Artificial Intelligence-Driven Construction of Virtual Experimental Environments for Information Technology Teaching

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Abstract: *In information technology experimental teaching, traditional virtual simulation environments face limitations such as contextual rigidity, monotonous interaction, and cognitive load mismatch. To break through these bottlenecks, we propose a framework for constructing an artificial intelligence-driven virtual experimental environment, which is developed from three aspects: intelligent educational forms, multi-agent computational models, and self-evolving semantic associations. First, we establish virtualized representations and multimodal interaction modalities, and clarify the generation mechanism of dynamic experimental scenarios and the spatial logic for adaptive regulation of cognitive load; second, we construct a computational model based on multi-agent collaboration to achieve behavioral modeling of experimental objects, state graph evolution driven by heterogeneous data, and a reinforcement learning framework for intention recognition and feedback generation; finally, we design the self-evolution mechanism of the virtual experimental environment, including dynamic resource organization guided by domain knowledge graphs, adaptation of virtual instrument operation logic via generative adversarial networks, and semantic annotation and path optimization of multimodal interaction trajectories. This framework provides a systematic theoretical model and technical pathway for virtual experimental environments in information technology teaching.*

Keywords: *artificial intelligence, virtual experimental environment, information technology teaching, multi-agent collaboration, knowledge graph, generative adversarial network, cognitive load regulation.*

Introduction

Information technology experimental teaching is a core link in cultivating learners' computational thinking and engineering practical abilities. Traditional virtual experimental environments usually adopt preset scripts and fixed interaction interfaces, which makes it difficult to adapt to individual cognitive differences and dynamic inquiry needs. With the penetration of artificial intelligence technologies, constructing a virtual experimental environment with context awareness, adaptive regulation, and self-evolution capabilities has become an important research direction. The significance of this research lies in the following aspects: first, through intelligent virtual representation and interaction modalities, we can break through the spatial and temporal constraints of physical experimental conditions and expand both the coverage breadth and content depth of experimental teaching; second, the introduction of multi-agent collaboration and reinforcement learning mechanisms enables the virtual environment to recognize learners' intentions and generate real-time feedback, thereby improving the teaching guidance efficiency during the experimental process; third, the establishment of a self-evolution framework driven by knowledge graphs and generative adversarial networks allows for dynamic organization of experimental resources and automatic adaptation of operation logic, thus reducing the maintenance cost of the environment. The above research has both necessity and theoretical value for promoting the intelligent transformation of information technology experimental teaching environments.

1. Intelligent Educational Forms and Cognitive Architecture of Virtual Experimental Environments

1.1 Virtualized Representation and Interaction Modalities in Information Technology Experimental Teaching

In information technology experimental teaching, virtualized representation transforms experimental objects, processes, and results that originally rely on physical devices into computable and reconfigurable digital entities through symbolic abstraction, geometric mapping, and dynamic data visualization. This representation system includes topological descriptions of experimental components, sequential logical expressions of signal flows, and parametric modeling of state variables, enabling experimental elements to evolve independently in virtual space without physical constraints. The granularity and dimensionality of virtualized representation directly affect learners' cognitive depth regarding experimental principles: overly coarse representation may lose key causal chains, while overly fine representation may cause information overload[1].

The construction of interaction modalities revolves around multimodal perceptual fusion, encompassing a vision-dominant operation interface, auditory event reminders, and haptic force rendering. In the virtual experimental environment, interaction modalities not only serve the functions of command input and result output, but also enhance learners' sense of presence and operational precision regarding experimental phenomena through redundant coding and complementary mapping across modalities. For example, the visual modality presents the light effect changes of circuit on-off states, while the auditory modality synchronously provides the transient clicking sound of relay engagement, and the two modalities are aligned on the temporal axis to form a unified causal experience. The design of interaction modalities should follow the dual-coding principle, meaning that the same experimental action generates consistent but not entirely repetitive information across different perceptual channels, thereby reducing ambiguity and improving the identifiability of representations. The setting of the time window tolerance for multimodal alignment has a significant impact on perceptual coherence: too small a tolerance may lead to modal decoupling, while too large a tolerance may introduce causal ambiguity. In desktop virtual environments where physical force feedback cannot be provided, the haptic modality can be substituted with vibration coding, mapping different experimental events to differentiated vibration patterns, thus achieving limited but effective participation of the haptic channel.

