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: *Given that the speed and direction of change in demand for digital-intelligent finance and business talent are different, various teaching methods and job-matching systems need to be developed by the training centre accordingly. The three levels of the proposed system are changes in teaching concepts, modifications to work systems and cooperative models, etc. The four Areas of Competence have been divided into the following four sub-areas: Data Perception, Logical Deduction, Decision Response and Value Evaluation, and based on this, the training content has been arranged in modules and a task-oriented immersive system has been developed. Dynamic Job Profiling is a virtual-reality collaborative task chain, and Personalised Path Generation in this paper is used to construct a job adaptation mechanism. Optimisation of Module and Function Mapping, Design of Dynamic Resource Scheduling Rules, Construction of an Effectiveness-Competency Calibration Model, Coordination of Teaching Elements and Job Requirements: An Investigation in this Paper. Provide the theoretical basis and technical path for the Design of the teaching model at the training centre in this paper.*

Keywords: *Digital-intelligent Finance and Business, Industry-education integration training centre, teaching model innovation, job adaptation, dynamic competency profile, task chain-based teaching.*

Introduction

The demand for job-related qualities in the area of digital-intelligent finance and business has changed from a few fixed functions to many different combinations of skills. As a result of the changes above, some deficiencies have appeared in the traditional practical training teaching system, such as a mismatch between teaching content and job requirements, a lack of competency cultivation and task scenarios, etc. As the foundation for the supply of educational resources and in response to the demands of the industry, new forms of teaching have started to be introduced by the industry-education integration training centre. On the one hand, with the addition of digital-intelligent technology to the workflow of finance and business, job tasks have changed; now they are data-driven, algorithm-assisted and cross-functional, so practical training and teaching need to move from training single skills to cultivating all-round decision-making abilities. At the same time, the standards for job competence are also changing constantly, so the training centre should have a sense of change and be able to adapt to all circumstances rather than sticking to a fixed teaching plan. At present, the problems in the areas of modular organisation of training elements, iterative mechanisms for teaching forms and quantitative methods for job adaptation are still theoretical deficiencies. Based on the above, this paper will first divide the competency areas to build a general system that includes paradigm shift, innovation mode and cooperation path, with the aim of providing practical theoretical support and technical solutions for the construction of the teaching model at the digital-intelligent finance and business industry-education integration training center.

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

1.1 Deconstruction of the Domain of Digital-Intelligent Finance and Business Competence and Reorganisation of Training Elements

The content of the area for digital-intelligent finance and business competency has long gone beyond traditional financial accounting and business analysis, and is now very diverse and constantly changing. According to the method of competency granularity decomposition, the four sub-domains of this competency domain are as follows: the data perception layer, the logical deduction layer, the decision response layer and the value evaluation layer. Collect all kinds of financial and operating data from all parts of the business system in the Data Perception Layer. The modules of logical deduction are the algorithms in the financial model, risk assessment and profit forecasting. The Decision-Response Layer will select one of the goals and determine how to prioritise it. The ValueEvaluationLayer sets how far back and how far off from the decision results. The first level of division will help us create a list of necessary skills for reorganising the training programmes at the centre.

Based on the sub-domains of competence listed above, the teaching materials at the training centre should be organised into modules of individual resources. The parts of the teaching are the data source interface, the simulation trading engine, the dynamic case generator, the interactive dashboard and the role-permission matrix. The division of the rules for reorganisation is in line with the granularity of competence; every part of a sub-domain is a "competency unit" that can be called and cascaded independently. The Data Perception Layer will be used to obtain the flow of real-time financial data and connect with the Business Intelligence tool, and the Logical Deduction Layer will be linked to quantitative modelling software and algorithm libraries. Build a semantic association graph of the elements to dynamically combine them at various levels and for different purposes in order to meet all the training requirements, such as single-skill training and overall business judgment[1].

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

With the progress of industry-education integration, the form of teaching for practical training has changed from the old fixed "command-and-control" model to an adjustable "perception-response" type. At the bottom of the iteration mechanism, there is bidirectional coupling between the flow of teaching data and job competency signals. On the one hand, at the same time during the course of practical training, operation trajectory, decision log and result sequence are recorded in real time to form feature vectors of the learners' competency states. At the same time, job task descriptions, changes in business rules and typical workflows at the industry level (not just the policy level) are also converted into structured parameters and injected into the teaching engine. The two drivers will be used to change the three levels of teaching forms: task difficulty, degree of help and frequency of feedback.

