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A Multi-Criteria Evaluation Method for Interactive Interface Layouts in Smart Digital Museums Based on RANCOM–LOPCOW–TOPSIS

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Abstract

Digitalization and intelligent interaction technologies are transforming museum services, making interactive interfaces important for cultural information access and user experience. Existing studies often examine aesthetics, usability, visual cognition, or emotional experience separately. To address this gap, this study proposes a multi-criteria evaluation method for interactive interface layouts in smart digital museums. The evaluation system includes nine indicators across layout aesthetics, visual cognition, and emotional experience: symmetry, density score, orderliness, total fixation duration, average pupil diameter, saccade count, pleasure, arousal, and dominance. Six layouts were evaluated using layout aesthetics calculations, an eye-tracking experiment with 32 participants, and the Pleasure–Arousal–Dominance (PAD) scale. Descriptive statistics were used to summarize the eye-tracking and PAD data. RANCOM and LOPCOW were used to calculate the subjective and objective weights, respectively, and TOPSIS was used to rank the layouts. Ranking robustness was examined through 54 weight-perturbation scenarios, while ranking agreement was assessed using Spearman's and Kendall's coefficients and four alternative multi-criteria decision-making (MCDM) procedures. L1 ranked first with a relative closeness of 0.876, followed by L5 and L6, while L4 ranked last with 0.120. The baseline ranking was retained in 51 of the 54 scenarios, with a consistency rate of 94.44%. Spearman's coefficients ranged from 0.943 to 1.000, and Kendall's coefficients ranged from 0.867 to 1.000. These results indicate relative ranking robustness under the tested scenarios and high agreement within the current dataset. Layouts with balanced spatial relationships, continuous functional modules, and clear visual paths showed more favorable descriptive patterns in visual cognition and emotional experience. The method provides a quantifiable and interpretable approach for comparing smart digital museum interface layouts, while its broader applicability remains to be examined.

Keywords: smart digital museum; interactive interface layout; multi-criteria decision-making; RANCOM–LOPCOW–TOPSIS; eye-tracking experiment; layout aesthetics; emotional experience



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1. Introduction

With the rapid development of digital technologies, intelligent systems, and immersive media, museum services are shifting from object-centered physical exhibitions toward smart digital experience models that integrate online exhibitions, virtual galleries, digital navigation, and intelligent interaction. Smart digital museums overcome the spatial, temporal, and display limitations of traditional museums by enabling users to access cultural

resources through web interfaces, mobile devices, and immersive platforms. These environments allow users to browse cultural artifacts, acquire knowledge, explore contextual information, and engage in interactive experiences [1,2]. In this context, the interactive interface serves as the primary gateway connecting users with digital cultural resources. Its design quality directly affects the efficiency of cultural information retrieval, users' understanding of the content, and their overall experience [3].

Interactive interfaces in smart digital museums serve both cultural communication and public service functions [4]. During interaction, users need to understand the navigation structure, identify exhibition information, and complete basic operations efficiently. Their experience is also influenced by the interface's visual organization, content arrangement, and overall atmosphere [5]. Therefore, the evaluation of smart digital museum interfaces should extend beyond aesthetics or usability alone. It should also consider design form, visual cognition, and emotional experience. In digital cultural contexts, an effective interface should lower the threshold for understanding, support visual attention, and provide a positive experience. These factors are therefore important criteria for evaluating interface design quality.

Existing studies on interactive interface evaluation provide an important foundation for optimizing smart digital museum interfaces. Some studies focus on interface layout, visual aesthetics, and structural organization, emphasizing the effects of symmetry, orderliness, simplicity, and information density on user perception [6–8]. Other studies examine usability, cognitive load, and visual behavior using task-performance measures, subjective scales, or eye-tracking data [9,10]. A further group of studies focuses on user experience, immersion, and satisfaction to explain the experiential value of digital exhibition interfaces [11,12]. Together, these studies address design features, cognitive behavior, and experiential outcomes. However, in the context of smart digital museums, a single-dimensional evaluation remains insufficient to represent the overall quality of an interface layout [13]. An evaluation based only on layout aesthetics may overlook users' information processing. An evaluation based only on eye-tracking or cognitive indicators may not capture emotional experience. An evaluation based only on subjective judgment may also be influenced by individual preferences and short-term emotional fluctuations. Interactive interface layout evaluation therefore has clear multi-criteria characteristics and requires a systematic framework that integrates layout features, visual cognition, and emotional experience [14,15].

Multi-criteria decision-making (MCDM) methods can integrate multiple evaluation indicators into a unified framework. Through criterion weighting, data standardization, and alternative ranking, they support the comprehensive evaluation of complex design objects [16]. Determining appropriate criterion weights is particularly important in interface design evaluation. Expert experience reflects professional design judgment, especially for criteria involving subjective evaluation, such as layout aesthetics and emotional experience. Objective data, in contrast, capture differences among alternatives and reduce reliance on expert preference alone. Accordingly, this study uses Ranking Comparison (RANCOM) to obtain expert-based subjective weights and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) to calculate objective weights from the indicator data. The two sets of weights are then combined. On this basis, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to calculate the relative closeness of each interface layout to the ideal solution and generate the final ranking.

