ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

The Application of Deep Reinforcement Learning in Optimizing Adaptive Interface for Art Design Interaction Feedback

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SUMMARY: *With the development of digital information transmission and human-computer interaction methods, the conventional human-computer interface design approaches have failed to meet the demands for aesthetics, convenience and personalization in artistic design spaces. This paper constructs a deep reinforcement learning-driven adaptive interface optimization framework, integrates user behavior, visual semantics, layout structure and feedback evaluation for state modeling, designs multi-objective reward mechanisms, experience replay and target network update strategies, and introduces application implementation and feedback closed-loop update mechanisms. The experiments are conducted based on 5100 interface samples and 68,000 interaction sessions. The results show that the proposed method reduces the average task completion time to 11.8 seconds, increases the effective click rate to 92.6%, achieves a user satisfaction rate of 4.53, has a comprehensive performance index of 0.912, and maintains good stability even under high complexity and high concurrency conditions. It provides an expandable technical path for the intelligent optimization of artistic design interfaces and the integration of human-computer interaction.*

Povzetek: This paper focuses on the optimization of the interactive interface in art design, and constructs a deep reinforcement learning framework that integrates visual semantics, layout structure, user behavior, and multiple objective rewards. It also includes experience summaries and feedback loop update mechanisms. After testing 5100 interface samples and 68,000 interaction sessions, the average task completion time was reduced to 11.8 seconds, the effective click-through rate reached 92.6%, the comprehensive performance value was 0.912, demonstrating excellent real-time and practicality.

KEYWORDS: *Art design interface; Deep reinforcement learning; Interface layout optimization; Visual feedback; Strategy update; Interaction adaptation*

1 Introduction

With the development of digital technology, intelligent computing technology and visual communication technology, the interface display mode has shifted from a purely static presentation to a dynamic response based on user interaction experience. In the field of art design, the interface should be able to convey information while also taking into account its visualization, integrity, operability and feedback. However, based on human experience, heuristic rules or limited user testing can only optimize the layout and interaction process to a certain extent. When facing users' individual preferences, rapidly changing feedback mechanisms and complex interaction design, it becomes powerless. For example, it is difficult

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https://doi.org/10.65102/is2026096
Published: 30 April, 2026

to adapt, update slowly, and lack individuality. Especially in the interactive environment of art design, users' perception of color matching, graphic layout, controller position and visual rhythm is subjective and cannot be simply achieved through rigid regulations for long-term effective optimization.

Furthermore, with the application of virtual exhibition halls, online customization design, cultural and creative display spaces and holographic visualization transmission technology, the service objects and scenarios of art design are becoming increasingly diverse. Different types of electronic products, personalized preference settings and interaction methods are all testing the adaptability and universality of the interface. This requires the interface system not only to respond quickly to users' operational behaviors, but also to take into account the information orderliness, aesthetics and guidance in the limited space, which indicates that the optimization of interface design is no longer limited to local corrections of individual layout variables, but involves the overall challenges of visual symbol interpretation, user operation simulation, feedback judgment integration and adaptive mechanism decision-making. The lack of autonomous learning intelligent optimization algorithms cannot solve this problem. Therefore, interface design may have style imbalance, interaction redundancy or feedback delay, which in general leads to poor user experience.

In this context, deep reinforcement learning provides a worthy idea for the adaptive optimization of interface self-adaption. Different from relying on fixed rules, it emphasizes that the system learns continuously through interaction, by perceiving the environment, choosing actions, receiving feedback and correcting strategies in a cyclic process, gradually finding more suitable adjustment methods. Introducing this mechanism into the interactive scenarios of art design means that the interface is no longer just a passive response, but can continuously optimize its own performance based on user behavior and feedback changes. For art design interfaces that need to balance efficiency, aesthetics and individual expression, this ability has practical significance. Of course, the problem of art design is different from the optimization of general functional interfaces. It also includes the influence of visual semantics and aesthetic preferences, as well as the constraints of interaction behaviors and scene goals. Therefore, how to describe the state characteristics of the interface, how to construct a reward mechanism that can simultaneously reflect efficiency and aesthetic orientation, and how to ensure the stability and reliability of the strategy update process are still key aspects that need to be further addressed.

This paper focuses on the research process of the adaptive interface feedback optimization of art design based on deep reinforcement learning: including the process of interface state modeling, action space division, reward mechanism design and feedback loop update, and conducting experimental verification of validity and feasibility. In summary, we hope to provide an expandable method framework for intelligent interface optimization for art design scenarios; at the same time, it can inspire the research of deep reinforcement learning in the intersection of human-computer interaction and visualization design; and lay a method foundation for subsequent intelligent auxiliary design with complex aesthetic tasks.

2 Related Work

The learning cycle of "state perception - action decision - reward feedback" is the core foundation of deep reinforcement learning, and it has demonstrated strong potential in areas such as dynamic control, self-regulation optimization, and multi-objective coordinated decision-making. Zorain et al. (2025) utilized this technology to optimize the automatic gain settings of the unmanned aerial vehicle's attitude control system, proving that it can implement changes in control parameters in complex environments, thereby enhancing the system's robustness [1]. Luo et al. (2023) introduced this method into the teaching scenario based on wireless network environment and proved that the algorithm has the characteristics of fast resource scheduling and response speed [2]. Ruan et al. (2025) proposed a personalized path planning scheme under a multi-level information incentive mechanism, further demonstrating the learning ability of DRL for users' dynamic change processes and the feedback information obtained [3]. These studies provide certain reference value for us to understand the user preference identification, strategy update, and feedback optimization in the interface of artistic design.

For the optimization of BIM green building design and multi-objective coordination problems, Pan et al. (2024) conducted in-depth research and proposed that through deep reinforcement learning, a dynamic equilibrium state can be achieved among various design restrictions and performance indicators [4]. Similarly, Parekh et al. (2024) in their research confirmed the practicality of this method in complex design environments, indicating that deep reinforcement learning can handle engineering problems with multiple evaluation indicators [5]. In the modification process of the artistic design interface, optimization often considers not only response speed but also visual layout, layout coordination, aesthetic degree, and interaction smoothness, among other aspects. Therefore, these studies have a good reference effect on the multi-objective adaptive interface optimization framework constructed in this paper.

