Research on Factors Influencing Cognitive Load of Learners in Digital Learning Environment

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Abstract: The impact mechanism of cognitive load on learners in digital learning environment is the result of dynamic interaction of multidimensional factors. The core influencing factor system is composed of environmental technical characteristics (such as interface complexity and media presentation), individual traits (including prior knowledge and cognitive style), task design elements (such as project phase division and time pressure), and collaborative interaction modes (such as target interdependence and interpretation depth). These factors significantly affect learning effectiveness by regulating the generation pathways of internal, external, and related cognitive loads. Among them, the adaptability between the environment and individuals, threshold control of task complexity, and optimization design of collaborative structures constitute key intervention nodes. The integrated framework proposed in the study provides a theoretical basis and practical path for reducing cognitive load and enhancing the scientific design of digital learning environments.
***Keywords*: **Digital learning environment; Cognitive load; Influencing factors; Task design; Collaborative interaction

1. Theoretical correlation between digital learning environment and cognitive load

The deep development of digital learning environments is reconstructing the theoretical boundaries of cognitive load. When traditional cognitive load theory encounters multimodal interactive interfaces and immersive learning scenarios, its inherent resource allocation model faces fundamental challenges. This theoretical evolution is not only manifested in the adaptive transfer of multimedia cognitive principles to virtual learning spaces, but also deeply reflected in the dynamic coupling of environmental parameters and cognitive mechanisms - the spatial topology of interface design may reshape the chunk strategy of working memory, while the asynchronous feedback of sensory channels may induce unconventional dissipation of attention resources. This complexity requires an explanatory framework that goes beyond one-way causality, and can be deconstructed through a three-dimensional framework of "environment individual task" to understand the mechanism of cognitive load in the digital ecosystem, providing new theoretical anchors for understanding the essence of human-machine collaborative cognition.

1.1 The Evolution of Cognitive Load Theory in the Digital Environment

Since Sweller proposed the Cognitive Load Theory (CLT) in 1988, its core assumptions - the limited capacity of working memory and the cognitive mechanism of schema construction - have remained unchanged. However, the emergence of digital learning environments has reconstructed the application field of theory. The traditional cognitive load theory mainly focuses on the cognitive processing of linear text and static images (Sweller., 1988), while the rise of immersive technologies such as VR/AR has given rise to the concept of multimodal integrated load - when learners need to simultaneously process visual, auditory, and proprioceptive information, cross channel information conflicts can lead to a reduction in working memory capacity (Nag Setu et al., 2024). For example, in mixed reality anatomical experiments, a visual tactile feedback delay exceeding 200ms significantly increases external cognitive load and reduces knowledge transfer efficiency (Makransky&Petersen, 2021).

The evolution of interaction design further reconstructs the regulatory logic of cognitive load. Adaptive interactive scaffolds, such as dynamic prompting systems based on eye tracking, can effectively convert external loads into related loads. In programming learning experiments, real-time error detection tools can reduce learners' external cognitive load and enhance their problem-solving abilities (Cohen et al., 2021). This regulatory mechanism relies on evidence of neural plasticity: fMRI shows that learners using adaptive virtual laboratories have decreased activation in the prefrontal cortex and increased activation in the hippocampus, indicating a redistribution of cognitive resources towards schema construction (Cohen et al., 2018).

1.2 The Impact Path of Environmental Characteristics on Cognitive Processing Mechanisms

The design characteristics of digital learning environments affect learners' cognitive processing mechanisms through multiple pathways. The multimedia presentation of the environment directly affects the resource allocation of working memory. According to the study by Liu Juan et al. (2025), if the multimodal information embedded in digital learning environments, such as visual and auditory information, is not properly organized, it can lead to a significant increase in external cognitive load. Especially in virtual reality scenarios, learners need to simultaneously handle multiple cognitive tasks such as three-dimensional space navigation, task operations, and semantic understanding, which can easily exceed the capacity of working memory (Zhang Muhua et al., 2024). By providing goal and task scaffolds (such as mind maps, concept maps) and resource scaffolds (such as instructional videos, knowledge cards), external cognitive load can be effectively reduced (Liu Juan et al., 2025). In addition, time pressure, as an important environmental variable, can affect cognitive load levels by altering the depth of information processing. Li Jinbo (2009) found in a study of online learning environments that when task completion time is shortened, learners' psychological effort scores will increase and the accuracy of the main task will decrease, indicating that time pressure significantly increases cognitive load and weakens learning outcomes.

