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Optimization Analysis of Course Content and Teaching Methods of E-commerce Major under the Mode of School-enterprise joint Innovation

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SUMMARY: *With the convergence of job data, platform logs and curriculum resources, the course organization mode and teaching scheduling logic of e-commerce major are being refined and adjusted. Focusing on the collaborative reconstruction of course content and teaching methods in the school-enterprise joint scenario, this paper constructs an optimization framework consisting of post task mapping, curriculum unit reorganization, learning behavior collection and feedback decision-making, and designs a collaborative optimization algorithm for school-enterprise joint teaching methods, which unifies the coding and weight calculation of enterprise job requirements, curriculum knowledge points, classroom interaction records and training results. The experiment took three course modules of e-commerce operation, live broadcast marketing and data analysis as objects, and carried out verification on two groups of teaching samples of 120 students. In the evaluation process, the indexes such as topic matching rate, post coverage rate, method responsiveness and interaction depth are introduced for comprehensive evaluation. The results show that the optimization scheme improves the topic matching rate from 76.4% to 88.6%, the job coverage rate from 74.8% to 87.9%, and the platform interaction index is significantly positively correlated with the stage performance. Ablation results show that the task mapping, behavior feedback and joint update module jointly support the synergy effect and operation stability. This paper provides a reusable method basis for the computational reconstruction of e-commerce professional course content and the implementation of school-enterprise joint teaching.*

Povzetek: Ta članek vzpostavlja sodelovalni okvir za e-trgovinske tečaje in učne metode v okviru sodelovanja med šolo in podjetjem ter z uporabo analize vedenja in izračuna uteži uresničuje reorganizacijo kurikularnih enot in prilagajanje učnih poti. Eksperimentalni rezultati kažejo, da se je stopnja ujemanja tem povečala s 76,4 % na 88,6 %, stopnja pokritosti delovnih nalog s 74,8 % na 87,9 %, interakcija na platformi pa je statistično značilno pozitivno povezana z dosežki po posameznih fazah.

KEYWORDS: *E-commerce courses; Behavioral data analysis; Collaborative optimization algorithm*

1 Introduction

The evolution of platform economy, the reorganization of data link and the expansion of intelligent decision-making mechanism are continuously changing the organization method of e-commerce business, and also promoting the transformation of e-commerce professional curriculum system from empirical arrangement to data-driven structured organization. In this context, the school-enterprise alliance no longer stops at the co-construction of training bases

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and job internship arrangements, but enters the collaborative stage of curriculum content mapping, task process disassembly, platform behavior collection and teaching feedback linkage. The operation rules, traffic mechanism, transformation path and content production logic on the enterprise side are entering the teaching scene in the form of data features, task labels and decision constraints. The course modules, knowledge units, training projects and evaluation links on the college side also need to complete the fine-grained docking with the real business process. For the construction of e-commerce specialty, whether the course content can accurately undertake the post ability structure, and whether the teaching methods can be dynamically adjusted according to the interactive data of the platform, has become an important basis for the quality of course organization and the effectiveness of practical training.

Focusing on intelligent decision-making and feature modeling in e-commerce platforms, foreign scholars have formed a more systematic research accumulation. Valencia-Arias et al. reviewed artificial intelligence and recommendation system in e-commerce, and pointed out that platform intelligence is expanding from commodity distribution to user intention recognition and interactive decision support [1]. Zhang et al. reviewed the research on knowledge graph embedding recommendation, emphasizing that semantic relationship expression can enhance the association characterization between complex objects [2]. Wu et al. summarized the application path of graph neural network in recommendation system, and proposed that graph structure propagation is suitable for dealing with multi-type behavior relationships [3]. Gao et al. further summarized the challenges, methods and development directions of graph neural network recommendation, which provided a technical context for complex interaction scene modeling [4]. Li et al. summarized the evolution characteristics of recommender systems in recent years, and believed that multi-source feature fusion and dynamic preference update have become the core support [5]. Harasic et al. studied the progress of federated recommender systems and showed that cross-agent co-training can improve the modeling effect under the condition of maintaining data boundaries [6]. Klimashevskaia et al. analyzed the influence of popularity bias on the distribution of recommendation results and revealed that the ranking mechanism would change the resource exposure structure [7]. Deldjoo et al. discussed the evolution direction of recommendation research from the perspective of fairness, and pointed out that the output of algorithms should take into account both efficiency and allocation rationality [8]. Jin et al. further summarized the fair-aware recommendation method, which provided reference for collaborative optimization under multi-objective constraints [9]. The related results provide a clear and direct technical reference frame for this research.

Compared with the rapid advancement of intelligent modeling on the platform side, if the course construction of e-commerce is still based on fixed chapter order, static case combination and unified classroom arrangement, the course content is difficult to accurately map the enterprise task chain, and the teaching implementation is difficult to connect with real-time business logic. In the school-enterprise joint scenario, the course unit, operational objectives, content types, user feedback, delivery rhythm and platform rules form a multi-dimensional correlation structure. Teaching methods also need to be continuously modified according to classroom interaction records, training operation trajectories and task completion performance. Therefore, the research expression for technical journals should not stay at the level of experience induction, but should incorporate course knowledge points, post ability items, platform behavior characteristics and teaching feedback signals into a unified representation space, and form a computable, comparable and verifiable collaborative framework. Based on this orientation, this paper constructs a collaborative framework of school-enterprise e-commerce course content and teaching methods, designs a collaborative optimization algorithm of school-enterprise joint teaching methods, and combines experimental Settings, data collection, index design and statistical analysis to verify the effect of course content adaptation, teaching implementation effect, platform interaction behavior correlation, framework comparison and ablative results. In order to provide a research basis supported by computer methods for curriculum reconstruction and teaching scheduling of e-commerce majors.

2 Related work

2.1 Research on the Course Content Construction of E-commerce with the Support of Data Technology

The construction of e-commerce course content supported by data technology is shifting from experience splicing to structured organization oriented to task chain and data chain. Luo et al. sorted out the causal inference in recommendation and pointed out that intervention effect identification and counterfactual analysis were helpful to distinguish surface clicks and real preferences, which provided ideas for the identification of post ability orientation in course content screening [10]. Liu et al. studied the multimodal recommendation system and believed that the joint modeling of text, image and behavioral signal could improve the representation quality of the object, which provided a technical basis for the introduction of product description, visual marketing and user feedback into the curriculum system [11].

Yu et al. summarized the self-supervised learning method in the recommendation system and showed that unlabeled interaction data can form a stable representation through contrastive learning and mask prediction, which makes platform logs, browsing trajectories and training operation records feasible to enter the course reconstruction process [12]. Li et al. sorted out the application path of graph network and sequence network in session recommendation, and emphasized that short-term behavior sequence and relationship propagation can jointly characterize the user decision-making process, which has inspiration for the organization of course units such as live broadcast operation, content delivery and transformation analysis [13].

Wei et al. proposed a recommendation model for e-commerce platform, which jointly enhanced feature expression through explicit information compensation and implicit information mining, so as to improve the matching accuracy in complex scenes [14]. These studies show that the content construction of e-commerce courses has the computing foundation from data representation, relationship modeling to content matching. The association between course knowledge points, post task items, platform behavior flow and evaluation results is no longer just an experience correspondence, but can be uniformly described, compared and continuously updated. On this basis, the course content can be reorganized around task chain, ability chain and data chain, and provide content units, interfaces and verification basis for subsequent collaborative optimization of teaching methods.

