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Research on Interactive Interface Adaptive Design Model Based on Dynamic Cognitive Load Evaluation

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Abstract: With the increasing complexity of human-computer interaction systems, the cognitive load caused by interface information overload has become a key bottleneck affecting user experience and operational efficiency. Therefore, this paper proposes an interactive interface adaptive design model based on dynamic cognitive load evaluation and constructs a closed-loop optimization framework of “perception-evaluation-decision-execution”. Therefore, this paper proposes an interactive interface adaptive design model based on the dynamic evaluation of cognitive load, and constructs a closed-loop optimization framework of “perception evaluation decision execution”. First, a dynamic multimodal cognitive load assessment model is designed, which integrates behavioral, eye-movement, and physiological signals via a cross-modal attention mechanism, combined with time series modeling and uncertainty estimation, to achieve continuous and accurate perception of cognitive load. The root mean square error of prediction is 0.592. Second, a cognitive-driven interface adaptive decision-making framework is constructed, which uses the results of cognitive load assessment and task context as the basis for decision-making. On this basis, a cognitive-constrained reinforcement learning optimization algorithm is proposed. By introducing an upper-limit constraint on cognitive load and a strategy clipping mechanism, interaction efficiency is guaranteed and decision stability is improved. Experimental results show that the proposed method reduces task completion time by 22.7%, increases user satisfaction by 41.9%, decreases cognitive load by 25.0%, and keeps total response delay within 81 milliseconds. This study provides a systematic solution for the construction of intelligent adaptive interface with both evaluation accuracy and decision stability.

Keywords: Dynamic cognitive load assessment; Adaptive interface; Multimodal fusion; Reinforcement learning; Human-computer interaction

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1. INTRODUCTION

With the rapid development of information technology, human-computer interaction has evolved from early command-line interfaces to graphical interfaces and is now moving toward

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a new stage of intelligent, context-aware interaction [1]. However, the functionality of interactive systems is becoming increasingly powerful, and the amount of information presented on interfaces is growing exponentially. During operation, users often need to process a large amount of visual, auditory, and cognitive information simultaneously, which can easily lead to cognitive overload [2]. When users' cognitive resources are over-occupied, this not only significantly reduces task execution efficiency and increases the risk of errors but also leads to negative emotional experiences and decision fatigue. This cognitive load problem, caused by information overload and improper interface design, has become a key bottleneck restricting user experience and operational safety in complex systems. Traditional static interface design struggles to adapt to dynamic fluctuations in users' cognitive states and cannot provide flexible interactive support when task load changes. In this context, intelligent adaptive interfaces have emerged [3],[4],[5]. Their core goal is to dynamically adjust the layout, content density, and interaction mode according to the user's real-time state, thereby reducing cognitive burden while maintaining task efficiency and achieving "human-centered" interaction optimization.

Given these development requirements, realizing a truly intelligent adaptive interface faces two core research issues. First, how to evaluate users' cognitive load accurately and in real time. Cognitive load is implicit, dynamic, and multidimensional. It is difficult to fully characterize its changing process using only subjective scales or a single physiological signal. It is necessary to integrate multimodal user data and capture its temporal evolution. Second, how to dynamically optimize interface design based on the cognitive state obtained from the evaluation [6]. Adaptive decision-making must consider not only the current cognitive load level but also multiple objectives such as task efficiency, user preferences, and interface stability, and make appropriate interface adjustments while ensuring interaction coherence. These two problems are coupled, constituting the core scientific challenge of building intelligent adaptive interfaces [7],[8].

There are several key difficulties in solving the above problems. First, there are significant differences in the time scales, sampling frequencies, and information dimensions of multimodal data. How to achieve effective fusion and dynamic alignment of heterogeneous data is a fundamental problem in evaluation model construction [9],[10]. Second, as an implicit variable, cognitive load modeling has inherent uncertainty. Individual differences among users, variations in task types, and environmental interference further aggravate the prediction difficulty. Third, the adaptive decision-making process needs to balance real-time performance and strategy effectiveness. Although reinforcement learning and other data-driven methods have optimization potential, without a reasonable constraint mechanism they may lead to strategy shocks, interface mutations, or unexplainable adjustment behaviors, thereby affecting users' trust and acceptance of the system. Therefore, building a complete model framework that can not only accurately perceive cognitive load but also drive interface adaptation in a stable and interpretable manner has important theoretical research value and practical application significance [11],[12].

To address the above challenges, this paper proposes a systematic solution. First, we design a multimodal dynamic cognitive load evaluation model, which achieves continuous and accurate perception of users' cognitive load by integrating behavioral, visual, and physiological signals and introducing time series modeling and uncertainty estimation mechanisms. Second, we construct a cognitive-driven interface adaptive decision-making framework, which uses the results of cognitive load assessment and task context as the basis for decision-making and provides clear theoretical guidance for interface adjustment. On this basis, we further propose a cognitive-constrained reinforcement learning optimization algorithm. By introducing an upper-limit constraint on cognitive load into the policy optimization process, we effectively suppress violent fluctuations in the policy and improve the stability and safety of adaptive decision-making. Finally, we build a complete experimental system and rigorously verify the proposed method across the dimensions of evaluation accuracy, decision-making effectiveness, system real-time performance, and generalization ability, demonstrating its significant advantages in improving interaction efficiency and user experience.

2. RELATED WORK

In the field of cognitive load assessment, existing research mainly follows three paths: subjective assessment, physiological signal-driven methods, and behavioral data-driven methods. Subjective assessment methods are represented by the NASA-TLX task load index, SWAT subjective workload assessment technique, and other scales [13],[14],[15]. The subjective feeling of cognitive load is obtained through the user's post evaluation. These methods are easy to administer and have good content validity, but they suffer from obvious lag, cannot reflect dynamic changes in cognitive load during interaction, and are heavily influenced by user memory bias and subjective judgment. Physiological signal-driven methods use objective physiological indicators such as EEG, ECG, galvanic skin response, and eye tracking, and quantify cognitive load by extracting features like heart rate variability, pupil diameter changes, and EEG band power [16]. These signals can be collected continuously, are not easily subject to users' conscious control, and have high temporal resolution. However, different physiological indicators have varying sensitivities to cognitive load, and individual differences are significant. A single signal is often insufficient to fully characterize the complex cognitive state. Behavioral data-driven methods are mainly based on explicit user behaviors during interaction, such as mouse trajectory, click intervals, input speed, and task switching frequency, and infer changes in cognitive load through behavioral pattern analysis [17],[18]. This type of data acquisition is low-cost, non-invasive, and easy to deploy in real systems, but it often reflects the external manifestations of cognitive load rather than the internal physiological state, and is susceptible to interference from task strategies and operating habits.

