Research on Teaching Model Innovation and Job Adaptation in the Digital-Intelligent Finance and Business Industry-Education Integration Training Center

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Abstract: *The competency requirements for digital-intelligent finance and business are shifting towards a multi-dimensional and dynamic structural transformation, and the training center needs to construct an appropriate teaching model and job matching mechanism. This study proposes a three-layer framework that includes a teaching paradigm transformation, a job adaptation mechanism, and a collaborative adaptation path. By deconstructing the competency domain into four sub-domains of data perception, logical deduction, decision response, and value evaluation, this study achieves a modular reorganization of training elements and constructs a task-driven immersive framework. This study adopts dynamic job profiling, a virtual-real collaborative task chain, and personalized path generation to form a job adaptation mechanism. By optimizing the mapping between modules and functions, designing dynamic resource scheduling rules, and establishing an effectiveness and competency calibration model, this study achieves the coordination of teaching elements and job requirements. This research provides a theoretical basis and a technical path for the teaching model design of the training center.*

Keywords: *digital-intelligent finance and business; industry-education integration training center; teaching model innovation; job adaptation; dynamic competency profile; task chain-based teaching*

Introduction

The job competency requirements in the field of digital-intelligent finance and business are undergoing a profound transformation from static functional descriptions to dynamic competency combinations. The traditional practical training teaching system, when responding to this transformation, reveals prominent problems such as a disconnect between teaching content and job requirements, as well as a separation between competency cultivation and task scenarios. As a key carrier connecting educational supply and industry demand, the industry-education integration training center demonstrates the necessity of its teaching model innovation in two aspects. On the one hand, after digital-intelligent technologies are embedded into the workflow of finance and business, job tasks present new characteristics such as data-driven processes, algorithm-assisted operations, and cross-functional collaboration, which require that practical training teaching shift from single-skill training to comprehensive decision-making competency cultivation. On the other hand, job competency standards are in a state of continuous evolution, and the training center needs to possess the ability of dynamic perception and adaptive adjustment rather than sticking to a preset teaching plan. Current research still has theoretical gaps in areas such as the modular organization of training elements, the iterative mechanism of teaching forms, and the quantitative methods for job adaptation. Based on this, this study starts with the deconstruction of competency domains and constructs an integrated framework that includes paradigm transformation, innovation mechanisms, and collaborative paths, aiming to provide actionable theoretical guidance and technical solutions for the teaching model design of the digital-intelligent finance and business industry-education integration training center.

1. The Logic of Teaching Paradigm Transformation in the Digital-Intelligent Finance and Business Training Center

1.1 The Deconstruction of the Digital-Intelligent Finance and Business Competency Domain and the Reorganization of Training Elements

The composition of the digital-intelligent finance and business competency domain has transcended the scope of traditional financial accounting and business analysis, presenting multi-dimensional and dynamic characteristics. Based on the competency granularity decomposition method, this competency domain can be deconstructed into four sub-domains: the data perception layer, the logical deduction layer, the decision response layer, and the value evaluation layer. The data perception layer focuses on extracting structured and unstructured financial and business signals from heterogeneous business systems. The logical deduction layer focuses on the algorithmic expression of financial models, risk assessment, and profit prediction. The decision response layer involves resource allocation and trading strategy generation under multi-objective constraints. The value evaluation layer performs quantitative backtracking and deviation attribution of decision outcomes. This hierarchical deconstruction provides a clear competency mapping basis for the reorganization of training elements in the training center.

Corresponding to the above competency sub-domains, the teaching elements of the training center need to shift from discrete resources to modular combinations. The teaching elements include data source interfaces, a simulation trading engine, a dynamic case generator, interactive dashboards, and a role-permission matrix. The reorganization rules are based on the matching of competency granularity, encapsulating the elements associated with each sub-domain into "competency units" that can be independently invoked and cascaded. For example, the data perception layer connects to real-time financial data streams and business intelligence tools, while the logical deduction layer links to quantitative modeling software and algorithm libraries. By establishing a semantic association graph among the elements, this approach enables dynamic assembly across levels and tasks, thereby supporting the full-spectrum training needs from single-skill training to comprehensive business judgment[1].

1.2 The Iteration Mechanism of Practical Training Teaching Forms in the Industry-Education Integration Scenario

In the industry-education integration scenario, the practical training teaching form evolves from a fixed "command-execution" model to an adaptive "perception-response" model. The core of the iteration mechanism lies in the bidirectional coupling between the teaching data flow and the job competency signals. On the one hand, the operation trajectories, decision logs, and result sequences generated during the practical training process are captured in real time, forming feature vectors that reflect the learners' competency states. On the other hand, the job task descriptions, business rule changes, and typical workflows from the industry side (beyond the policy level) are converted into structured parameters and injected into the teaching engine. The deviation generated by comparing these two drives the teaching form to undergo continuous adjustments across three dimensions: task complexity, assistance granularity, and feedback density.