2.2 Research on the collaborative mechanism of school-enterprise joint teaching methods

The research on the collaboration mechanism of school-enterprise joint teaching methods is shifting from experience coordination to the joint optimization path relying on relationship modeling and behavior computing. Zhang et al. proposed a multi-view enhanced graph neural network to improve the recommendation performance by extracting preference features from different relationship levels [15]. This idea shows that curriculum tasks, enterprise projects, classroom activities and evaluation nodes can be represented as multi-type associated objects. Wang et al. studied the joint learning framework of project recommendation and trust prediction based on graph neural network, and believed that the synchronous modeling of interaction relationship and trust relationship could improve the matching accuracy [16], which provided reference for the mechanism design of both schools and enterprises in teaching division of labor, resource allocation and task collaboration.

Wu et al. proposed the UBAR model, which combined user behavior perception and knowledge graph to depict the preference formation process [17], indicating that dynamic behavior trajectory and semantic structure could enter the decision-making process in cooperation. Wang et al. proposed the KLGCN model, which introduced knowledge graph information into the lightweight graph convolution structure to enhance the representation ability [18], indicating that the association propagation effect can still be maintained with low computational complexity. Wang et al. further studied the knowledge graph-aware deep graph convolutional network, using residual connections and dense connections to improve the ability of high-order information propagation [19]. These studies show that the school-enterprise joint teaching method should not stay at the static arrangement level, but should put post ability, course unit, process behavior and evaluation feedback into a unified graph structure, and form a computable teaching organization mechanism through relationship propagation, weight update and collaborative matching, and provide support for subsequent algorithm construction. It can be seen that graph representation learning and knowledge enhancement methods in the field of computer science have provided a more stable technical foundation for task allocation, resource selection and feedback linkage in school-enterprise joint teaching. And make the teaching process with traceable, comparable and iterative characteristics.

2.3 Limitations of existing studies

As knowledge graph recommendation, relationship propagation modeling and multi-context collaborative algorithms continue to enter the computing scene of e-commerce platform, the organization of course content and the design of teaching methods have the technical conditions to complete the reconstruction with the help of computer methods. Zhao et al. proposed AGRE algorithm, which combined multi-path embedding with RNN encoder to deal with high-order semantic association in knowledge graph [20], indicating that the sequence dependence and cross-module jump relationship between complex task chains can be represented into the unified calculation process through serialization. Li et al. studied the KGIE model, which enhanced the object representation ability under the linkage mechanism of interactive embedding and graph convolutional propagation [21], indicating that the mapping relationship between course units, job skills and training tasks can be jointly updated through the graph structure. Huang et al. proposed a confidence aware embedding method of knowledge graph to incorporate relationship credibility into the representation learning process [22], which provides a basis for the differential treatment of enterprise task weights, curriculum resources weights and evaluation signal weights in the school-enterprise joint scenario. Wu et al. studied a multi-context-aware recommendation algorithm, which incorporated time, scene and behavioral background into the modeling process [23]. This orientation shows that the collaboration of teaching methods should not only be based on static curriculum schedule or fixed process, but should be adjusted by combining training stages, task types and interaction states. Wang et al. proposed a relationship-aware attention GCN model to improve the effect of knowledge dissemination through relationship weight allocation [24], which further shows that resource allocation, task assignment and feedback update in school-enterprise joint teaching can be based on interpretable association propagation. See Table 1 for a comparison of related studies.

Table 1: Comparison of related studies.

Reference	Method	Application Object	Evaluation Basis	Main Finding	Applicability Boundary
Zhao et al. [20]	Multi-path embedding and RNN encoding	Knowledge graph recommendation	Path representation and sequential association	Higher-order relations can be modeled in a serialized manner	Insufficient expression of task coupling in teaching scenarios
Li et al. [21]	Joint propagation of interaction embedding and graph convolution	Representation learning for recommender systems	Updating effect of interaction relations	Graph structures can enhance the strength of object mapping	Lack of direct characterization of course content units
Huang et al. [22]	Confidence-aware knowledge graph embedding	Recommendation relation representation	Relation confidence modeling	Different weights can be incorporated into a unified learning process	Still limited in adapting to differences in school-enterprise resources
Wu et al. [23]	Multi-context-aware recommendation algorithm	Multi-scenario recommendation	Joint modeling of time, scenario, and behavior	Context collaboration can improve dynamic matching	Insufficiently detailed description of classroom interaction chains
Wang et al. [24]	Relation-aware attention GCN	KG-enhanced recommendation	Relation propagation and attention allocation	Relational propagation has strong interpretability	Insufficient support for the teaching feedback closed loop

Although the existing research has formed strong computing and representation capabilities, most of the results still focus on commodity recommendation, user preference modeling and platform matching, and the research goals focus on click through rate, ranking accuracy and intention recognition. The direct expression for computational organization of course content and collaborative adjustment of teaching methods is still insufficient. In addition, teaching scenarios contain multi-source heterogeneous information such as course knowledge, job tasks, classroom behaviors and evaluation feedback, so it is difficult for a single relational learning or a single context modeling to completely cover the collaborative logic in the school-enterprise joint environment. Therefore, it is necessary to build a unified framework that can handle content mapping, method adjustment, behavior feedback and effect verification at the same time, and form a relationship propagation and weight update mechanism for teaching collaboration at the algorithm level. On this basis, this paper carries out follow-up research to make up for the application gap of existing results in the curriculum organization and teaching implementation of e-commerce majors. The comparison shown in Table 1 further shows that the existing model has the potential to be transferred to the teaching scene in terms of computational expression, but the course content, enterprise task and classroom interaction have not been placed in the same optimization link, which also constitutes the direct starting point for the subsequent framework design and experimental verification of this paper, and forms the method interface system for curriculum reconstruction.

3 Methods

3.1 The collaborative framework of school-enterprise e-commerce course content and teaching methods

This paper constructs a collaborative framework of school-enterprise e-commerce course content and teaching methods. The framework takes enterprise job tasks, platform business rules, course knowledge units, classroom interaction records and training evaluation results as unified inputs, and integrates content organization, method configuration, behavior feedback and effect verification into the same calculation process. The framework design no longer considers the course content as a static collection of chapters, nor understands the teaching method as a fixed process, but transforms the job requirements, platform data and learning behavior into computable features together, so that the reorganization of course content and the adjustment of teaching methods can be completed synchronously in a unified link. Its goal is to map the business logic of enterprise side product operation, content production, traffic distribution, user conversion and re-purchase maintenance to the internal of the course system, and improve the suitability of course content and the accuracy of method implementation through continuous feedback and update.

1) Task parsing layer

This layer is responsible for the standardized parsing of the enterprise task set T, the course knowledge set K, and the ability item set A, and generates the initial association matrix between the course units and the post tasks. The mapping strength is defined as follows:

$$M_{i,j} = \alpha \mathrm{Sim}(K_i, T_j) + \beta \mathrm{Cov}(A_i, T_j) \tag{1}$$

where $M_{i,j}$ represents the mapping strength between course unit K_i and post task T_j. Sim represents semantic similarity; Cov denotes capacity coverage; α and β are the weight coefficients. This formula is used to determine the basic position of the course content when it enters the enterprise task chain, and to provide a constraint boundary for the subsequent content reorganization.