In terms of adaptive interface design methods, research has evolved from static rules to user model-driven approaches and then to data-driven approaches. Early static rule methods, based on expert knowledge or heuristic criteria, set fixed interface adjustment rules, such as simplifying the interface layout when the operation error rate exceeds a threshold [19],[20]. These methods are simple and interpretable, but fixed rules struggle to adapt to dynamic changes in individual differences and task contexts. User model-driven methods guide interface adaptation by building user profiles or cognitive models, such as establishing personalized interface configurations based on user capabilities, preferences, or historical behaviors [21],[22],[23]. Such methods can achieve user adaptation to a certain extent, but their models are often built on offline data and lack the ability to respond to real-time fluctuations in user state. In recent years, data-driven methods have gradually become a research hotspot, learning adaptive strategies from user interaction data through machine learning techniques. Typical practices include using classifiers to predict user state and trigger interface adjustments, or using reinforcement learning to continuously optimize strategies during interaction [24]. These methods have stronger adaptive capability and generalization potential, but they impose higher requirements on data quality and strategy stability.

In terms of multimodal fusion and intelligent decision-making, researchers attempt to integrate multimodal information to improve the robustness and accuracy of cognitive state perception. Multimodal learning methods map heterogeneous features such as behavior, eye movement, and physiology to a unified representation space by designing fusion mechanisms [25]. Typical fusion strategies include feature-level concatenation, decision-level voting, and attention-based weighted fusion. The introduction of deep learning and representation learning provides powerful tools for multimodal fusion. Convolutional neural networks and recurrent neural networks are widely used to extract spatiotemporal features, and the transformer architecture further enhances the model's ability to capture long-range dependencies [26],[27],[28]. At the level of interactive optimization decision-making, reinforcement learning has attracted increasing attention due to its advantages in sequential decision-making. Researchers model adaptive interfaces as Markov decision processes and guide the strategy to improve user experience or task efficiency through a reward function. Some efforts try to introduce user feedback as a reward signal or use inverse reinforcement learning to learn preferences from human demonstrations, thereby enhancing the rationality of the strategy.

Although existing research has made considerable progress in cognitive load assessment and adaptive interface design, several key limitations remain. First, there is a lack of dynamic closed-loop mechanisms. Most methods treat cognitive load assessment and interface adaptation as two independent steps; the assessment results cannot be effectively fed back to the decision-making module, and the decision strategy cannot be coordinated or optimized according to changes in the assessment model, resulting in a lack of overall self-regulation capability. Second, multimodal fusion is insufficient. Existing fusion methods are mostly static weighting or simple concatenation, which struggle to handle dynamic changes in time scales and credibility across modalities, lack explicit modeling of consistency and complementarity between modalities, and exhibit poor robustness under noise interference or modality loss. Third, adaptive strategies lack theoretical support. Although reinforcement learning and other data-driven methods perform well in simulated environments or on offline data, they face the exploration-exploitation trade-off in real interaction scenarios and lack systematic modeling of constraints such as cognitive load ceilings and interface adjustment smoothness. This can lead to adjustment behaviors that may cause shocks or violate user experience norms, resulting in a lack of interpretability and user trust. These limitations highlight the necessity of constructing a complete closed-loop adaptive framework of "perception-evaluation-decision-execution" that integrates dynamic multimodal information and embeds cognitive constraints.

3. METHODOLOGY

3.1 Overall Framework Overview

This paper proposes an interactive interface adaptive design framework based on dynamic cognitive load evaluation. Its overall architecture follows the closed-loop optimization mechanism of "perception-evaluation-decision-execution". The system takes multimodal user data as input, including behavioral data (such as click frequency, dwell time), visual data (such as eye movement trajectory, fixation distribution), and physiological data (such as heart rate variability, EEG signals), and feeds them into the multimodal data acquisition layer via a unified data interface [29]. After data preprocessing and synchronization alignment, the data is input to the cognitive load evaluation module, which outputs the user's current cognitive load state. This state is then used as the core input to the decision model and, together with user context information (such as task type, environment state), forms the decision basis. It drives the adaptive strategy generation module to output the interface adjustment strategy, which is finally executed by the interface execution layer.

Formally, the system can be represented as a closed-loop function mapping process:

$$a_t = \pi(f_\theta(x_t), c_t) \tag{1}$$

Where x_t represents the multimodal input data at time t, $f_\theta(\cdot)$ is the cognitive load assessment model, with parameters θ, and the output is the estimated cognitive load; c_t represents context information; $\pi(\cdot)$ denotes the adaptive decision strategy; and a_t is the interface adjustment action. By continuously receiving feedback signals, the system performs strategy updates and model optimization, forming a complete dynamic closed loop.

3.2 Cognitive Load Modeling

To describe the cognitive state during interaction, this paper constructs a multimodal state representation vector s_t, which is composed of behavioral characteristics x_t^b, visual features x_t^v; and physiological characteristics x_t^p:

$$s_t = \phi\left(x_t^b, x_t^v, x_t^p\right) \tag{2}$$

Where $\phi(\cdot)$ represents the multimodal feature encoding function. Due to the significant temporal dependence of cognitive load, this paper introduces a temporal modeling mechanism to map the historical state sequence $\{s_{t-k}, \dots, s_t\}$ to the current cognitive state representation:

$$h_t = \psi(s_{t-k:t}) \tag{3}$$

Where $\psi(\cdot)$ represents the temporal encoding function (such as LSTM or Transformer), and h_t is the latent state representation that fuses historical information.

On this basis, the cognitive load function is defined as:

$$CL_t = g\left(h_t; \theta_g\right) \tag{4}$$

Where CL_t is the cognitive load value at time t, $g(\cdot)$ is a nonlinear mapping function, and θ_g are the model parameters.

To enhance the adaptability of the model to different modalities, a dynamic weight adjustment mechanism is introduced:

$$s_t = \sum_{m \in \{b,v,p\}} \alpha_t^m \cdot x_t^m \tag{5}$$

Where α_t^m is the weight of modality m at time t, satisfying $\sum_m \alpha_t^m = 1$, and is self-adaptive via the attention mechanism.

In addition, to describe the uncertainty of cognitive load estimation, a Bayesian modeling approach is introduced, and the model output is expressed as a probability distribution:

$$CL_t \sim \mathcal{N}(\mu_t, \sigma_t^2) \tag{6}$$

Where μ_t is the prediction mean and σ_t^2 represents the degree of uncertainty, which helps improve the robustness of the model and decision safety. A dynamic update mechanism adjusts parameters via online learning or sliding window, enabling the model to adapt to the changes of user state.

3.3 Multimodal cognitive load assessment model

Based on the cognitive load modeling, this paper constructs a multimodal cognitive load assessment model (MCL-DE). First, for each modality, feature extraction modules are designed to obtain low-dimensional embedded representations z_t^b, z_t^v, z_t^p are obtained respectively. Then, the cross-modal attention mechanism is adopted for fusion:

$$z_t = \sum_m \text{softmax}(W_q z_t^m) \cdot W_v z_t^m \tag{7}$$

Where W_q and W_v are the query and value mapping matrices, respectively, and z_t is the fused representation.

