

A Study on Computer Simulation and User Experience Evaluation for Product Interface Design from the Perspective of Human-Computer Interaction

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The current user interface design processes do not include early quantitative estimates of how users interact with and experience an interface. Therefore, when poor usability and unsatisfactory user experience are discovered, the issues often emerge only after the product has been released. This paper proposes using an interface design analysis method that incorporates insight into user interface interaction modeling, computer simulation, and user experience evaluation within a human-computer interaction context. By formally modeling the interface structure, user tasks, and operational behaviors, computer simulations may be used to predict the user's path, the success of their task completion, and the distribution of errors. The simulation results are then validated against multi-dimensional user experience evaluation indicators. This enables the systematic evaluation and optimization of interface design during the early stages of development. Experimental results show that the simulated user operation paths maintain 88% consistency with real user behavior under interface scheme S1, with the lowest average completion time for core tasks at 32 seconds; in S5, the highest error frequency is 8.1%. After simulation-driven optimization, task completion time is reduced to 32–44 seconds, and the overall user experience score improves to above 4.0/5. The research results demonstrate that the proposed method provides a model- and data-driven approach for early-stage validation and experience evaluation during the design of an interface.

Keywords: human-computer interaction modeling; interface interaction simulation; user experience prediction; operational path simulation; task performance evaluation

1. INTRODUCTION

Digital products are increasing in both complexity and frequency of use, which has changed what is meant by an interface: instead of being merely a display of information, it now involves user cognition, interaction and action. The interface design quality determines the usability of the sys-

tem, its efficiency, and the overall user experience. Human-Computer Interaction (HCI) research has found that today's interface has a much broader scope than simply serving as a visual representation. The interface has become the fundamental interaction point between the user's cognitive processes and the functional logic of the system; the resulting change has transformed the scope of the interface design to one that comprises artistry, engineering technical limitations,

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and analysis of human factors [1]. By taking a comprehensive view of the interface design from the perspective of information systems engineering, and by applying computer simulation and quantitative assessment techniques to the analysis of interfaces, the design team can significantly reduce the costs associated with iterative design processes, while increasing the scientific rigor and verifiability of the design decisions being made [2].

Current studies indicate that product interface design presents numerous obstacles in practical settings. Multiple factors such as cognitive load, task structure or interface layout impact user interaction behavior. Design decisions are heavily influenced by judgments based on experience [3–4] as the dynamic characteristics cannot be accurately defined during the design phase. Conversely, the absence of a uniform quantitative modeling method for user experience, which is based on subjective experiences and objective behaviors, and the lack of clear correlation between different evaluation indicators, hinder the use of these results in design feedback [5–6]. A balance exists between the artistic expression of interface design and engineering performance limitations, which creates difficulties when considering visual style, information density, and interaction efficiency under a common analytical framework. These issues are strongly represented in the literature [7–8].

Several different research methods have been suggested for addressing the above difficulties. Usability engineering and user testing is one of the methods for determining the success of an interface design through a series of experiments performed by real users; however, this approach requires the actual involvement of real users to ensure valid results, which can result in high cost and time delays in providing feedback on the tested product [9–10]. In addition, cognitive models or task analysis are often used to formally define how users operate, but this typically includes a detailed description of the local process, without unifying the overall interface structure or multi-tasking scenarios [11–12]. In recent years, computer simulation has been used to simulate user behavior and interaction flows. However, related research often uses simulation results for operational efficiency, path optimality, or time cost analysis. There is a lack of clear mapping between simulation outputs and user experience evaluation indicators, and a unified methodological framework for experience prediction and verification has not yet been formed. This makes it difficult for simulation analysis in the interface design stage to directly serve user experience evaluation and design decision optimization [13–14].

To address the lack of early quantitative verification of user interaction behavior and experience results in the interface design stage, this paper proposes a comprehensive method integrating interface interaction modeling, user behavior computer simulation, and experience evaluation from a human-computer interaction perspective. First, this study formally models the interface structure, functional hierarchy, and user tasks, transforming design elements into computable interaction parameters. Then, based on a simulation model, it analyzes the user operation path, task execution process, and potential error distribution. Building upon this, it introduces multi-dimensional user experience evaluation indicators to verify the correspondence between simulation results and

user experience performance. Based on this, it establishes an interface design feedback and optimization mechanism, constructing a closed-loop interface design evaluation system driven by simulation analysis and guided by experience prediction. By achieving predictable and quantifiable verification of user experience in the early stages of design, this method provides continuous feedback and theoretical support for the optimization of interface design.

2. HUMAN-COMPUTER INTERACTION SIMULATION AND EXPERIENCE INTEGRATION METHOD FOR EARLY-STAGE EVALUATION OF INTERFACE DESIGN

2.1 Construction of Interface Interaction Model Based on Human-Computer Interaction Theory

From the perspective of human-computer interaction, a product interface is not a static, visual outcome. It is an interactive medium in which users and systems continuously exchange information via perception, cognition, and operation. Therefore, interface modeling needs to cover three dimensions: the structural layer, the task layer, and the behavioral layer [15–16]. In this study, the goal of modeling interface interaction features is defined as follows. Without introducing experimental data, interface design elements, user task logic, and operation-behavior mappings are transformed into formal models that are computable and suitable for simulation. This provides a consistent input for subsequent user behavior simulation and user experience evaluation.

The structural interface has a functional grouping of all interfaces combined into an ordered series of functional units. Each functional unit must have both a precise meaning associated with its interaction, a weight through a visual aspect [17–18]. To describe the structural relationship between functional units in the interface, this paper uses a directed graph to model the interface hierarchy and jump logic. The interface structure can be represented as:

$$U = \{u_1, u_2, \dots, u_n\} \quad (1)$$

In Formula (1), U represents the set of interface functional units, and u_i represents the i -th interface unit. Its attributes are described by position parameters, information density parameters, and interaction trigger attributes, used to characterize the engineering features of the interface in terms of visual layout and functional distribution.