2) Content reorganization layer

According to the mapping matrix, the system combines the case base, knowledge point sequence, tool module and training resources to form the course topic cluster oriented to business process. The recombination score for topic u is expressed as follows.

$$G_u = \sum M_{u,j} + \lambda \mathrm{Res}_u + \mu \mathrm{Con}_u + \nu \mathrm{Diff}_u \tag{2}$$

where G_u represents the overall score of topic u; Res_u represents resource integrity. Con_u denotes content cohesion; Diff_u represents the difficulty gradient harmony value. λ, μ and ν are the regulation coefficients. This formula is used to filter the content modules that enter the main teaching link to keep the course content consistent with the enterprise task rhythm.

3) Method matching layer

According to the content theme characteristics, task attributes and classroom status, this layer jointly configured the methods of explanation, case breakdown, platform demonstration, group collaboration and project training. The adaptation value of method m to topic u is defined as follows:

$$S_{u,m} = \eta \mathrm{Feat}_u + \theta \mathrm{Task}_u + \rho \mathrm{State}_u + \sigma \mathrm{Pref}_u \tag{3}$$

where $S_{u,m}$ denotes the adaptation value; $Feat_u$ represents the topic feature vector. $Task_u$ represents task complexity; $State_u$ represents the status of classroom implementation; $Pref_u$ represents the learned preference aggregation result. This formula is used to generate method combination weights so that the teaching organization changes synchronously with the content structure.

4) Behavior feedback layer

The system collects click, stay, submit, discuss, revise, transform simulation and review records from the teaching platform and enterprise training platform, and compresses them into the learning state index:

$$L_s = \omega_1 Act_s + \omega_2 Time_s + \omega_3 Comp_s + \omega_4 Corr_s + \omega_5 Inter_s \tag{4}$$

Here, L_s represents the state value of student s; Act_s is activity; $Time_s$ represents the time consumption of the task. $Comp_s$ denotes the degree of completion; $Corr_s$ is the correctness of the result. $Inter_s$ stands for depth of interaction. This formula transforms discrete behavior signals into continuous feedback variables for collaborative adjustment.

5) Collaborative update layer

According to the stage feedback, the enterprise tutor and the course teacher jointly modify the content weight and method configuration, and the update rule is written as follows:

$$U_u^{t+1} = U_u^t + \delta(\bar{L}_u^t - E_u^t) + \gamma(F_e^t + F_c^t) \tag{5}$$

where U_u^{t+1} represents the updated content weight;$\bar{L}_u^t$ represents the phase-average learning state. E_u^t stands for goal expectation; F_e^t represents enterprise side feedback; F_c^t stands for course side feedback; Let δ and γ denote the update step size. This formula reflects the joint correction effect of both the school and the enterprise in the same link.

Effect output layer

The framework finally outputs the synergy index, which measures the comprehensive performance of the course content and teaching methods in the same round:

$$Q = \tau_1 Match + \tau_2 Inter + \tau_3 Stab \tag{6}$$

where Q represents the synergy index; $Match$ indicates the content matching degree. $Inter$ denotes the depth of interaction. $Stab$ stands for implementation stability. This formula not only serves for framework comparison, but also provides a unified evaluation caliber for subsequent ablation experiments.

In order to clearly present the computational relationship between curriculum content reorganization, teaching method matching, platform behavior feedback and collaborative update in e-commerce major under the school-enterprise joint scenario, Figure 1 establishes an overall framework composed of data input, feature representation, relationship modeling, collaborative decision-making, result output and feedback loop. The figure integrates enterprise post data, platform business rules, course knowledge units, student behavior logs, training evaluation records and teaching resource databases into a unified link, and shows the organization, calculation and update process of course content and teaching methods in the same system through hierarchical processing.

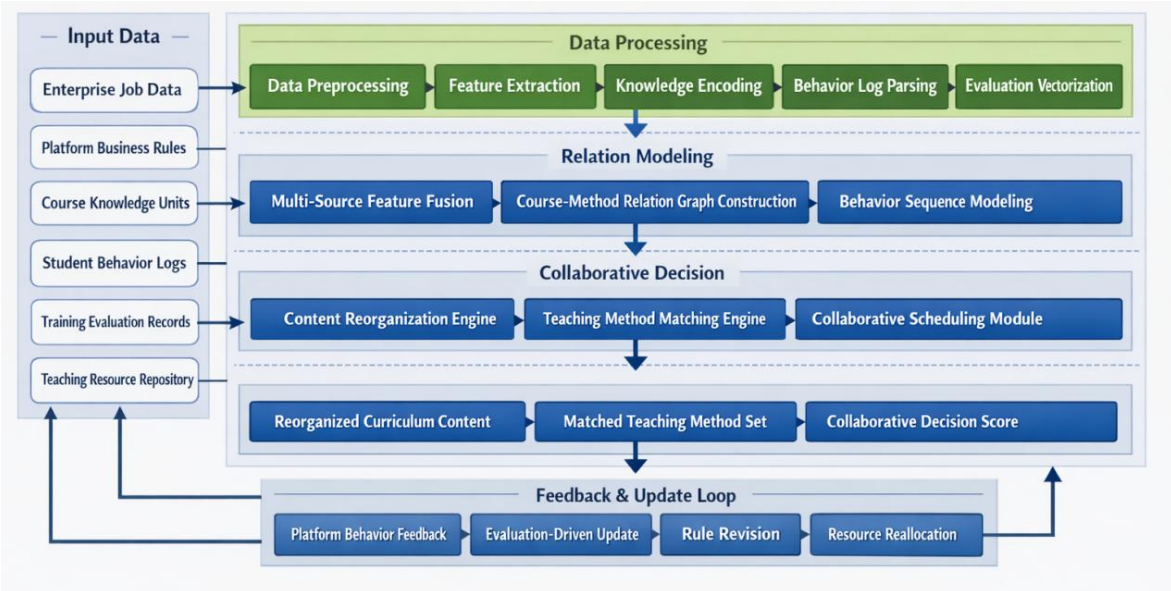

Figure 1: School-enterprise collaborative computing framework for e-commerce course content and teaching methods.

3.2 Collaborative optimization algorithm of school-enterprise joint teaching method

The collaborative optimization algorithm of school-enterprise teaching methods takes the course theme, job task, platform interaction and stage evaluation as the unified input, and completes the dynamic calculation and scheduling of teaching methods in the process of multi-source feature coding, relationship propagation and joint update. The algorithm does not regard teaching, case, training, review and other methods as mutually independent fixed units, but according to the changes of enterprise tasks, content difficulty distribution and classroom feedback status, continuously adjust the combination and order of methods, so that the course implementation can maintain a balance between content adaptation and implementation efficiency. Before the algorithm runs, the course topics, task goals and resource types are discretized, and the student behavior records are compressed into time series features, so as to complete multi-source collaboration in a unified representation space.