1.2 Artificial Intelligence-Driven Generation Mechanism of Dynamic Experimental Scenarios

The generation of dynamic experimental scenarios relies on the modeling of a triadic component consisting of learner states, experimental objectives, and domain knowledge. The artificial intelligence system constructs an implicit cognitive trajectory vector by analyzing the learner's operation sequences and historical performance, and uses this vector as the prior condition for scenario generation. The generation process adopts a conditional variational autoencoder or a diffusion model to synthesize, under given knowledge point constraints and difficulty levels, experimental initial conditions, fault injection points, or parameter perturbation ranges that match the current learning needs. This generation is not a random combination but follows the causal consistency constraints of experimental logic, ensuring that the generated scenarios are solvable and pedagogically reasonable in a physical or algorithmic sense.

The dynamism of scenario generation is reflected in a closed-loop regulation mechanism. After the learner completes a set of operations in the current experimental scenario, the system extracts key behavioral features (such as operation duration, error types, and parameter adjustment step sizes) and feeds them back into the conditional space of the generation model. The model then adjusts the complexity and guidance intensity of the next scenario according to a preset teaching strategy network. This mechanism avoids the rigid defects of fixed experimental scripts and enables the experimental scenario to approach the learner's zone of proximal development. Meanwhile, the generation module maintains an internal scenario validity verification submodule, which is used to filter out candidate scenarios that violate fundamental experimental laws or produce logical paradoxes, thereby ensuring that the dynamic generation process always remains within the teachable domain[2].

1.3 Spatial Logic for Adaptive Regulation of Learners' Cognitive Load

The spatial logic of the virtual experimental environment adaptively regulates learners' cognitive load from three dimensions: scene layout, viewpoint control, and information density. The spatial layout organizes experimental instruments, control panels, and data display areas into a hierarchical nested architecture according to usage frequency and functional relevance, placing high-frequency interactive components within the reachable radius of the central visual field while folding auxiliary reference information into collapsible sidebars. When the system detects that the learner's gaze hot zone frequently jumps among multiple components, it aligns the related components in two-dimensional or three-dimensional space through spatial remapping, thereby reducing extraneous cognitive load caused by visual search and mental rotation.

The adaptive regulation of information density is based on real-time assessment of working memory occupancy. The system utilizes eye-tracking or entropy changes in operation sequences to estimate the learner's current information processing margin, and accordingly adjusts the number of parameter adjustment sliders, waveform channels, or the level of detail in status prompt texts presented simultaneously in the virtual environment. Under low occupancy, the spatial logic allows all experimental elements to be unfolded to facilitate inquiry-based discovery; under high occupancy, the spatial logic automatically collapses non-core components and retains only the interaction entry points necessary for the current task. This regulation process follows the principle of progressive disclosure, without actively intervening in the learner's operational intentions; instead, through dynamic changes in spatial visibility, it shifts redundant information to the peripheral visual field or delays its loading, thereby achieving implicit management of cognitive load.

2. Computational Model of Virtual Experimental Environment Based on Multi-Agent Collaboration

2.1 Behavioral Modeling of Experimental Objects and Design of Agent Rule Base

Behavioral modeling of experimental objects abstracts the physical entities in the virtual environment (such as circuit components, optical lenses, and mechanical linkages) into agent units that possess state variables, input-output interfaces, and behavior functions. Each agent internally encapsulates the corresponding physical laws or logical constraints, for example, the voltage-current relationship of a resistor element and the truth-table mapping of a logic gate. The behavioral modeling adopts a hybrid architecture of hierarchical finite state machines and continuous differential equations, where the discrete layer is used to handle mode switching during the experimental process (such as switch closure and gear adjustment), and the continuous layer is used to describe the analog evolution of signals. The coupling among agents is realized through a port-connector model, which ensures the conservative transfer of energy or information and avoids generating non-physical causal anomalies[3].

The design of the agent rule base is organized around the granularity of knowledge points in experimental teaching as a set of production rules and constraint conditions. The rule base contains three types of rules: basic physical property rules (such as the encoded representations of Ohm's law and Kirchhoff's laws), operation response rules (such as continuous resistance changes caused by rotating the slider of a rheostat), and fault simulation rules (such as the injection methods for open circuits, short circuits, or parameter drift). The construction of the rule base adopts an ontological approach, defining the core concepts in information technology experiments (voltage, current, frequency, duty cycle, etc.) and their relationships as a directed graph, with rules serving as edge functions connecting concept nodes. The rule base also has an extensible interface, allowing the import of new component definition files or custom rule scripts, so as to accommodate the reconfiguration requirements of experimental content at different levels.

