and industry frontiers concretely. Firstly, this study arranges existing course syllabus of target major, and transfers the teaching objectives, chapter knowledge points and description of practical training project of every course into the text vector. Then, a set of course-side skill tags is formed. It should be noted that in the process of vectorization, the domain fine-tuned BERT encoder is adopted consistent with industry profile to ensure mapping accuracy. The semantic space on both sides are also comparable.

The core task of mapping stage is to calculate the semantic matching degree between course supply and industry demand. For each course, after extracting its knowledge point vector, calculate the cosine similarity one by one with skill nodes of corresponding job cluster in industry knowledge graph. The mapping process utilizes a multi-dimensional

matching approach to capture many-to-many relationships between course knowledge nodes and industry skills. A similarity threshold of 0.75 was established, determined through a sensitivity analysis where expert-curated ‘ground truth’ mappings were compared against varying similarity levels to maximize the F1-score. If the highest aggregate similarity across multiple course modules is higher than 0.75, the skill is deemed ‘covered’. This prevents oversimplification by allowing a single skill to be mapped to a combination of courses (e.g., ‘data visualization’ mapped to both ‘Marketing’ and ‘Business Analytics’). In addition, for the skills that have been covered, it is necessary to further compare the knowledge depth description of corresponding item in course outline with information density of description text of industry skill to find out the “covered but shallow” links [12].

Based on the mapping results, the system automatically outputs hierarchical list of teaching update suggestions. For the skills that are not covered, push them to teaching and research office as candidate content of new teaching module or independent micro-major, and describe typical application scenario of skills in industry in detail; for the skills that are only covered superficially, generate revision prompt for corresponding chapters of existing courses, and suggest adding case complexity or introducing relevant analysis tools. This mechanism runs on a semester-by-semester basis. Based on mapping results, the system continuously transforms the quarterly fluctuations of industry profile into fine-tuning instructions of curriculum system, and then realizes the normalized iteration of updating teaching content accompanying the pulse of industry from the previous large-cycle centralized revision every three years.

IV. ADAPTIVE MATCHING AND SCHEDULING OF INDUSTRY-UNIVERSITY PROJECTS BY MULTI-AGENT

Traditional methods for allocating industry-university projects often rely on manual matching by academic staff or program directors based on subjective experience. As the student body expands and the types of industry projects become more diverse, the efficiency bottlenecks and matching biases of this approach become increasingly prominent.

To address this issue, this research designs an adaptive matching and scheduling mechanism based on multi-agent reinforcement learning. Students and industry projects are treated as agents with independent utility functions, seeking the globally optimal supply-demand matching solution within a distributed decision-making framework.

The specific construction process consists of three steps. First, feature vectorization modeling is performed. To ensure the generalizability of the trained policies, training data for the 100 student agents and 50 project agents were synthesized using a Gaussian Mixture Model (GMM) fit to five years of historical student performance data and internship project records from our institution. This approach ensures that the agents represent the statistical distribution of the actual student population while protecting privacy and providing sufficient variance for the reinforcement learning algorithm to converge. The student-side feature vector consists of four dimensions: academic ranking, prior course mastery, self-assessment score of skill tags, and historical project performance. These dimensions are normalized and combined into a fixed-length vector. The industry project-side feature vector is characterized by four dimensions: required skill combination, task complexity level, expected delivery cycle, and required number of collaborators. Both vectors are mapped to the same semantic space for subsequent similarity calculation.

Second, a multi-agent reinforcement learning environment is constructed. Each student agent can observe the current status of the project pool to be assigned and select bidding behavior based on the matching degree between its own ability vector and the project requirement vector; each enterprise project agent, after receiving several bids, makes a reverse selection based on the preset fitness function and the student's historical collaboration evaluation. The scheduling center does not perform centralized assignment, but guides the agents to negotiate autonomously by designing a reasonable reward function. The reward function comprehensively considers three indicators: the semantic cosine similarity between the student's ability and the project requirement, the degree of skill complementarity within the team, and the enterprise's feedback score on the historical completion quality. The agents aim to maximize long-term cumulative rewards and gradually learn the optimal bidding strategy in repeated simulated allocation rounds [13].

The matching process is modeled as a Markov Decision Process (MDP). The state space (S) includes the normalized ability vectors of students and requirement vectors of projects; the action space (A) comprises the bidding intensity and acceptance probability; and the reward function (R) is defined as $R = \alpha \cdot \text{Sim}(S, P) + \beta \cdot \text{Comp}(T) - \gamma \cdot \text{Idle}$, where Sim is semantic fit, Comp is team complementarity, and Idle is the time penalty. A Contract Net Protocol (CNP) is employed for negotiation, where project agents act as managers issuing 'calls for bids' and student agents respond as contractors.