Furthermore, it is also widely applied in the field of joint control of complex systems. For instance, Zhang et al. (2024) applied it to combine multi-objective optimization methods to complete edge-cloud joint scheduling tasks, thereby improving resource utilization and response efficiency [6]. Zhang et al. also carried out joint path planning and resource allocation work in the context of unmanned aerial vehicle-assisted communication. This indicates that this method can handle distributed cooperative decision-making tasks in high-dimensional and large-action-space scenarios [7].Their findings suggest that deep reinforcement learning is also effective for collaborative decision-making problems involving high-dimensional action spaces. Shen et al. (2022) applied deep reinforcement learning to the adaptive control of train doors in subway tunnels, verifying its application value in real-time feedback scenarios [8]. Tang et al. (2025) conducted multi-objective optimization research for intelligent medical buildings, further demonstrating the scalability of deep reinforcement learning in complex environment regulation and comprehensive performance improvement [9]. Overall, the existing research has laid the foundation for the application of deep reinforcement learning in dynamic optimization, real-time feedback, and multi-objective design, but research on adaptive interface optimization with feedback in art design is still relatively insufficient, especially in aspects such as visual semantic expression of the interface, user aesthetic preference modeling, and collaborative optimization of interaction experience and design aesthetics. There is still room for further in-depth exploration. The related research contents and inspirations for this paper are shown in Table 1.

Table 1: Related Research Contents and Inspirations for This Paper

No.	Research Topic	Core Content	Implications for This Study
[1]	Adaptive Control Optimization	Adaptive gain adjustment in UAV attitude control based on deep reinforcement learning	Provides control-oriented insights for dynamic strategy updating and feedback regulation in artistic design interfaces
[2]	Network Design Optimization	Application of deep reinforcement learning to wireless network design optimization to improve resource allocation and real-time response capability	Offers a reference for interface resource scheduling and response optimization driven by interaction feedback
[3]	Personalized Feedback Optimization	Construction of personalized optimization pathways using multimodal data and real-time feedback mechanisms	Provides support for user behavior modeling, preference recognition, and real-time interface adaptation
[4]	Multi-objective Design Optimization	Multi-objective optimization for green building design to coordinate different performance indicators	Provides a reference for the coordinated optimization of interface aesthetics, functionality, and interaction efficiency
[5]	Multi-criteria Collaborative Design	Joint optimization of multiple criteria in complex design scenarios	Supports joint modeling of multidimensional design indicators in artistic design interfaces
[6]	Collaborative Resource Scheduling	Combination of deep reinforcement learning and multi-objective optimization for edge-cloud collaborative scheduling	Provides ideas for interface system deployment and computational resource allocation
[7]	Joint Decision Optimization	Joint optimization of trajectory design and resource allocation in communication scenarios	Provides a reference for interface decision modeling under high-dimensional action spaces
[8]	Real-time Feedback Control	Adaptive control optimization in real-time scenarios based on deep reinforcement learning	Provides an application basis for designing closed-loop interaction feedback updating mechanisms
[9]	Intelligent Environment Multi-objective Optimization	Comprehensive performance optimization and environment regulation for intelligent buildings	Provides an extended direction for comprehensive performance evaluation of artistic design interfaces

3 Application of Deep Reinforcement Learning in Adaptive Interface Optimization for Artistic Design Interaction Feedback

3.1 Interface State Modeling in Artistic Design Interaction Feedback Scenarios

In the context of artistic design interaction feedback, interface optimization does not merely adjust based on a single click action. Instead, it needs to comprehensively consider various dimensions such as user operation process, visual attention distribution, interface layout characteristics, style semantic expression, and feedback evaluation results. To enable deep reinforcement learning to accurately perceive changes in the interface environment, this paper models the interface state as a multi-source fusion state space composed of user behavior characteristics, visual semantic characteristics, layout structure characteristics, and feedback response characteristics.

Specifically, at time t, the interface state is denoted as S_t, and its definition is:

$$S_t = \{U_t, V_t, L_t, F_t\} \tag{1}$$

Among them, U_t represents user interaction behavior characteristics, mainly including click count, duration of stay, scroll depth, and frequency of visiting hotspots; V_t represents visual semantic characteristics, mainly including color contrast, layout hierarchy, concentration of visual focus, and style consistency; L_t represents interface layout structure characteristics, including module position, control size, information density, and area spacing; F_t represents feedback response characteristics, including satisfaction score, error operation rate, task completion time, and interaction interruption rate. To enhance the expression ability of states, this paper vectorizes these multi-dimensional features and constructs a unified state representation:

$$s_t = [u_t, v_t, l_t, f_t] \tag{2}$$

In the formula, u_t, v_t, l_t, and f_t correspond to the eigenvectors of each subspace. Considering that the characteristic quantities have significant differences in their units, it is necessary to normalize the original data. The normalization expression is:

$$x_t = \frac{x_t - x_{min}}{x_{max} - x_{min}} \tag{3}$$

Based on this, in order to depict the dynamic evolution process in the art design interaction, this paper introduces a state encoding function to fuse multiple source features, obtaining the implicit state representation of the interface:

$$h_t = \phi(W_u u_t + W_v v_t + W_l l_t + W_f f_t + b) \tag{4}$$

Here, W_u, W_v, W_l, W_f are the mapping matrices of various features, b is the bias term, and $\phi(\cdot)$ is the nonlinear activation function. The ht obtained through fusion can more completely describe the comprehensive performance of the interface in the current interaction stage. Further considering that user feedback has temporal continuity, this paper introduces the state information of the previous moment into the current state update process to form a dynamic state representation:

$$\tilde{h}_t = \psi(h_t, \tilde{h}_{t-1}) \tag{5}$$

Here, $\psi(\cdot)$ represents the temporal state update function. Through this process, the model can simultaneously retain the current interface features and historical interaction trajectory information, making the state modeling more in line with the change patterns of the art design interface during continuous use. The framework of art design interaction feedback interface state modeling driven by deep reinforcement learning is shown in Figure 1. This modeling method can better reflect the dynamic feedback characteristics of the art design interface and lay a foundation for the subsequent design of action space and learning of optimization strategies.