User interaction with an interface is not random, but is defined by the user completing a goal-directed task [19–20]. The sequence of operations that make up a user's task is defined by fixed start and end points.

$$T = \{\tau_1, \tau_2, \dots, \tau_m\} \quad (2)$$

In Formula (2), T is the set of user tasks, and τ_j is the j -th task. This definition establishes a formal correspondence

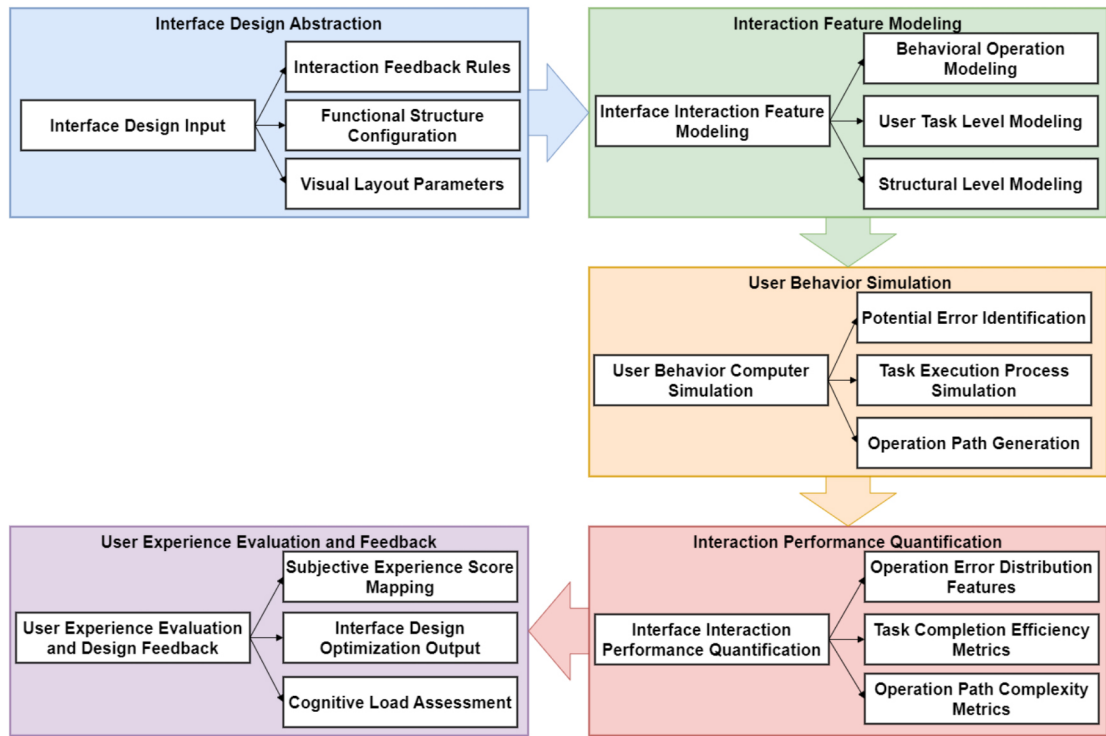


Figure 1 Framework of human-computer interaction-driven interface simulation and experience evaluation method.

between the interface functional structure and the user's goal, shifting the interaction analysis from the interface presentation layer to the task-driven layer.

At the behavioral level, user operations are modeled as state transition processes occurring under the interface structure and task constraints [21–22]. This paper takes the user's operation process in the interface as a state sequence.

$$S = (s_0, s_1, \dots, s_k) \quad (3)$$

In Formula (3), s_0 represents the initial state of the task; s_k represents the completed state of the task; intermediate states correspond to the user's operation results on different interface units. State transitions are influenced by both interface structure constraints and task objectives.

Based on this modeling, the complexity of interface interaction is used to measure the operational load of interface design from an engineering perspective. It is defined by combining the depth of the interface structure and the length of task operations as follows:

$$C = \sum_j^m = 1\alpha_j \cdot |S_j| \quad (4)$$

In Formula (4), C is the overall interaction complexity of the interface. S_j is the length of the state sequence for task τ_j ; α_j is the task weight coefficient.

After unified modeling of interface structure, task logic, and user behavior, this study then introduces the effect of user cognitive load during interaction. Cognitive load is treated as an important bridge between artistic expression and engineering constraints in interface design [23–24]. The cognitive load function is defined as:

$$L = f(\rho, d, \lambda) \quad (5)$$

In Formula (5), L represents the user's cognitive load level during interface interaction; ρ represents the interface information density parameter; d represents the interface hierarchy depth; λ represents the unit task operation frequency. This function is used to determine the overall influence of interface visual organization and interaction logic on the user's cognitive resource consumption.

To present the above modeling ideas and their position in the methodology used in this study, a method framework is constructed based on the analysis in this section, as shown in Figure 1.

Figure 1 illustrates the complete process of interface design simulation and evaluation. Starting from the visual layout, functional structure, and interaction feedback rules of the interface design input, it goes through formal modeling of interaction features, including three levels: interface structure, user tasks, and operational behaviors. Then, it enters the user behavior computer simulation stage, generating operation paths, simulating task execution, and identifying potential mis-operations. Subsequently, the interface interaction performance is quantified by operation path complexity, task completion efficiency, and operation error distribution. Finally, cognitive load assessment, subjective experience score mapping, and design optimization suggestions are output, achieving closed-loop analysis and optimization from design input to user experience feedback.

2.2 Design of Computer Simulation Engine for User Interaction Behavior

After formal modeling of interface interaction features, computer simulation of user behavior is used to transform the

Table 1 User behavior computer simulation parameters and value ranges.

Parameter Category	Parameter Name	Symbol	Value Range
Interface Attributes	Visual Saliency Weight	ω	0.1–1.0
Interface Attributes	Information Density Coefficient	σ	0.2–0.9
Interaction Logic	Unit Logical Distance	δ	1–5
User Behavior	Operational Stability Coefficient	μ	0.8–1.2
Feedback Characteristics	Feedback Clarity Parameter	η	0.3–1.0

static interface structure into a dynamic interaction process, enabling engineering prediction of user operations during the design stage [25–26]. This study defines user behavior simulation as: the process of repeatedly calculating user operation decisions, path selection, and time consumption under given interface structure and task constraints. Its goal is not to reproduce individual differences, but rather to characterize the systematic impact of interface design on overall interaction performance and user experience [27–28].