Based on the above analysis, this study proposes a RANCOM–LOPCOW–TOPSIS-based evaluation framework for interactive interface layouts in smart digital museums. The methodological contribution lies in the problem-specific construction and application of this framework rather than in the development of a new MCDM algorithm. The contribution

is reflected in three aspects. First, the study constructs a layout-level indicator system that integrates computational layout aesthetics, eye-tracking-based visual cognition, and PAD-based emotional experience. Second, it combines RANCOM subjective weighting with LOPCOW objective weighting to incorporate both expert design judgment and data-driven differences among layout alternatives. Third, it applies TOPSIS together with weight-sensitivity and method-comparison analyses to provide an interpretable basis for comparing smart digital museum interface layouts.

2. Related Work

2.1. Smart Digital Museum Interfaces

Smart digital museums integrate digital technologies, intelligent interaction, and public cultural services to create accessible cultural experiences. Rather than simply transferring physical exhibitions online, they reorganize cultural resources through digital content, virtual spaces, and interactive experiences [17,18]. In this process, the interactive interface becomes the main entry point through which users access exhibition information, navigation functions, and cultural content.

From a functional perspective, smart digital museum interfaces support information services, cultural communication, and user guidance [19,20]. They enable users to browse exhibits, search for information, understand cultural content, and receive interactive feedback. Interface design quality therefore affects not only task completion but also users' perception and understanding of cultural content.

Existing studies have examined digital museums, virtual museums, and online exhibition systems from several perspectives, primarily focusing on technology implementation, content presentation, and user experience. Research on technology implementation has explored how virtual reality, augmented reality, three-dimensional modeling, panoramic navigation, and multimodal interaction can improve exhibition accessibility and immersion [21,22]. Studies on content presentation have emphasized the effects of digital resource organization, exhibit information structure, and cultural narrative paths on knowledge communication [23]. Research on user experience has focused on outcomes such as usability, immersion, satisfaction, learning effectiveness, and visit intention [24].

Overall, previous studies provide useful insights into the technological implementation, content organization, and user experience of smart digital museums. However, relatively little attention has been paid to the layout-level evaluation of interactive interfaces. Because interface layout affects how users perceive, search for, and understand cultural information, it should be examined as a distinct evaluation object.

2.2. Multidimensional Evaluation Indicators for Interfaces

For interactive interface layout evaluation, the selected indicators should reflect not only the formal organization of interface elements but also users' visual cognition and emotional responses during interaction.

At the level of design features, interface layout is an important factor affecting users' initial perception and subsequent information processing. The position, size, spacing, hierarchy, and visual prominence of interface elements shape users' overall understanding of the content structure [25–27]. Existing studies on interface aesthetics commonly evaluate layout quality in terms of symmetry, balance, density, simplicity, and orderliness [28]. These indicators translate formal interface features into relatively objective data and help reduce reliance on aesthetic preference alone. For smart digital museum interfaces, a well-organized layout can improve the overall visual impression and help users identify the main exhibition area, navigation entries, and explanatory content.

At the level of visual cognition, interface evaluation should examine how users observe, search for, and process interface information. Eye-tracking can provide behavioral evidence of attention allocation and gaze activity through indicators such as fixation duration, pupil diameter, saccade count, and gaze path [29,30]. Total fixation duration describes cumulative fixation activity during the task, while pupil diameter reflects the magnitude of pupil response, and saccade count reflects the frequency of gaze shifts and information confirmation across interface areas [31]. Compared with subjective evaluation alone, eye-tracking indicators provide continuous behavioral data that can help characterize users' visual cognition during interface interaction.

At the level of emotional experience, smart digital museum interface evaluation should also consider users' basic emotional responses during interaction [32]. Unlike conventional task-oriented interfaces, museum interfaces are intended not only to support efficient operation but also to provide a positive, comfortable, and controllable experience through appropriate visual organization. The PAD model describes emotional states in terms of pleasure, arousal, and dominance. These dimensions reflect positive feeling, emotional activation, and perceived control in relation to an interface layout [33]. In this study, emotional experience refers to the immediate responses associated with layout structure rather than deeper experiences such as cultural empathy or immersive narrative engagement.

Overall, previous studies have examined layout aesthetics, visual cognition, and user experience from different perspectives, but these dimensions are often considered separately. For smart digital museum interfaces, layout structure, visual-search behavior, and emotional response should be considered within the same evaluation process. An integrated indicator system is therefore needed for comprehensive layout evaluation.