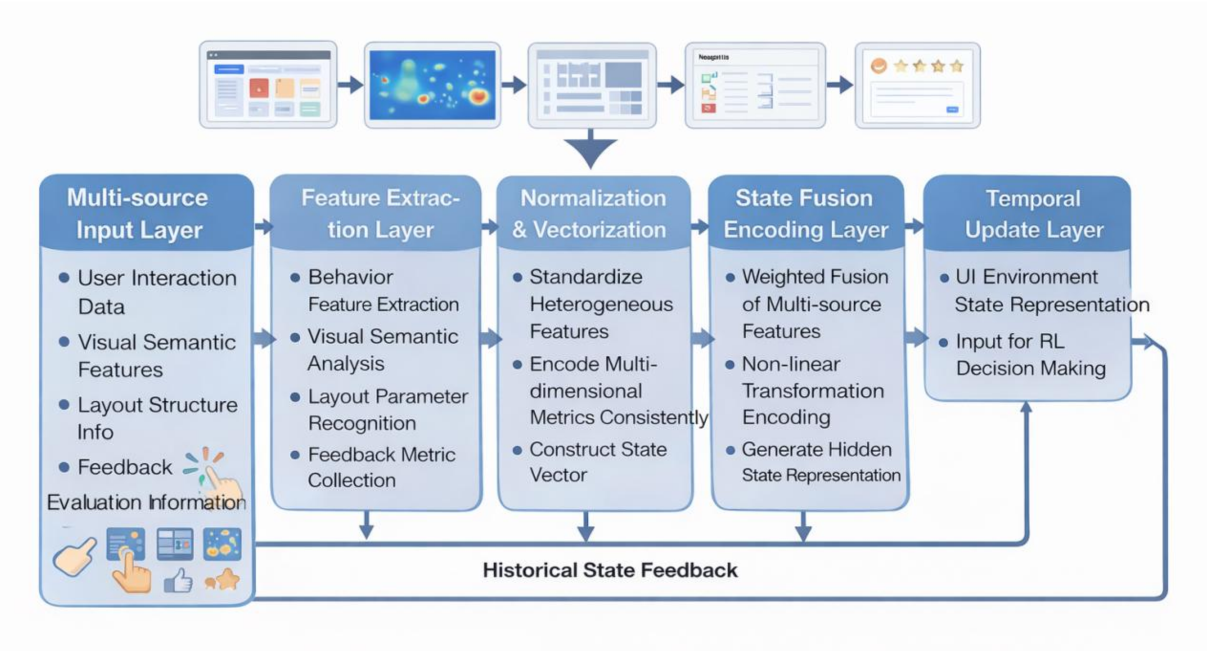

Figure 1: The state modeling framework for art design interaction feedback interface driven by deep reinforcement learning

3.2 Design of State Action Space and Reward Mechanism for Adaptive Interface Optimization

After completing the modeling of interface states, in order to enable deep reinforcement learning to continuously optimize the interactive interface of art design, it is necessary to further construct a state action space and reward mechanism oriented towards adaptive decision-making. This paper abstracts the interface optimization process as a Markov decision process, which is represented as:

$$M = \langle S, A, P, R, \gamma \rangle \tag{6}$$

where, S is the interface state space, A is the action space, P is the state transition probability, R is the reward function, and γ is the discount factor. Based on the state representation obtained in Section 3.1, this paper defines the action space as a set of controllable adjustments for interface layout, visual style, and information organization methods, to ensure that the strategy learning can not only reflect the characteristics of art design but also respond to real-time user feedback.

Considering that the interface optimization of art design has multi-dimensional linkage features, a single action is difficult to effectively reflect the real adjustment process. Therefore, this paper adopts a combined action representation method, and defines the action at time t as:

$$a_t = \{a_t^p, a_t^s, a_t^c, a_t^h, a_t^v\} \tag{7}$$

Among them, a_t^p represents the action for adjusting the position of interface elements, a_t^s represents the action for adjusting the size and spacing, a_t^c represents the action for switching the color scheme and visual style, a_t^h represents the action for reorganizing the information hierarchy, and a_t^v represents the action for controlling the visibility and display priority of modules. To avoid the excessive action space causing instability in training, this paper discretizes the continuous interface adjustments into several limited operation levels, such as leftward movement, rightward movement, enlargement, reduction, enhancement of contrast, weakening of interference, etc., enabling the strategy network to complete decision search within a controllable range.

Because the reward mechanism largely determines how the policy evolves, its design is especially important in art design interface optimization.This paper studies the interface of artistic design, which needs to take into account both interaction efficiency and visual aesthetics as well as user experience. Therefore, a multi-objective weighted reward function is proposed:

$$r_t = \lambda_1 E_t + \lambda_2 A_t + \lambda_3 U_t - \lambda_4 M_t - \lambda_5 D_t \tag{8}$$

Among them, "E_t" represents the interaction efficiency benefit, mainly used to reflect the reduction in task completion time and the degree of simplification of operation paths; "A_t" is the aesthetic matching benefit, used to measure the coordination of color selection, the balance of layout, and the clarity of visual hierarchy; "U_t" is the user satisfaction benefit; "M_t" is the error operation penalty item; and "D_t" represents the interface fluctuation penalty item, used to suppress the visual jumps caused by frequent adjustments. Further, the interaction efficiency reward can be expressed as:

$$E_t = \alpha_1 \frac{T_{t-1} - T_t}{T_{t-1}} + \alpha_2 \frac{N_{t-1} - N_t}{N_{t-1}} \tag{9}$$

where, T_t is the task completion time, and N_t is the number of operations required to complete the task. This formula can reflect the degree of efficiency improvement in completing the interaction task after interface optimization. The related action space and reward correlation indicators are shown in Table 2.

Table 2: Adaptive Interface Optimization Action Space and Reward Mechanism Design

Action category	Specific adjustment content	Trigger basis	Primary optimization goal	Associated reward indicators
Layout position adjustment	Moving the position of buttons, menus, image or text modules	Click hot zone offset, visual focus dispersion	Improving accessibility and layout coordination	Interaction efficiency reward, incorrect operation penalty
Size and spacing adjustment	Adjusting the size of controls, blank space spacing, module proportion	High accidental touch, reading congestion, unclear hierarchy	Improving operation convenience and reading comfort	Interaction efficiency reward, user satisfaction reward
Color scheme and style switching	Modifying the main color, contrast, texture and visual style	Low aesthetic score, insufficient visual recognition	Improving aesthetic matching and visual consistency	Visual aesthetic matching reward, user satisfaction reward
Information hierarchy reorganization	Adjusting the priority of titles, main text, and prompt information	Long information retrieval time, imbalance of attention distribution	Strengthening information organization and cognitive clarity	Interaction efficiency reward, visual aesthetic matching reward
Visibility and priority control	Controlling the display order of	High page load, excessive	Reducing cognitive load and interface	User satisfaction reward, interface

Action category	Specific adjustment content	Trigger basis	Primary optimization goal	Associated reward indicators
	modules, hiding redundant elements	interference information	interference	fluctuation penalty

Through the above design, the state space can accurately describe the dynamic characteristics of the art design interaction interface, the action space can cover the key adjustment dimensions such as layout, style, and information organization, and the reward mechanism uniformly constrains efficiency, aesthetics, and stability, thereby providing clear decision-making basis for the subsequent deep reinforcement learning strategy optimization.

3.3 Interface Layout and Interaction Feedback Optimization Process Driven by Deep Reinforcement Learning

This paper further constructs a deep reinforcement learning-driven interface layout and interaction feedback optimization process. This process takes the art design interface as the interaction environment, with the strategy network as the core decision module. Through the closed-loop iteration of "state perception - action execution - feedback collection - parameter update", the interface layout and display strategy are continuously optimized. Considering that interface adjustments have continuous feedback and stage evolution characteristics, this paper adopts an optimization method based on value function approximation to evaluate the long-term returns of each candidate action in the current state. The state-action value function is expressed as:

$$Q(s_t, a_t) = r_t + \gamma \max_{a_{t+1}} Q\,(s_{t+1}, a_{t+1}) \tag{10}$$

where s_t represents the current interface state, a_t represents the executed action, rt is the immediate reward, and γ is the discount factor. To reduce the impact of sample correlation on the stability of training, this paper introduces an experience replay mechanism, storing the interaction samples (s_t, a_t, r_t, s_{t+1}) in the memory pool, and updating the policy network through mini-batch sampling. Its loss function is defined as:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}[\,y_i - Q(s_i, a_i; \theta)]^2 \tag{11}$$

where θ is the network parameters, N is the sample batch size, and the target value yi is:

$$y_i = r_i + \gamma \max_{a'} Q\,({s'}_i, a'; \theta^-) \tag{12}$$

where θ^- represents the target network parameters. Through the alternating update of the main network and the target network, it can avoid excessive oscillation of the estimated value during the training process and improve the convergence of the interface optimization strategy.