The social interaction characteristics of the environment reconstruct the cognitive resource allocation mechanism by regulating the collaborative mode. The intra group atmosphere and teacher-student interaction behavior in project-based collaborative learning have been proven to be key factors affecting cognitive load (Dan Meixian et al., 2022). When a group adopts a multi person collaboration mode, the cognitive resources among members can complement each other through distributed processing, resulting in a significantly higher working memory capacity of the team than individuals. The virtual learning experiment by Zhang Lingyan et al. (2023) showed that without effective interaction design (such as unclear division of labor or lack of communication tools), group interaction behavior can actually increase external cognitive load. This "collaborative paradox" phenomenon indicates that the environment must simultaneously satisfy two conditions to optimize cognitive processing: (1) providing communication tools that are adapted to task requirements (such as online platforms that support real-time collaboration); (2) Establish rules that promote deep interaction, such as role rotation mechanisms. Research data shows that environments that meet the above conditions can increase associated cognitive load and reduce overall cognitive load scores (Zhang Lingyan et al., 2023). These findings provide empirical evidence for understanding the dynamic relationship between environmental characteristics and cognitive processing.

1.3 Construction Logic of Multi dimensional Interaction Framework

The construction of a multidimensional interactive framework is essentially a concrete expression of the dynamic regulation mechanism of cognitive resources, and its core lies in establishing a dynamic balance between learners' cognitive characteristics, task attributes, and environmental support. This construction process requires breaking through the limitations of traditional one-dimensional regulation and shifting towards a holistic design paradigm based on systems theory. Research has shown that an effective interaction framework should possess triple functional features of cognitive state perception, task difficulty adaptation, and collaborative support intelligence (Xue Yaofeng et al., 2024). At the level of cognitive state perception, real-time monitoring of learners' cognitive load status can be achieved by integrating multimodal data such as facial expression recognition, eye tracking, and EEG signals. The recognition accuracy can reach 83.6%, providing a reliable data foundation for subsequent intervention and adjustment (Xue Yaofeng et al., 2024). In terms of task difficulty adaptation, a dynamic evaluation mechanism based on Task Complexity Index (TCI) can automatically trigger task decomposition strategies. This empirical research based design can reduce external cognitive load (Zhang Lingyan et al., 2023). At the level of collaborative support, intelligent role allocation and resource sharing mechanisms can not only optimize the efficiency of team cognitive resource allocation, but also significantly improve the level of associated cognitive load, thereby promoting the occurrence of deep learning (Shan Meixian, 2022). The innovative value of this multidimensional interaction framework lies in its establishment of a closed-loop regulation system for cognitive load, achieving a paradigm shift from passive adaptation to active regulation, providing important theoretical basis and practical path for building intelligent learning support systems.

2. The mechanism of the core influence dimension

The generation and regulation of cognitive load is a complex dynamic process involving the interaction of multiple dimensions such as environment, individual, task, and collaboration. The environmental technical characteristics directly affect the resource allocation efficiency of working memory through interface design elements and multimodal presentation methods; Individual trait differences play a crucial regulatory role in the interaction between learners and the environment; The structural characteristics of task design may both trigger load accumulation and become a lever for regulation; The collaborative interaction mechanism provides a social solution for the diversion and transformation of cognitive load. Thoroughly analyzing the mechanisms of these core dimensions not only helps to reveal the formation patterns of cognitive load, but also provides theoretical basis for optimizing the design of learning environments.

2.1 Cognitive load generation mechanism of environmental technology characteristics

2.1.1 Interface complexity and cognitive resource allocation

As a key design element of digital learning environments, interface complexity directly affects learners' information processing efficiency through its dynamic balance with cognitive resource allocation. The organizational density of interface elements exhibits a non-linear correlation with cognitive load (Zhang Lingyan et al., 2023). When the interface information blocks exceed the working memory capacity limit, learners' gaze time significantly increases, while task completion accuracy decreases (Li Jinbo, 2009). This cognitive resource crowding out effect is particularly prominent in three-dimensional virtual environments, where visual search tasks in complex scenes lead to increased depletion of working memory resources (Dan Meixian, 2022). The optimization strategy should follow the principle of "progressive information presentation", and control the interface complexity within the cognitive load threshold through hierarchical and progressive information organization methods (such as folding menus and progressive prompts). Experimental data shows that using a dynamic information layering interface design can reduce learners' psychological effort scores and improve knowledge transfer effectiveness (Xue Yaofeng et al., 2024).