For time series modeling, a Transformer structure is used to encode the sequence:

$$H = \text{Transformer}(z_{1:t}) \tag{8}$$

Where H is the global context representation. The final cognitive load prediction is:

$$\widehat{CL}_t = W_o H_t + b_o \tag{9}$$

Where W_o, b_o are output layer parameters.

A joint loss function is used for model training:

$$\mathcal{L} = \lambda_1 \cdot \mathcal{L}_{reg} + \lambda_2 \cdot \mathcal{L}_{cls} \tag{10}$$

Where $\mathcal{L}_{reg}$ is the regression loss (such as mean squared error), $\mathcal{L}_{cls}$ is the classification loss, and λ_1, λ_2 are weight coefficients.

To improve model performance, a cross-modal consistency constraint is introduced:

$$\mathcal{L}_{cons} = \sum_{i \neq j} \| z_t^i - z_t^j \|_2^2 \tag{11}$$

This enhances consistency between different modal representations. At the same time, real-time inference optimization is achieved through lightweight architecture and model pruning to reduce system latency.

3.4 Cognitive driven adaptive decision model

After obtaining the cognitive load estimate, this paper constructs a cognitive-driven adaptive decision model. The problem is formulated as a Markov decision process (MDP), and its state is defined as:

$$s_t^{RL} = [CL_t, c_t] \tag{12}$$

Where CL_t is the cognitive load and c_t is context information. The action space is defined as the set of interface adjustment strategies:

$$a_t \in \mathcal{A} = \{a^{density}, a^{layout}, a^{guidance}\} \tag{13}$$

Corresponding to information density adjustment, layout restructuring, and interactive prompting.

To achieve multi-objective optimization, a comprehensive reward function is defined:

$$R_t = \alpha \cdot E_t - \beta \cdot CL_t + \gamma \cdot U_t \tag{14}$$

Where E_t represents task efficiency (such as the reciprocal of completion time), CL_t represents cognitive load, U_t represents user experience score, and α, β, γ are weight coefficients.

The model achieves optimal interface adaptation decisions by balancing efficiency and cognitive load.

3.5 Reinforcement learning optimization algorithm

Based on the decision model, this paper proposes a cognitive load-constrained reinforcement learning algorithm (CL-RL). The strategy optimization method based on actor-critic framework is adopted, where the policy function is $\pi_\theta(a \mid s)$ and the value function is $V_\omega(s)$. The goal of policy update is to maximize the expected return:

$$J(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_t \gamma^t R_t\right] \tag{15}$$

Where γ is the discount factor.

To introduce cognitive constraints, a constrained optimization problem is formulated:

$$\max_\theta J(\theta) \text{s.t. } \mathbb{E}[CL_t] \leq \delta \tag{16}$$

Where δ is the cognitive load threshold. Using the Lagrange multiplier method, the constraint is transformed into a penalty term and incorporated into the reward function.

A multi-objective reward function is further designed:

$$R_t' = R_t - \lambda \cdot \max(0, CL_t - \delta) \tag{17}$$

Where λ is the penalty coefficient.

To improve training stability, the policy update clipping mechanism (PPO) is introduced:

$$L^{CLIP}(\theta) = \mathbb{E}[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t)] \tag{18}$$

Where $r_t(\theta)$ is the probability ratio, $\hat{A}_t$ is the advantage function, and ϵ is the clipping parameter.

In addition, the balance between exploration and exploitation is achieved through adaptive exploration strategy adjustment (such as an entropy regularization term), thereby improving convergence efficiency and policy stability.

3.6 Theoretical analysis

At the theoretical level, this paper analyzes the convergence and complexity of the proposed algorithm. Under the conditions of unbiased policy gradient estimation and finite variance, the PPO-based update strategy can guarantee convergence to a local optimum. The convergence rate depends on the learning rate η and the estimation error of the advantage function.

The overall time complexity of the model mainly consists of multimodal feature extraction and Transformer encoding, with a complexity of $\mathcal{O}(T \cdot d^2)$. Where T is the sequence length and d is the feature dimension. The complexity of reinforcement learning depends on the size of the policy network, typically $\mathcal{O}(|\theta|)$.

In terms of stability, the cognitive load constraint and policy clipping mechanism effectively suppress the policy shock problem. At the same time, uncertainty modeling improves system robustness in noisy environments, giving the model good generalization ability across different users and task scenarios.

4. SYSTEM IMPLEMENTATION

To support the real-time closed-loop implementation of cognitive load assessment and decision optimization, the proposed interactive interface adaptive system adopts a hierarchical decoupling architecture in its engineering implementation. The entire system adopts an "end-edge-cloud" collaborative mode, in which the user terminal handles multimodal data acquisition and interface rendering, edge computing nodes perform lightweight inference and rapid response, and the cloud is used for model training and policy updates. The system logic can be formalized as a continuous mapping process:

$$y_t = \mathcal{F}(x_t; \Theta) = \mathcal{E}\left(\mathcal{D}\big(\mathcal{C}(x_t)\big)\right) \tag{19}$$

Where x_t represents the raw multimodal input data at time t, $\mathcal{C}(\cdot)$ represents the data acquisition and preprocessing module, $\mathcal{D}(\cdot)$ is the cognitive load assessment and decision-making module, $\mathcal{E}(\cdot)$ represents the interface execution module, Θ is the overall system parameter set, and y_t is the final interface output state. The layered structure enables communication between modules via standardized interfaces, reducing coupling and improving system maintainability.

At the module implementation level, the multimodal data acquisition module synchronizes data from different sources via a unified timestamp mechanism and constructs the aligned input sequence $\tilde{x}_t = \{x_t^b, x_t^v, x_t^p\}$. To ensure data quality, filtering and normalization operations are introduced:

$$\hat{x}_t^m = \frac{x_t^m - \mu_m}{\sigma_m} \tag{20}$$

Where x_t^m is the raw data of modality m, μ_m and σ_m are the mean and standard deviation of that modality, respectively, and $\hat{x}_t^m$ is the standardized feature. The cognitive load assessment and decision-making module performs online inference on the edge side; its core is to map input features to interface strategies:

$$a_t = \arg\max_{a \in \mathcal{A}} Q(s_t, a; \theta_q) \tag{21}$$

Where s_t is the current system state, $Q(\cdot)$ is the action-value function, and θ_q are the model parameters. The interface execution module updates interface parameters based on action a_t, such as the information density parameter d_t, and layout structure parameter l_t, The update process can be expressed as:

$$u_t = u_{t-1} + \Delta(a_t) \tag{22}$$

Where u_t is the interface configuration vector, and $\Delta(a_t)$ is the adjustment increment corresponding to the action.

