Construction of a Trinity Teaching System Based on "Computational Thinking + Artificial Intelligence + X"

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Abstract: *As artificial intelligence technologies continue to permeate multidisciplinary domains, how to effectively integrate computational thinking, artificial intelligence methodologies, and domain-specific knowledge within a teaching system has become a structural issue that demands urgent resolution. This study proposes a framework for constructing a trinity teaching system based on "Computational Thinking + Artificial Intelligence + X." It first analyzes the core characteristics of computational thinking and its positioning in interdisciplinary contexts, clarifies the logical starting point for embedding artificial intelligence technical elements into the teaching system, and establishes the alignment between X-domain knowledge representation and the other two components. On this basis, the study constructs the structured pathway of the system through decomposition of competency dimensions and ternary mapping relationships among knowledge units, organizes integrated teaching content via task chains, and designs system elasticity and extensible interfaces oriented toward dynamic adaptation. It further analyzes the constraints on the co-evolution of the three elements during the teaching process, establishes regulation parameters and optimization directions for cognitive load, and proposes a system self-updating capability along with a cross-cycle effectiveness evaluation framework. This system provides a computable and scalable structured solution for the organization of interdisciplinary teaching content.*

Keywords: *computational thinking; artificial intelligence; teaching system; ternary mapping; task chain; cognitive load regulation*

Introduction

Currently, the rapid development of computational thinking and artificial intelligence technologies is profoundly reshaping the ways of knowledge organization and competency cultivation pathways across various professional fields. However, the organic integration of the formal logic of computational thinking, the data-driven methods of artificial intelligence, and the domain-specific knowledge of a particular field (X-domain) still lacks a systematic construction method at the teaching system level. Existing attempts often simply superimpose or linearly sequence the three components, resulting in semantic fragmentation among knowledge points and an imbalance in cognitive load. Therefore, it is clearly necessary to study a teaching system that can simultaneously accommodate abstract modeling ability, algorithm-driven capability, and domain adaptation capacity. The core significance of this study lies in providing a structured construction framework that does not depend on specific technical implementation details, but instead offers actionable design principles from aspects such as decomposition of competency dimensions, mapping of knowledge units, organization of task chains, and operational regulation. By establishing ternary mapping relationships and an elastic expansion mechanism, the system can adapt to the switching of different X-domains and the iterative updates of artificial intelligence technologies, thereby maintaining cross-cycle effectiveness.

1. Foundations for the Integration of Computational Thinking, Artificial Intelligence, and the X-Domain

1.1 Core Characteristics of Computational Thinking and Its Positioning in Interdisciplinary Contexts

The essence of computational thinking lies in decomposing complex problems into computable and executable sequences of steps, with its core characteristics encompassing abstraction, decomposition, pattern recognition, and algorithm design. Abstraction extracts key information from specific contexts while ignoring irrelevant details; decomposition divides large tasks into more manageable subtasks; pattern recognition serves to identify common structures across different situations; and algorithm design constructs deterministic or probabilistic solution paths. In the interdisciplinary context, computational thinking is no longer confined to computer science internally, but rather serves as a general framework for problem description and solving, embedded into the processes of knowledge generation and transmission across different disciplines. Within the teaching system oriented toward "Artificial Intelligence + X," the role undertaken by computational thinking is to act as a bridge connecting abstract logic and domain-specific problems, that is, to provide a formalized operational language that enables the structured alignment of artificial intelligence methods with concepts from the X-domain. This positioning implies that computational thinking functions not only as an instrumental mode of reasoning, but also as an analytical paradigm at the metacognitive level, used to coordinate semantic differences and operational granularities among different knowledge systems[1].

1.2 The Technical Elements of Artificial Intelligence and the Logical Starting Point for Embedding Them into the Teaching System

The technical elements of artificial intelligence mainly include data representation modules, learning algorithm modules, and inference and decision-making modules. Data representation involves feature extraction, vectorization, and embedding representations; learning algorithms cover paradigms such as supervised, unsupervised, and reinforcement learning; and inference and decision-making include probabilistic graphical models, logical inference, and output interpretation of deep networks. When embedding these elements into the teaching system, the logical starting point lies in identifying which AI capabilities possess the fundamental attribute of cross-domain transferability. Specifically, the generality of classification and regression, the structural discovery capability of clustering and dimensionality reduction, and the adaptive mechanism of sequential decision-making — these three types of capabilities do not depend on domain-specific knowledge, and therefore are suitable as stable modules to be prioritized for embedding in the teaching system. The embedding approach emphasizes a reversible mapping path from problem definition to algorithm selection: given a problem statement from the X-domain, learners can reversely locate the corresponding AI technical elements and their operational positions within the framework of computational thinking. This logical starting point ensures that the underlying layers of the teaching system remain clear, and prevents frequent restructuring of the content structure due to excessively rapid technological iteration.