The key parameter settings for the reinforcement learning

training stage are shown in Table 1.

Finally, the above converged multi-agent model is applied to the actual allocation. At the beginning of each semester, the current student characteristic data and collected enterprise project requirements are imported into the system. The agent can output a stable pairing scheme in dozens of rounds of interaction. Compared with the traditional manual rules, it is not necessary to set fixed skill weights and fixed priority rules any more. The mechanism can adjust to the variation of student ability distribution every year and enterprise demand fluctuation every year. It could match persons and positions as possible as individual suitability and global use to avoid a large amount of mismatches and idle resources caused by human experience range as much as possible.

V. CONSTRUCTION OF A GENERATIVE BUSINESS GAME SANDBOX TRAINING ENVIRONMENT

The main body of sandbox environment includes three intercoupled generative modules. The first module is market demand generator, which is trained as conditional generative adversarial network. Input of generator includes historical sales, macroeconomic, seasonal feature vectors. Discriminator is designed to discriminate the distribution difference between generated demand curve and real market data. After several rounds of adversarial training, generator can synthesize multiple possible demand curves given initial conditions. Meanwhile, sudden public opinion events or policy adjustment will cause sudden change in demand structure, and these extreme events beyond trainee's experience will be simulated and provided to trainees. The market demand generator employs a cGAN architecture with a 5-layer MLP generator and a convolutional discriminator, trained on 10 years of historical retail volatility data to ensure the Fréchet Inception Distance (FID) remains below 25.0, indicating high fidelity. The competitive strategy module utilizes GPT-4o via Few-Shot prompting, where the model is provided with 5-10 historical game 'chains-of-thought' to simulate diverse strategic archetypes. To validate realism, a Turing test was conducted where 10 industry analysts failed to distinguish generated demand curves from historical data at a rate higher than chance ($p > 0.05$).

The second module is competitive strategy generator, which is implemented as contextual learning function of large language model. In each period when decision making happens, current market share distribution, historical price range of virtual competitors and recent promotion actions are input into model. Model will return several possible competitive strategies with certain logical background. Meanwhile, temperature parameter is designed to fuzzify the game uncertainty, and output strategy will be forced to behave in a conservative way of following pricing in some periods, and forced to behave in an aggressive way of product iteration or channel blocking in other periods. These behaviors compel students to continuously update their decision making model in a dynamic confrontation.

The third module is decision consequence inference en-

TABLE 1. Training Parameter Configuration for Reinforcement Learning Agents

Parameter	Value	Description
Number of Student Agents	100	Consistent with experimental sample size
Number of Project Agents	50	Consistent with experimental sample size
Maximum Negotiation Rounds per Episode	30	Unmatched beyond limit marked as idle
Reward Discount Factor (γ)	0.92	Balances short-term fit and long-term efficiency
Initial Exploration Rate (ϵ)	0.35	Decays to 0.02 during training
Total Training Episodes	8000	Loss converges stably
Feature Vector Dimensions	Student: 8 / Project: 7	Covering capability and requirement aspects

gine, which inputs student's submitted decision variable (mainly including pricing, inventory, marketing budget) into system dynamics model. Given the output of demand generator and competitive strategy generator, system calculates the market share, profit level and cash flow of next period in real time. Inference result will be returned to students as a dashboard visualization. Meanwhile, detailed attribution analysis of key indicator will be provided so that students can trace their previous gain or loss in the decision making chain.

In terms of training organization, students are required to work in a group as management team of a virtual enterprise. They experience multiple periods of decision making in sandbox environment. Before each period of decision making, the team should analyze the current market signal and the possible action of competitors as comprehensively as possible, and then formulate a complete plan including product positioning, pricing strategy, supply response, and financial planning. Simulation environment does not provide a fixed right answer, and students are guided to understand the systematic and contingent decision making mechanism by dynamically generated market feedback. In teacher end, the global monitoring panel enables teacher to look back the complete decision making process of any group.