The three stages of the iteration process are deviation detection, parameter mapping and form reconstruction, and so on. Cluster analysis can be employed to determine how far the competency deficiencies of the learners are from the requirements of the job. The range of teaching interference in changing something is called a parameter, such as the constraint conditions of a case or the display level of prompt information. Change the position of the training window, modify the order of tasks, dynamically assign cooperative roles, and add a new kind. Therefore, the teaching form at the training centre will no longer be fixed in one way but will change according to the actual circumstances of education and industry at different times, and an ideal level of teaching pressure can be maintained at all times.

1.3 Construction of a Job Task-Driven Immersive Teaching Framework

The lowest level of division in the structure of the immersive teaching framework is a job task, and the whole closed-loop system is based on task input and competency output. At the bottom of the framework is the job task knowledge base; it contains standardised descriptions of all tasks in the organisation, input-output specifications, competency standards, etc., such as financial analysis, fund allocation and risk control. In the middle is the task parsing and scenario generation module; it will break down each job into a series of steps, important decision points and error handling scenarios, build three-dimensional virtual environments, data panels, etc., accordingly. At the top is the interaction and evaluation layer; it records the sequence of learner operations, time spent, decision results in tasks, and so on, to build a multi-modal behaviour data stream.

The three types of immersion are first-person view, closed-loop environmental feedback and task narrative coherence. The student is placed in a simulated business environment and given a particular job; as soon as there are some tasks, they must be completed on time, and the conditions of the environment will change instantly to create a causal and noticeable learning experience. The three problems in the Design of the framework are: hierarchical consistency of task granularity (that is to say, tasks of different complexities should have the same descriptive syntax), low latency of situational response (interaction should not cause cognitive overload), and alignment between evaluation indicators and task prototypes (they should be in line with the actual working conditions). Based on the above framework, the training centre will change the general indicators of competence into specific and observable sequences of tasks to shift the form of teaching organisation from "content-oriented" to "task-oriented"[2].

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

2.1 A Digital Model Method for Dynamic Job Competency Profiles

A dynamic job competency profile is not the same as a fixed competency model, and its main feature is that it has added the dimension of time and task context to achieve real-time representation and prediction of the competency states required for a job. Many kinds of data are used to build the model, such as job task description text, behaviour sequences in operation logs, performance indicators of decision results, and state parameters of the business environment. Based on the above heterogeneous information, vectorisation is used to map it into a common embedding space and obtain a job competency vector. Each item in this vector is an organised and summarised attribute of a competency, such as data sensitivity, efficiency of model invocation, accuracy of anomaly detection, etc.; the corresponding dimension weights will be changed dynamically according to the environment of the task.

The change in shape will be done gradually and little by little. After each practical training task is finished, the system will backpropagate the deviation of the learner's actual performance from the preset job standards and update the parameter distribution of the job competency vector. It is the combination of a time-decay window and Bayesian online learning; that is to say, more weight is given to recent task data and stable long-term features are retained. Granularity of the job profile can also be changed dynamically, and at the level of tasks, a fine-grained factor-level model is used; for cross-job collaboration, these profiles are combined into a role-level vector. A digital model of the job can now be calculated and compared, so we will adjust the teaching staff dynamically according to this model rather than rigidly.

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

A collaboration architecture for virtual reality synchronisation is employed to link the logic of all operating units in the physical training area with that of the computational model of a digital simulation environment, and task-chain organisation units are established. A task chain has many sub-tasks, and these sub-tasks are arranged in a sequence; each sub-task is connected to both a physical operation interface in the real world and a virtual data environment in the virtual world. For example, in the task chain of cash flow management, a virtual environment can be used to simulate changes in the market and policy for payment terms, and a real environment can be employed for the operation of the fund allocation panel. The virtual end outputs the constraint condition, the real end returns the decision signal, and these two ends are connected in a closed loop by a low-latency communication protocol. According to the difficulty of the work, both the length and the number of branches in the task chain will change dynamically[3].

The first is that the chain organisation can divide and distribute the work at all levels and show the links among them more clearly. All the subtasks fall into one of the three categories: entity-dominated, virtual-dominated or balanced, and the architecture will allocate resources and interaction weights accordingly. The link in the task chain is called a "state transfer node", and it stores the output indicators of the previous link (such as fund balance and risk exposure) to be used as the input conditions for the next link in the simulation of sequential decision constraints in real business operations. It has an irregular structure, and if a learner goes too far off the correct path in a particular sub-task, a repair sub-chain will be automatically added to provide a lower-level version of virtual assistance or entity prompts. Virtual-reality collaborative task chains have been used in some places to strengthen the links and coordination among the links in the traditional training and teaching model.