1.3 Alignment of X-Domain Knowledge Representation with Computational Thinking and Artificial Intelligence

The X-domain represents any professional field that possesses an independent knowledge system, and its knowledge representation methods typically include symbolic rules, empirical discriminative criteria, and quantitative models. In order to achieve effective alignment with computational thinking and artificial intelligence, it is necessary to perform formalized transformation on the native knowledge of the X-domain. The alignment approach consists of three operational levels: the first level is the mapping of entities and attributes, which transforms objects, attributes, and relationships in the X-domain into computable data structures, such as tensors, graph structures, or symbol tables. The second level is the alignment of processes and algorithms, which maps the operational workflows of the X-domain into decomposition steps in computational thinking, and then matches each step to specific artificial intelligence algorithm components. The third level is the unification of evaluation metrics, which converts the performance measures of the X-domain (such as error tolerance, response time, and resource consumption) into loss functions or constraint conditions in machine learning. This alignment is not a simple technical application, but a bidirectional semantic adaptation—computational thinking provides structured decomposition tools, artificial intelligence provides data-driven inference capabilities, and the X-domain contributes problem contexts and validation bases. During the alignment process, the three parties mutually adjust their respective representational granularities, ultimately forming an interoperable organizational form of teaching content[2].

2. Structured Construction Path of the Trinity Teaching System

2.1 Decomposition of Competency Dimensions and Ternary Mapping Relationships of Knowledge Units

The decomposition of competency dimensions requires breaking down learners' comprehensive capabilities into independently cultivable basic units from the perspective of cognitive operations. For the trinity system, three competency dimensions are set as abstract modeling ability (derived from computational thinking), algorithm-driven capability (derived from artificial intelligence), and domain adaptation capacity (derived from the X-domain). Abstract modeling ability corresponds to the logical structure category and process abstraction category within knowledge units; algorithm-driven capability corresponds to the data representation category and model optimization category; and domain adaptation capacity corresponds to the semantic mapping category and constraint expression category. The ternary mapping relationships are established on the basis of the correspondence rules between these competency dimensions and knowledge units, and the rules require that each knowledge unit simultaneously belongs to the intersection areas of at least two competency dimensions, thereby avoiding system fragmentation caused by the single-attribute nature of knowledge units.

The specific implementation of the mapping relationships adopts the association matrix method. Row vectors represent knowledge units, column vectors represent competency dimensions, and matrix elements take values from {0, 1, 2}, where 0 indicates no direct association, 1 indicates a supportive association, and 2 indicates a core association. If a knowledge unit simultaneously receives core associations from two or three dimensions, that unit is marked as a hub node in the system. The dynamic adjustment mechanism of the ternary mapping relationships allows the competency dimensions to be re-weighted during system operation; for example, when the data characteristics of the X-domain shift, the weight of domain adaptation capacity increases, and the corresponding knowledge units transition from supportive associations to core associations. This association-matrix-based mapping approach provides a computable structured description, facilitating subsequent teaching content arrangement and resource allocation.

2.2 Organization Strategy for Integrated Teaching Content Based on Task Chains

A task chain is a set of task sequences with progressive dependencies, where each task simultaneously carries operational requirements from the three dimensions of computational thinking, artificial intelligence, and the X-domain. The design principle of task chains emphasizes that the output of preceding tasks directly serves as the input of subsequent tasks, forming a dual inheritance relationship of data flow and control flow. A typical three-stage task chain includes the following: the first type of task focuses on raw data cleaning and structured representation in the X-domain, where the decomposition decisions of computational thinking play a dominant role; the second type of task feeds the structured data into artificial intelligence models for training and parameter tuning, where algorithm-driven capability becomes the core; and the third type of task requires deriving interpretable conclusions in the X-domain based on model outputs, where domain adaptation capacity and abstract modeling ability work collaboratively. The length and branching structure of task chains can be adjusted according to the target granularity of the system, with short chains suitable for single-skill validation and long chains suitable for cross-chapter comprehensive content integration.