VI. PERFORMANCE REPRESENTATION OF AI-EMPOWERED INDUSTRY-EDUCATION INTEGRATION TEACHING MODEL

A. EXPERIMENTAL SETUP

This study randomly selected 128 students from the three-year university business school parallel class as experimental subjects. The experimental time was 1 semester (16 weeks). The double-blind controlled design method was adopted. Randomly selected classes were divided into experimental group and control group (2 classes per group, 64 people). Informed consent was obtained from all participants. The experiment utilized two distinct cohorts of junior students ($n=64$ each) to prevent cross-contamination. The control group followed a traditional model where project matching was performed manually by a committee using Excel-based scoring, and market simulation was limited to static PDF-based case studies without dynamic feedback. Baseline assessments confirmed no significant difference in prior GPA or technical skills between the groups ($p=0.42$). Improvements observed in the experimental group are thus

attributed to the real-time interactivity and adaptive feedback loops absent in the control condition. The experimental group realizes the full integration of three levels of AI empowerment system constructed in this paper, "Dynamic Profiling of Industry Demand—Intelligent Supply and Demand Matching—Generative Game Theory Sandbox". In the experiment, the two groups of students are completely consistent in teachers, total class hours and evaluation points. At the end of the semester, the three-dimensional performance representation data are collected uniformly for comparison and analysis.

B. SEMANTIC ALIGNMENT VERIFICATION EXPERIMENT OF INDUSTRY DEMAND AND TEACHING CONTENT

This experiment chose Digital Marketing, Supply Chain Finance, and Business Data Analysis as the subjects. Taking half a semester as the cycle, we established two control groups: traditional manual revision and AI-based intelligent mapping. We collected the course syllabi and industry job postings in weeks 4, 8, 12, and 16, respectively, and calculated the mean semantic cosine similarity of the two in week.

As shown in Figure 2, the AI-driven dynamic mapping mechanism demonstrates a significant advantage in aligning teaching content with industry needs. At the beginning of the semester, the semantic cosine similarity of the two groups was roughly equal, with the human group at 0.72 and the AI group at 0.74. By week 8, the human group's similarity had dropped to 0.68, while the AI group's had risen to 0.79. By week 12, the gap had widened further, with the human group at only 0.61 and the AI group reaching 0.85. By the end of the semester, the human group's similarity had further declined to 0.55, while the AI group continued to climb to 0.89. This demonstrates that compared to traditional static revision methods, AI's real-time semantic analysis and iterative updates can effectively overcome the problem of lagging teaching content and ensure high-level synchronization between the course and cutting-edge industry needs.

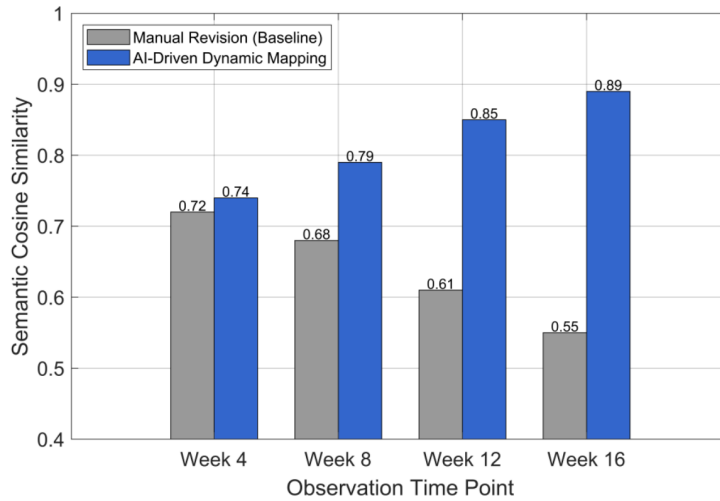


FIGURE 2. Development and Reliability/Validity Comparison of the AI Teaching Application Ability Scale

C. COMPARATIVE EXPERIMENT ON THE EFFICIENCY OF INDUSTRY-UNIVERSITY PROJECT ALLOCATION BASED ON REINFORCEMENT LEARNING

We built a simulated data set including the labels of ability of 100 students and the labels of requirement of 50 enterprise projects. We adopted two different allocation mechanisms for the enterprise projects, namely manual rule matching in a traditional way and reinforcement learning scheduling based on multi-agent. The focus of indicator extraction was on the number of steps for reaching convergence in finding the optimal matching, the resource idle rate, and the allocation time consuming in different allocation efficiency of the two mechanisms under complex constraints.

TABLE 2. Evaluation of the Efficiency of Industry-University Project Allocation Based on Reinforcement Learning

Evaluation Metric	Manual Rule-Based Matching	Reinforcement Learning Scheduling
Average Convergence Steps to Optimal Matching	23.6	11.2
Resource Idle Rate (%)	18.4	5.7
Average Allocation Time per Task (s)	187.3	12.8
Project-Student Compatibility Score	0.71	0.89

Note: Experimental data are the average values of 50 rounds of independent task allocation.