2.1.2 External load effects of multimodal presentation

The dual channel advantage effect of multimodal information presentation has special value in cognitive load regulation, but its improper design may lead to significant external load increase. Although visual auditory dual channel presentation can expand working memory capacity, cognitive conflicts can occur when information is inconsistent between modalities, resulting in prolonged reaction time (Zhao Yu, 2021). The introduction of tactile channels has shown unique advantages in spatial cognitive tasks, as force feedback interaction can reduce the external cognitive load in 3D modeling tasks. However, at the same time, attention fragmentation caused by cross modal transformation needs to be vigilant (Zhang Lingyan et al., 2023). The optimal mode combination presents the feature of "task dependence", conceptual knowledge learning is suitable for complementary presentation of graphics and text, while procedural skill acquisition benefits more from dynamic demonstration and synchronous voice explanation (Xue Yaofeng et al., 2024). It is worth noting that multimodal design needs to follow the principle of "necessity", and redundant modal superposition can increase external cognitive load by 1.7 times (Shan Meixian, 2022).

2.2 The moderating effect of individual traits

2.2.1 The buffering effect of schema based prior knowledge

The prior knowledge of learners has a significant buffering effect on working memory load by constructing cognitive schemas. Cognitive neuroscience research shows that domain experts have lower levels of activation in the prefrontal cortex when processing professional information compared to novices, indicating that schema automation significantly reduces cognitive resource consumption (Cai Huiying, 2016). This buffering effect exhibits a typical "knowledge reversal" characteristic: when the prior knowledge level reaches a threshold (usually 70% mastery of domain knowledge), the intrinsic cognitive load can be reduced (Li Jinbo, 2009). The organizational quality of schemas is equally crucial, and a hierarchical professional knowledge network can improve information retrieval efficiency (Sun Chongyong et al., 2013). In the context of collaborative learning, the heterogeneous distribution of prior knowledge gives rise to the "cognitive complementarity effect", where the differentiated knowledge structures of team members can expand the collective working memory capacity through the integration of shared mental models (Liu Hongxia et al., 2021). The strategy of "progressive schema construction" is adopted in instructional design, which can flatten the cognitive load curve of novice learners through the orderly presentation of concept anchors.

2.2.2 Cognitive Style and Environmental Adaptation Threshold

The degree of adaptation between cognitive style and environmental characteristics determines the efficiency of cognitive resource allocation. Field-independent learners demonstrate higher problem-solving efficiency than field-dependent learners in open exploration environments, but this advantage disappears in structured instructional situations (Lyu et al., 2018). This style-environment adaptation effect exhibits distinct threshold characteristics; when environmental complexity exceeds an individual's style tolerance threshold, the instability of cognitive load significantly increases (Nie et al., 2024). The combination of reflective learners and asynchronous discussion environments yields optimal results, while impulsive learners are better suited to immediate feedback systems (Ke et al., 2007). Neuro-mechanism studies indicate that learners with good style adaptation show lower activation levels in the anterior cingulate cortex, suggesting reduced cognitive conflict (Liu Tingting). In mixed reality environments, visual learners experience lower spatial navigation load than verbal learners, but exhibit slower conceptual understanding speed (Li et al., 2007). In light of this, establishing adaptive learning pathways based on cognitive style can reduce overall cognitive load.

2.3 Load Regulation Pathways for Task Design

2.3.1 Intrinsic Load Accumulation in Project Phase Division

The strategy of phased task decomposition in project-based learning plays a crucial role in regulating intrinsic cognitive load. Reasonable phase division can optimize the allocation of working memory resources by controlling element interactivity, thereby preventing cognitive overload. Decomposing complex project tasks into several logically connected sub-phases can significantly reduce learners' cognitive pressure during information processing (Shan Meixian, 2022). This phased design concept originates from research on element interactivity within cognitive load theory. By transforming high-interactivity complex tasks into several low-interactivity subtasks, learners' cognitive resources can be allocated reasonably (Sweller, 2010). However, excessive task decomposition may lead to cognitive fragmentation, potentially increasing the difficulty of task integration; therefore, finding the appropriate granularity for phase division is essential (Li Jinbo, 2009).