In the specific execution, the system first receives user interaction data and interface state vectors, and then the policy network outputs the current optimal layout adjustment action, including module position fine-tuning, information hierarchy rearrangement, color style switching, and visibility control, etc. After the action is executed, the system records the user's stay duration, click hit rate, task completion efficiency, and satisfaction feedback in real time, and calculates the reward value based on this, and then feeds the new state back to the policy network to complete the next round of decision-making.With iterative training, the model progressively learns effective adjustment strategies for different art design scenarios, allowing the interface to improve in aesthetics, interaction efficiency, and feedback stability in a coordinated way. The overall optimization process for interface layout and interaction feedback under deep reinforcement learning is presented in Figure 2.

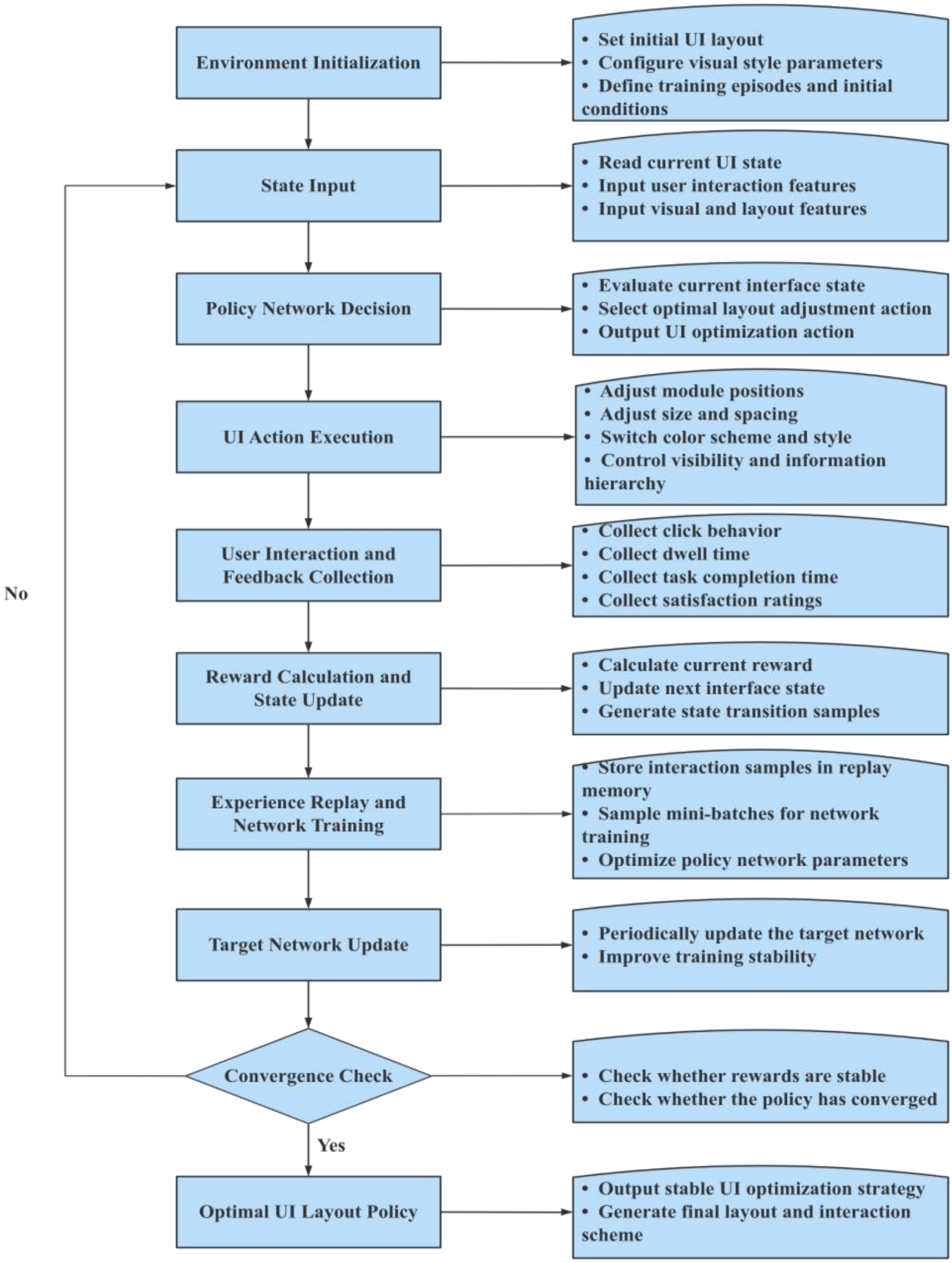

Figure 2: Flowchart of Interface Layout and Interaction Feedback Optimization Driven by Deep Reinforcement Learning

3.4 Application Implementation and Feedback Loop Update of Adaptive Interface Optimization

To make deep reinforcement learning practically applicable to interactive interface optimization in art design, this study builds, on the basis of the state representation, action selection, and policy training described above, an application-oriented implementation framework together with a feedback-driven updating mechanism. Rather than simply calling a policy obtained from offline training, the proposed framework links interface perception, policy inference, action execution, user feedback acquisition, and online updating within one integrated system.

From the perspective of implementation, this paper divides the adaptive interface optimization platform into the data perception layer, the strategy decision-making layer, the interface execution layer, and the feedback update layer. Among them, the data perception layer is used to obtain real-time data such as user click paths, dwell time, page scrolling positions, visual focus points, and satisfaction evaluations; the strategy decision-making layer is used to make judgments on interface operation behaviors under a given state vector; the interface execution layer maps the decision results to layout position adjustments, color style switching, module visibility control, and information hierarchy reorganization; the feedback update layer calculates the comprehensive feedback value based on the interaction results and decides whether to trigger online strategy updates. At time t, the strategy output is:

$$\mathrm{o_t} = \pi_\theta(\mathrm{s_t}) \tag{13}$$

where, s_t is the current interface state, $\pi_\theta(\cdot)$ is the strategy network, and o_t is the interface optimization action output. To ensure that the model output can smoothly act on the real interface, this paper introduces a constraint mapping mechanism at the action execution end, converting the original strategy output into deployable interface adjustment quantities, whose expression is:

$$\mathrm{a_t^*} = \rho(\mathrm{o_t}, \Omega) \tag{14}$$

where, $\rho(\cdot)$ represents the deployment mapping function, Ω represents the interface design constraint set, including layout boundaries, visual balance, information density upper limit, and interaction accessibility threshold. This design can avoid the strategy network generating excessive adjustments in the later training stage, ensuring that the interface update process conforms to the aesthetic and usability requirements in the art design scenarios.