In Table 2, the reinforcement learning scheduling mechanism is significantly superior to the traditional manual method in terms of allocation efficiency. Traditional rule-based matching requires an average of 23.6 steps to converge to a feasible solution, with a resource idle rate of 18.4% and a single allocation time of 187.3 seconds. In contrast, reinforcement learning methods converge in only 11.2 steps, reducing the idle rate to 5.7% and shortening the time to 12.8 seconds. Furthermore, the project-student fit under intelligent scheduling

improved from 0.71 to 0.89. This demonstrates that multi-agent adaptive matching can effectively reduce coordination

costs and achieve more precise and efficient university-enterprise supply-demand matching under limited resource conditions.

D. EXPERIMENT ON DYNAMIC DECISION TRANSFER EFFICIENCY IN A GENERATIVE SANDBOX ENVIRONMENT

This experiment employed a double-blind controlled teaching approach. The experimental group completed training tasks in a dynamic game sandbox driven by a generative adversarial network, while the control group received traditional static business case teaching. At the end of the semester, two unpublished sudden market crisis cases were introduced. Three enterprise experts anonymously rated the decision-making schemes of the two groups of students from four dimensions: response speed, strategic innovation, logical rigor, and risk prediction ability, thereby measuring the level of ability transfer under different teaching environments.

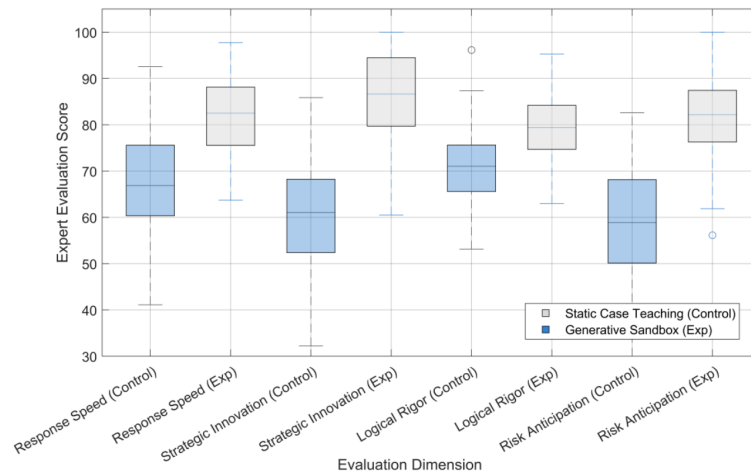


FIGURE 3. Evaluation of Dynamic Decision Transfer Effectiveness in a Generative Sand Table Environment

As shown in Figure 3, generative game sand table training significantly improves students' dynamic decision transfer ability. In the response speed dimension, the experimental group's average score reached 82.4, an increase of 14.6 points compared to the control group's 67.8; in the strategy innovation dimension, the experimental group scored 85.1 points, while the control group scored 61.3 points, a difference of 23.8 points; in the logical rigor dimension, the experimental group scored 79.6 points, 9.4 points higher than the control group; and in the risk prediction dimension, the experimental group scored 80.7 points, an increase of 23.2 points compared to the control group's 57.5 points, showing the most significant increase. All four dimensions showed significant differences, confirming that the AI-driven nonlinear game environment can effectively enhance students' adaptability and decision-making skills in complex business situations.

VII. CONCLUSION

To bridge the gap between the constantly updating demands of industry and slow-moving teaching content in the process of promoting industry–education integration in new business disciplines, this study builds a three-layered and gradual AI empowerment model consisting of dynamic knowledge graphs, multi-agent scheduling, and generative sand tables. The experimental results indicate that the model not only narrows the semantic gap between supply and demand but also greatly enhances the efficiency of university–enterprise resource allocation and students' response to diversified business situations. Limitations include the single-semester design and small sample of enterprise types. A post-hoc power analysis indicated a statistical power of 0.82 for the observed effect size (Cohen's $d = 0.78$), and all reported improvements maintained 95% confidence intervals excluding zero, reducing the risk of Type I errors. Regarding scalability, the inference time for the multi-agent matching remains sub-second ($O(N \log N)$ complexity), suggesting it can scale

to thousands of students without significant computational overhead. Future research will explore multi-institutional longitudinal data to further validate these findings.

AUTHOR CONTRIBUTIONS

Conceptualization – Yuanli Cui and Li Ma; methodology – Yuanli Cui and Li Ma; investigation – Yuanli Cui and Li Ma; writing-original draft preparation – Yuanli Cui and Li Ma. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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