In the simulation process, the user is abstracted as a decision-making subject driven by task objectives, and their operational performance within the interface is described by state transition probabilities [29–30].

$$P_{ij} = g(\omega_i, \delta_{ij}) \quad (6)$$

In Formula (6), P_{ij} represents the probability that a user can transition from interface unit u_i to u_j under the current task constraint; ω_i represents the visual saliency weight of interface unit u_i ; δ_{ij} represents the interaction logic distance between units, used to reflect the combined influence of interface layout and functional association on user decision-making.

The time taken for a user to complete an interface operation is modeled as a function jointly determined by the interface structure complexity and operation proficiency, expressed as:

$$t_k = h(c_k, \mu) \quad (7)$$

In Formula (7), t_k denotes the execution time of the k -th operation. c_k represents the interaction complexity parameter of this operation. μ is the user operation stability coefficient. It controls the range of time variation across different operation stages in the simulation. During full task execution, the main outputs of user behavior simulation are the operation path sequence and the cumulative time cost. The total task completion time is defined as:

$$T = \sum_{k=1}^K t_k \quad (8)$$

In Formula (8), T represents the total time for a user to complete a single task. K denotes the number of operations required for the task. This result provides a direct input for later evaluation of interface interaction efficiency.

During simulation, mis-operations are treated as a direct result of mismatch between interface design and user cognition. Their probability is jointly determined by interface information density and operation feedback strength. It is defined as:

$$E = q(\sigma, \eta) \quad (9)$$

In Formula (9), E represents the probability of mis-operation per unit task; σ represents the interface information density parameter; η represents the operation feedback clarity parameter.

To ensure that the simulation model has a consistent computational basis under different interface schemes and task conditions, this study introduces a unified parameter configuration system in user behavior simulation, as shown in Table 1.

Table 1 shows the unified constraints on the core parameters involved in the simulation, allowing differences in the artistic expression of interface design to be incorporated into the engineering simulation model through parameter changes. Independent parameter settings ensure the sensitivity of simulation results to adjustments in interface structure and interaction logic, while avoiding interference from non-design factors in the user experience evaluation process.

2.3 Quantitative Indicators for Interaction Performance in Experience Evaluation

After completing the interface interaction feature modeling and computer simulation of user behavior, the simulation system outputs the user's operation sequence, time consumption, and error trigger records under given interface structure and task constraints. This section presents a set of quantitative indicators for interaction performance that directly correspond to the goals of product interface design, transforming the subjective judgment of interface designer quality into comparable and calculable engineering results [31–32]. The consistency principle of “task-operation-feedback” is applied to the construction of indicators in human-computer interaction, mapping out simulation output to core metrics such as path complexity, execution efficiency, and error risk while maintaining a unified mathematical expression enabling the comparison of different interface solutions [33–34].

The complexity index of an interface operation path is established by analyzing the structural characteristics of user operation paths to describe interface state transitions and display the cognitive burden on users when performing a task [35]. The index is calculated directly using the simulation-derived state transition sequence, and its mathematical structure is:

$$C_p = \sum_i^{N_s} = 1\omega_i^C \cdot d_i \quad (10)$$

To determine the time taken to perform a task, a task completion efficiency metric is introduced. This metric

Table 2 Interface design features and corresponding scheme descriptions.

Interface Scheme ID	Design Type	Core Interaction Strategy	Visual Organization Characteristics
S1	Shallow Navigation	Flat information architecture with functions concentrated on a single-level interface	Simple layout, clear visual hierarchy, short navigation paths
S2	Sidebar Partition	Left-side main menu with partitioned management, combining primary and secondary operation areas	Stable structure, clear functional divisions, strong sense of visual balance
S3	Modular Card	Card-style functional units organized in parallel, supporting quick switching	Clear module boundaries, strong visual rhythm, moderate information density
S4	Multi-level Hierarchy	Multi-level menus expanded step by step, systematic function classification	Clear structural hierarchy, strong visual progression, high logical clarity
S5	Context-guided	Dynamic prompts and context-based function presentation, reducing irrelevant information	High visual dynamism, flexible interface, strong sense of interaction context

is used to measure the extent to which interface design constrains the rhythm and continuity of the user's operations. It is directly calculated from the operation time sequences recorded by the simulation system, the expression of which is:

$$E_t = \frac{T_r}{T_s} \quad (11)$$

Based on the mis-operation behaviors recorded during the simulation, an interface operation error rate metric is obtained. This metric is used to quantify the risk level of the interface in terms of information presentation and operational feedback. Its calculation is expressed as follows:

$$R_e = \frac{N_e}{N_o} \quad (12)$$

According to the above individual indicators, a comprehensive interaction performance index is introduced, which weights and integrates path complexity, task efficiency, and error risk. Its mathematical expression is:

$$P_c = \alpha C_p + \beta(1 - E_t) + \gamma R_e \quad (13)$$

In Formula (13), P_c represents the comprehensive interaction performance index of the interface, and α , β , γ represent the weight coefficients of path complexity, efficiency loss, and error risk in the overall evaluation, respectively. This index is used to support the engineering comparative analysis of different interface design schemes.

After completing the interface interaction feature modeling and user behavior computer simulation, the simulation system outputs the user's operation sequence, time consumption, and error trigger records under a given interface structure and task constraints. To clearly demonstrate the design features and interaction logic of different interface schemes, Table 2 summarizes the five experimental schemes.

Table 2 presents the systematic classification and corresponding description of five interface design schemes in terms of structural features and interaction logic. Each scheme is qualitatively characterized in terms of three dimensions: design type, core interaction strategy, and visual

organization. These dimensions indicate the design evolution from flat structures to deeper hierarchies, and from static layouts to dynamic guidance.