The key to organizing integrated teaching content lies in the coverage relationships between task chains and knowledge units, rather than one-to-one correspondences. A task chain usually covers multiple knowledge units, and a knowledge unit may also appear in different task chains; this many-to-many relationship enhances the reusability and flexibility of teaching content. The difficulty gradient of task chains is controlled through three parameters: the recursion depth or loop nesting level in computational thinking, the interpretability requirements of artificial intelligence models, and the number of prerequisite dependencies of X-domain knowledge. The boundary conditions of a task chain are defined as the input specifications at the chain head and the output acceptance criteria at the chain tail, both of which jointly establish the basis for determining whether a task chain has been completed. This organizational strategy avoids the mechanical splicing sensation caused by linearly arranging content according to disciplines, and instead connects knowledge points from the three dimensions along task execution paths[3].

2.3 System Elasticity and Extensible Interface Design for Dynamic Adaptation

System elasticity refers to the ability of the teaching system to maintain structural stability when faced with new knowledge infusion or technological iteration. The elasticity design is carried out at two levels: vertical elasticity is embodied in the granularity adjustability of competency dimensions, meaning that each competency dimension can be further subdivided into sub-dimensions without disrupting the basic framework of the ternary mapping; horizontal elasticity is embodied in the replaceability of the X-domain, meaning that when the X-domain switches from one professional direction to another, only the domain-specific knowledge units and the mapping matrix need to be updated, while the core skeleton of computational thinking and artificial intelligence remains unchanged. The evaluation indicators for elasticity include the cost of system restructuring (the proportion of knowledge units that need to be modified) and the system convergence speed (the change in sparsity of the mapping matrix after new knowledge is embedded)[4].

The extensible interface is designed to support the integration of third-party content modules, and the interface specification includes three types of standards. The first is the data interface standard, which stipulates that the data format of the X-domain must support conversion to a general tensor structure. The second is the algorithm interface standard, which requires that the integrated artificial intelligence components provide a unified calling protocol, including declarations of input and output dimensions and specifications of hyperparameter ranges. The third is the knowledge unit registration standard, which requires that newly added knowledge units declare their association values with competency dimensions according to the format of the association matrix. The interface adopts a loosely coupled approach, meaning that the integrated modules and the system kernel communicate only through the aforementioned standard protocols and do not depend on specific implementation details. The extensible interface also reserves a version management mechanism, allowing the same interface to simultaneously support the coexistence of content modules of different versions, thereby facilitating a smooth transition for content replacement needs arising from technological updates.

3. System Operation Mechanism and Effectiveness Regulation Model

3.1 Analysis of Constraints on the Co-Evolution of the Three Elements during the Teaching Process

The co-evolution of the three elements refers to the dynamic process in which computational thinking, artificial intelligence, and the X-domain mutually influence each other and adjust their respective representational forms during the teaching process. The constraints are divided into two categories: internal constraints and external constraints. Internal constraints arise from the operational boundaries of the three dimensions themselves: the algorithmic expression of computational thinking requires that problems possess discretizable characteristics; the data-driven nature of artificial intelligence demands the existence of a sufficient number of labeled examples or definable reward signals; and the knowledge integrity of the X-domain requires that key semantics not be lost due to simplification. These three types of internal boundaries mutually constrain one another. For example, highly abstract symbolic knowledge from the X-domain may not directly provide the training samples required by artificial intelligence; in such cases, computational thinking needs to intervene by designing a surrogate task to generate an approximate data distribution. The identification of internal constraints is typically achieved by examining the entries with a value of 0 in the association matrix of knowledge units, as these zero-association positions represent the links that are difficult to couple naturally among the three elements.

External constraints originate from the temporal and resource limitations during the operation of the teaching system. In the temporal dimension, the total amount of cognitive operations that learners can process within a single teaching cycle is finite, which constrains the number of iterations and the depth of feedback in the co-evolution of the three elements. In the resource dimension, different X-domains vary significantly in their demands for computational resources and data storage; therefore, the system must adjust the complexity of artificial intelligence models and the granularity of abstraction layers in computational thinking under a given resource budget. These constraints collectively define a feasible region within which the system can only achieve coordinated adjustments among the three elements. When the constraint boundaries shift, the original state of coordination will lose its balance, and it becomes necessary to restore a stable evolutionary trajectory by reallocating the weights of the competency dimensions[5].