2.3. Multi-Criteria Comprehensive Evaluation

The evaluation of interactive interface layouts in smart digital museums has typical multi-criteria characteristics. Layout quality, visual-search behavior, and emotional experience jointly contribute to the overall evaluation. The quality of an interface layout therefore cannot be assessed adequately using a single indicator and instead requires trade-offs among multiple criteria. Multi-criteria evaluation methods provide a systematic framework for complex design alternatives. They usually involve indicator-system construction, data standardization, weight determination, and alternative ranking and are suitable for problems involving multiple indicators and alternatives [34]. In design research, these methods have been applied to product selection, user-requirement prioritization, service-quality evaluation, and interactive interface comparison [35–37]. Compared with single-indicator approaches, multi-criteria methods can integrate data from different sources, units, and attributes into a unified framework.

In multi-criteria evaluation, criterion weights directly affect the final ranking. Subjective weighting methods reflect expert experience and design judgment and are suitable for criteria involving professional assessment, such as layout aesthetics and emotional experience [38]. Objective weighting methods determine weights from the variation and information contained in the evaluation data, thereby reducing the influence of human preference [39]. For smart digital museum interface layout evaluation, relying solely on expert weighting may make the results overly dependent on individual experience, while relying solely on objective weighting may overlook design goals and the evaluation context. A combined subjective–objective weighting approach is therefore appropriate for this type of problem.

(1) Ranking Comparison (RANCOM) is a subjective weighting method based on expert rankings [40]. Compared with methods such as the Analytic Hierarchy Process (AHP) and the Best–Worst Method (BWM), RANCOM does not require a large number of

precise pairwise comparisons. Instead, it derives normalized weights by ranking criterion importance and transforming the ranking relationships. This reduces the judgment burden on experts in complex evaluation contexts. RANCOM also allows criteria to have equal importance and tolerates minor uncertainty in expert judgments. It is therefore suitable for design evaluation problems that require professional expertise while avoiding excessive comparison burden.

(2) Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) is an objective weighting method based on logarithmic percentage change [41]. Through normalization and logarithmic transformation, it reduces the effects of dimensional differences and extreme values on weight calculation. It is suitable for multi-source, heterogeneous, and unbalanced data. The evaluation in this study combines layout-aesthetics calculations, eye-tracking data, and emotional ratings. Because these indicators come from different sources and use different units, LOPCOW is suitable for calculating the objective weights.

(3) The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used MCDM ranking method. Its basic principle is that the optimal alternative should be as close as possible to the positive ideal solution and as far as possible from the negative ideal solution [42]. TOPSIS calculates the distances between each alternative and the positive and negative ideal solutions, derives a relative closeness coefficient, and produces the final ranking. The calculation process is clear and the results are intuitive. The method can also accommodate indicators with different attributes, including benefit and cost criteria, and has been widely used in engineering evaluation, alternative selection, and design decision-making [43]. Combining RANCOM, LOPCOW, and TOPSIS makes it possible to incorporate expert judgment, data differences, and proximity to the ideal solution within the same evaluation process.

Overall, previous studies provide a theoretical and methodological foundation for smart digital museum interface evaluation, but three limitations remain. First, many studies focus on digital exhibition technologies or overall system experience and pay insufficient attention to the design quality of interface layouts. Second, existing studies often examine interface aesthetics, visual cognition, or user experience separately and lack an indicator system integrating all three dimensions. Third, some studies rely on either subjective evaluation or objective data alone, making it difficult to balance expert judgment and user behavioral evidence. To address these gaps, this study develops an integrated indicator system for smart digital museum interface layouts and applies the RANCOM–LOPCOW–TOPSIS framework. Different from studies that directly apply existing multi-criteria decision-making methods to interface evaluation, this study emphasizes the problem-specific construction of an evaluation framework for smart digital museum layouts. The framework links layout structure, visual search behavior, and emotional response within the same decision-making process, thereby improving the explanatory value of the evaluation results rather than merely producing a scheme ranking.

3. Evaluation Model for Interactive Interface Layout Design in Smart Digital Museums

3.1. Model Framework

The proposed evaluation model for interactive interface layouts in smart digital museums is shown in Figure 1. The framework consists of three stages: evaluation-indicator construction, criterion-weight calculation, and comprehensive layout evaluation. First, nine indicators are identified across three dimensions—layout aesthetics, visual cognition, and emotional experience—to form the evaluation system. Second, RANCOM is used to calculate expert-based subjective weights, while LOPCOW is used to calculate objective weights. These weights are then combined to obtain the final criterion weights. Finally,

TOPSIS is used to construct a weighted normalized decision matrix and calculate the distances between each layout and the positive and negative ideal solutions, together with the relative closeness coefficient. These calculations generate the comprehensive ranking of the interface layouts. The framework is therefore intended as a problem-specific evaluation procedure for smart digital museum interface layouts.