In the feedback loop update stage, this paper combines user interaction efficiency, aesthetic evaluation, satisfaction changes, and error operation situations to construct closed-loop feedback indicators:

$$\mathrm{g_t} = \beta_1\mathrm{c_t} + \beta_2\mathrm{q_t} + \beta_3\mathrm{m_t} - \beta_4\mathrm{e_t} \tag{15}$$

where, η is the update step size, θ^t is the parameter estimation based on the latest interaction samples.

In practical applications, each time the system modifies the interface, it also collects feedback information, conducts strategy analysis and updates. This forms a closed-loop mechanism of "interface adjustment - user response - feedback quantification - strategy update - further adjustment". Compared with traditional static interface design, this method can dynamically adjust the page layout and style parameters based on interaction situations, enhancing the flexibility of the interface in diversified and artistic design. The application implementation and feedback-loop updating functions of the adaptive interface optimization framework are summarized in Table 3.

Table 3: Design of Application Implementation and Feedback Loop Update Functions of Adaptive Interface Optimization

Module Layer	Main Function	Input Content	Output Result	Application Role
Data Perception Layer	Collect user behavior and visual feedback information	Clicks, dwell time, scrolling, heatmap regions, ratings	Multi-source interaction data	Provides real-time support for state updating
Strategy Decision Layer	Invoke the policy network to generate optimization actions	Current state vector, historical feedback	Layout and style adjustment scheme	Completes adaptive interface decision-making
Interface Execution Layer	Map strategy outputs to actual interface adjustments	Action outputs, design constraints	New interface configuration	Ensures that optimization results are deployable and visually presentable
Feedback Update Layer	Quantify interaction results and trigger online learning	Satisfaction, efficiency, misoperation rate	Comprehensive feedback values and updated parameters	Builds a continuously iterative closed loop
Strategy Maintenance Layer	Preserve stable strategies and suppress abnormal fluctuations	Historical strategies, current update results	Optimized policy model	Improves the long-term operational stability of the system

4 Results

4.1 Dataset and Experimental Scenario Construction

To verify the practical effectiveness of the proposed method in optimizing the adaptive interface for interactive feedback in art design, we constructed an experimental data set based on interface samples, user interaction logs, and subjective evaluation information. We conducted comparative tests in various art design application scenarios. The data mainly included three typical scenarios: digital exhibition interface, poster customization interface, and cultural and creative e-commerce display interface. These scenarios have strong visual design characteristics and also contain rich interaction feedback information, which can well reflect the application features of art design interfaces. During the experiment implementation, screenshots of the interfaces, layout parameters, click trajectories, dwell times, scroll depths, task completion times, and satisfaction ratings were collected simultaneously. Based on this, a data system composed of interface features, behavioral feedback, and evaluation results was formed. To avoid overly simplistic samples, the tests were conducted on both desktop and mobile platforms, and users with different aesthetic preferences were involved in the interaction process to make the obtained data closer to the dynamic changes in real usage scenarios. The final dataset includes 5,100 interface samples, 68,000 interaction sessions, and 10,200 subjective evaluation records, providing a solid basis for subsequent data preprocessing, metric calculation, and ablation analysis. The experimental scenarios and data sets are shown in Table 4.

Table 4: Composition of Dataset and Experimental Scenarios

Scenario Number	Experimental Scenario	Interface Sample Number	Interaction Session Number	Subjective Evaluation Number	Main Task
S1	Digital Exhibition Guide Interface	1800	24,600	3,600	Navigation Search and Visual Guidance Optimization
S2	Art Poster Customization Interface	1600	21,300	3,200	Layout Adjustment and Style Matching Optimization
S3	Cultural and Creative E-commerce Display Interface	1700	22,100	3,400	Information Hierarchical and Interaction Efficiency Optimization
Total	—	5,100	68,000	10,200	—

4.2 Data Preprocessing

To ensure the effectiveness and stability of the model training as well as the accuracy of the experimental results, after the data set was constructed, we carried out unified preprocessing on the original samples. This step mainly involved preprocessing in terms of edge interface layout parameters, user interaction logs, visual semantic features, and subjective evaluation data. Due to the presence of a small number of missing items during the collection process, these shortcomings were supplemented using the method of averaging neighboring samples; for some categorical features such as interface style type, color scheme, and terminal device category, they were numerically processed.For continuous features, such as dwell time, task completion time, module area proportion, and satisfaction score, they are normalized according to the method described in Section 3.1. At the same time, to reduce the interference of abnormal interaction records on model training, the standard score method is used to identify abnormal samples, whose expression is:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{16}$$

where xi is the sample feature value, μ is the mean of this feature, and σ is the standard deviation. When ｜zi｜ > 3, this sample is determined as an abnormal value and is removed. After the above processing, this paper divides the data into training set, validation set, and test set in a ratio of 7:2:1, providing a unified data basis for subsequent evaluation index calculation and model performance analysis.

4.3 Evaluation Indexes

To comprehensively evaluate the application effect of deep reinforcement learning in the adaptive interface optimization for artistic design interaction feedback, this paper constructs an evaluation index system from four dimensions: interaction efficiency, operation accuracy, user subjective experience, and comprehensive optimization performance. Considering that artistic design interfaces not only emphasize task completion efficiency but also value visual experience and aesthetic feedback, the evaluation process takes into account both objective behavior data and subjective perception results to ensure the completeness and credibility of the experimental conclusion.

Interaction efficiency is measured by the average task completion time, which is expressed as:

$$T_{avg} = \frac{1}{N}\sum_{i=1}^{N} T_i \tag{17}$$

Among them, T_i represents the time required for the i-th sample to complete the specified task, and N represents the number of test samples. The smaller the T_{avg}, the more conducive the interface layout is to enabling users to complete the operation quickly. The accuracy of the operation is represented by the effective click rate:

$$A_{click} = \frac{C_{valid}}{C_{total}} \times 100\% \tag{18}$$

Among them, C_{valid} represents the number of valid clicks, and C_{total} represents the total number of clicks. This indicator can reflect whether the position of interface elements and the design of information hierarchy are clear and reasonable.