In the input phase, the system constructs the course topic matrix, the post task matrix, and the method candidate matrix. The coupling value between course topics and post tasks is defined as follows:

$$R_{i,j} = a_1 M_{i,j} + a_2 D_{i,j} + a_3 P_{i,j} \tag{7}$$

Here, $R_{i,j}$ represent the comprehensive coupling value between topic i and task j, $M_{i,j}$ represent the content mapping strength, $D_{i,j}$ represent the degree of difficulty coordination, and $P_{i,j}$ represent the degree of platform rule adaptation. This formula is used to determine the degree of participation of each topic in the enterprise task chain. The candidate teaching methods were then initially scored as follows:

$$Y_{u,m} = b_1 S_{u,m} + b_2 C_m + b_3 E_m \tag{8}$$

Here, $Y_{u,m}$ represents the initial score of method m acting on topic u, $S_{u,m}$ represents the adaptation value, C_m represents the cost of method, and E_m represents the stability of method execution. This formula is used to filter inefficient methods that are not suitable to enter the current round schedule.

In the core computing phase, the algorithm uses relation propagation and local update to execute in parallel. Topic nodes, task nodes and method nodes enter the heterogeneous graph structure first, and the edge weights are jointly modified according to the behavior feedback and historical effects of the current round. The representation of node u after round t is updated as follows:

$$H_u^{t+1} = \mathrm{ReLU}\left(W_1 H_u^t + W_2 \sum_{v \in N(u)} q_{u,v} H_v^t \right) \tag{9}$$

Here, H_u^{t+1} denotes the updated node representation, $N(u)$ denotes the set of neighborhood nodes connected to u, and $q_{u,v}$ denotes the edge weights. This formula is used to incorporate job changes, task pacing, and method presentation into the topic representation. Based on the updated representation, the algorithm computes the method selection probability as follows:

$$\Pr(m|u) = \frac{\exp(Z_{u,m})}{\sum_k \exp(Z_{u,k})} \tag{10}$$

Here,$\Pr(m|u)$ represents the probability of selecting method m under topic u, and $Z_{u,m}$ represents the joint score between topic and method. This formula is used to generate a set of method candidates that can be ranked.

Before the platform behavior feedback enters the next round of scheduling, it needs to complete state normalization and exception compression. The state value of the student group in round t is defined as follows:

$$B^t = c_1 \bar{L}^t + c_2 \bar{I}^t + c_3 \bar{F}^t \tag{11}$$

Here, B^t represents the group behavior state, $\bar{L}^t$ represents the average learning state, $\bar{I}^t$ represents the average interaction depth, and $\bar{F}^t$ represents the average task completion. This formula is used to describe the current operating state of the teaching link. Then, the system performs a joint modification of the method weights based on the behavior state:

$$W_m^{t+1} = W_m^t + \gamma(B^t - \hat{B}^t) + \delta(G_m^t - \hat{G}_m^t) \tag{12}$$

Here,W_m^{t+1} represents the updated method weight, $\hat{B}^t$ represents the target behavior state, G_m^t represents the effectiveness value of method m in this round, and $\hat{G}_m^t$ represents the desired level of this method. The formula reflects the synchronous correction effect of platform feedback and implementation results on method scheduling.

In the output phase, the algorithm generates the method sequence corresponding to the course topic and gives the comprehensive collaborative score:

$$O = \mu_1 Q + \mu_2 \bar{Y} + \mu_3 \bar{B} + \mu_4 \bar{G} \tag{13}$$

Here, O represents the collaborative optimization output value, Q represents the comprehensive collaborative index defined in the previous section, $\bar{Y}$ represents the average method score, $\bar{B}$ represents the average behavior state, and $\bar{G}$ represents the average implementation effectiveness. This formula is used to filter the sequence of methods that eventually enter the teaching execution layer. In order to ensure the availability of the algorithm in the school-enterprise joint environment, the system synchronously outputs teacher side suggestions and enterprise mentor side suggestions after each round of update. The former is mainly for classroom organization and resource allocation, and the latter is mainly for task authenticity and job fit. If there is a significant deviation between the two types of proposals, the system will preferentially retain the combination that is beneficial to both the content chain and the task chain, and record the difference back to the database for the next round of training.

Figure 2 illustrates the overall structure of the proposed algorithm. The left side is the input of course topics, job tasks, teaching resources and behavior logs, the middle part is the coupling calculation, heterogeneous graph propagation, probability sorting, state correction and weight update module, and the right side outputs the sequence of teaching methods, collaborative scores and feedback records. The vertical arrow represents the main link from data input to execution output, and the horizontal loop represents the joint backtransmission of teacher evaluation, enterprise evaluation and platform log. The figure shows that the collaborative optimization of school-enterprise teaching methods is not a simple experience adjustment, but relies on multi-source data, relationship modeling and continuous updating to complete the method calculation process, and maintains the overall stability and consistency between curriculum objectives, job requirements and classroom execution rhythm.

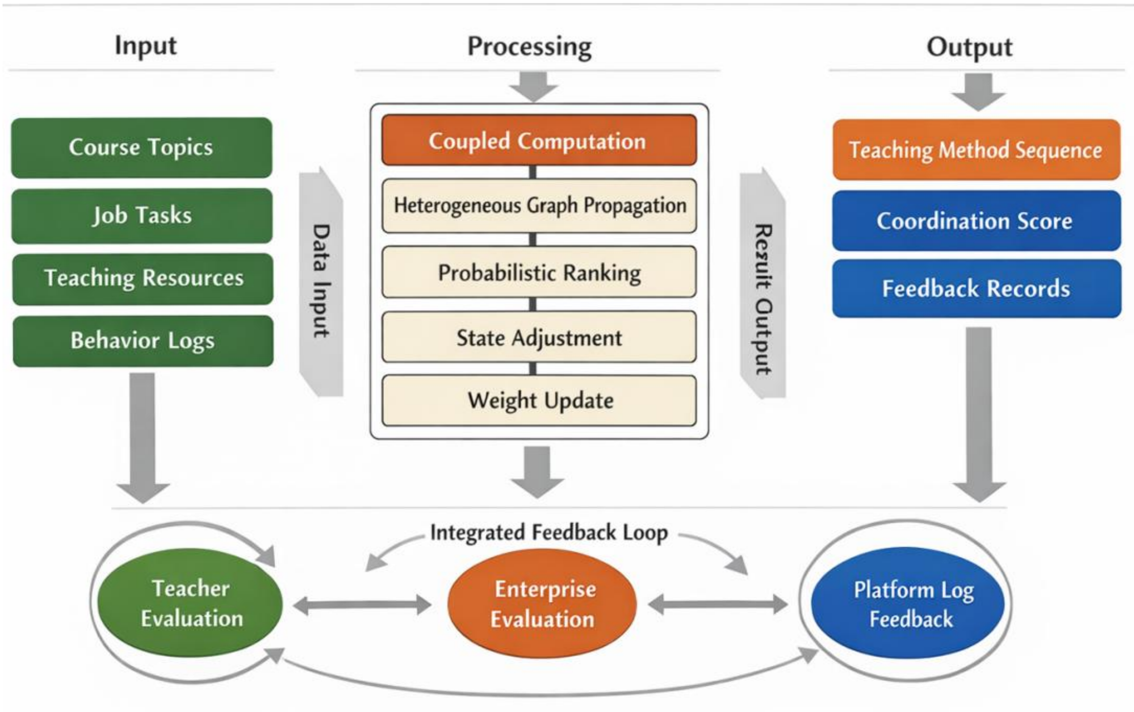

Figure 2: Structure diagram of the collaborative optimization algorithm for school-enterprise teaching methods.