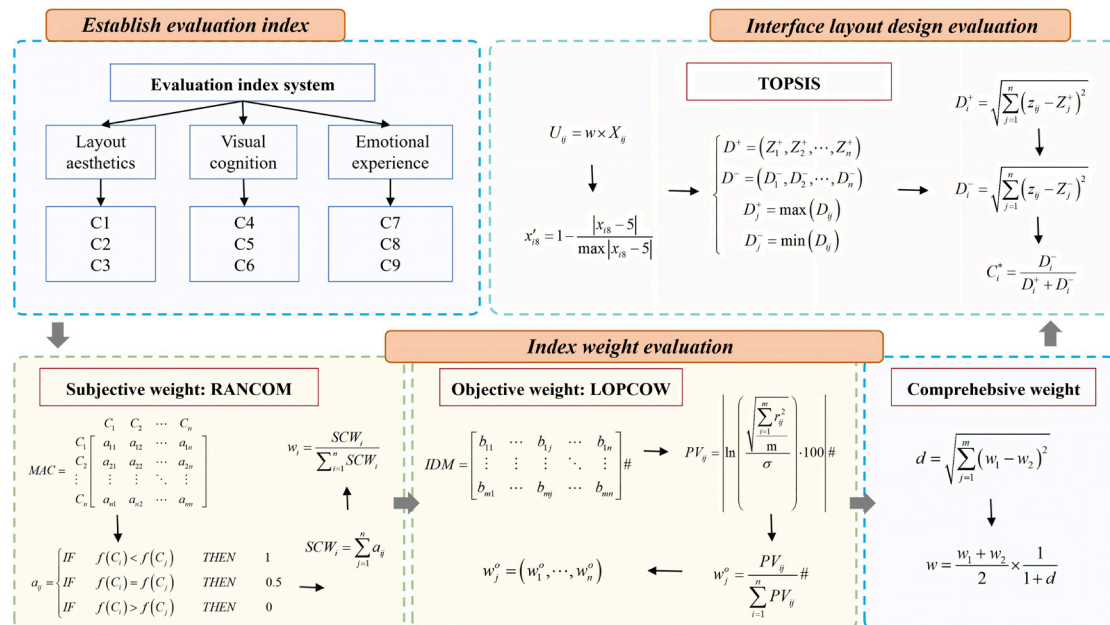


Figure 1. Block diagram of the model framework.

3.2. Construction of the Evaluation Indicator System

This study constructs an evaluation indicator system for interactive interface layouts in smart digital museums from three dimensions: layout aesthetics, visual cognition, and emotional experience. The indicators were selected according to the research objective. Because the study focuses on layout-level evaluation rather than full-system usability assessment, the indicators needed to reflect layout structure, visual-search behavior, and basic emotional response directly. They also needed to be measurable under controlled experimental conditions through layout calculations, eye-tracking data, and subjective ratings. Based on these principles, a framework consisting of nine indicators was constructed, as shown in Table 1.

The layout-aesthetics dimension was selected because spatial organization is the most direct feature of an interface layout. Symmetry (C1), density score (C2), and orderliness (C3) were adopted to describe the balance, spatial distribution, and visual sequence of interface elements. The density score was calculated with reference to an optimal occupied-area ratio of 50% [28]. A higher C2 value indicates closer proximity to this optimal level rather than a denser interface. These indicators can be calculated from the positions, sizes, and spatial relationships of interface modules and are therefore suitable for simplified wireframe layouts.

The visual-cognition dimension was selected because layout quality affects how users search for and process interface information. Total fixation duration (C4), average pupil diameter (C5), and saccade count (C6) were adopted to describe cumulative fixation activity, pupil response, and gaze shifts between interface areas. Average pupil diameter was treated as a supplementary indicator because it may be affected by luminance, fatigue, individual differences, emotional activation, and cognitive processing. These eye-tracking indicators provide behavioral evidence of attention allocation and gaze activity during the search task.

In the present target-search task, lower C4 values indicated less cumulative fixation, while lower C6 values indicated fewer gaze shifts following successful target identification. A lower C5 value represented a smaller pupil response and was used only as a supplementary indicator. These directions were task-specific and were not assumed to apply universally to open-ended browsing or engagement-oriented tasks.

Table 1. Evaluation indicator system for interface layout design.