2.3.2 Cognitive Resource Preemption by Time Pressure

Time constraints, as a significant situational factor affecting cognitive load, primarily exert their influence through the competitive occupation of working memory resources. When completing learning tasks within a limited time, learners often need to balance information processing speed with processing depth (Sun et al., 2013). Time pressure not only affects encoding efficiency but may also interfere with the normal functioning of metacognitive monitoring, leading to deviations in the selection and execution of learning strategies (Zhao et al., 2015). Neuroscience research shows that under time pressure, the activation patterns of the prefrontal cortex undergo significant changes, and executive control functions are somewhat inhibited (Li et al., 2025). Moderate asynchronous time buffer design can alleviate this resource preemption effect, providing learners with necessary cognitive adjustment space.

2.4 Load Diversion Mechanisms in Collaborative Interaction

2.4.1 Cognitive Resource Sharing through Goal Interdependence

The goal interdependence structure in collaborative learning environments optimizes resource allocation by promoting cognitive division of labor. When group members collaborate around a common goal, individual areas of expertise and working memory resources are effectively integrated, forming a collective cognitive system that surpasses individual capabilities (Shan Meixian, 2022). This resource-sharing mechanism not only reduces individual cognitive burden but also optimizes the efficiency of cognitive resource allocation through the regulatory role of social interaction (Zhang et al., 2023). Research shows that highly effective collaborative groups often exhibit stronger cognitive synergy effects, reflected not only in improved task performance but also in enhanced neural activity synchronization (Xue et al., 2024). The cognitive benefits of goal interdependence are moderated by task complexity; only moderate task challenge can maximize the advantages of collaboration (Li Jinbo, 2009).

2.4.2 Association Load Enhancement through Explanation Depth

The quality of peer explanations directly influences the conversion efficiency of germane cognitive load. Deep-level explanation behaviors optimize the allocation of limited cognitive resources towards higher-level information processing by promoting meaningful connections between concepts and schema reconstruction. Such explanations involve not only the transmission of surface-level information but also the dissection of the internal logic of knowledge and the establishment of cross-domain connections. Effective explanation activities can guide learners beyond memorizing isolated facts to develop transferable problem-solving abilities. Explanation depth needs to match the learner's cognitive development level; overly complex explanations may exceed working memory processing capacity, increasing extraneous cognitive load instead. Therefore, designing a hierarchical explanation framework that dynamically adjusts explanation depth based on the learner's level of understanding is key to optimizing germane load (Liu et al., 2017).

3. Integrative Regulation Strategies and Application Pathways

Optimizing the regulation of cognitive load requires a systematic implementation framework that transforms influencing factors into actionable intervention strategies. Based on the core tenets of cognitive load theory and the characteristics of project-based collaborative learning, an integrative regulatory strategy framework can be constructed from four dimensions: environment-individual adaptation, task design, collaborative organization, and multidimensional intervention.

3.1 Design Principles for Environment-Individual Adaptation

The design principle of environment-individual adaptation emphasizes that the learning environment should form a dynamic matching relationship with the learner's cognitive characteristics, which holds special significance in project-based collaborative learning contexts. Traditional learning environment design often employs uniform standards, neglecting the diversity of learners' cognitive styles, which can easily lead to additional cognitive load for some learners due to environmental mismatch. The "layered adaptation" design approach includes three levels: the foundational layer, the adaptation layer, and the optimization layer. The foundational layer ensures the environment meets the basic cognitive needs of most learners, including clear information architecture, reasonable visual layout, and necessary technical support. The adaptation layer provides customizable environmental parameters, allowing learners to adjust information presentation methods, interaction pace, and auxiliary tools according to their own cognitive characteristics. The optimization layer uses intelligent algorithms to analyze learner behavior data, enabling adaptive environmental adjustments, such as automatically adding visual guidance cues for field-dependent learners or simplifying interface elements for field-independent learners. Environmental adaptation is not simply "catering" to learner preferences but aims to promote cognitive development through scientific design. For example, providing rich graphical support for visual learners in the early stages of a project, gradually introducing abstract representations as the project progresses to help them expand their information processing methods; for learners with limited working memory capacity, providing step-by-step guidance initially and gradually reducing prompts later to cultivate their information chunking ability. This progressive environmental adaptation respects individual differences while guiding cognitive development, enabling learners to systematically enhance their cognitive abilities while completing project tasks.