3.3 Experimental setup and evaluation method

3.3.1 Data acquisition and preprocessing

Learning data collection was carried out from three dimensions: course content reconstruction, teaching method scheduling and platform interactive feedback. The resulting data included course unit tests, stage training results and enterprise tutor ratings, and all evaluations were entered into the database according to a unified standard. The process data was automatically collected by the background interface of the teaching platform and the training platform, which included login frequency, resource access sequence, page stay time, task submission record, discussion interaction times and operation revision trajectory. Before the original data entered the analysis module, missing fields were eliminated, duplicate records were merged and abnormal timestamps were corrected, and then the alignment was completed according to the course topic, task number and student anonymous identification. Then, the text records, behavior sequences and scoring results are encoded to form three input variables: content features, method features and behavior features. In order to ensure the stability of the subsequent statistical results, the preprocessing stage synchronously completes interval normalization, category label mapping and hash desensitization processing, and writes the processed data into a unified sample table for subsequent evaluation index calculation and collaborative algorithm verification. In the interface layer, the system completed multi-source back transmission through the course resource interface, behavior log interface and evaluation feedback interface, and the sampling accuracy was unified to the second window to ensure that the data of different modules were comparable on the same time axis. The processed sample retains the topic cluster number, method combination number and task chain position index at the same time, which provides direct input support for subsequent relationship modeling.

3.3.2 Indicator design and statistical analysis

The index design was carried out on four levels: course content adaptation, teaching method implementation, platform interactive feedback and comprehensive collaborative output. The content side indicators include topic matching rate, post coverage rate, resource connection degree and case applicability, which are used to measure the mapping degree between course topics and enterprise post tasks and the coherence of content organization. The method side indicators include task completion rate and classroom interaction responsiveness, which are used to reflect the execution status of teaching methods in different course topics and task chains. The behavioral indicators used platform interaction index, resource access depth and discussion response frequency to describe students 'participation level and interaction intensity in the teaching platform and training platform. The outcome side indicators include stage grades, enterprise tutor ratings and comprehensive output values, which are used to evaluate the overall implementation effect after the course content reorganization and teaching method scheduling. The statistical analysis was completed jointly by Python and SPSS, and the significance of each index between the experimental group and the control group was compared, and the p value, effect size, 95% confidence interval and test power were reported. In order to analyze the correlation degree between platform interaction behavior and learning outcomes, Pearson correlation coefficient and multiple linear regression coefficient were further calculated. Ablation analysis set three configurations of de-task mapping module, de-behavior feedback module and de-joint update module, which were compared with the complete collaborative framework to identify the independent contributions of each module to course content matching, method scheduling and platform collaborative effect.

4 Results and discussion

4.1 Adaptation effect after course content optimization

In order to visually present the difference between the experimental group and the control group in the level of course content adaptation, Figure 3 shows the columnar comparison results of four indicators: topic matching rate, post coverage rate, resource cohesion and case applicability.

The four indicators correspond to the mapping degree between course topics and post tasks, the coverage of course content to enterprise ability items, the structural coherence in the process of resource organization, and the task applicability level of enterprise cases after entering the classroom.

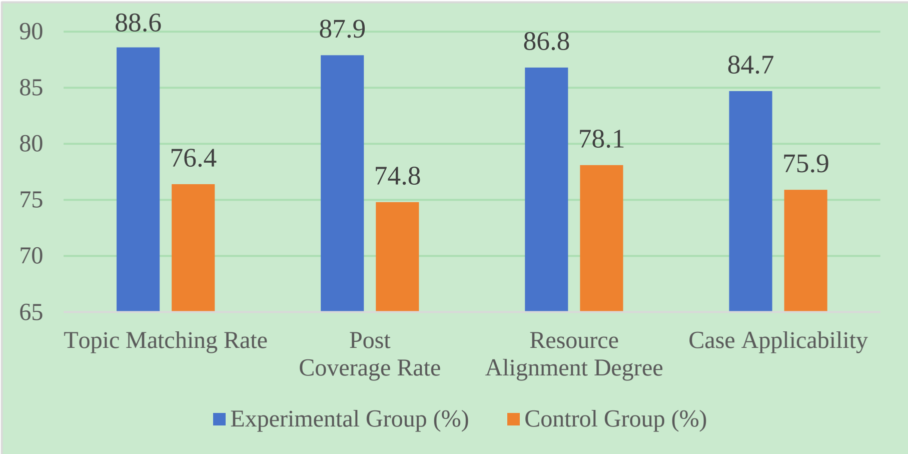

Figure 3: Rendering of course content adaptation

Figure 3 shows that the experimental group performs better than the control group in all four indicators. The topic matching rate was improved from 76.4% to 88.6%, and the difference was 12.2%. The job coverage rate increased from 74.8% to 87.9%, with a difference of 13.1%; The degree of resource connection increased from 78.1% to 86.8%, with a difference of 8.7%. The case applicability is improved from 75.9% to 84.7%, and the difference is 8.8%. From the perspective of intra-group dispersion, the standard deviations of the four indicators in the experimental group were 4.9, 5.2, 5.4 and 5.1, respectively, and those in the control group were 6.1, 6.4, 6.0 and 5.8, respectively, indicating that the collaborative framework not only improved the level of content adaptation, but also made the course organization results more centralized and stable. The improvement of topic matching rate and post coverage rate was greater, indicating that the collaborative link between post task analysis and knowledge unit reorganization had formed strong support. The simultaneous rise of resource cohesion and case applicability indicates that the content arrangement is no longer limited to material superposition, but can maintain good continuity in task sequence, resource invocation and case integration.

The statistical test results are shown in Table 2. All four indicators in the experimental group reached significant levels, and the effect size was in the medium to high range as a whole. The effect sizes of topic matching rate and post coverage rate were 0.81 and 0.78, respectively, and the 95% confidence intervals did not cross the zero value, indicating that the improvement of mapping between course content and post tasks had strong practical significance. The effect sizes of resource cohesion and case applicability were 0.63 and 0.67, respectively, which also indicated that the course materials after content reorganization formed stable advantages in organization mode and scene embedding. The test power of the four indicators is higher than 0.80, indicating that the sample size can support the current comparison results. This result shows that the adaptation improvement after course content optimization does not come from a single dimension, but the result of task parsing, topic reorganization and feedback update.

Table 2: Statistical results for comparison of course content adaptation effects.

Indicator	Difference (%)	p-value	Effect Size (Cohen's d)	95% Confidence Interval	Statistical Power
Topic Matching Rate	12.2	<0.001	0.81	[0.49, 1.12]	0.91
Job Task Coverage Rate	13.1	<0.001	0.78	[0.46, 1.09]	0.89
Resource Alignment Degree	8.7	0.002	0.63	[0.31, 0.94]	0.84
Case Applicability	8.8	0.001	0.67	[0.35, 0.98]	0.86

Further analysis shows that this adaptation improvement is not a surface change formed by simply increasing the number of cases, but comes from the continuous effect of the content-side computing mechanism. The task analysis layer generates the topic mapping results according to the post semantics and ability coverage relationship, and then the content reorganization layer reorganizes the knowledge units, operation processes and resource granularity, so that a more stable many-to-many connection is formed between the course topics and the enterprise tasks. The platform-side behavior records play a correction role in the update process. After the signals such as access order, stay time and revision frequency are written back to the content weight, the low relevance topics are gradually weakened, and the high response topics are given higher organizational priority. The content chain formed in this way not only maintains the integrity of the curriculum system, but also enhances the fit with the real business process.