2.2 Heterogeneous Data-Driven Evolution of Experimental Process State Graphs

The evolution of experimental process state graphs uses a directed graph structure to depict the transition trajectory of system states in the virtual experiment. The nodes in the state graph correspond to global state snapshots of the experimental environment, including the current parameter values, connection topologies, and operating modes of all agents; the directed edges are annotated with operation events or time advancement steps that trigger state transitions. Heterogeneous data sources include learner operation logs (discrete event sequences), sensor simulation data (continuous signal waveforms), and intermediate variables generated by rule base reasoning. The data fusion layer performs timestamp alignment and semantic annotation on all signals, forming a unified state transition event stream that drives the state graph to expand hop by hop from the initial node.

The dynamic management of the evolution process adopts an incremental graph construction and pruning strategy. The system generates the state graph in real time during experiment execution, rather than pre-enumerating all possible paths. When the learner performs an operation, the system checks whether the outgoing edges of the current state node already contain a transition target with the same operation label; if such a target exists, the system directly jumps to it; otherwise, it invokes the simulation engine to compute the new state and adds a new node and edge. To prevent the state graph from expanding indefinitely, the system evaluates the similarity between the new state and historical nodes (e.g., using Euclidean distance or structural hashing), and if the similarity exceeds a threshold, it merges the new state into an existing node through equivalence class merging. The evolved state graph is preserved as a structured record of the experimental process, supporting subsequent stage backtracking and visualization of operation paths.

2.3 Reinforcement Learning Framework for Intention Recognition and Feedback Generation

The intention recognition module maps the learner's operation sequences to implicit experimental goals or strategic choices. This module is modeled based on a partially observable Markov decision process, where the operation sequences serve as observation sequences and the intention categories serve as hidden states. The module employs a long short-term memory network or a self-attention encoder to extract temporal features from the operation history, and outputs a probability distribution over intentions, such as "tune to the resonant frequency," "verify the parallel current division rule," or "locate a short-circuit fault." The accuracy of intention recognition is updated in a delayed manner by comparing the recognition results with the compliance of subsequent operation feedback, so as to avoid excessive interference from a single misjudgment on the system[4].

The feedback generation module adopts a dual-agent deep reinforcement learning architecture, in which one agent is responsible for content generation and the other for timing and modality selection. The state space includes the currently recognized intention category, the evolution position in the state graph, and the learner's historical behavioral statistics; the action space comprises generating prompt texts, highlighting key components, playing demonstration animations, or waiting silently. The reward function is designed based on operation efficiency metrics and the degree of deviation from the state graph path: when the learner's subsequent operations gradually approach the standard path corresponding to the recognized intention, a positive reward is given; when repeated ineffective operations occur, a negative reward is imposed. The offline training of the reinforcement learning framework is conducted on a pre-built standard experimental path library, while a lightweight policy network is adopted for online inference to ensure real-time feedback responses.

3. Self-Evolving Construction and Semantic Association Mechanism of Virtual Experimental Environment

3.1 Dynamic Organization of Experimental Resources Guided by Domain Knowledge Graph

The domain knowledge graph takes the knowledge system of information technology experimental teaching as its backbone, and organizes concept nodes (such as "analog-to-digital conversion," "sampling theorem," and "clock synchronization") and relationship edges (prerequisite dependencies, analogical mappings, and typical applications) into a directed heterogeneous graph. The graph is constructed by extracting conceptual hierarchies from course syllabi and experimental lab manuals, and by incorporating the sequential constraints in typical experimental steps to form knowledge paths. Each node is attached with computable attributes, including difficulty coefficients, indices of related experimental cases, and sets of replaceable components. The graph maps nodes into a low-dimensional vector space through structural embedding techniques, so that semantic similarity can be quantified as vector distance, thereby providing a comparable metric basis for subsequent dynamic organization of resources[5].

The dynamic organization mechanism of experimental resources calculates the reachable subgraph and resource invocation weights based on the position of the learner's current operation node in the knowledge graph. The system maintains a resource pool that contains virtual facilities such as an experimental component library, an oscilloscope panel, and signal generators. After the learner's operational intention is recognized, the system locates the corresponding concept node in the graph and expands one or two layers of neighborhood along the relationship edges, extracting the associated resource types and invocation frequency statistics of the nodes within the neighborhood. Based on this information, the resource organization module places high-frequency associated resources in working memory, while low-frequency resources are loaded lazily or retrieved on demand. The mapping relationship between resources and the graph supports incremental updates: the integration of new experimental resources is bound to the corresponding concept nodes in the graph through semantic annotation, without the need to retrain the global model, thereby achieving scalability and lightweight maintenance of resource organization.