This iteration process follows a closed-loop control logic, which includes three stages: deviation detection, parameter mapping, and form reconstruction. Deviation detection uses clustering algorithms to identify the gap between the learners' competency shortcomings and the job standards. Parameter mapping quantifies this gap into teaching intervention strategies, such as adjusting the constraint conditions of a case or changing the presentation level of prompt information. Form reconstruction is then manifested as the layout switching of the training interface, the rearrangement of task steps, or the dynamic assignment of collaborative roles. This mechanism enables the teaching form of the training center to no longer be fixed to a preset template, but to evolve nonlinearly based on the real-time signals from both the education and industry sides, thereby maintaining the teaching tension within an appropriate range at all times.

1.3 Construction of a Job Task-Driven Immersive Teaching Framework

The immersive teaching framework takes job tasks as the basic organizational units and constructs a complete closed loop from task input to competency output. The bottom layer of the framework is the job task knowledge base, which stores standardized task descriptions, input-output specifications, and competency standards from different functional domains (such as financial analysis, fund allocation, and risk control). The middle layer is the task parsing and scenario generation module, which breaks down each job task into sub-steps, key decision points, and exception branches, and accordingly generates three-dimensional virtual scenes, data dashboards, and role identities. The top layer is the interaction and evaluation layer, which records the learners' operation sequences, time consumption, and decision results during task execution, thereby forming a multimodal behavioral data stream.

The immersion features are realized through a first-person perspective, an environmental feedback closed loop, and task narrative coherence. Specifically, a learner enters a simulated business environment in a specific job role, receives task events pushed along a timeline, and each operation triggers an immediate change in the environmental state, thereby forming a causal and visualizable learning experience. The framework construction needs to address three key design issues: the hierarchical consistency of task granularity, meaning that tasks of different complexities share a unified descriptive syntax; the low latency of situational response, ensuring that interaction does not cause cognitive disruption; and the alignment between evaluation indicators and task prototypes, avoiding detachment from actual job conditions. Through this framework, the training center can transform abstract competency indicators into operational and perceivable task execution sequences, thereby achieving a shift in teaching organization from a "content-centered" to a "task-centered" approach[2].

2. An Innovative Mechanism for Practical Training Teaching Models Based on Job Adaptation

2.1 A Digital Modeling Method for Dynamic Job Competency Profiles

The dynamic job competency profile differs from the static competency model, and its core lies in introducing the time dimension and the task context dimension to achieve real-time representation and prediction of the competency states required for a job. The modeling process is based on multi-source data fusion, including job task description texts, behavior sequences in operation logs, performance indicators of decision results, and state parameters of the business environment. This process adopts vectorized representation learning technology to map the above heterogeneous information into a common embedding space and constructs a job competency vector. Each dimension of this vector corresponds to a clustered and compressed competency factor, such as data sensitivity, model invocation efficiency, and anomaly identification accuracy, and the dimension weights are dynamically adjusted according to the task scenario.

The dynamic nature of the profile is realized through an incremental update mechanism. After each practical training task is completed, the system back-propagates the deviation between the learner's actual performance and the preset job standards to update the parameter distribution of the job competency vector. Specifically, this process adopts a combination of a time-decay window and Bayesian online learning, assigning higher weights to recent task data while retaining long-term stable features. In addition, the granularity of the job profile can be adaptively adjusted: fine-grained factor-level modeling is adopted during task switching, while the profile is aggregated into a role-level vector in cross-job collaboration scenarios. This digital modeling method provides a computable and comparable job benchmark for subsequent teaching organization, shifting job adaptation from static matching to dynamic calibration.

2.2 A Virtual-Real Collaborative Task Chain-Based Teaching Organization Architecture

The virtual-real collaborative architecture achieves time synchronization and logical coupling between the operational entities in the physical training space and the computational models in the digital simulation environment, thereby forming task chain-based organizational units. A task chain is defined as a sequence consisting of several sub-tasks with predecessor-successor relationships, and each sub-task corresponds to both a physical operation interface on the real side and a virtual data environment on the virtual side. For example, in a cash flow management task chain, the virtual side simulates market fluctuations and payment term rules, while the real side allows the learner to operate a fund allocation panel. The virtual side outputs constraint conditions, and the real side returns decision signals, and the two sides form a closed loop through a low-latency communication protocol. The length and the number of branches of the task chain are dynamically set according to the complexity of the job profile[3].