No.	Evaluation Dimension	Evaluation Indicator	Indicator Meaning	Indicator Attribute
C1	Layout aesthetics	Symmetry	Reflects the degree of balance of interface elements in the vertical, horizontal, and diagonal directions	Benefit
C2	Layout aesthetics	Density score	Measures the closeness of the occupied-area ratio to the optimal screen coverage of 50%	Benefit
C3	Layout aesthetics	Orderliness	Reflects the degree of consistency between the interface layout and users' visual browsing sequence	Benefit
C4	Visual cognition	Total fixation duration	Reflects the cumulative duration of fixation events during the visual-search trial	Cost
C5	Visual cognition	Average pupil diameter	Reflects the average pupil response during the visual-search trial	Cost
C6	Visual cognition	Saccade count	Reflects the frequency of visual shifts between interface areas	Cost
C7	Emotional experience	Pleasure	Reflects users' emotional response to the layout scheme	Benefit
C8	Emotional experience	Arousal	Reflects the emotional activation or stimulation level induced by the layout	Moderate
C9	Emotional experience	Dominance	Reflects users' sense of control over the interface structure and browsing path	Benefit

The emotional-experience dimension was selected because smart digital museum interfaces also serve as cultural-experience media. Pleasure (C7), arousal (C8), and dominance (C9) were adopted from the PAD model to describe users' basic emotional responses to the layouts, including positive feeling, activation level, and perceived control.

3.3. RANCOM–LOPCOW Combined Weighting Model

3.3.1. Subjective Weighting Based on RANCOM

To determine the subjective importance of each evaluation indicator, this study used RANCOM to calculate the subjective weights. The expert evaluation was conducted by a panel of five professors and associate professors, each with more than five years of relevant research or practical experience. The panel included two experts in interface design and user experience, one expert in digital museum or cultural heritage design, one expert in industrial design, and one expert in multi-criteria decision-making or design evaluation.

The experts were selected according to three criteria: a relevant disciplinary background, experience in design or interface evaluation, and familiarity with multi-criteria evaluation problems. Before the ranking task, they were provided with the research purpose, the six layout samples, and definitions of the nine evaluation indicators. Each expert independently ranked the indicators according to their importance for evaluating interactive interface layouts in smart digital museums. The ranking criteria included the relevance of each indicator to layout quality, visual cognition, and emotional experience. Indicators considered equally important were allowed to receive the same ranking level.

The individual rankings were first summarized by calculating the mean rank of each indicator. The preliminary integrated ranking was then reviewed by the expert panel. Differences among the individual rankings were discussed until a consensus ranking was reached. Agreement among the experts was assessed by comparing their individual rankings during the panel review; no separate statistical agreement coefficient was calculated. The final consensus ranking was used as the input for the RANCOM subjective-weighting procedure. RANCOM then transformed the ranking relationships into a comparison matrix and calculated the normalized subjective weight of each indicator. The specific steps are as follows.

Step 1. Define the criteria ranking

Experts rank $C_1, C_2, \dots, C_n$ according to the importance of each evaluation indicator in the evaluation of smart digital museum interface layouts. When two or more indicators have similar importance, they may be assigned the same ranking level.

Step 2. Establish the Ranking Comparison matrix

Based on the expert ranking results, any two indicators are compared pairwise to establish the Ranking Comparison matrix (MAC). The comparison result is denoted by a_{ij} , whereas the MAC can be expressed as follows:

$$MAC = \begin{matrix} & \begin{matrix} C_1 & C_2 & \cdots & C_n \end{matrix} \\ \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} & \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \end{matrix} \quad (1)$$

where n denotes the number of criteria, and a_{ij} is determined using Equation (2). Here, $f(C)$ is the importance function of criterion C .

$$a_{ij} = \begin{cases} IF & f(C_i) < f(C_j) & THEN & 1 \\ IF & f(C_i) = f(C_j) & THEN & 0.5 \\ IF & f(C_i) > f(C_j) & THEN & 0 \end{cases} \quad (2)$$

Step 3. Calculate the Summed Criteria Weights

Based on the MAC, the comparison values in the corresponding row of each criterion are summed to obtain the Summed Criteria Weight (SCW), as shown in Equation (3):

$$SCW_i = \sum_{j=1}^n a_{ij} \quad (3)$$

Step 4. Calculate the final criteria weights

The comparison scores of all criteria are normalized to obtain the RANCOM subjective weight w_i^s , where the i -th row contains the approximate preference value of criterion C_i . The criterion weight is calculated as follows:

$$w_i^s = \frac{SCW_i}{\sum_{i=1}^n SCW_i} \quad (4)$$

Thus, the subjective weight vector of the evaluation indicators can be obtained as follows: $W^s = (w_1^s, w_2^s, \dots, w_n^s)$.

3.3.2. Objective Weighting Based on LOPCOW

To calculate the objective weights of the evaluation indicators, this study uses the LOPCOW method. The method determines the degree of variation among indicators across the alternatives through normalization and logarithmic percentage-change calculations.

Step 1. Construct the Initial Decision Matrix

Assume that the evaluation object includes m interactive interface layout schemes and n evaluation indicators. The Initial Decision Matrix (*IDM*) is constructed as shown in Equation (5):

$$IDM = \begin{bmatrix} b_{11} & \cdots & b_{1j} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mj} & \cdots & b_{mn} \end{bmatrix} \quad (5)$$

where b_{ij} denotes the original value of the i -th layout scheme for the j -th evaluation indicator.