3.2 Generative Adversarial Network Adaptation of Virtual Instruments and Operational Logic

The generative adversarial network adaptation of virtual instruments aims to address the operational logic mismatch between predefined instrument panels and dynamic experimental scenarios. The generator takes the experimental goal description vector (including the required measurement type, precision range, and interaction mode) as input, and outputs the panel layout parameters, control component types, and their response functions of the virtual instrument. The discriminator judges whether the generated panel conforms to efficient operational logic based on operational efficiency statistics from real experimental scenarios (such as the number of clicks required to complete a measurement and the step error in parameter adjustment). The two form an adversarial training process, in which the generator gradually learns to produce instrument interfaces that match the scenario, while the discriminator forces the generated results to approach the implicit ergonomic constraints.

The adaptation process also takes into account the causal consistency between instrument operational logic and the experimental process. The generator internally integrates a differentiable virtual instrument simulation module, which performs a simulation run on the output panel during the generation phase: it injects a set of typical operation sequences and checks whether the output readings satisfy the corresponding physical relationships (for example, when the voltage is adjusted, the current should be observed to change according to Ohm's law). If the simulation output violates the basic physical properties, a penalty term is added to the loss function, driving the generator to correct the panel parameters or component wiring logic. After convergence through adversarial training, the virtual instrument can automatically adjust interface details for different experimental stages, for example, highlighting the Bode plot display window and hiding irrelevant DC ranges in frequency response tests, thereby reducing operational redundancy[6].

3.3 Semantic Annotation and Path Optimization of Multimodal Interaction Trajectories

Semantic annotation of multimodal interaction trajectories uniformly represents the operation logs, eye-tracking gaze points, voice commands, and parameter adjustment curves generated by learners in the virtual experimental environment as a time-stamped heterogeneous event stream. The annotation process adopts a hierarchical semantic model: the low-level annotation maps each event to a basic action category (selecting, rotating, connecting, and reading); the middle-level annotation combines continuous event sequences into functional units (building a bridge circuit, measuring gain, and recording threshold values); and the high-level annotation infers experimental strategies from the sequence of functional units (the verify-revise-verify mode or the gradual approximation mode). The annotation algorithm is based on conditional random fields or temporal convolutional networks, and uses pre-annotated small-sample trajectories for supervised learning to achieve automated semantic decomposition of unannotated trajectories.

The path optimization module takes the annotated semantic trajectory as input and searches for a more optimal operation sequence in the state graph space for reference by subsequent learners. The optimization objective function comprehensively considers the number of operation steps, time cost, and semantic correctness constraints, among which the correctness constraints are provided by the domain knowledge graph (for example, "the circuit must be closed before measuring voltage" serves as a hard constraint). The path search adopts a heuristic algorithm, and the cost estimate from the current node to the target node is based on the historical statistical time consumption of semantic units. The optimized output path is not a single standard answer; instead, multiple equivalent paths and their applicable conditions (such as variant routes suitable for different cognitive styles) are generated through clustering. These optimized paths are stored back into the knowledge graph as additional prior information for experimental resource organization, thus forming a closed loop of self-evolution.

Conclusion

Centered on the construction of an artificial intelligence-driven virtual experimental environment for information technology teaching, we have proposed a systematic theoretical framework from three dimensions: intelligent educational forms, multi-agent collaborative computational models, and self-evolving semantic association mechanisms. Regarding the intelligent educational forms of the virtual experimental environment, we have clarified the design principles of virtualized representation and interaction modalities, and revealed the generation mechanism of dynamic experimental scenarios and the adaptive regulation logic of cognitive load; regarding the multi-agent collaborative computational model, we have established behavioral modeling and rule bases for experimental objects, a heterogeneous data-driven state graph evolution method, and a reinforcement learning-based intention recognition and feedback generation architecture; regarding the self-evolving construction and semantic association mechanisms, we have proposed a dynamic resource organization strategy guided by domain knowledge graphs, a generative adversarial network-driven adaptation method for virtual instruments, and semantic annotation and path optimization techniques for multimodal interaction trajectories. Future research can be carried out in the following directions: exploring the application of multimodal large models in experimental scenario understanding and generation to enhance the environment's ability to parse natural language instructions and complex operational intentions; investigating cross-scenario knowledge transfer mechanisms to enable the virtual environment to reuse learned strategies and resources across different information technology experiment courses; and further optimizing the real-time constraints of online inference to reduce computational resource overhead in large-scale deployment.

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