2.4 Closed-Loop Feedback Mechanism for Simulation Prediction and Experience Evaluation

After determining the quantitative indicators for interface interaction performance, this study integrates simulation results with user experience evaluation to form a simulation-driven experience evaluation and design feedback mechanism for early-stage interface design decisions [36–37]. The core of this mechanism lies in establishing a stable mapping relationship between simulation output indicators and user subjective experience dimensions, enabling the interface design scheme to have a valid experience evaluation basis before entering the real-world-application stage, thereby embedding user experience control into the engineering design process rather than during a post-event correction phase [38–39].

The evaluation process is based on the use of performance metrics obtained from interactions during the simulation phase to create an experience-performance mapping model. Methods are then created to take engineering measurements such as path complexity, task efficiency, and error risk and convert them into cognitive load, operational smoothness, and perceived reliability at the user experience level. To fully define the overall effect of the simulation metrics on the user experience level, a prediction value is created for the interface experience using the following formula:

$$U_p = \sum_j^{N_m} = 1\lambda_j \cdot M_j \quad (14)$$

To verify the consistency between the simulated experience prediction and the real user experience evaluation, a consistency evaluation function is introduced to quantitatively align the predicted experience value with the user

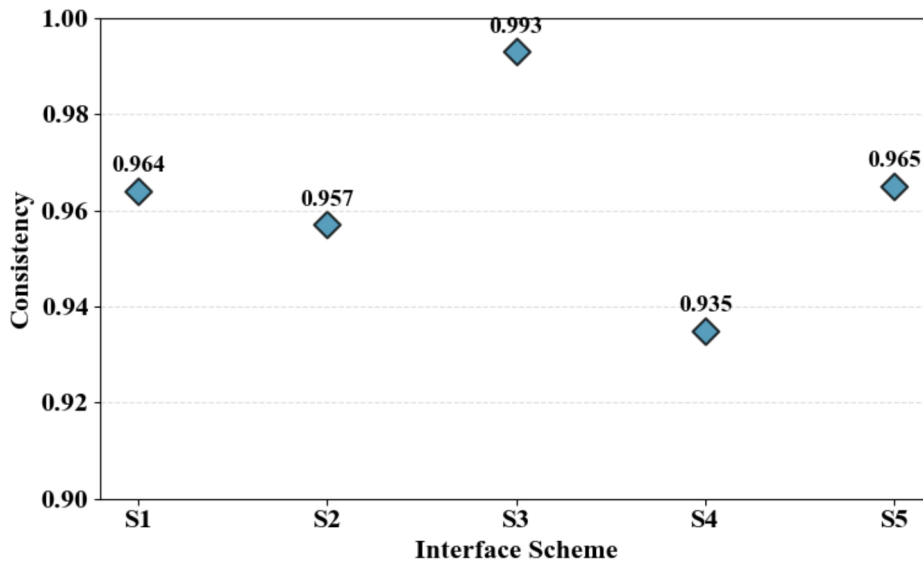


Figure 2 Comparison of consistency accuracy of different interface schemes.

experience scores collected during the experimental phase. Its mathematical form is:

$$A_c = 1 - \frac{|U_p - U_r|}{U_r} \quad (15)$$

In Formula (15), A_c represents the level of consistency between simulation predictions and real user experience. U_r denotes the average score obtained from user experience experiments. This metric is used to evaluate the reliability of simulation results at the experiential level.

Based on the consistency evaluation results, a feedback adjustment term for interface design is constructed. This term is used to guide targeted adjustments of interface structure and interaction logic. Its expression is defined as follows:

$$\Delta D = \kappa(1 - A_c) \quad (16)$$

In Formula (16), ΔD represents the interface design feedback adjustment; κ is the design adjustment sensitivity coefficient; A_c refers to the consistency level of the current interface scheme. This adjustment is used to constrain the range of interface optimization, ensuring that design modifications align with the degree of experience deviation.

Based on the above evaluation and feedback mechanism, interface design optimization no longer relies on empirical judgment. Instead, dynamic correction is achieved through a feedback loop coupling simulation results with experience evaluation. Figure 2 presents the consistency accuracy levels of different interface schemes.

Figure 2 shows the differences in consistency accuracy of different interface schemes. S3 reaches 0.993, the highest value among all schemes. This is mainly because its interface structure and interaction logic have formed a relatively stable and clear operation mode in the design stage, making the simulation model's abstraction of user behavior characteristics highly consistent with the actual usage process. The consistency accuracies of S1 and S5 are 0.964 and 0.965

respectively, which are at a high level. This is related to their relatively clear interaction flow and concentrated distribution of user operation strategies, thereby reducing the discrepancy between simulation prediction and real behavior. S2 is 0.957, slightly lower than S1, indicating that it has a certain degree of diversity in functional organization or feedback rhythm, increasing the uncertainty of behavior prediction. The consistency accuracy of S4 drops to 0.935. The results show that interface schemes with clear interaction logic and moderate complexity can better improve the consistency between simulation predictions and real user experience.

3. INTERFACE SIMULATION AND USER EXPERIENCE EVALUATION EXPERIMENTAL DESIGN

3.1 Experimental Objects and Interface Design Schemes

For this research, the selected experimental object is a product interface with a clear functional hierarchy and continuous operational flow, providing modelability and comparability of HCI behaviour, regardless of simulation or experience measurement. The product interface consists of three key interaction links: information perception, task decision-making, and operational feedback. The functional structure of the experimental object interface consists of three key components: the main task entry point, terrain for key functions, and areas for result feedback. The hierarchical organization increases the likelihood that users complete continuous operation tasks with no additional cognitive burden. The interface design has a unified design language constraint in the visual display, thus creating a controlled color system, layout proportion, and graphic symbols to reduce the impact of visual style differences on interaction behaviour and experience measurement.