The subjective experience of users is measured by the average satisfaction level, and its expression is:

$$S_{user} = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{19}$$

Among them, S_i represents the user's rating for the visual effect of the interface, the smoothness of interaction, and the overall experience. The higher the satisfaction level, the more it indicates that the optimized interface better conforms to the user's aesthetic preferences and usage expectations. To further evaluate the model's comprehensive adaptability to artistic design features, this paper constructs a comprehensive performance index:

$$P_{com} = \omega_1\widehat{A}_{click} + \omega_2\widehat{S}_{user} + \omega_3\widehat{M}_a - \omega_4\widehat{T}_{avg} \tag{20}$$

Here, $\widehat{A}_{click}$, $\widehat{S}_{user}$, $\widehat{M}_a$, and $\widehat{T}_{avg}$ represent the normalized effective click rate, user satisfaction, aesthetic matching degree, and average task completion time, respectively. ω1 to ω4 are the corresponding weights. The aesthetic matching degree $\widehat{M}_a$ is obtained by normalizing and weighting the results of three aesthetic evaluations: color coordination, layout balance, and style consistency. The rating data comes from the subjective evaluation of users during the testing phase and the expert review results. The weights ω_1 to ω_4 in the comprehensive performance index are determined through the validation set optimization to ensure the balance of interaction efficiency, subjective experience, and aesthetic expression. This index can comprehensively reflect the overall performance of the interface in terms of efficiency, aesthetics, and interaction experience. Through the above evaluation system, this paper can examine the actual effectiveness of the proposed method in the task of optimizing artistic design interfaces from multiple aspects.

4.4 Abandonment Study

The experiment adopts a two-stage verification method of "offline pre-training + online feedback fine-tuning". The complete model first completes the initial strategy learning on the training set, and then performs small-step strategy updates based on new collected feedback during the testing interaction process; the "remove feedback closed-loop update" scheme only retains the fixed parameters obtained from offline training and no longer executes online updates. To verify the actual contribution of each key module to the interface optimization effect, this paper conducts an abandonment study under the same data set and training parameters. Using the complete model as the benchmark, three control schemes are set to remove visual semantic state encoding, remove multi-objective reward mechanism, and remove feedback closed-loop update, respectively, to compare the interface optimization performance under different module absence conditions. The abandonment experiments still use average task completion time, effective click rate, user satisfaction, and comprehensive performance index as evaluation criteria, and the results are shown in Table 5.

Table 5: Comparison of Abandonment Experiment Results

Model Scheme	Average Task Completion Time T_{avg}/s	Effective Click Rate A_{click}/%	Users' Satisfaction S_{user}	Comprehensive Performance Index P_{com}
Complete Model	11.8	92.6	4.53	0.912
Remove Visual Semantic State Encoding	13.1	90.2	4.21	0.874
Remove Multi-objective Reward Mechanism	12.7	88.9	4.18	0.852
Remove Feedback Closed-loop Update	12.9	89.7	4.24	0.861

From the results, the complete model performs optimally in all four indicators, indicating that the state modeling, reward design, and closed-loop update mechanism proposed in this paper have a strong collaborative effect. Among them, after removing visual semantic state encoding, the average task completion time increases from 11.8 s to 13.1 s, and the user satisfaction decreases from 4.53 to 4.21, indicating that the color, hierarchy, and style semantic information in the artistic design interface provides important support for strategy learning. After removing the multi-objective reward mechanism, the effective click rate decreases most significantly, from 92.6% to 88.9%, indicating that a single feedback is difficult to simultaneously balance efficiency and aesthetic goals. After removing the feedback closed-loop update, the comprehensive performance index drops from 0.912 to 0.861, reflecting that online feedback correction has a significant effect in improving the stability and continuous adaptability of the strategy. Overall, each module has a positive contribution to the model performance improvement, and the reward mechanism and closed-loop update have a more prominent impact on the final optimization effect.

5 Discussion

5.1 Performance Advantage Analysis Compared with Existing Interface Optimization Methods

To verify the practical advantages of the method proposed in this paper in the adaptive interface optimization for artistic design interaction feedback, this paper selects the rule-driven interface optimization method, the genetic algorithm optimization method, the traditional reinforcement learning method, and the ordinary deep reinforcement learning method as the comparison objects, and analyzes them from four dimensions: average task completion time, effective click rate, user satisfaction, and comprehensive performance indicators. The comparison of the comprehensive performance of different methods is shown in Table 6.

Table 6: Performance Comparison of Different Interface Optimization Methods

Method	Average Task Completion Time T_{avg} /s	Effective Click Rate A_{click}/%	User Satisfaction S_{user}	Comprehensive Performance Indicator P_{com}
Rule-driven Interface Optimization Method	15.4	86.7	3.92	0.781
Genetic Algorithm Optimization Method	13.8	88.6	4.08	0.826
Traditional Reinforcement Learning Method	13.1	89.4	4.16	0.847
Ordinary Deep Reinforcement Learning Method	12.4	90.8	4.34	0.881
This paper method	11.8	92.6	4.53	0.912

The results show that although the rule-driven method has lower implementation complexity, it is difficult to adapt to changes in user preferences and is prone to response lag and rigid layout adjustment in complex interface scenarios; the genetic algorithm can improve the layout search ability to a certain extent, but its optimization process deviates from the real-time interaction requirements; the traditional reinforcement learning method has dynamic decision-making capabilities, but its convergence speed and policy stability in high-dimensional state spaces are still limited. In contrast, this paper method effectively enhances the continuous adaptation ability and multi-dimensional goal coordination ability of interface optimization by introducing visual semantic state modeling, multi-objective reward mechanism, and feedback closed-loop update. Experimental results show that the average task completion time of this paper method is reduced to 11.8 s, which is 0.6 s shorter than the ordinary deep reinforcement learning method and 3.6 s shorter than the rule-driven method; the effective click rate reaches 92.6%, user satisfaction reaches 4.53, and the comprehensive performance indicator reaches 0.912, which are 1.8%, 0.19, and 0.031 higher than those of the ordinary deep reinforcement learning method, respectively, indicating that this paper method shows more obvious advantages in interaction efficiency, aesthetic adaptation, and overall optimization effect.

5.2 Verification of Model Adaptability and Stability under Complex Interaction Feedback Conditions

To further verify the adaptability and stability of the method proposed in this paper under complex interaction feedback conditions, this paper introduces three types of perturbation factors: enhanced feedback noise, increased user preference fluctuations, and increased multi-task switching frequency, and divides the scene complexity into 5 levels for testing. The trend of the comprehensive performance indicators of each method under different complexity conditions is shown in Figure 3.