Step 2. Normalize the *IDM*

The normalized value is calculated using the linear min–max normalization method. Moreover, for a cost criterion, Equation (6) is used, whereas for a benefit criterion, Equation (7) is employed:

$$r_{ij} = \frac{b_{\max} - b_{ij}}{b_{\max} - b_{\min}}, \text{ if } j \text{ is a cost criterion} \quad (6)$$

$$r_{ij} = \frac{b_{ij} - b_{\min}}{b_{\max} - b_{\min}}, \text{ if } j \text{ is a benefit criterion} \quad (7)$$

Step 3. Calculate the Percentage Value of Each Criterion

The Percentage Value (*PV*) is obtained by calculating the ratio between the root mean square value of each attribute and its standard deviation to reduce the difference caused by data magnitude. This is expressed as follows:

$$PV_{ij} = \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m r_{ij}^2}{m}}}{\sigma} \right) \times 100 \right| \quad (8)$$

Step 4. Calculate the Objective Weights

Based on the percentage value of each indicator, the LOPCOW objective weight is calculated as follows:

$$w_j^o = \frac{PV_{ij}}{\sum_{i=1}^n PV_{ij}} \quad (9)$$

Based on Equations (8) and (9), higher objective weights are assigned to indicators that show larger and more informative logarithmic percentage changes among alternatives. Meanwhile, the influence of scale differences and extreme values is reduced. Finally, the objective weight vector is obtained as follows: $w_j^o = (w_1^o, \dots, w_n^o)$.

3.3.3. Combined Weight Calculation

To account for both expert judgment and differences in the objective data, this study combines the RANCOM subjective weights with the LOPCOW objective weights. Euclidean distance quantifies the distance between two points in Euclidean space [44] and is calculated as follows:

$$d = \sqrt{\sum_{j=1}^m (w_j^s - w_j^o)^2} \quad (10)$$

The initial combined weight is then calculated as follows:

$$w = \frac{w_j^s + w_j^o}{2} \times \frac{1}{1 + d} \quad (11)$$

where d denotes the Euclidean distance, w represents the adjusted initial combined weight coefficient, w_j^s is the weight coefficient obtained by the first method, and w_j^o represents the weight coefficient obtained by the second method.

To ensure that the combined weights meet the normalization requirement, the initial combined weights are normalized to obtain the final combined weight w_j , as shown below:

$$w_j = \frac{\tilde{w}_j}{\sum_{j=1}^n \tilde{w}_j} \quad (12)$$

Finally, the combined weight vector is obtained as follows: $W = (w_1, w_2, \dots, w_n)$.

3.3.4. TOPSIS Method

The core idea of TOPSIS is to evaluate the overall performance of each alternative by comparing its distances from the positive and negative ideal solutions. The positive ideal solution is a virtual alternative in which all indicators reach their optimal values, whereas the negative ideal solution is a virtual alternative in which all indicators reach their worst values. A better-performing alternative is closer to the positive ideal solution and farther from the negative ideal solution. The specific steps are as follows.

Step 1. Construct the Weighted Decision Matrix

Assume that $U = (u_{ij})_{m \times n}$ is a weighted decision matrix with m rows and n columns. It is calculated as follows:

$$U_{ij} = w \times X_{ij} \quad (13)$$

Step 2. Determine the Positive and Negative Ideal Solutions

The positive and negative ideal solutions are calculated according to the attribute of each criterion. They are denoted by D^+ and D^- , respectively, as defined below:

$$\begin{cases} D^+ = (Z_1^+, Z_2^+, \dots, Z_n^+) \\ D^- = (D_1^-, D_2^-, \dots, D_n^-) \\ D_j^+ = \max(D_{ij}) \\ D_j^- = \min(D_{ij}) \end{cases} \quad (14)$$

where D_j^+ and D_j^- represent the maximum and minimum values of the j -th evaluation indicator, respectively.

Step 3. Calculate the Distances From Each Scheme to the Positive and Negative Ideal Solutions

The Euclidean distance is used to calculate the distance between the i -th scheme and the positive ideal solution, as well as the distance between the i -th scheme and the negative ideal solution. These distances are denoted by D_i^+ and D_i^- , respectively, and are expressed as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^n (z_{ij} - Z_j^+)^2} \quad (15)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (z_{ij} - Z_j^-)^2} \quad (16)$$

Step 4. Calculate the Relative Closeness

The relative closeness is denoted by C_i^* , and is calculated as follows:

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \quad (17)$$

Step 5. Rank the Schemes

The alternatives are ranked according to the calculated relative closeness coefficient. A larger value indicates that an alternative is farther from the negative ideal solution and closer to the positive ideal solution and therefore has better comprehensive performance.