2.3 Construction Strategy for Data-Driven Individualised Learning Paths

The input for the personalisation of the learning path is the difference matrix between the dynamic job competency profile and the learner's current competency status, and then a path-search algorithm is used to find an optimal sequence of sub-tasks and a resource allocation plan. The rows of the difference matrix are the observed values of the various competency factors in the learner, the columns are the job benchmark values, and the normalized differences are the priority weights. Path Generation is a kind of constrained graph search algorithm, and the nodes in this graph are the teaching activity modules of the training centre (such as specific task chains, simulation cases, interaction modules), and the edges represent the prerequisite relationships and learning transfer costs among these teaching activities. The aim of the search is to reduce the competency gap in the given time and budget.

A Path Has Been Generated, and Now Real-time Replanning is Needed. The new behaviour data produced by the learner in the execution stage continuously updates the competency state vector of the learner, and thus the difference matrix is altered. If it is too large, the system will start replanning, save the completed teaching activity nodes, and then recompute the remaining part of the path. Increase the smoothing coefficient and add a confidence interval mechanism to reduce oscillations; that is, the path will only be corrected after several consecutive updates show the same direction of deviation. Data empowerment can also be shown in the creation of path diversity; for the same difference matrix, several equivalent paths can be generated by the system (e.g., one focused on logical deduction and another on data operations), and these can be selected by the learner or the teacher according to different needs for adaptability and autonomy. Therefore, the teaching supply at the training centre will be changed from uniform distribution of content to personalised combination[4].

3. Collaborative Adaptation Path of Teaching Elements and Job Requirements

3.1 Optimisation of the Mapping Relationship Between Teaching Modules and Occupational Functions

The Map of Teaching Modules and Occupational Functions should be changed from fixed correspondence to optimised dynamic association. The old mapping method links each teaching module to only one occupational function and does not consider the cross-competencies among functions or the knowledge transfer among modules; therefore, there is a problem of module redundancy and incomplete coverage of occupational functions. According to the competency factor association matrix, different weights are given to the various competency factors in different ways to represent each teaching module, and threshold vectors for the required competency factors are also set for each occupational function in the Optimisation Method. To achieve the goal of module combination, a maximisation matching problem is set up, and this problem is solved iteratively by means of a weighted matching algorithm on a bipartite graph; that is to say, the objective is to maximise the overlap in module content and the uniqueness of functions. Calculate the matching gain of modules and functions at each iteration, and if it is lower than the preset threshold, then stop and output the near-optimal module-function allocation scheme.

Fluctuations in the Mapping Optimisation can be shown by the two feedback loops. First, the competency increment data of a learner after completing a module is used to adjust the competency factor weights of that module. For example, if a module can improve the data model better than expected according to the original plan, then the weight coefficient of that dimension will be increased, and as a result, the relative contribution of the other dimensions will be reduced. Second, after updating the job profile of an occupational function, its threshold vector will be changed, and then a rematching process will be automatically started to adjust the correspondence among modules and functions. A cool-down period will be added to the re-matching process to avoid many corrections due to small differences in profiles. The optimisation result is in the form of a mapping probability matrix, and the contribution of each module to the different functions is a value between 0 and 1. According to the matrix above, we can arrange the order and combination of teaching modules. A mapping probability matrix can be used to find common modules of functions and avoid construction redundancy; thus, it is possible to increase the utilisation efficiency of resources and improve the accuracy of job matching[5].

3.2 Dynamic Configuration and Scheduling Rules for Interactive Practical Training Resources

Interactive practical training resources are virtual scene assets, simulation data streams, interactive control libraries, behaviour log collection channels, etc.; their configuration and scheduling should be based on the principles of task-driven operation and load balancing. The first way to realise dynamic allocation is to build a resource demand prediction model; based on this model, given the current number of active task chains, the complexity level of the job profile and the learner's past resource consumption rate, a pre-allocation plan for all kinds of resources in the coming time can be obtained. The type of prediction is a long short-term memory network, and at the same time, it is continuously updated in a rolling fashion to find resource bottleneck nodes in advance. To enhance the stability of the prediction, a residual connection has been added; that is to say, the prediction error of the previous time window is taken as an auxiliary input to form an error-compensation loop. Distribute the results of the resource pre-allocation to all execution nodes as a resource-task binding table, and the corresponding computing and storage capacities have been reserved.