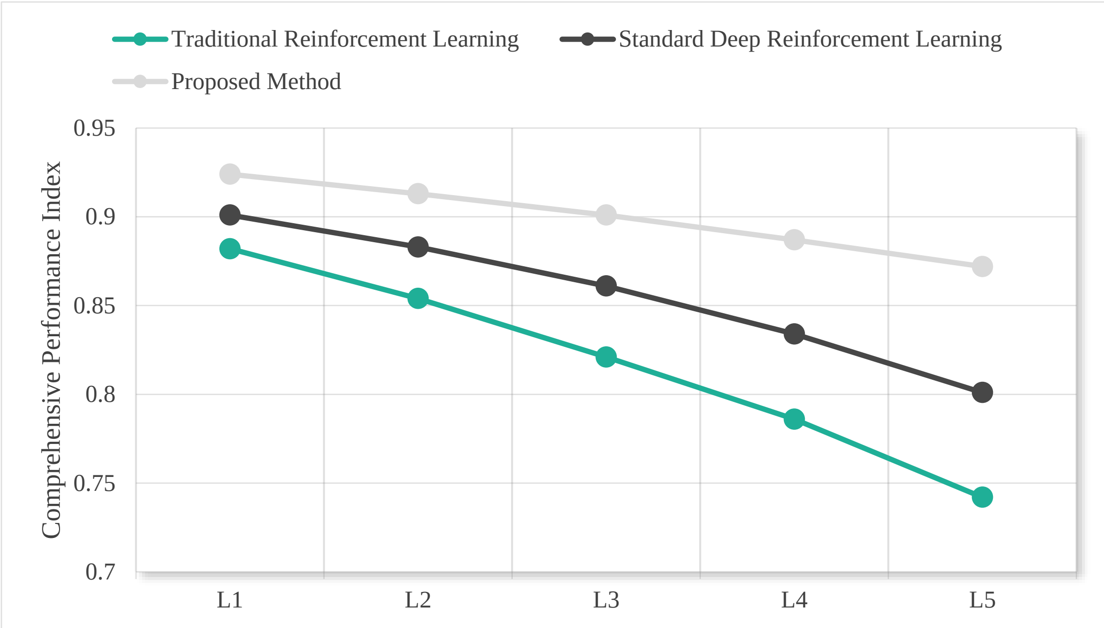

Figure 3: Line graph showing the changes in comprehensive performance indicators of different methods under complex interactive feedback conditions

Overall, as the complexity of the interaction feedback continuously increases, the performance of each model shows a downward trend, but the degree of decline varies significantly. The traditional reinforcement learning method is greatly affected by state disturbances under high complexity conditions, and the performance fluctuation is the most obvious; the ordinary deep reinforcement learning method can maintain a certain stability, but it still shows a significant attenuation under complex preference changes and continuous feedback shocks. In contrast, the method proposed in this paper, by leveraging visual semantic state modeling, multi-objective reward constraints, and feedback loop update mechanism, can more effectively absorb dynamic feedback information and maintain higher policy stability. From Figure 3, it can be seen that the comprehensive performance indicators of this method decrease from 0.924 in the low complexity scenario to 0.872 in the high complexity scenario, with an overall decrease of only 0.052; while the ordinary deep reinforcement learning method decreases from 0.901 to 0.801, a decrease of 0.100; the traditional reinforcement learning method decreases from 0.882 to 0.742, a decrease of 0.140. Especially at the highest complexity level, this method is 0.071 and 0.130 higher than the ordinary deep reinforcement learning method and the traditional reinforcement learning method, respectively, indicating that it has stronger adaptability and better operational stability in complex interaction feedback environments.

5.3 Calculation of Resource Consumption and Feasibility Assessment for Large-scale Applications

To evaluate the deployment feasibility of the method proposed in this paper in large-scale art design interaction scenarios, this paper further tested the changes in the average response time of each method under different concurrent user scales, and used these changes to measure the computational resource consumption level and online service capability of the model. The curves of the average response time changes of each method under different concurrent conditions are shown in Figure 4. As the number of concurrent users continues to increase, the response times of each method all show an upward trend, but the growth rates are significantly different. The rule-driven method has a relatively fast response in the early stage, but lacks dynamic adaptation ability in complex interface adjustment tasks; the traditional reinforcement learning method has large fluctuations in response under high concurrency conditions; the ordinary deep reinforcement learning method has a certain stability, but the resource occupation increases rapidly. In contrast, the method proposed in this paper controls the online inference cost by using state compression representation, policy reasoning constraints, and feedback closed-loop update mechanism, while ensuring the optimization effect.

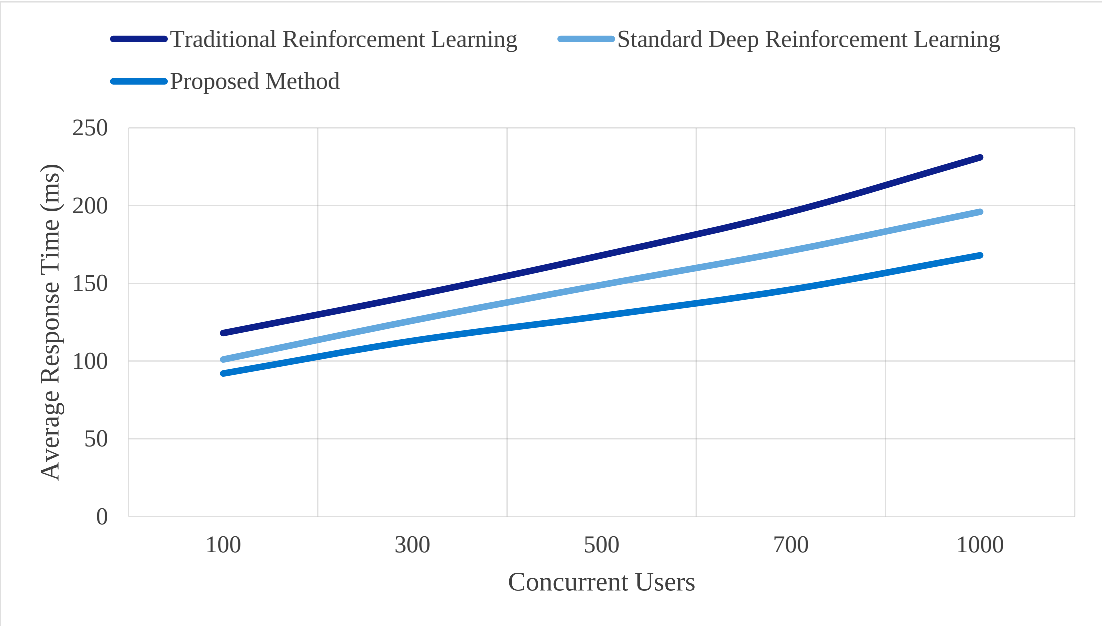

Figure 4: Curve chart showing the average response time variations of each method under different concurrency scales

From Figure 4, it can be seen that when the concurrent user scale increases from 100 to 1000, the average response time of the method proposed in this paper increases from 92 ms to 168 ms, a total increase of 76 ms; the ordinary deep reinforcement learning method increases from 101 ms to 196 ms, an increase of 95 ms; the traditional reinforcement learning method increases from 118 ms to 231 ms, an increase of 113 ms. Especially under the condition of 1000 concurrent users, the method proposed in this paper is 28 ms shorter than the ordinary deep reinforcement learning method and 63 ms shorter than the traditional reinforcement learning method, indicating that it has better real-time response capability and engineering deployment feasibility in large-scale application scenarios.