3.2 Regulation Parameters and Optimization Directions for Cognitive Load

Cognitive load here specifically refers to the total amount of cognitive resources that learners bear while simultaneously processing the formal logic of computational thinking, the algorithmic procedures of artificial intelligence, and the domain knowledge of the X-domain. The regulation parameters are set from three dimensions respectively. For the computational thinking dimension, the regulation parameters include the number of abstraction levels (the span from concrete instances to general patterns) and the decomposition granularity (the number of subtasks into which each task is divided). For the artificial intelligence dimension, the regulation parameters include the model interpretability level (ranging from end-to-end black boxes to fully transparent decision trees) and the number of degrees of freedom in hyperparameter tuning. For the X-dimension, the regulation parameters include the density of domain terminology (the number of new concepts appearing per unit of teaching content) and the path length of prerequisite knowledge dependencies. These parameters are expressed in normalized numerical values, all with a value range of[0, 1], to facilitate subsequent weighted summation and comparative analysis.

The objective function for the optimization direction is set to keep the comprehensive cognitive load index below a preset threshold, provided that the core knowledge units of the ternary mapping are effectively covered. The optimization process adopts the gradient descent idea in parameter space but does not assume that the function is differentiable; in practice, it is implemented by discretely adjusting the level of each parameter and observing the quality feedback from learners' completion of task chains. A better regulation direction is to reduce the recursion depth in computational thinking rather than to decrease the number of abstraction levels, because the latter is more likely to compromise the semantic integrity of the X-domain. For the artificial intelligence dimension, it is preferable to reduce the degrees of freedom in hyperparameters rather than to lower model interpretability, because the latter would weaken the verifiable relationship with X-domain knowledge. The real-time adjustment of regulation parameters is based on the complexity increment of intermediate representations produced during the execution of task chains; when the increment exceeds the threshold, a parameter reduction in the corresponding dimension is triggered.

3.3 System Self-Updating Capability and Cross-Cycle Effectiveness Evaluation Framework

System self-updating capability refers to the ability of the teaching system to adjust its own structure and parameter configurations based on accumulated operational data without the need for external designer intervention. The self-updating mechanism is built upon version-based management of the knowledge unit association matrix. After each teaching cycle, the system collects data such as the access frequency of each knowledge unit, the completion time of task chains, and the actual observed values of cognitive load, and uses these data as inputs to update the association matrix weights for the next cycle. The updating rules follow two principles: implicit connections between knowledge units that frequently show zero associations but are actually used frequently by learners will be newly added as weak associations (with the value adjusted from 0 to 1); knowledge units that have not been triggered for a long time and have no strong associations with other units will be marked as eligible for dormancy and placed into an alternative repository rather than being directly deleted. The self-updating process reserves an interface for manual review, but the review action does not alter the automatically generated weight suggestions; it only records discrepancies for subsequent threshold calibration[6].

The cross-cycle effectiveness evaluation framework is used to determine whether the system still maintains the coverage and synergy efficiency from its initial design objectives after multiple teaching cycles. The evaluation indicators include stability coefficients from three dimensions: the computational thinking dimension focuses on the skewness change in the distribution of abstraction levels; the artificial intelligence dimension focuses on the shift in repeated patterns of the model component invocation sequences; and the X-dimension focuses on the drift of forgetting curve parameters for domain knowledge units. The cross-cycle evaluation adopts a sliding window approach, calculating the mean and variance of the above stability coefficients over groups of three cycles; when the variance exceeds the preset tolerance range, a structural review of the system is triggered. The effectiveness threshold is set such that when the proportion of core associations in the association matrix falls below 15% of its initial value, a rollback mechanism is activated to restore the system to the previous stable version. This framework does not rely on external benchmark datasets but generates evaluation conclusions entirely based on the system's internal operation logs.

Conclusion

This study has completed the framework design of the "Computational Thinking + Artificial Intelligence + X" trinity teaching system from three levels: integration foundations, structured construction paths, and operation mechanisms with regulation models. The system resolves the semantic alignment problem among the three dimensions through decomposition of competency dimensions and ternary mapping of knowledge units, achieves progressive organization of integrated teaching content by utilizing task chains, and designs elastic structures and extensible interfaces to support dynamic adaptation. At the operational level, the constraints of co-evolution are clarified, regulation parameters and optimization directions for cognitive load are proposed, and a version-based self-updating mechanism of the association matrix along with a cross-cycle effectiveness evaluation framework is established. Future research directions include migrating the framework to concrete content instances in different X-domains to verify the convergence behavior of the association matrix, exploring adaptive learning algorithms for cognitive load regulation parameters, and investigating the quantitative relationship between stability coefficients and system architecture in cross-cycle evaluation. In addition, the high-dimensional extension of ternary mapping when multiple X-domains coexist also warrants further exploration.

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