The advantage of the chain-based organizational architecture lies in its support for the splitting and reorganization of task granularity and the explicit modeling of dependencies. Each sub-task can be labeled as entity-dominated, virtual-dominated, or balanced, and the architecture accordingly allocates resources and interaction weights. The connection point between task chains is defined as a "state transfer node," which records the output indicators of the previous chain (such as fund balance and risk exposure) and uses them as input conditions for the next chain, thereby simulating the sequential decision constraints in real business operations. The architecture also incorporates an abnormal chain-breaking mechanism: when a learner shows a cumulative deviation from the job profile in a certain sub-task, the system automatically inserts a repair sub-chain, providing a reduced-order version of virtual support or entity prompts. Through the virtual-real collaborative task chain, the practical training teaching model achieves a leap from discrete operations to process coherence.

2.3 A Data-Empowered Personalized Learning Path Generation Strategy

The personalized learning path generation takes the difference matrix between the dynamic job competency profile and the learner's current competency state as its input, and outputs the optimal sub-task sequence and resource allocation scheme through a path search algorithm. The rows of the difference matrix correspond to the measured values of the learner's various competency factors, the columns correspond to the job benchmark values, and the normalized differences form the priority weights. The path generation adopts a constrained graph search method, in which the nodes of the graph are the teaching activity units stored in the training center (such as specific task chains, simulation cases, and interaction modules), and the edges represent the prerequisite dependencies and learning transfer costs between the teaching activities. The search objective is to maximize the reduction of competency differences while satisfying time and resource constraints.

After the path is generated, real-time replanning is also required. The new behavioral data generated by the learner during the execution process continuously updates the learner's competency state vector, which causes the difference matrix to change. The system triggers replanning according to a set threshold, retains the completed teaching activity nodes, and recalculates the remaining path. To avoid frequent oscillations, a smoothing factor and a confidence interval mechanism are introduced, and the path is adjusted only when multiple consecutive updates all point to the same direction of deviation. Data empowerment is also reflected in the generation of path diversity: for the same difference matrix, the system can output multiple equivalent paths (such as those focusing on the logical deduction type or those focusing on the data operation type), which can be selected by the learner or the instructor, thereby balancing adaptability and autonomy. This strategy shifts the teaching supply of the training center from unified content distribution to on-demand combinatorial delivery[4].

3. The Collaborative Adaptation Path between Teaching Elements and Job Requirements

3.1 The Optimization of the Mapping Relationship between Teaching Modules and Occupational Functions

The mapping relationship between teaching modules and occupational functions needs to shift from static correspondence to dynamic association optimization. The traditional mapping method fixes a single teaching module to a specific occupational function, which ignores the competency crossover between functions and the knowledge transfer between modules, resulting in the coexistence of module redundancy and incomplete function coverage. The optimization method is based on a competency factor association matrix, representing each teaching module as a weighted combination of several competency factors, while representing each occupational function as a threshold vector of the required competency factors. The mapping relationship is transformed into a maximization matching problem of using module combinations to cover functional requirements, and the solution adopts a bipartite graph weighted matching algorithm, using module content overlap and function uniqueness as the dual objective functions for iterative calculation. This algorithm calculates the matching gain between modules and functions in each iteration, stops when the gain falls below a preset threshold, and outputs a near-optimal module-function allocation scheme.

The dynamic nature of the mapping optimization is reflected in two feedback loops. First, the competency increment data generated by the learner after completing a module is used to correct the competency factor weights of the module. For example, if a module actually improves data modeling capabilities more than its initial setting, the system increases the weight coefficient for that dimension while correspondingly reducing the relative contributions of other dimensions. Second, after the job profile of an occupational function is updated, its threshold vector shifts, and the system automatically triggers a rematching process to adjust the correspondence between modules and functions. The rematching process introduces a cooling time parameter to avoid frequent reorganizations caused by minor fluctuations in the profile. The optimization result is presented as a mapping probability matrix, in which the contribution of each module to different functions is represented by a value between 0 and 1. Based on this matrix, the sequence and combination of teaching modules can be reorganized. The mapping probability matrix can also be used to identify shared modules across functions, reduce redundant construction, and improve resource utilization efficiency and job adaptation accuracy[5].