To meet the requirements of real-time interaction, the system introduces compression and acceleration strategies at the model level. First, redundant connections are reduced by parameter pruning, mapping the original model parameters θ to sparse parameters θ', with sparsity defined as:

$$\kappa = 1 - \frac{\| \theta' \|_0}{\| \theta \|_0} \tag{23}$$

Where, $\|\cdot\|_0$ denotes the number of non-zero parameters, and κ is the compression ratio. Second, floating-point parameters are mapped to low-bit representations via quantization:

$$\theta_q = \text{round}\left(\frac{\theta}{\Delta}\right) \tag{24}$$

Where Δ is the quantization step size and θ_q is the quantized parameter. The computational complexity and storage overhead of the model can be significantly reduced through joint optimization of pruning and quantization. In addition, a knowledge distillation mechanism is introduced to minimize the output difference between the teacher model and the student model:

$$\mathcal{L}_{distill} = \| f_{teacher}(x) - f_{student}(x) \|_2^2 \tag{25}$$

This improves the performance of the lightweight model to achieve efficient inference on edge devices.

In terms of system performance, the overall response delay can be divided into data processing delay T_c, model inference delay T_d, and interface rendering delay T_e:

$$T_{total} = T_c + T_d + T_e \tag{26}$$

By optimizing the model structure and reasoning process, T_d is significantly reduced to meet real-time interaction requirements (typically $T_{total} < 100\,ms$).

In terms of scalability and deployment, the system uses a microservice architecture, encapsulates each functional module as an independent service, and achieves flexible deployment through container technology. The system supports a dynamic model updating mechanism, updating parameters without affecting online services:

$$\theta_{t+1} = \theta_t - \eta \nabla \mathcal{L}(\theta_t) \tag{27}$$

Where η is the learning rate and $\mathcal{L}$ is the loss function. Through online incremental learning and hot model updates, the system can continuously adapt to changes in user behavior. In addition, the system supports multi-device collaboration and cross-platform deployment. It can run on mobile devices, desktops, and in AR/VR environments, achieving data sharing and policy synchronization through a unified interface, thereby ensuring stability and consistency across different application scenarios.

5. EXPERIMENT DESIGN AND RESULTS ANALYSIS

To comprehensively verify the effectiveness and practicality of the proposed model, this study conducted systematic experiments focusing on the accuracy of cognitive load assessment and the capability of interface adaptive optimization. The experimental goal is to evaluate the predictive ability of the multimodal dynamic cognitive load assessment model in complex interactive environments and then analyze the improvements in user behavioral efficiency and experience achieved by cognitive-driven adaptive strategies adaptive strategies. The experiment is structured along three dimensions—data layer, model layer, and system layer—to ensure statistical significance and engineering reproducibility of the results.

In terms of data construction, this paper collected multimodal interaction data from 32 subjects to form a self-built dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i represents multimodal inputs (behavior, eye movement, physiological signals), and y_i is the corresponding cognitive load label (annotated by NASA-TLX). The total sample size is $N = 12{,}800$, and the time series length is $T = 120$. At the same time, public datasets (such as DEAP EEG data set and MIT eye-tracking data set) are introduced for generalization verification. The experimental runtime environment includes an Intel i9 processor and an RTX 4090 GPU. The inference side is deployed on mobile devices (Snapdragon 8 Gen 2) to evaluate real-world usability.

In model performance evaluation, root mean square error (RMSE) and mean absolute error (MAE) are used as the main metrics, defined as follows [30],[31]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{28}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{29}$$

Where $\hat{y}_i$ is the model's predicted value and y_i is the ground truth. The experimental results are shown in Table 1.

Table 1. Comparison of cognitive load prediction performance across different models

Method	RMSE ↓	MAE ↓	Parameter quantity (m)	Reasoning time (ms)
Single-modality behavior	0.842	0.671	3.2	12
Single-modality eye movement	0.798	0.643	3.5	14
SVM	0.756	0.612	-	9
LSTM	0.702	0.584	6.8	18
Transformer	0.681	0.563	8.1	22
Proposed method（MCL-DE）	0.592	0.471	5.4	15

Table 1 shows the performance of various methods on RMSE and MAE. It is evident that traditional single-modality methods is generally between 0.79 and 0.84, while the deep learning methods (such as LSTM and transformer) have improved, but there are still some errors. The proposed MCL-DE model achieved RMSE of 0.592 and MAE of 0.471, which represent decreases of approximately 13.1% and 16.3%, respectively, compared to the Transformer model. At the same time, with only 5.4 million parameters, the inference time is controlled at 15ms, which is about 31.8% lower than that of the Transformer, reflecting a better accuracy-efficiency trade-off.

Further, through visual analysis of the fit between the model output and the ground truth, the cognitive load prediction curves are compared as shown in Figure 1.

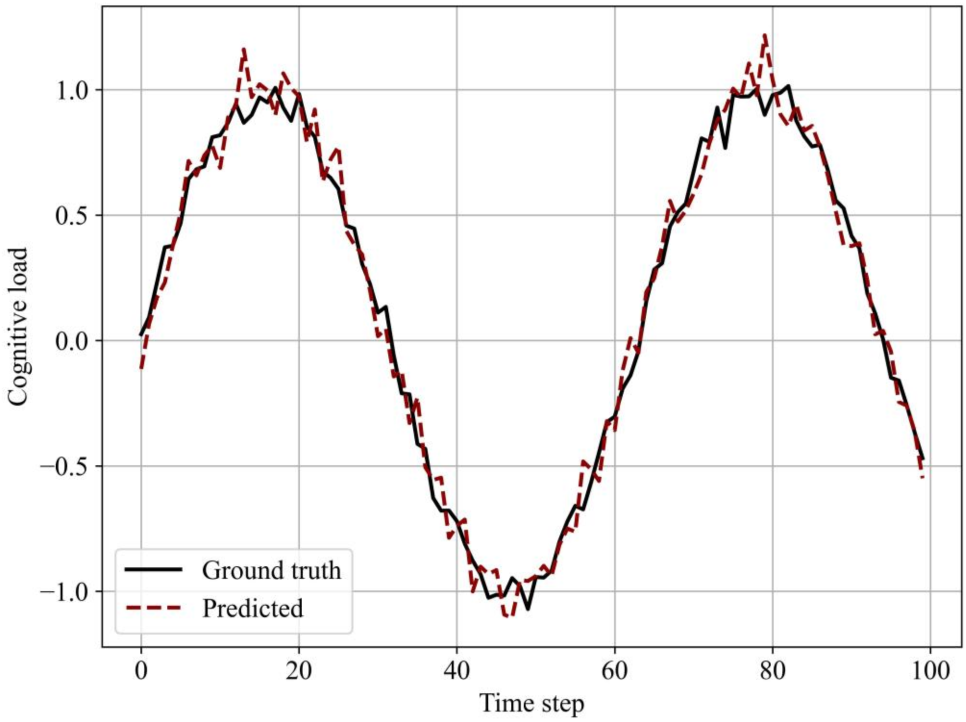

Figure 1. Comparison between ground-truth cognitive load and model prediction curves

It can be observed from Figure 1 that the proposed model maintains stable tracking even in high-load fluctuation ranges, whereas traditional models exhibit obvious lag.