5.4 Analysis of the application value of model results in the optimization of art design interfaces

In addition to the improvement in performance indicators, the value of this method in the optimization of art design interfaces also lies in the transferability and scene adaptability in the practical application level. To further illustrate the application significance of the model results, this paper combines three typical scenarios: digital exhibition and navigation interface, art poster customization interface, and cultural and creative e-commerce display interface, and summarizes and analyzes the actual performance after optimization. The relevant results are shown in Table 7. It can be seen that the adaptive optimization mechanism driven by deep reinforcement learning not only can shorten the time for users to complete core tasks, but also can improve the visual hierarchy, aesthetic matching degree and interaction smoothness of the interface. In the digital exhibition scenario, the model through strengthening visual focus guidance and navigation hierarchical organization enables users to locate the target content faster; in the art poster customization scenario, the model can dynamically adjust the layout and color style based on interaction feedback, improving the style adaptability; in the cultural and creative e-commerce scenario, the model through optimizing information sorting and module visibility relationship enhances the browsing efficiency and purchase guidance ability of the display interface.

Table 7: Application value performance of model results in different art design scenarios

Scenario	Primary optimization content	Task completion time reduction/%	User satisfaction improvement	Visual aesthetic matching degree improvement/%	Comprehensive performance indicator Pcom
Digital exhibition navigation interface	Strengthening visual guidance and navigation hierarchical optimization	18.7	0.41	9.8	0.903
Art poster customization interface	Dynamic adjustment of layout structure and color style	15.9	0.52	12.6	0.918
Cultural and creative e-commerce display interface	Optimization of information sorting and module visibility relationship	17.4	0.47	10.9	0.914

It can be seen from Table 7 that the task completion time reduction in all three scenarios is over 15%, and user satisfaction has increased by 0.41, 0.52 and 0.47 respectively, and the comprehensive performance indicators are all stable at above 0.90. Among them, the comprehensive performance indicator of the art poster customization interface reaches 0.918, indicating that this method has more prominent application potential in art design tasks emphasizing aesthetic expression and individual generation. Overall, the proposed method has good scene generalization ability and engineering implementation value, which can provide effective support for the intelligent optimization of art design interfaces.

5.5 Comparison with related research and discussion on method innovation

Based on the relevant research in Chapter 2, existing deep reinforcement learning studies mainly focus on control optimization, resource scheduling, multi-objective decision-making and intelligent environment regulation, although the effectiveness of this method in dynamic optimization has been verified, research on the optimization of art design interaction feedback interfaces is still relatively limited. Existing studies emphasize efficiency improvement, path search or resource allocation, and pay insufficient attention to the collaborative relationship between interface visual semantics, aesthetic preferences and interaction experience. Therefore, in the art design scenario, it is often difficult to balance functional optimization and aesthetic expression. In contrast, this paper introduces deep reinforcement learning into the task of interface optimization in art design, no longer treating the interface as a static display object, but modeling it as an evolving system with sustainable perception, dynamic decision-making, and feedback update, thereby enhancing the alignment of the method with the actual scenario.

From the perspective of method design, the innovation of this paper mainly lies in three aspects: (1) In terms of state representation, it does not merely model based on a single interaction information, but integrates user behavior data, visual semantic features, interface layout structure, and feedback evaluation results within the same framework, enabling the strategy network to not only identify the behavioral changes during the operation process, but also grasp the semantics and expression characteristics in the art design scenario, thereby enhancing the sufficiency of state description. (2) Regarding the design of the reward function, we combine the characteristics of art design tasks that balance functionality and aesthetics, and incorporate interaction efficiency, aesthetic matching degree, user satisfaction, and the impact of incorrect operations into the optimization goals, no longer being limited to the training method driven by a single indicator. Therefore, it is more suitable for handling interface optimization problems in complex scenarios. (3) In the process of system implementation, a feedback closed-loop update mechanism oriented towards practical applications is introduced, enabling the model to continuously adjust the existing strategies based on real-time interaction results. As a result, the model shows stronger adaptability in online use and better long-term stability. Based on the experimental results mentioned earlier, it can be seen that the comprehensive performance indicators of this method reach 0.912, which is not only higher than the 0.881 of ordinary deep reinforcement learning methods, but also significantly better than traditional reinforcement learning and rule-driven methods, indicating that the proposed method has certain innovative value in technical path and application effect. Overall, this paper has carried out a relatively systematic expansion in the integration of deep reinforcement learning and art design interface optimization, providing a reference implementation idea for subsequent related research.

6 Conclusion

This paper focuses on the task of optimizing the adaptive interface for art design through interactive feedback. It has developed a deep reinforcement learning method that integrates multi-source state modeling, combined action decision-making, multi-objective reward constraints, experience replay training, and feedback loop update. Experimental results show that this method outperforms rule-driven, genetic algorithms, traditional reinforcement learning, and ordinary deep reinforcement learning methods in terms of average task completion time, effective click rate, user satisfaction, and comprehensive performance indicators. The comprehensive performance indicator reaches 0.912; it still maintains 0.872 under the highest complexity condition, and the average response time is 168 ms when there are 1000 concurrent users. It also demonstrates good transfer and adaptation capabilities in digital exhibition, art poster customization, and cultural and creative e-commerce scenarios. The results show that deep reinforcement learning can effectively support both dynamic optimization and real-time deployment in art design interfaces.

Further analysis reveals that the advantages of our proposed method extend beyond the improvement of individual performance indicators. It can also achieve coordinated optimization in the three major goals of "efficiency - aesthetics - response". By incorporating users' behavioral characteristics, graphical representation information, layout structure parameters, and subjective evaluation results into the state representation, the model can better perceive changes in the interface. Additionally, due to the introduction of multi-objective incentives and feedback update mechanisms, the entire system can continuously correct and optimize its optimization path during real interaction, thereby enhancing the robustness, adaptability, and personalized expression degree of the interface object layout process. Moreover, ablation experiments and experiments in complex environments have demonstrated that visual semantic encoding, reward design, and online update mechanisms are powerful aids to the overall performance of the model.

Overall, this paper systematically explores the application path of deep reinforcement learning in optimizing the interactive feedback interface of art design from three aspects: method construction, system implementation, and experimental verification. It provides a new research perspective for intelligent interface design and the integration of human-computer interaction. Of course, we should also recognize the shortcomings in this study, such as the long-term aesthetic preference model of users still needs further in-depth exploration, and the applicability of style transfer in different cultural backgrounds still requires more experimental verification. Future work may incorporate richer multimodal perception data, broader cross-platform interaction samples, and generative design mechanisms to improve the model’s generalization ability, interpretability, and practical value in complex art design tasks.

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