4.2 Implementation effect of teaching method improvement

The implementation effect of the improved teaching method is mainly reflected in three aspects: task promotion efficiency, classroom response state and method switching stability. Under the support of the school-enterprise collaboration framework, the teaching activities of the experimental group no longer rely on a fixed rhythm, but are dynamically scheduled according to the course theme, post task and platform behavior feedback. The control group still organized explanations, exercises and case discussions in the conventional order. Although the classroom advancement maintained the basic integrity, it showed obvious fluctuations in task acceptance and interaction cohesion. Combined with the eight-week teaching records, it can be seen that the experimental group shows higher implementation consistency in most stages, and can still maintain a stable completion state when the complexity of the task increases.

In terms of task promotion effect, the completion rate of the experimental group increased from 72.4% to 81.6% in the first 3 weeks, and briefly dropped to 77.8% in the fourth week due to the difficulty of the task, then increased to 86.9% in the sixth week, and reached 90.3% in the eighth week. Although there were also ups and downs in the control group, the overall growth rate was maintained between 68.9% and 76.2%, and the growth rate was significantly smaller. The results show that the collaborative optimization algorithm can adjust the combination order of teaching, demonstration, collaboration and practical training in time according to the coupling strength between course topics and post tasks, keep the teaching methods in sync with the content structure, and reduce the execution fluctuation caused by high-density task weekly. The related changes are shown in Figure 4.

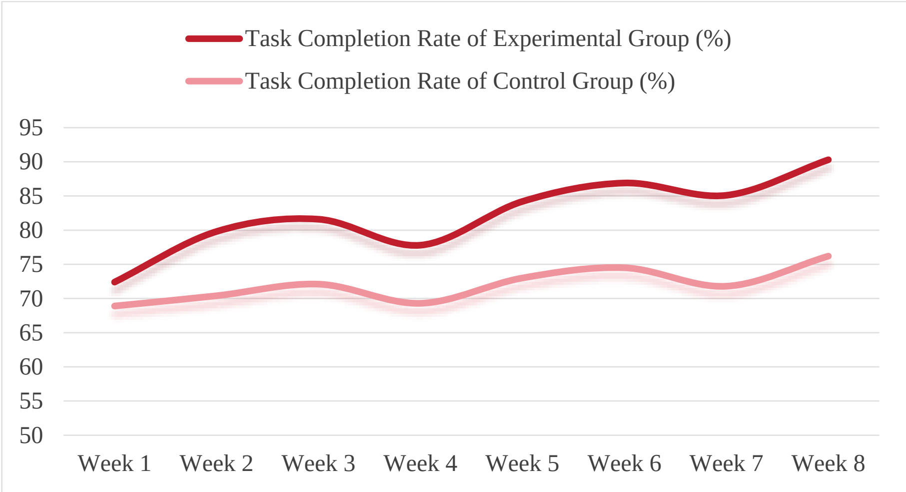

Figure 4: Teaching task completion rate change curve.

Figure 4 shows that the experimental group formed a clearer upward trend after the fifth week, while the control group showed a significant decline in the fourth and seventh weeks, indicating that the static organization mode lacked sufficient adjustment ability when the task switching was frequent. Further comparing the discrete situation, the standard deviation of task completion rate in the experimental group is 5.7, and that in the control group is 8.4, indicating that the improved teaching method has higher stability in continuous implementation. Especially in the teaching units with long task chains such as content planning, platform operation and data analysis, the method combination of the experimental group can better adapt to the requirements of topic progression and task splitting, so its task completion is more balanced.

The improvement of classroom interaction status is also obvious. In the experimental group, after a slight correction from week 1 to week 2, it rose to 79.5% in week 5, 84.1% in week 7, and remained at 82.7% in week 8. For the control group, it fluctuated between 60.7% and 71.2%. This change shows that after the introduction of behavior state recognition, stage feedback update and enterprise task write-back, the classroom method configuration is no longer limited to unified push, but can be adjusted in time according to student behavior signals such as click, discussion, revision and submission. The related changes are shown in Figure 5.

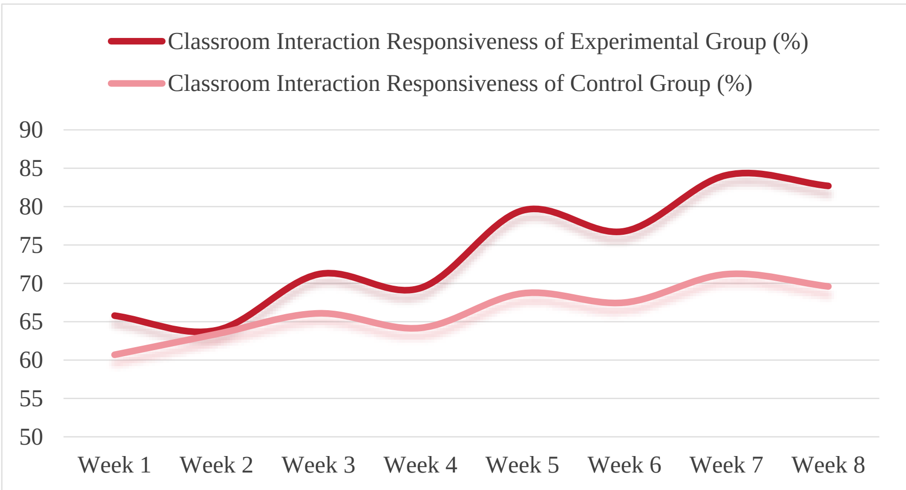

Figure 5: The change curve of classroom interaction responsiveness.

Figure 5 reflects that the interaction responsiveness of the experimental group was significantly higher than that of the control group in the middle and late stages, and the transition between peak and valley values was smoother, indicating that a better synergistic relationship was formed between method switching and topic advancement. The improvement of interaction responsiveness was not only reflected in the increase of speech frequency, task follow-up speed and discussion participation, but also reflected in the more timely response of students to platform prompts, resource calls and enterprise task feedback. Synthesizing the two groups of change processes, it can be seen that the implementation effect of the improved teaching method mainly comes from three aspects: first, the method matching process enhances the correspondence between classroom tasks and post goals; Secondly, the platform feedback mechanism shortens the time interval of method correction. Third, the school-enterprise bilateral evaluation feedback improves the accuracy of method scheduling.

4.3 Relationship between platform interaction behavior and learning outcomes

In order to investigate the correlation strength between platform interaction behavior and learning outcomes, this section first compares the interaction changes of the two groups of students in the teaching cycle, and then analyzes the explanatory role of behavioral signals on learning performance combined with statistical results. The interactive behavior of the platform is mainly composed of the depth of resource click, the frequency of discussion response, the number of task revisions and the speed of submission and follow-up. All records are returned synchronously by the teaching platform and the enterprise training end. On the whole, the interaction level of the experimental group was higher than that of the control group in most weeks, and it could still maintain a more stable upward trend in the stage of high task density, indicating that the school-enterprise joint collaboration framework could timely transform the platform feedback into the basis for scheduling teaching methods.