The Scheduling Rule is to use a PriorityQueue and Elastic Scaling together. According to the weights of the three factors, more weight will be given to the various practical training tasks; that is to say, the position of the task in the chain (preceding tasks will be given higher priority), the urgency of the deviation in the job profile, and the remaining time limit for that task. Change the weight coefficients dynamically according to the actual load conditions of the training centre; when the load is high, increase the weight of the task position to ensure process continuity, and when the load is low, increase the weight of the deviation degree to speed up competency repair. If there are no resources, determine which ones are needed at that time and then start elastic scaling. For parallelizable resources (such as data stream instances), the number of replicas will be dynamically increased up to the upper limit of the allowed number of replicas according to the capacity of the physical resource. For exclusive resources (such as some interactive controls), management will be done by time-slicing round-robin or task queuing, and the queue timeout threshold will be a fixed proportion of the remaining time limit for that task. There is also a resource-release condition for the schedule; that is to say, after a task has been completed or has exceeded the alloted time without a response, its resources will be automatically released to prevent deadlocks. The configuration and scheduling system above will ensure the stable operation of the training centre and provide good service even when there are many users and tasks.

3.3 A Quantitative Calibration Model for Teaching Effectiveness and Job Competence

A quantitative calibration model is used to establish a mathematical conversion rule for the teaching effectiveness index and the job competency index, and thus the problem of their different dimensions and collection methods is solved. Behavioural data that can be observed during the period of practical training are indicators of teaching effectiveness, such as the proportion of completed tasks, accuracy of decisions, response time and efficiency in using resources. The index of job competency is based on the factor score of competency in the dynamic job profile, such as anomaly detection sensitivity and rationality of model parameter tuning. A two-hidden-layer neural network will be used to construct the calibration model; the input layer will be the vector of teaching effectiveness indicators, the output layer will be the vector of predicted competency scores, and the hidden layers will learn a nonlinear mapping function.

Training and Updating of the Model are done incrementally. The first mapping relationship is based on the rules in the job task knowledge base, and then, according to the paired data generated by learners in their actual training (the teaching effectiveness records for the same task and the subsequent job simulation evaluation results), the model parameters are continuously optimised. Backpropagation is used to update the calibration error, and a regularisation term is added to avoid overfitting. The two ways to use the output of the model are: the first is to convert teaching effects into estimated competency values and observe changes in learning. Conversely, it will determine the necessary level of teaching quality for a particular group of students and select suitable teaching materials and other resources. The calibration model above will determine how much the teaching evaluation results at the training centre affect the demand for a job, and then a closed-loop adjustment mechanism will be established.

Conclusion

The theoretical basis of the present study on teaching model innovation and job adaptation at the Digital-Intelligent Finance and Business Industry Education Integration Training Centre is the three-level framework of competency domain deconstruction, job adaptation mechanisms and collaborative adaptation paths. Present the four-layer structure of the digital-intelligent finance and business competency domain and the corresponding reorganization rules for training elements in this paper; explain the closed-loop iteration mechanism of teaching forms in the industry-education integration scenario; design an immersive teaching framework based on job tasks as the basic unit, etc. In order to achieve the goal of job adaptation at this level, this paper puts forward a digital model of dynamic job competency profiles, a virtual-real collaborative task chain-based teaching organisation architecture, and a data-driven personalised learning path generation strategy. Collaborative adaptation refers to the changes and additions in teaching modules and occupational functions that occur due to changes in circumstances, and at the same time, it is also a set of rules for organising interactive practical training resources and a quantitative calibration model of teaching effectiveness and job competency introduced in this paper. In the future, we will study the group competency profile and collaborative adaptation mechanism in multi-job collaboration, learn about global resource optimisation scheduling algorithms for task chains, develop self-evolution methods for teaching intervention strategies based on reinforcement learning, and improve the adaptive ability and job-adaptation accuracy of the teaching model in the training center.

Fund Projects

This study is supported by a project funded by the Education Department of Hainan Province. Project title: Research on the Reconstruction of Digital-Intelligent Finance and Business Job Competencies under the Background of Hainan's Customs Closure Industrial Upgrading: From the Perspective of Integrated Construction of Industry-Education Integration Bases. Project number: Hnjg2026-182.

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