When designing the user interface, multiple design schemes need to be created to meet the same requirements. The layouts of the interface elements, locations of functional entry points and structure of interaction paths must all be modified to provide a common visual style. All the user interface design schemes must then be converted to a common data structure for computer simulation by the unified interface model specification, which guarantees the same expression of the hierarchy of all interface elements, attributes of all interface elements, and mapping relationships of all operations at the engineering level. The modeling process guarantees that the different designs can be compared with each other in the simulation environment, thus providing a solid basis for the subsequent simulation of user behavior and for comparison of the consistency of experience.

To support the overall goals of interface simulation and user experience evaluation, a corresponding set of user tasks is established during the design stage of the experimental interface. Each task is directly linked to a key functional node in the interface and has a clear starting point and completion condition. The mapping between the interface design scheme and the user tasks is fixed before the experiment began. This prevents extra variables caused by differences in task understanding during the experiment. By developing the experimental object and the interface scheme in a unified way, a consistent structural foundation is formed between artistic design expression and engineering simulation analysis. This provides a reproducible experimental environment for subsequent simulation runs and the collection of user experience data.

3.2 User Task Settings and Simulation Condition Configuration

This study establishes user tasks and simulation operating conditions during the experimental phase, focusing on the research objectives of interface simulation and evaluation of user experience. Therefore, the structural consistency of simulated user behaviour results and actual interaction scenarios is maintained through this method of using the same setting for both cases. The user task settings are based on the core function structure of the interface to develop a sequence of user task operations based on how users experience the product, to construct a representation of the operational processes associated with acquisition of information, selection of functionality and confirmation of result for example into a set sequence with clearly defined start and end states. Each of the above user tasks corresponds with a specific functional path through the interface; therefore, they all have a fixed operational objective, which is described during the task definition phase, ensuring no changes to the execution logic of any of the tasks, regardless of the experimental conditions under which they are performed.

When configuring the simulation condition (tasks and input variables), user behavior is tracked as a continuous process (perceptual input, cognitive decisions, and operational execution) and is embedded into the computer simulation model via parameterization. User operations on

the interface are represented as discrete events, wherein each event represents a change in the state of an interface component. The simulation system automatically updates the user behavior state during operation according to task constraints and interface structure. This method of configuration enables the comparison of user operational paths (as well as operational rhythm) across different interface design schemes and provides stable input conditions for the analysis of simulation output results later.

To minimize the influence of experimental variables on the outcome of simulation experiments, the experimental setting is kept as constant as possible during the duration of the experiment. Timing of interface response, system feedback time delays, and rules for recognizing an operation are set up using the same values for all experimental test conditions, thereby limiting potential interference with the experiment by having the system perform differently during the various user behaviour simulations. The user behaviour variables are constrained at the task level to ensure that user behaviors are governed by the same rules for the same task performed under different interface designs. Thus, the only source of variation in the simulation outputs is the interface structure and interaction between the two interfaces themselves. This creates a very consistent simulation environment that the research method used for the simulation can apply during the experimental phase, creating a basis for valid comparison of both the results of the interface simulation and the resultant user experience evaluation data.

3.3 Multidimensional Experimental Data Acquisition and Evaluation Process

This study establishes a data collection and processing workflow during the experimental stage to ensure consistency when analyzing interface simulation results and user experience evaluation. The workflow involves the use of both behavioral log and subjective experience data. Similarly, simulation predictions and real-life user interactions are supported by this data basis. Experimental data is obtained from two sources. The data on actual user interaction behavior is one such source. Another source of information is standardized user experience evaluation data. During data collection, both types are connected and stored using unified task identifiers and interface scheme labels.

Public human-computer interaction datasets are utilized to gather and categorize data on actual user interaction behavior. This study utilizes user behavior and HCI-related datasets published in the UCI Machine Learning Repository. Users in real-world multi-interface settings generate these datasets by performing predetermined tasks. Monitoring of system-level events automatically records the data. Consistently stored data includes user clicks, state changes on the interface, and corresponding timestamps. A particular record represents a user operation event. Task identifiers and interface context descriptions are both included in the package. The simulation model's definitions of operation events align with the semantics underlying the event structure. Raw interaction logs are cleaned, filtered and re-coded during data preprocessing.

Table 3 Statistics for experimental data sources and collection scale.

Data Category	Data Source	Sample Size	Main Data Content
Behavioral Log Data	Public user behavior and human–computer interaction datasets from the UCI Machine Learning Repository	5200	Operation events, timestamps, interface states
Simulation Output Data	Interface simulation system developed in this study	5200	Operation paths, step sequences
User Experience Evaluation Data	Standard System Usability Scale (SUS) questionnaire structure	260	Usability scores
Task Configuration Records	Experimental task definition files	12	Task objectives and path constraints
Interface Scheme Identifier Data	Experimental interface design files	4	Interface structure and functional layout

Operations types, time granularity, and interface element identifiers are aligned with simulation output data. The ensuring of structural equivalence facilitates model validation and result analysis.

User experience evaluation data is supplemented using publicly available standardized questionnaire datasets. The System Usability Scale (SUS) released reference data structure is the framework used to determine how users experience user's usability and the recording of this user experience feedback following task completion is completed as per the SUS's scoring dimensions/scoring methods as detailed in the official documentation. The user experience evaluation results are scored in raw form (no weighting or normalization is applied to the raw scores) during collection to ensure the transparency of subsequent analysis of these results. Subjective data related to the user experience evaluation is matched to the corresponding behaviour log data at the data-level using the same task number for each task.

After data collection, multi-source data is uniformly organized and summarized during the experimental stage. This supports the reproducibility of subsequent analyses. Structured behavioral logs and experience evaluation data are classified into three categories: simulation prediction data, real behavior data, and subjective experience data. All data are managed under the same experimental identification system. To clarify experimental scale and data coverage, the composition of the experimental dataset is summarized, as shown in Table 3.

The data types, sources, scale, and content composition of the experiment are summarized in Table 3, and illustrate the correspondence between data from different behavioral and evaluation layers. Behavioral log data and simulation output data, among other things, exhibit the same sample size as their structural alignment between real user interaction records and simulated operation paths, which provides guidance for subsequent analysis of consistency. The subjective perception of interface usability is measured using a standardized SUS questionnaire used in user experience evaluation data. Task configuration records and interface scheme identification data, viewed from the perspective of experimental control and design constraints, define the task objectives, scope, and structure of the interface. This data system creates a complete closed loop with respect to content, order and quantity, providing standardized and reproducible

data support for the correlation modeling of simulation outcomes and user experience evaluation.