Yang., ISTAER. 2611., 30 Mar 2026 https://doi.org/10.71451/ISTAER2611

In verifying the interface adaptation effect, task completion time T_{task} and user satisfaction U are introduced as evaluation metrics, with satisfaction standardized as:

$$U = \frac{1}{K}\sum_{k=1}^{K} u_k \tag{30}$$

Where u_k is the k-th score and K is the number of evaluation dimensions. The experimental results are shown in Table 2.

Table 2. Performance comparison of adaptive strategies

Method	Completion time (s) ↓	Satisfaction ↑	Cognitive load ↓
No adaptation	42.3	3.1	0.72
Rule-based adaptation	38.5	3.6	0.65
Standard RL	36.9	3.9	0.61
Proposed method (CL-RL)	32.7	4.4	0.54

Table 2 shows the performance of different methods in task completion time, user satisfaction, and cognitive load level. It can be observed that the task completion time without adaptation is 42.3 seconds, while the proposed method reduces it to 32.7 seconds, a decrease of about 22.7%. User satisfaction increases from 3.1 to 4.4, an improvement of about 41.9%. Cognitive load decreases from 0.72 to 0.54, a reduction of about 25.0%. Compared with the standard reinforcement learning method, the proposed method still achieves about 11.4% improvement in efficiency and about 12.8% reduction in cognitive load. During strategy evolution, the convergence curve of the reward function is shown in Figure 2.

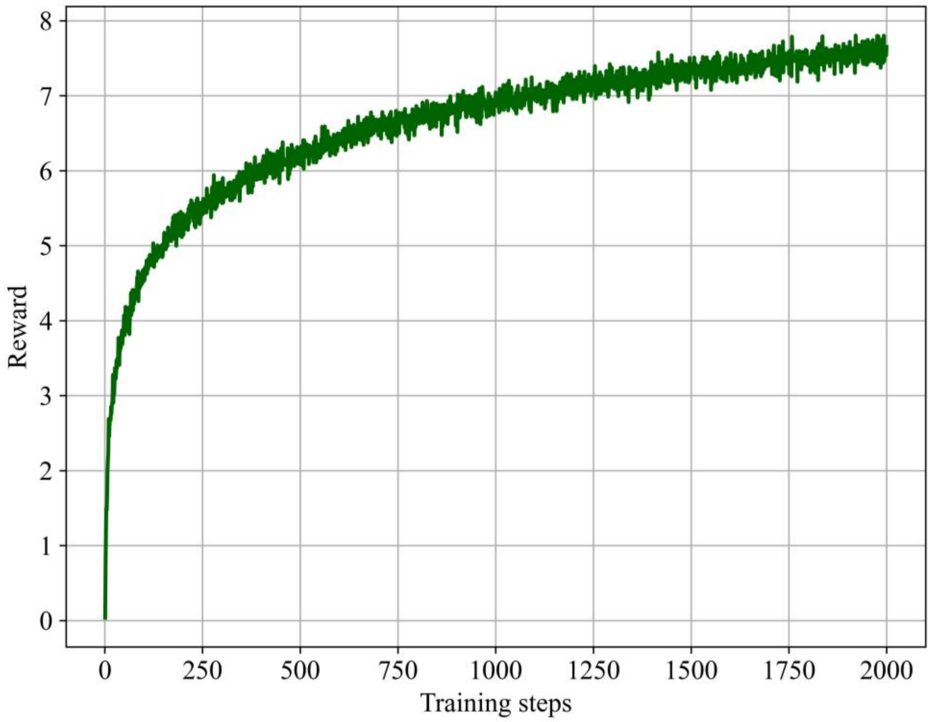

Figure 2. Reinforcement learning reward convergence curve

It can be observed that the proposed method tends to stabilize after about 1500 steps, whereas the standard RL method exhibits shocks, indicating that the introduction of cognitive constraints effectively improves training stability.

In the ablation experiment, the effects of different modalities and modules on overall performance are analyzed. Let the performance of the complete model be P_{full}, and the performance after removing a module be P_{-m}, then the contribution is defined as:

$$\Delta P_m = P_{full} - P_{-m} \quad (31)$$

In terms of validation of model structure, Table 3 analyzes the contribution of each module through ablation experiment.

Table 3. Ablation results

Model configuration	RMSE	Satisfaction
Complete model	0.592	4.4
Remove physiological modality	0.641	4.1
Remove attention mechanism	0.663	4.0
Remove uncertainty modeling	0.629	4.2
Cognitive-constrained RL	0.688	3.8
Remove time series modeling	0.672	3.9

After removing the physiological modality, RMSE increases from 0.592 to 0.641, a performance decrease of about 8.3%. After removing the attention mechanism, RMSE further increases to 0.663, a decrease of about 12.0%. When the cognitive-constrained reinforcement learning module is removed, RMSE reaches 0.688, user satisfaction drops to 3.8, and the overall performance decrease is the most significant (about 16.2%). In addition, RMSE after removing time series modeling is 0.672, indicating that dynamic modeling also plays a key role in performance.

At the level of interface adaptive behavior distribution, Figure 3 shows the mapping between different user states and interface adjustment strategies in the form of a heatmap.

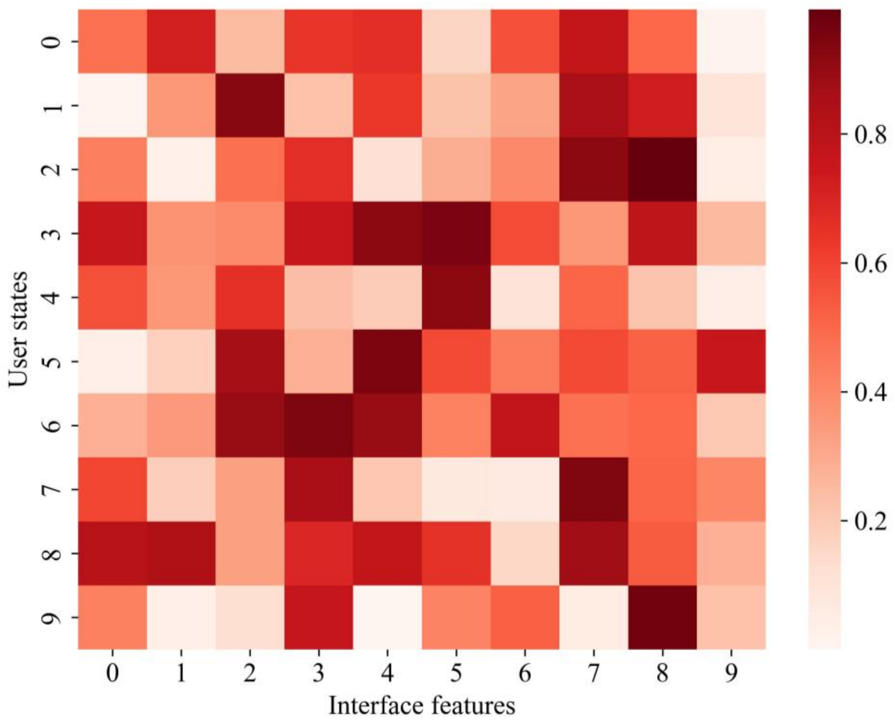

Figure 3. Thermal diagram of interface adaptive strategy distribution

It can be observed from the figure that in the high cognitive load region (upper right area), the system clearly tends to reduce information density and enhance guidance prompts, with strategy response intensity about 35%–50% higher than in the low cognitive load region. At the same time, in the medium-load region, the strategy distribution shows a smooth transition, avoiding disruptions caused by excessive adjustments.