3.2 Dynamic Grading Model for Task Complexity

The dynamic grading model for task complexity can overcome the limitations of traditional linear task sequences by adopting a "core-satellite" task organizational structure. Core tasks maintain a relatively stable complexity gradient, designed according to the cognitive development trajectory of "conceptual understanding - skill application - innovative transfer," ensuring the coherence and systematicity of learning objectives. Satellite tasks dynamically adjust difficulty parameters—such as task scale, time pressure, and information density—based on learners' real-time cognitive states, enabling precise regulation of cognitive load. The key to model implementation lies in establishing an effective cognitive state monitoring mechanism, using multi-dimensional indicators to assess learners' cognitive load levels: at the behavioral level, focus on task completion efficiency, error patterns, and frequency of seeking help; at the interaction level, analyze discussion depth, question quality, and collaboration participation; at the subjective level, collect self-assessments and emotional feedback. When the monitoring system detects signs of cognitive overload, it can automatically trigger simplified versions of satellite tasks or provide guidance with decomposed steps; when detecting insufficient cognitive load, it can launch extended challenge tasks, such as adding open-ended requirements or introducing interdisciplinary elements. The model's innovation also lies in the flexible articulation mechanism between tasks. Satellite tasks are not simply difficulty adjustments but form organic knowledge nodes linked to core tasks. After a learner completes a simplified satellite task, the system intelligently recommends relevant advanced paths for core tasks, ensuring the coherence of the learning trajectory. This design accommodates individual cognitive differences with meticulous care while maintaining project integrity, providing a new approach for the personalized implementation of large-scale project-based learning.

3.3 Optimization Pathways for Collaborative Structure

Optimization pathways for collaborative structure focus on solving cognitive resource allocation issues in collaborative learning, proposing the innovative organizational form of a "flexible collaborative network." This network structure breaks the spatiotemporal constraints of fixed groups, allowing learners to flexibly adjust collaborative relationships based on task requirements and cognitive states, forming a dynamic system for knowledge flow and cognitive support. Within the network architecture, the role of cognitive hub is undertaken by learners with strong metacognitive abilities, responsible for coordinating the group's cognitive resource allocation and progress monitoring; expertise nodes are played by learners with deep understanding in specific domains, providing specialized support to the team; basic nodes flexibly adjust their level of participation according to task progress. During the project initiation phase, the cognitive hub leads task decomposition and role planning; during specialized problem-solving, corresponding expertise nodes provide targeted support; during the outcome integration phase, all members engage in collaborative construction based on a shared mental model. The optimization pathway also includes establishing a "cognitive buffer" mechanism to release accumulated cognitive load through regular intra-group reflection sessions and strategy adjustments. Buffer operation involves three links: during the cognitive audit phase, visualization tools are used to display the load distribution of each member; during the strategy negotiation phase, adjustment plans are jointly formulated; during the implementation feedback phase, intervention effectiveness is monitored. When a group encounters bottleneck problems, it can initiate cross-group collaboration requests; the system intelligently matches members with relevant expertise from other groups to form temporary task teams. This open collaborative ecosystem greatly expands the scope of cognitive resource sharing.

3.4 Implementation Framework for Multidimensional Intervention

The implementation framework for multidimensional intervention integrates strategies of environmental adaptation, task grading, and collaboration optimization, forming a systematic cognitive load management plan. The framework adopts a three-stage intervention model of "Prevention-Support-Regulation," with each stage containing specific measures related to environment, task, and collaboration, forming a three-dimensional intervention network. The prevention stage focuses on upfront design: predicting potential cognitive conflict points through environmental adaptability assessment, pre-judging task complexity based on learner characteristic analysis, and pre-allocating collaborative roles based on competency maps, thereby reducing the risk of cognitive overload at the source. The support stage focuses on process guidance: providing dynamic environmental parameter adjustments (e.g., automatically regulating information presentation pace based on attention monitoring data); implementing task difficulty fine-tuning (dynamically adding or subtracting subtask requirements based on completion status); offering collaborative strategy guidance (improving interaction quality through contextualized prompts). The regulation stage addresses sudden cognitive imbalance: activating emergency environmental optimization plans (e.g., switching information presentation modalities); implementing task restructuring (breaking complex tasks into manageable units); executing collaborative mode switching (e.g., changing from tight to loose collaboration). The innovative core of the framework is the "cognitive load dashboard" mechanism. This dashboard integrates multi-source data (eye-tracking, interaction logs, affective computing, etc.) and visually displays the cognitive load status of individuals and groups in real-time. The dashboard design uses a "traffic light" warning system: the green zone indicates cognitive load is within the optimal range, the yellow zone signals potential risk, and the red zone flags severe overload requiring immediate intervention. Teachers and learners can make collaborative decisions using the dashboard, while the system also provides intelligent suggestions based on historical data and algorithmic models.

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