4. SIMULATION RESULTS AND USER EXPERIENCE EVALUATION

4.1 Simulation Prediction and Verification of User Operation Paths

This experiment uses a simulation model to model user operation paths under different interface design schemes to analyze the distribution characteristics and consistency of user interaction behaviors in these schemes. The experimental subject is a typical product interface, which includes multiple functional modules and hierarchical operation tasks. In the experiment, users need to complete continuous operations from interface startup to the target function. The operation path of each task is recorded accurately. The number of operation steps, the operation path complexity and the path error rate of the operation path are recorded. With this method, the experiment evaluates the ability of simulation model to predict user operation path, and analyzes the consistency of simulation model and real-user behavior. The results are shown in Figure 3.

As illustrated in Figure 3, S1 has a consistency score of 0.88, with 8 operation steps, 12 path complexity steps, and 6.5% path error rate, showing high path stability and low prediction bias, which suggests, essentially, synchronization between the simulated path and the actual operation. S2 and S3 exhibit a slight reduction in consistency, with S3 reaching 18 steps in path complexity and achieving 12.3% path error rate, indicating that its interface structure introduces additional path offsets and redundant operations during operation. With a moderate increase in the number of operation steps and path complexity, S4 and S5 experience lower path consistency at 0.82 and 0.81, respectively, while their path error rates are 9.6% and 8.9%, suggesting that the stability of user operation paths is on the decline as the complexity of the interface structure increases. In general, the results indicate that there is a strong correlation between the number of operation steps and path complexity and their consistency. A simplified interface structure and more

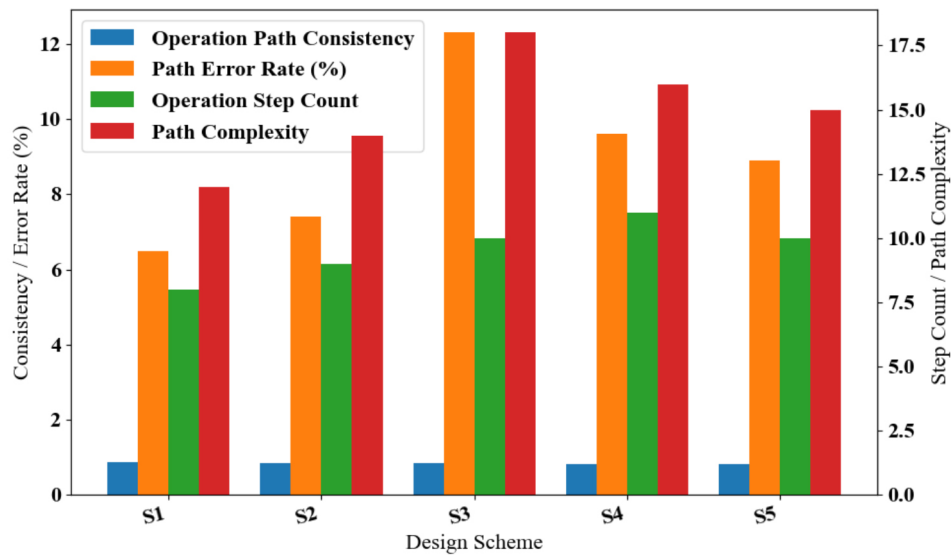


Figure 3 Simulation results analysis of user operation path.

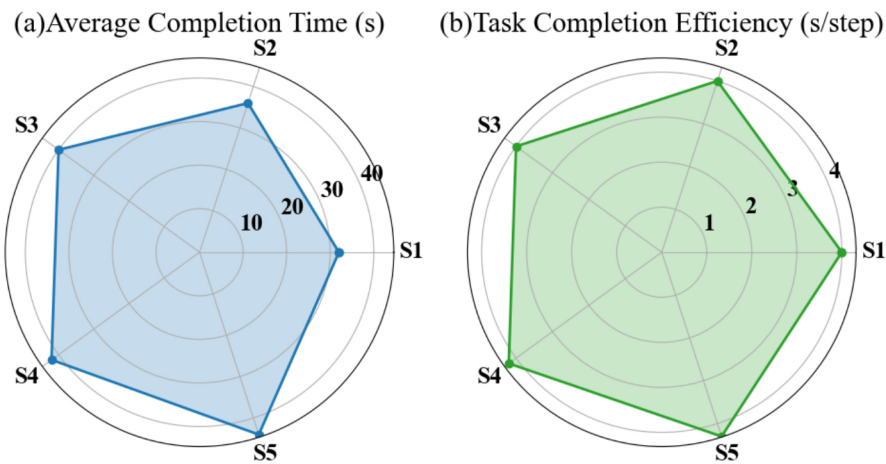


Figure 4 Interface interaction efficiency analysis. Figure 4(a). Comparison of user core task completion time. Figure 4(b). Comparison of task completion efficiency

concentrated operation paths result in a smaller deviation between the simulation prediction results and the user's actual behavior. By means of this analysis, it is possible to quantify the rationality of the interface structure in a straightforward manner.

4.2 Interface Interaction Efficiency Results

In addition to the analysis of the simulation result of user operation path, to verify the effectiveness of the proposed method, this section analyzes the impact of different interface schemes on user experience of using the system to improve the efficiency of completing tasks. The experimental study compares the time and efficiency needed to complete main tasks when the user is presented with different interfaces, and analyzes the impact, on the overall efficiency, of each interface structure and interaction logic. The experimental results are shown in Figure 4.