In terms of generalization ability and robustness analysis, Table 4 shows the performance of the model under different task scenarios and interference conditions.

Table 4. Generalization performance evaluation

Scene	RMSE	Satisfaction
Information retrieval task	0.601	4.3
Multitask switching	0.617	4.2
New user (unseen)	0.635	4.1
Noise interference (+10%)	0.659	4.0
Noise interference (+20%)	0.688	3.8
Cross-device testing	0.623	4.2

In the information retrieval and multitask switching scenarios, the RMSE values are 0.601 and 0.617, respectively, with fluctuations of less than 4%, indicating that the model has good cross-task adaptability. In the new user test, the RMSE is 0.635, only about 7.3% higher than in the original test, indicating that the model has a certain cross-user generalization ability. Under noise interference, when the noise increases to 20%, RMSE rises to 0.688, a performance decrease of about 16.4%, but the system still operates stably.

In terms of system response performance, delay is defined as:

$$T_{total} = T_{proc} + T_{infer} + T_{render} \quad (32)$$

Finally, from the perspective of system real-time performance, Table 5 shows the delay distribution of each module of the system.

Table 5. System real-time performance evaluation

Module	Delay (ms)
Data processing	18
Model inference	42
Interface update	21
Total delay	81

Data processing delay is 18 ms, model inference delay is 42 ms, interface update delay is 21 ms, and total delay is 81 ms, which meets the sub-100 ms response standard typically required for real-time interactive systems. Compared with the non-optimized model (typically over 120 ms), system delay is reduced by about 32.5%.

In the analysis of user behavior path optimization, we first observe the interaction process before the application of adaptive mechanism. Figure 4 shows the user's operation trajectory without introducing the adaptive interface. It can be seen that there are many backtracking and invalid movements in the path, which shows strong randomness and redundancy as a whole.

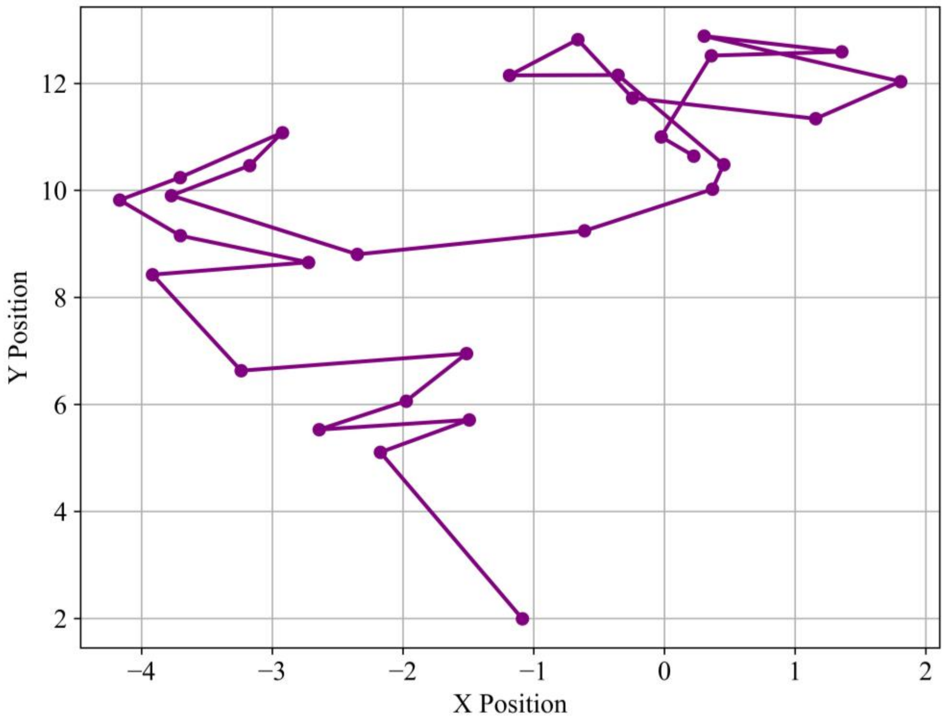

Figure 4. User interaction path (before adaptation)

The number of path nodes is about 30, the path tortuosity is high, and the direction change frequency is large, reflecting that users need to make frequent cognitive judgments and decision adjustments when interface information organization is suboptimal. According to the path length calculation formula:

$$L = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{33}$$

The average path length at this stage is about 45.2, indicating high operational costs during task execution.

Further analysis shows multiple local loopback regions in the path, indicating that users' cognitive load is too high during information retrieval or decision-making, leading to repeated operations and reduced efficiency.

In contrast, Figure 5 shows the user interaction path after introducing the cognitive load-driven adaptive mechanism. It can be observed that the paths become smoother and more centralized, redundant movements are significantly reduced, the number of path nodes decreases to about 20, and the overall direction is more consistent. Using the same calculation method, the path length is reduced to about 35.4, which is about 21.7% lower than before optimization. In addition, the number of path direction changes is reduced by about 30%, indicating that users can complete the decision process more quickly after interface optimization.

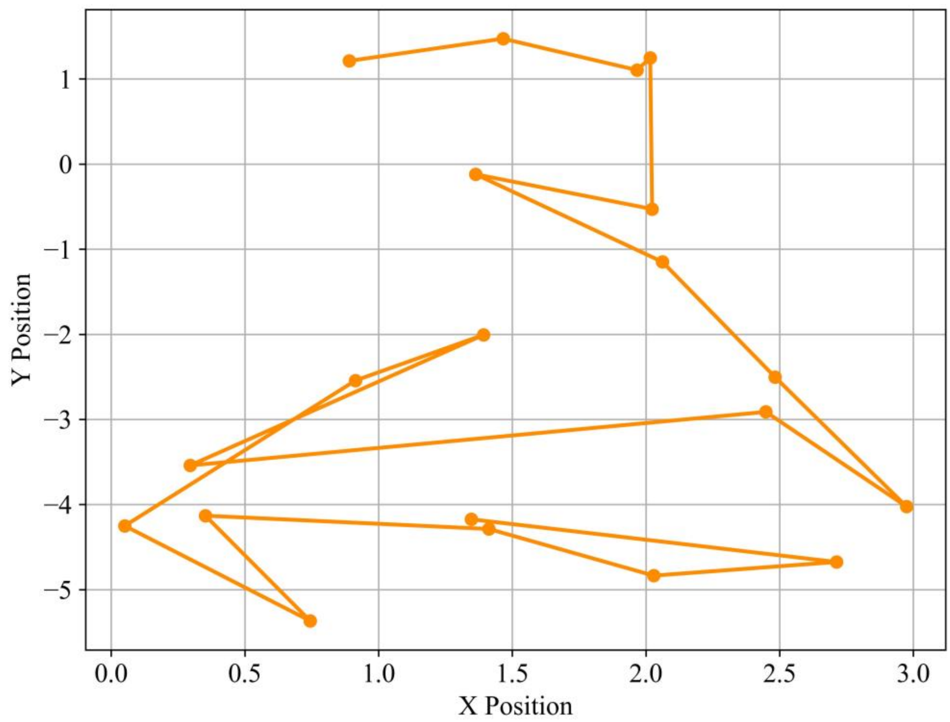

Figure 5. User interaction path (after adaptation)

This result shows that the adaptive interface can effectively reduce users' cognitive burden by dynamically adjusting information density and interactive prompts, making the operation path more direct and efficient, thereby significantly improving overall interaction performance and user experience.