The interaction index in the experimental group increased from 58.3 in the first week to 71.8 in the third week, fell to 66.4 in the fourth week due to task switching, increased again after the fifth week, and reached 83.7 in the eighth week. The control group only fluctuated between 52.1 and 64.8 during the same period. In the experimental group, the increase was more obvious from week 5 to week 8, indicating that the method matching module had completed more effective dynamic adjustment according to the state of resource access, task submission and interactive response in the middle and late stage. In contrast, although the control group also showed a local rise, the fluctuation range was large, and the retention time of the high value was short, indicating that the static organization method lacked sufficient support when the task switched frequently. The related changes are shown in Figure 6.

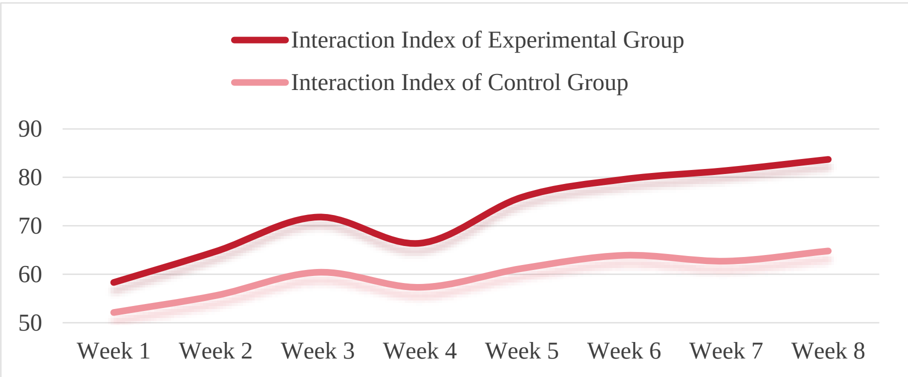

Figure 6: The change curve of platform interaction behavior.

Figure 6 reflects that the interaction in the experimental group changed more smoothly in the middle and late stages, and the transition between peak and valley values was more natural. This difference shows that the click, stay, discussion and revision signals on the platform side have been able to participate in the revision of course content and the update of teaching methods after unified coding, instead of just passively recording. The statistical results are shown in Table 3. The Pearson correlation coefficient between interaction index and stage performance in the experimental group was 0.82, which was significantly higher than 0.49 in the control group. The correlation coefficient between resource access depth and task completion quality was 0.77, and the correlation coefficient between discussion response frequency and enterprise mentor rating was 0.73, both of which reached a significant level. The multiple regression results further showed that the standardized regression coefficient of interaction index on stage performance was 0.68, indicating that platform interaction behavior had become an important source of prediction of learning outcomes. It can be confirmed that the platform interaction in the school-enterprise joint teaching scenario not only bears the function of process recording, but also constitutes an important feedback basis for course content adjustment and method scheduling. And maintain high stability.

Table 3: Statistical results of the learning outcome relationship.

Indicator Relationship	Correlation Coefficient (Experimental Group)	Correlation Coefficient (Control Group)	p-value	Standardized Regression Coefficient
Interaction Index – Stage Achievement	0.82	0.49	<0.001	0.68
Resource Access Depth – Task Completion Quality	0.77	0.43	0.001	0.61
Discussion Response Frequency – Enterprise Mentor Rating	0.73	0.38	0.002	0.57

4.4 Comparison of school-enterprise collaborative teaching framework

Based on the previous itemized analysis, this section further uses comprehensive indicators to compare the overall operation effect of different collaborative frameworks. The comparison of school-enterprise collaborative teaching framework mainly focuses on four indicators: course content matching rate, method scheduling accuracy, platform collaborative responsiveness and comprehensive output value. The complete collaboration framework, the de-task mapping framework, the de-behavior feedback framework, and the traditional static organization scheme were tested in parallel under the same experimental conditions. The overall results show that the complete collaborative framework maintains the highest level in all four indicators, indicating that the framework can simultaneously deal with multiple relationships between post tasks, course topics and platform behaviors, and form a relatively stable linkage mechanism between content reorganization and method scheduling.

From the specific results, the course content matching rate of the complete collaborative framework is 90.2%, the method scheduling accuracy is 88.7%, the platform collaborative responsiveness is 88.5%, and the comprehensive output value is 91.3. The overall performance is significantly better than the other three schemes. The content matching rate of the de-task mapping framework dropped to 78.8%, indicating that job task analysis was still the basic support of curriculum restructuring. The platform collaborative responsiveness of the de-behavior feedback framework decreases to 78.8%, which indicates that the behavior writeback mechanism has a direct impact on the method update. The traditional static organization scheme is at the lowest level in the four indicators, and the comprehensive output value is only 74.1, which shows that the content arrangement under the fixed order is difficult to adapt to the change of enterprise tasks. The relevant comparison results are shown in Figure 7.

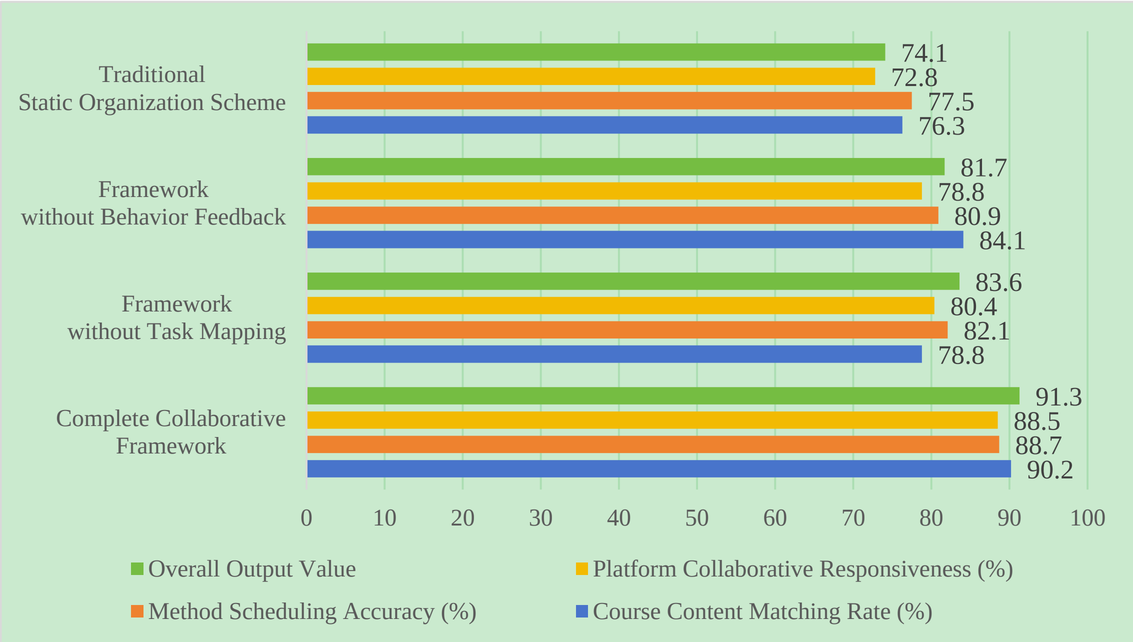

Figure 7: Comparison results of school-enterprise collaborative teaching framework.