Arousal (C8) reflects the emotional activation level associated with an interface layout. Because a higher value does not necessarily indicate better design quality, arousal was treated as a moderate indicator. The PAD scale uses a 1–9 response format; therefore, 5 was set as the ideal arousal value, and the original arousal score was converted into closeness to this ideal level, as shown in Equation (18):

$$x'_{i8} = 1 - \frac{|x_{i8} - 5|}{\max|x_{i8} - 5|} \quad (18)$$

4. Experimental Design and Data Collection

4.1. Evaluation Samples

This study used interactive interface layouts from smart digital museums as the evaluation samples. Between January and February 2026, 276 interface cases were collected from official digital museum websites and online platforms, including the National Museum of China and provincial- and municipal-level digital museum platforms in China. The collected interfaces included basic functions such as cultural-content presentation, navigation guidance, information description, and interaction-entry points.

The inclusion criteria were as follows: (1) the interface presented museum or cultural-heritage content; (2) the layout included identifiable functional areas; (3) the interface supported browsing, navigation, or information access; and (4) the image resolution was sufficient for layout analysis. The exclusion criteria included incomplete interface information, poor image quality, substantial differences in core functions, excessive decorative effects, repeated layout structures, and interfaces that could not be abstracted into comparable modules. After screening, 62 valid interface cases were retained for layout classification.

The KJ classification was conducted by three researchers: one expert with more than five years of experience in interface design and user-experience evaluation and two doctoral candidates in industrial design. Their research backgrounds covered industrial design, interface design, and user experience. First, the researchers independently reviewed the 62 retained cases and extracted the main layout features, including the main display area, navigation area, information-description area, interaction-entry area, and auxiliary-function area. Second, similar layout structures were grouped according to module position, area proportion, and spatial organization. Disagreements were discussed among the three researchers. If consensus could not be reached, the expert made the final decision. Based on the classification results, six representative layout types were selected according to three criteria: the layout type appeared repeatedly in the collected cases, showed clear differences from other types in spatial organization, and retained the main functional structure of smart digital museum interfaces. The six layouts were labeled Layout A (L1), Layout B (L2), Layout C (L3), Layout D (L4), Layout E (L5), and Layout F (L6), as shown in Figure 2.

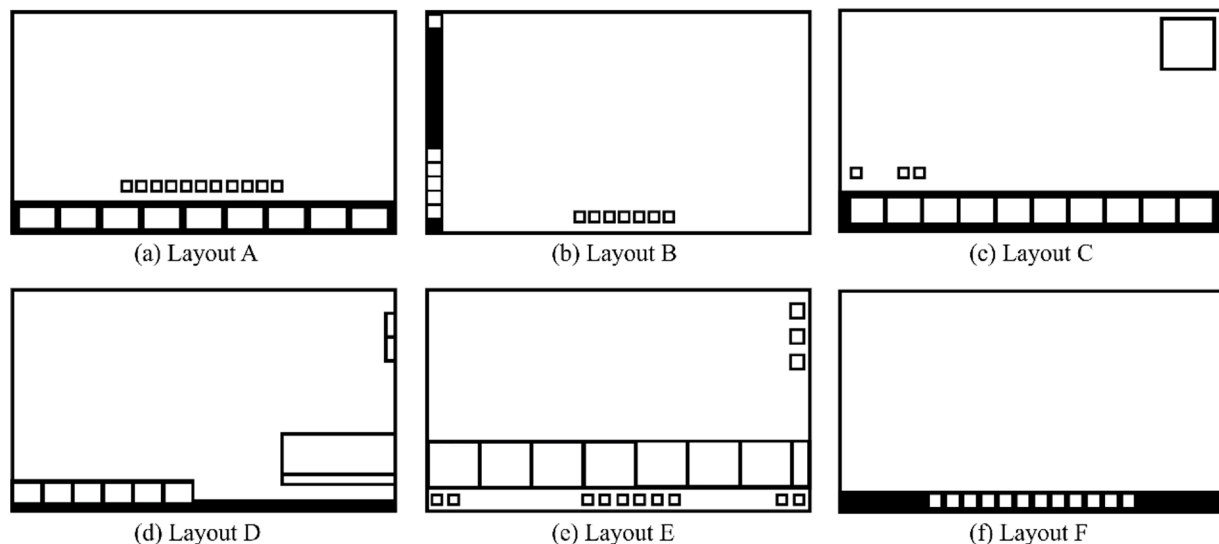


Figure 2. Interface layout evaluation samples.

To minimize the influence of color schemes, artifact images, textual content, brand identity, and decorative elements on the evaluation, the samples were abstracted while their basic layout structures were retained. The main functional areas were converted into standardized black-and-white rectangular wireframe modules. Only the positional relationships, relative area proportions, and spatial organization of the modules were retained. All samples used the same canvas size and visual-presentation format to support comparison in the eye-tracking experiment, PAD evaluation, and multi-criteria analysis. The findings should therefore be interpreted as layout-level evaluation evidence rather than as a complete evaluation of fully designed digital museum interfaces.