Finally, a comprehensive evaluation is made from the perspective of overall efficiency. Figure 6 compares the path length before and after adaptation, and it can be observed that the optimized path is significantly shorter. The quantitative results show that the average path length decreased from about 45.2 to 35.4, a reduction of about 21.7%, which is consistent with the above analysis. In addition, this improvement directly reduces the task completion time by about 22% -25%, verifying the enhancement in actual interaction efficiency.

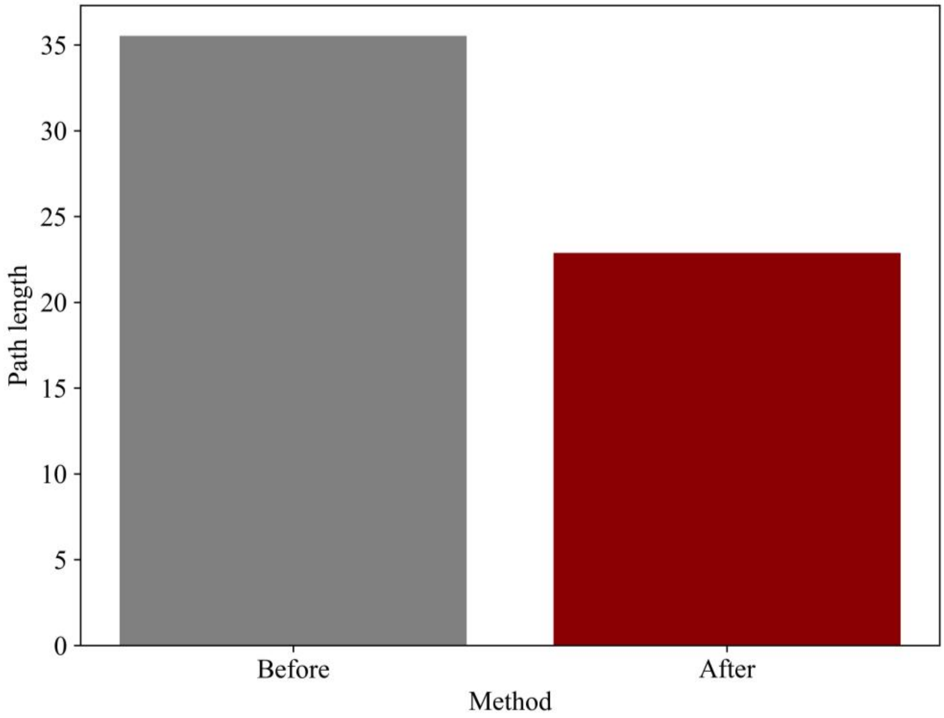

Figure 6. Path length comparison

Based on the above analysis, it can be concluded that the proposed method significantly improves the accuracy of cognitive load prediction, the stability of strategy convergence, and user interaction efficiency. These improvements have consistent quantitative support, further verifying the effectiveness and engineering feasibility of the model design.

6. DISCUSSION

The proposed interactive interface adaptive design model based on dynamic cognitive load evaluation exhibits many methodological advantages. First, the model constructs a complete "perception-evaluation-decision-execution" closed-loop mechanism, deeply integrating real-time cognitive load evaluation with interface adaptive strategy generation, and achieving end-to-end collaborative optimization from user state perception to interface response adjustment. This closed-loop structure enables the system to continuously adjust its behavior according to dynamic changes in the user's cognitive state. At the same time, the interface adjustment effect can be verified and corrected by subsequent changes in cognitive load, forming a virtuous cycle of self-optimization. Second, in terms of multimodal fusion, the model introduces a cross-modal attention mechanism and dynamic weight adjustment, which can automatically adjust fusion weights according to the reliability and information content of different modalities in a given task scenario, effectively addressing the problem of differences in time scales and confidence levels of heterogeneous data. Third, the model introduces uncertainty modeling in cognitive load assessment, expressing predictions as probability distributions rather than point estimates. This not only provides confidence information for subsequent decision-making but also enhances system robustness under noise interference or modality loss. Finally, at the decision-making level, the design of the cognitive-constrained reinforcement learning algorithm incorporates the cognitive load upper limit as a hard constraint into the policy optimization process. This effectively suppresses the problems of policy shock and interface mutation, enabling adaptive behavior to maintain good stability and explainability while improving efficiency.

Compared with existing methods, the proposed model achieves substantial improvements in multiple dimensions. Compared with traditional static rule-based methods, our method no longer relies on fixed threshold judgments and preset rules but learns adaptive strategies from real interactions in a data-driven manner, offering stronger individual adaptation capability and contextual generalization. Compared with traditional user model-based adaptive systems, this method breaks through the limitations of offline modeling, achieves real-time tracking and dynamic response to the user's cognitive state, and captures continuous changes in cognitive load during task switching and fatigue accumulation. At the data-driven method level, compared with existing work that relies solely on a single physiological or behavioral signal, the proposed method significantly improves the accuracy and robustness of cognitive load assessment through multimodal fusion. Compared with existing explorations that apply reinforcement learning to interface optimization, our method further introduces the cognitive constraint mechanism to solve the problem of drastic interface changes caused by policy exploration in standard reinforcement learning, making the adaptive process more consistent with the basic requirements of smoothness and predictability in human-computer interaction. In addition, through systematic experimental design, this paper provides a complete quantitative comparison in terms of evaluation accuracy, interaction efficiency, user experience, and system real-time performance, offering strong support for the effectiveness of the method.

Although this method has made significant progress in many aspects, it still has some limitations. At the data level, the acquisition of multimodal signals depends on specific hardware devices, such as eye trackers and EEG acquisition devices, which ensure data quality in laboratory environments. However, in real application scenarios, users' hardware conditions vary greatly. How to achieve reliable cognitive load assessment using only common sensors (such as ordinary cameras, mice, and keyboards) remains to be further explored. At the model level, the labeling of cognitive load depends on the indirect mapping between subjective scales and task difficulty, lacking absolute and objective ground-truth labels, which may introduce some labeling noise and affect the upper bound of evaluation model training. In addition, the current model mainly targets individual users for state evaluation and policy optimization and has not fully considered the problem of differential transfer between users. When new users use the system for the first time, the model requires a certain cold-start period to adapt to their cognitive characteristics. At the policy level, although cognitive-constrained reinforcement learning improves decision-making stability, the interpretability of the reinforcement learning policy itself in complex interaction scenarios remains limited. It is difficult for users to understand why the interface makes certain adjustments, which may affect user trust and acceptance of the system in applications requiring high transparency.