Figure 7 shows that the complete collaborative framework not only dominates the result mean, but also shows a better balance among multiple indicators. Compared with the de-task mapping scheme, the complete framework has 11.4% higher matching rate of course content and 7.7 higher comprehensive output value. Compared with the de-behavior feedback scheme, the complete framework is 9.7% higher in platform collaborative responsiveness and 7.8 higher in method scheduling accuracy. This shows that even if a single module can maintain part of its operation capacity, it is difficult to support the complete collaborative link in the school-enterprise joint scenario. Furthermore, the index fluctuation of the complete framework is smaller in the medium-high intensity task stage, indicating that the unified representation, relationship propagation and joint update have formed a more mature computing mechanism.

It can be confirmed that the comparison results of school-enterprise collaborative teaching framework support the effectiveness of the proposed method in the course organization and teaching scheduling of e-commerce major. From the perspective of index structure, the content matching rate and method scheduling accuracy increased synchronously, indicating that the framework did not sacrifice classroom execution efficiency for content fit. The collaborative responsiveness of the platform and the comprehensive output value kept changing in the same direction, which also showed that there had been a closed-loop linkage between enterprise feedback, teacher adjustment and platform log. This result provides a clear reference for subsequent ablation experiments, and further shows that the complete collaborative framework has high application value in the scenario of school-enterprise joint e-commerce courses.

4.5 Results of ablation experiments

In order to further identify the independent contributions of each module to the overall collaboration effect, we conduct module-level ablation analysis based on the complete collaboration framework, focusing on the independent contributions of the three core modules of task mapping, behavior feedback and joint update to the system performance. The results show that the complete collaborative framework maintains the highest level in the four indicators of course content matching rate, method scheduling accuracy, platform collaborative responsiveness and comprehensive output value, indicating that there is an obvious synergy between task mapping, behavior feedback and joint update. The relevant results are shown in Table 4.

Table 4: Comparison of ablation experiment results (mean ± standard deviation).

Model Configuration	Course Content Matching Rate (%)	Method Scheduling Accuracy (%)	Platform Collaborative Responsiveness (%)	Overall Output Value
Complete Collaborative Framework	90.2 ± 4.1	88.7 ± 4.5	88.5 ± 4.3	91.3 ± 3.8
Without Task Mapping Module	80.4 ± 5.6	82.1 ± 5.2	80.7 ± 5.5	82.6 ± 4.9
Without Behavior Feedback Module	84.3 ± 5.1	79.8 ± 5.8	77.9 ± 6.0	81.4 ± 5.3
Without Joint Update Module	78.6 ± 6.3	76.9 ± 6.1	74.8 ± 6.5	76.8 ± 5.9

It can be seen from Table 4 that after removing the task mapping module, the matching rate of course content decreases by 9.8%, and the comprehensive output value decreases to 82.6, indicating that post task parsing is still the prerequisite support for course content restructuring. After removing the behavior feedback module, the platform collaborative responsiveness decreased from 88.5% to 77.9%, and the accuracy of method scheduling decreased synchronously, indicating that the platform log writeback had a direct correction effect on classroom scheduling. After removing the joint update module, the decline was the most obvious, and the comprehensive output value dropped to 76.8, and the fluctuations of the four indicators increased, indicating that once enterprise feedback, teacher adjustment and system update were disjointed, the linkage between course content and teaching methods would be difficult to maintain.

Overall, the complete framework is superior to any single module configuration, and its advantage does not come from single step enhancement, but from the continuous computation link formed by multi-source data, relationship propagation, and dynamic writeback. From the perspective of standard deviation, the dispersion degree of the four indicators of the complete framework is lower than that of the other configurations, indicating that the method has high stability under different weeks and different task densities. Table 4 further illustrates that although retaining a certain local mechanism alone can maintain some performance, it cannot support the overall closed loop of content organization, method selection and feedback correction in the school-enterprise joint scenario.

4.6 Discussion

The results of this study show that the collaborative framework of school-enterprise e-commerce course content and teaching methods is feasible in real teaching scenarios. The above results show that the course content matching rate, method scheduling accuracy, platform collaborative responsiveness and comprehensive output value are significantly better than the control scheme, indicating that a relatively stable linkage has been formed between enterprise task parsing, platform behavior writeback and joint update mechanism. Compared with the static course arrangement method, the post tasks, course topics, platform logs and evaluation records are incorporated into the unified computing link, so that the content reconstruction and method switching can be adjusted synchronously with the task intensity and interaction state. This advantage is not only reflected in the higher result mean, but also in the enhanced fluctuation convergence and execution stability.

In terms of implementation conditions, the framework of this paper adopts a modular organization method, which can not only be embedded in the existing teaching platform, but also facilitate the interface connection with the enterprise training end. The task mapping module ensures the semantic consistency between the course topic and the job ability, the behavior feedback module improves the timeliness of method scheduling, and the joint update module maintains the continuous closed loop between enterprise feedback, teacher judgment and system output. From the perspective of the scope of adaptation, the framework is not limited to a single course type. As long as the course content can be split into describable units and enterprise tasks can be represented as computable goals, the collaboration mechanism can be migrated to different modules such as platform operation, data analysis, and content planning. The follow-up work can continue to focus on lightweight deployment, cross-course migration, multi-platform interface compatibility and log audit optimization, so as to enhance the application ability of the framework in a larger scale school-enterprise joint environment.

5 Conclusion

Focusing on the collaborative reconstruction of e-commerce course content and teaching methods in the scenario of school-enterprise cooperation, this paper constructs a computing framework oriented to job tasks, course topics, platform behavior and evaluation feedback, and designs a collaborative optimization algorithm for teaching methods on this basis. Experimental results show that the proposed method is superior to the control scheme in terms of course content matching rate, method scheduling accuracy, platform collaborative responsiveness and comprehensive output value, indicating that task mapping, behavior feedback and joint update mechanism can jointly support course content restructuring and teaching implementation scheduling. There was a positive correlation between the platform interaction behavior and stage grades, task completion quality and enterprise tutor ratings, indicating that the platform log could provide a basis for the updating of teaching methods and the revision of course content.

The limitations are mainly reflected in three aspects: sample scope, platform environment and task structure. The experimental objects are focused on a single institution, and the school-enterprise collaboration data are from a limited number of course modules, so the applicability of the conclusions in larger scenarios still needs to be verified. Different enterprise platforms have different interface standards, task granularity and resource organization methods. Although the current framework can achieve unified representation and joint computing, it still needs more detailed compatible design in complex heterogeneous environments. At the same time, although data desensitization, permission control and feedback tracking mechanisms have been incorporated into the system process, they still need to maintain strict operational constraints under high-frequency interaction conditions.

The follow-up work can continue to focus on cross-course migration, lightweight deployment, multi-platform compatibility and log audit optimization, so as to enhance the portability and operation efficiency of the system in complex teaching environments. With the increasing depth of school-enterprise collaboration, course content reconstruction, teaching scheduling calculation and platform behavior analysis will rely on stable data interfaces and traceable feedback links. The results of this paper show that the digital construction of e-commerce professional courses should turn to a systematic organization method oriented to data representation, content calculation and closed-loop update, so as to provide computing support for school-enterprise joint teaching.

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