3.2 Dynamic Configuration and Scheduling Rules for Interactive Practical Training Resources

Interactive practical training resources include virtual scene assets, simulation data streams, interactive control libraries, and behavioral log collection channels, and their configuration and scheduling need to follow the principles of task-driven and load balancing. The core mechanism of dynamic configuration is a resource demand prediction model, which takes the number of currently active task chains, the complexity level of the job profile, and the learner's historical resource consumption rate as inputs, and outputs a pre-allocation plan for various types of resources within the next time window. The prediction adopts a long short-term memory network structure, which is updated in a rolling manner during the practical training process to identify resource bottleneck nodes in advance. To improve the robustness of the prediction, the model also introduces a residual connection, using the prediction error of the previous time window as an auxiliary input to form an error compensation loop. The resource pre-allocation results are issued to each execution node in the form of a resource-task binding table, with corresponding computing and storage capacities reserved.

The scheduling rules adopt a strategy that combines a priority queue with elastic scaling. Each practical training task is assigned a resource priority, which is calculated by weighting three factors: the position of the task in the chain (predecessor tasks receive higher priority), the urgent deviation degree of the job profile, and the remaining time limit of the task. The weight coefficients are dynamically adjusted according to the real-time load status of the training center: under high load, the weight of the task position is increased to ensure process continuity; under low load, the weight of the deviation degree is increased to accelerate competency repair. When resource contention occurs, the system allocates resources according to the priority order and simultaneously triggers the elastic scaling mechanism. For parallelizable resources (such as data stream instances), the system dynamically increases the number of replicas, with the upper limit of replicas determined by the physical resource capacity. For exclusive resources (such as specific interactive controls), the system handles them through time-slice round-robin or task queuing, and the queue timeout threshold is set to a fixed proportion of the remaining time limit of the task. The scheduling rules also include resource release conditions, which automatically reclaim resources after a task is completed or when a timeout occurs without a response, thereby avoiding deadlocks. This configuration and scheduling system ensures the operational stability and response efficiency of the training center under high-concurrency and multi-task environments.

3.3 A Quantitative Calibration Model for Teaching Effectiveness and Job Competency

The quantitative calibration model is used to establish a mathematical conversion relationship between teaching effectiveness indicators and job competency indicators, thereby eliminating the deviations caused by their different dimensions and collection methods. The teaching effectiveness indicators originate from the behavioral data in the practical training process, including observable variables such as task completion rate, decision accuracy, response latency, and resource utilization efficiency. The job competency indicators originate from the competency factor scores in the dynamic job profile, such as anomaly identification sensitivity and model parameter-tuning rationality. The calibration model adopts a two-hidden-layer neural network structure, with the input layer being the vector of teaching effectiveness indicators, the output layer being the vector of predicted competency scores, and the hidden layers learning the nonlinear mapping relationship.

Model training and updating adopt an incremental learning method. The initial mapping relationship is preset based on the rules in the job task knowledge base, and then the model parameters are continuously optimized by the paired data generated by the learners during the practical training process (the teaching effectiveness records corresponding to the same task and the subsequent job simulation evaluation results). The calibration error is adjusted through backpropagation, and a regularization term is introduced to prevent overfitting. The model output can be used in two directions. The forward direction converts teaching effectiveness into estimated competency values for learning progress monitoring. The reverse direction back-calculates the required teaching effectiveness thresholds based on the target competency gap, guiding the selection of teaching modules and resource allocation. This calibration model establishes a quantifiable and computable alignment mechanism between the training center's teaching evaluation and job requirements, thereby supporting closed-loop adaptation control.

Conclusion

This study constructs a theoretical framework for teaching model innovation and job adaptation in the digital-intelligent finance and business industry-education integration training center from three dimensions: competency domain deconstruction, job adaptation mechanisms, and collaborative adaptation paths. This study clarifies the four-layer structure of the digital-intelligent finance and business competency domain and the corresponding reorganization rules for training elements, explains the closed-loop iteration mechanism of teaching forms in the industry-education integration scenario, and designs an immersive teaching framework that takes job tasks as the basic unit. At the job adaptation level, this study proposes a digital modeling method for dynamic job competency profiles, a virtual-real collaborative task chain-based teaching organization architecture, and a data-empowered personalized learning path generation strategy. At the collaborative adaptation level, this study establishes a dynamic mapping optimization method between teaching modules and occupational functions, a configuration and scheduling rule for interactive practical training resources, and a quantitative calibration model for teaching effectiveness and job competency. Future research directions include: exploring group competency profiles and collaborative adaptation mechanisms in multi-job collaboration scenarios, researching global resource optimization scheduling algorithms across task chains, and developing self-evolution methods for teaching intervention strategies based on reinforcement learning, so as to further improve the adaptive level and job adaptation accuracy of the training center's teaching model.

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