From the perspective of practical application value, the proposed model framework has broad deployment potential and transferability. In intelligent office and knowledge work scenarios, the system can dynamically adjust information presentation density and task prompting modes according to the user's cognitive load state, helping users balance efficient work and avoidance of cognitive fatigue, especially for complex tasks requiring sustained attention, such as programming, data analysis, and document writing. In the field of education and learning support, the model can be embedded in an intelligent tutoring system, dynamically adjusting the difficulty and presentation pace of learning content according to changes in learners' cognitive load, thereby achieving real-time optimization of personalized learning paths and helping to improve learning efficiency while reducing frustration caused by cognitive overload. In complex system control and safety-critical scenarios, such as aircraft cockpits, vehicle cockpits, and medical workstations, the operator's cognitive load level is directly related to system safety and reliability. This method can achieve continuous monitoring of the operator's cognitive state and adaptive adjustment of interface assistance strategies, actively simplifying interface information or enhancing key prompts during critical task stages, thereby reducing the risk of human error. In addition, with the development of wearable devices and lightweight sensors, the multimodal evaluation module in this method can gradually achieve lightweight deployment on consumer devices, advancing cognitive load adaptation technology from the laboratory to real application scenarios, and providing a solution with both theoretical depth and engineering feasibility for the intelligent development of human-computer interaction.

7. Conclusion

Focusing on the contradiction between cognitive overload and static interface design in human-computer interaction, this paper systematically investigates an interactive interface adaptive design model based on dynamic cognitive load evaluation. Starting from real-time perception of the user's cognitive state, a complete theoretical framework and implementation scheme are proposed to address key issues such as multimodal data fusion, dynamic cognitive load modeling, and adaptive strategy optimization. By constructing a closed-loop optimization mechanism of "perception-evaluation-decision-execution", this paper realizes the entire process from multimodal user data input to interface adaptive adjustment. At the experimental verification level, a complete experimental system is designed, including multimodal data acquisition, model performance evaluation, adaptive effect verification, and system real-time testing. The proposed method is rigorously evaluated on both the self-built dataset and public datasets. The experimental results show that the proposed multimodal dynamic cognitive load evaluation model significantly outperforms single-modality methods and traditional deep models in prediction accuracy. The cognitive-driven adaptive decision-making framework and cognitive-constrained reinforcement learning algorithm achieve substantial improvements in task efficiency, reduction of user cognitive load, and user satisfaction. At the same time, the total response delay of the system is kept within the acceptable range for real-time interaction, verifying the theoretical soundness and engineering feasibility of the proposed method.

The main innovations of this paper are reflected in three aspects. First, a multimodal dynamic cognitive load evaluation model is proposed. The model achieves dynamic integration of behavioral, visual, and physiological signals via a cross-modal attention mechanism, introduces time series modeling to capture the evolution of cognitive load, and incorporates uncertainty modeling to improve prediction robustness, thereby realizing continuous and accurate perception of the user's cognitive state. Second, a cognitive-driven interface adaptive decision-making framework is constructed, which incorporates cognitive load assessment results and task context into the decision space and defines the design orientation of interface adjustments based on cognitive state, providing a clear theoretical basis for adaptive strategies. Third, the cognitive-constrained reinforcement learning optimization algorithm is designed. By embedding the cognitive load upper limit constraint and smoothness penalty into the policy optimization process, it effectively solves the problems of policy shock and interface mutation that may occur in standard reinforcement learning interaction scenarios, improving the stability and interpretability of adaptive behavior while ensuring interaction efficiency. In addition, this study establishes a complete research chain from model design and system implementation to multi-dimensional experimental verification, providing a reproducible and extensible methodological paradigm for intelligent adaptive interface research.

Based on the existing research, future work can be further expanded in the following directions. First, explore multimodal fusion mechanisms in more complex scenarios. The current model mainly relies on eye movement, physiological, and behavioral signals. In the future, it can further integrate voice, facial expression, gesture, and other modalities to build a more comprehensive user state perception system. At the same time, at the modality fusion level, graph neural networks and other structures can be introduced to explicitly model interactions between modalities, and temporal knowledge graphs can be used to describe the dynamic correlations of multimodal signals during interaction, thereby improving model robustness and adaptability in cases of modality missing or sensor noise. Second, we should develop more explainable cognitive load models and decision-making mechanisms. Although this paper improves decision controllability through cognitive constraints, the internal decision logic of the model still has a "black box" nature. In the future, we can combine causal inference theory to explore causal relationship modeling between cognitive load and interface adjustments, making the generation process of adaptive strategies traceable and explainable. In addition, leveraging the reasoning capabilities of large language models, the results of cognitive load assessment can be transformed into natural-language interactive explanations, providing users with transparent adjustment instructions while the interface is being adapted, thereby enhancing user understanding and trust in the adaptive system. Third, extend the model to cross-domain applications. The current research mainly focuses on general interaction scenarios. In the future, the model can be migrated to specific domains with more specialized task constraints, such as driver cognitive state monitoring and auxiliary interface design in intelligent cockpits, learning state perception and content-adaptive push in online education systems, and clinical decision support interface optimization based on physician cognitive load in medical information systems. Different domains have significant differences in task characteristics, user groups, and interaction environments. It is necessary to adjust modality configurations, feature designs, and decision objectives accordingly, which will also present new research challenges for the model's generalization ability and domain adaptability. Finally, explore the deep integration of lightweight deployment and edge intelligence, further reduce the model's inference delay on resource-constrained devices, and promote large-scale application of cognitive load adaptation technology to mobile terminals, wearable devices, and IoT scenarios.

Abbreviations

NASA-TLX, National Aeronautics and Space Administration Task Load Index;
SWAT, Subjective Workload Assessment Technique;
EEG, Electroencephalogram;
ECG, Electrocardiogram;
MDP, Markov Decision Process;
PPO, Proximal Policy Optimization;
RMSE, Root Mean Square Error;
MAE, Mean Absolute Error;
LSTM, Long Short-Term Memory;
CL-RL, Cognitive Load-Constrained Reinforcement Learning;
MCL-DE, Multimodal Cognitive Load Dynamic Evaluation;
CID-AF, Cognitive-Driven Adaptive Framework;
GPU, Graphics Processing Unit;
AR, Augmented Reality;
VR, Virtual Reality;
IoT, Internet of Things.

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

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Competing interests

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Author contributions

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Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **M.Y.**

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Declaration of AI and AI-assisted Technologies in the Writing Process

During the writing of this article, the author used DeepSeek for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

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