The results in Figure 4(a) show that the average time consumption is on the rise, with S1 averaging 32 seconds, S2 36 seconds, S3 40 seconds, S4 42 seconds, and S5 44 seconds. This apparent increase in task completion time is primarily attributed to the increase in complexity associated with the interface layout (more complex interface layout requires users to process more information and make more interactive decisions while executing their tasks which prolongs total operation time). As shown in Figure 4(b), the task efficiency of S1, S2, and S3 is approximately 4.0 seconds per step; however, it is 4.2 s for S4 and 4.3 s per step for S5. The increase in complexity of the interface layout results not only in an increase in overall time taken to complete the task, but also in additional time required for each unit of measure which then compounds upon itself. In conclusion, the results shown in figure suggest that the increase in complexity of the interface structure adversely affects the overall time required to complete a task, time, providing a clear direction for the optimization of the interface flow and hierarchical design of the respective interface layouts.

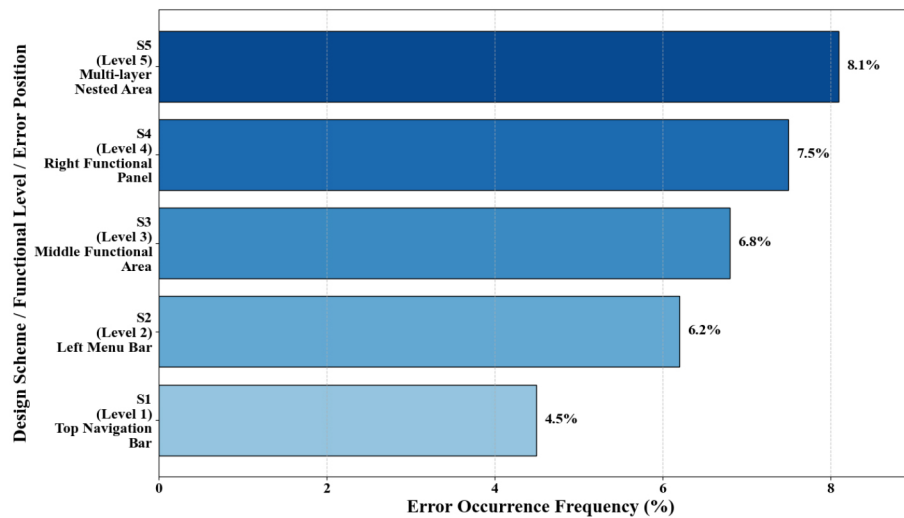


Figure 5 Analysis of the relationship between operation error distribution and interface structure.

4.3 Relationship between Operation Error Distribution and Interface Structure

This section examines the distribution of errors made by users when interacting with various interface designs, and takes into account the location of the error in relation to both the design of the interface and its functional hierarchy, and the task being performed. The experiment simulates the full interaction between the user and the task undertaken when using five different interface designs, and records the location, type of error made, and the functional hierarchy of items associated with that error in order to determine how interface design characteristics in terms of structure affect user behaviour with regard to mis-operation. The experiment is used to demonstrate the error distribution throughout the pages of an interface and to show how error frequency varies according to a user's increasing level within a functional hierarchy. By examining the functional hierarchy depths and complexity of layout among the five interface designs, the paper then discusses the effect that the interface structure has on mis-operation stability and the tolerance of the user. The results are given in Figure 5.

As depicted in Figure 5, the error distribution can be differentiated among five interface designs. As the number of levels in the functional hierarchy of the design increases, the number of errors increases. In S1, the majority of errors are associated with the top navigation bar, which has an error frequency of 4.5%, meaning that it is stable and not easily mis-operated. In S2, the error frequency associated with the left menu increases to 6.2%, indicating a greater load is placed on the user due to the introduction of additional divisions in the functional hierarchy (2nd level). In S3 and S4, the majority of errors are in the central functional area and the right-side panel (3rd and 4th levels), with an error frequency of 6.8% and 7.5%, respectively. This indicates that as the layout of the functional hierarchy becomes more complex, there is an increase in the number of times that users mis-operate the interface. In S5, the majority of errors are in a multi-layer nested operation area (5th level), with an error frequency of 8.1%. This indicates that as the number

of levels increases in depth within the functional structure, there is an increased likelihood that users make mistakes when attempting to perform an action by wrongly clicking on something and causing an error.

4.4 Consistency Verification of Simulation Prediction Indicators and User Experience Scores

This section analyzes the consistency between simulation prediction results and user experience evaluation from a quantitative perspective, aiming to verify the effectiveness and validity of the simulation model constructed to assess user experience. Experiments are conducted to simulate user operation behavior for five different interface design schemes, and corresponding user experience evaluation data is collected simultaneously. By comparing the consistency between simulation prediction results and actual user feedback in key dimensions such as operation path, task completion time, and error rate, the predictive ability of the simulation model for real-user experience is evaluated. The experimental results are shown in Figure 6.

Figure 6(a) shows that S1 is at the highest level in all three dimensions of path consistency, time consistency, and error rate consistency, reaching 88%, 95%, and 90%, respectively, reflecting a high degree of matching between simulation prediction results and actual user behavior at multiple levels. The consistency indices of S2 and S3 are slightly lower than those of S1, but overall remain in a high range. The differences in path consistency and time consistency are relatively limited, indicating that their simulation results have good stability in terms of behavioral timing and operational rhythm. S4 and S5 show that the three consistency indices have a gradual downward trend, with the path consistency and error rate consistency of S5 decreasing to 81% and 80%, respectively, indicating a widening deviation between simulation prediction and actual operation. The user experience score distribution in Figure 6(b) is generally consistent with the consistency results. S1 achieved the highest score

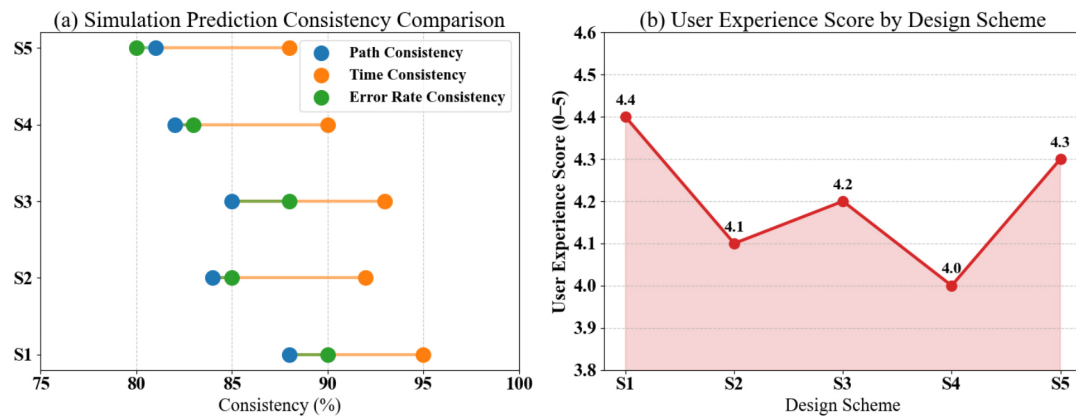


Figure 6 Consistency analysis of simulation prediction results and user experience evaluation. Figure 6(a). Consistency of simulation prediction path, time, and error rate. Figure 6(b). User experience score.

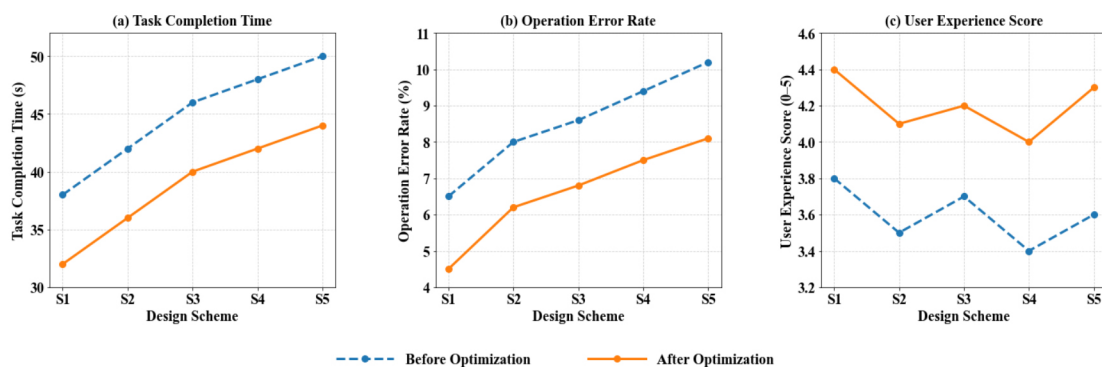


Figure 7 Analysis of the effects of simulation-driven interface optimization. Figure 7(a). Comparison of task completion times before and after optimization. Figure 7(b). Comparison of operation error rates before and after optimization. Figure 7(c). Comparison of overall user experience scores.

of 4.4/5, while the scores of S2, S3, and S4 decrease. Although S5 is at a low level in the consistency index, its user experience score remains at 4.3/5, indicating that subjective experience evaluation is influenced to some extent by visual style and factors related to interaction perception. In sum, the findings demonstrate that there is a very good overall relationship between the consistency of the simulation predictions and the user experience scores.

4.5 Simulation-Driven Interface Optimization Scheme and Effects

This section assesses how the improved usability of an interface that employs simulation technology influences the user's experience and the efficiency of performing tasks by offering improved usability compared to the original usability of the interface, as well as its overall design language and visual style. Five separate interface designs (Schemes 1 to 5) have been selected for analysis. The performance data for each of the key user experience metrics—task completion time, user errors, and overall experience—are gathered by comparing the before-and-after optimization performance of the interfaces. Additionally, the effectiveness of the simulation optimization under the constraints of artistic expression is assessed. Results of the assessment are shown in Figure 7.

Figure 7 illustrates the overall impact of simulation-driven optimization on interface interaction performance and user experience. In Figure 7(a), the completion time of the core task decreases synchronously across all schemes: S1 decreases from 38 s to 32 s, S3 from 46 s to 40 s, and S5 from 50 s to 44 s. As shown in Figure 7(b), operation error rates are decreasing systematically as the optimization is performed, with S1 being reduced from 6.5% to 4.5%, S2 from 8.0% to 6.2%, and S4 from 9.4% to 7.5% for operation errors. This is largely due to the clarified hierarchy between interface function relationships and the centralization of all interactive feedback locations. By clarifying the users' behaviors when making an operational judgment, users can operate more accurately with fewer accidental touches and misjudgment of the operation. In Figure 7(c), the user experience ratings have also improved as indicated by S1 and S5 having scores of 4.4 and 4.3 out of 5, respectively. There is no single visual factor responsible for the improvement of experience; instead, the combination of users completing their task more efficiently and having reduced risks of errors also improves their work output when interacting with interfaces, resulting in greater user satisfaction. In conclusion, Figure 7 shows that the implementation of optimized interfaces that provide feedback through simulations of operations produces a synergistic improvement in operational effectiveness, operational reliability, and overall user experience through the

modification of users' interaction structure by restructuring them through the constraints created by the path of least resistance for the successful interaction execution to perform similar operations.

5. CONCLUSIONS

This paper addresses the lack of preliminary quantitative verification in product interface design from a human-computer interaction perspective. It constructs an interface design analysis process based on interface interaction modeling, centered on computer simulation of user behavior, and constrained by user experience consistency verification. By transforming interface structure, task logic, and operational behavior into computable models, it achieves systematic prediction of interaction paths, execution efficiency, and error risks during the design phase. Experimental results show that, across different interface schemes, simulation predictions maintain high consistency with real user behavior in terms of path, time, and error rate. Based on this, the introduction of simulation-driven interface optimization significantly shortens the task completion time, reducing S1 from 38 s to 32 s and S5 from 50 s to 44 s, with the overall user experience score improving to above 4.0/5. By utilizing this approach without having to rely on a large-scale real-user study to conduct a forward evaluation and collaborate on the optimization of the interaction performance and user experience when using the interface, the design of the user interface can provide an engineering-verifiable analytical path from the usability testing to determining the application value of the user interfaces to the designers of complex interfaces in a quantitative manner.

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