4.2. Participants and Experimental Equipment

A total of 32 participants were recruited through campus notices and online invitations. The sample included 17 females and 15 males, aged 20–36 years, with a mean age of 25.4 years ($SD = 2.58$). The participants were mainly university students and young adults with higher-education backgrounds and represented both design-related and non-design-related fields. The inclusion criteria were normal or corrected-to-normal vision, no color blindness or color weakness, and the ability to complete the visual-search task independently. The exclusion criteria included visual impairments that could affect task performance, previous participation in similar eye-tracking experiments, and professional experience in digital museum interface evaluation or usability testing. Before the experiment, the participants reported their previous experience with digital museums and interface design. Most had general experience browsing digital interfaces, but none had participated in professional digital museum interface evaluation. All 32 initially recruited participants were retained after eye-tracking data screening. The researchers explained the procedure and precautions before the experiment, and written informed consent was obtained from all participants. The study was approved by the Science and Technology Ethics Review Committee of the College of Design and Art, Shaanxi University of Science and Technology (Approval No. SUST20260321; approval date: 21 March 2026).

The experimental equipment included a Tobii X120 eye tracker (Tobii, Stockholm, Sweden) with a sampling frequency of 120 Hz and an accuracy of approximately 0.4° . The stimuli were presented on a 23.8-inch monitor with a resolution of 1920×1080 pixels and a refresh rate of 60 Hz. The experiment was designed, presented, and recorded using ErgoLAB 3.0, and the data were subsequently processed and analyzed using SPSS 19.0.

Participants viewed the screen from a distance of approximately 60–70 cm. No chinrest was used. They were instructed to maintain a stable sitting position and minimize head movement. A nine-point calibration was conducted before the formal experiment and repeated until it met the acceptance criterion specified by the software.

The experiment was conducted in an indoor laboratory of approximately 42 m². Indoor lighting, noise, external light sources, and other potential disturbances were controlled to reduce their influence on the eye-tracking data and subjective ratings. Shading was also used to maintain a stable visual environment. The formal experiment began only after successful eye-tracking calibration.

4.3. Experimental Task and Procedure

Before the experiment, the researchers explained the procedure and precautions to the participants. Participants were informed that the same preset navigation touchpoint icon would be used as the search target in all six layouts. They were not required to memorize exhibit information or understand specific cultural content because the experiment focused on visual search, attention allocation, and emotional evaluation under different layout structures. An additional practice sample, which was not included in the formal experiment, was used to familiarize participants with the target icon, task requirements, and mouse operation. After the practice task, participants took a short break. The researchers then adjusted the eye-tracking device and completed gaze and position calibration. The formal experiment began only after successful calibration. The experimental procedure is shown in Figure 3.

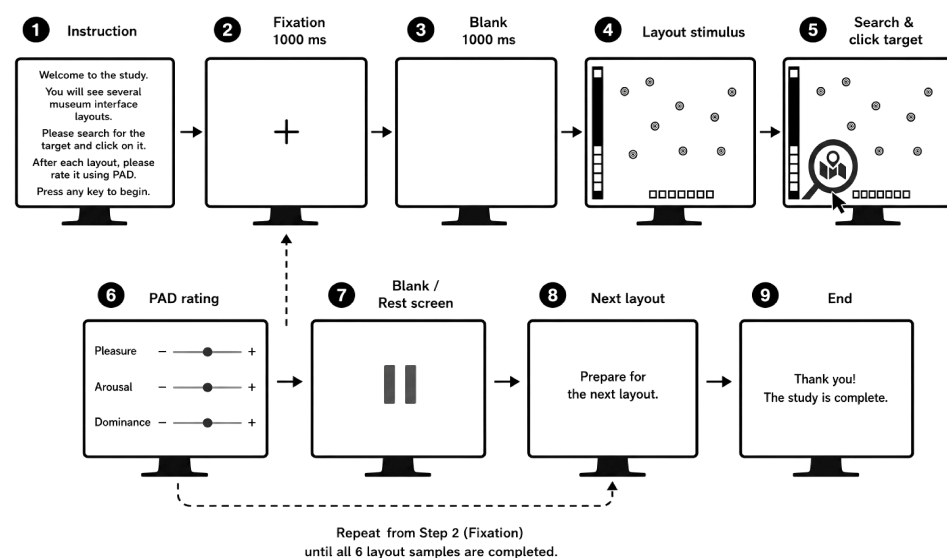


Figure 3. Experimental procedure.

The same target navigation icon was used in all six layouts. Its text, graphic form, color, size, and visual contrast were kept constant. The icon represented the same navigation function and was placed within the corresponding navigation or interaction-entry area of each layout. Its location followed the navigation position in the original interface structure and was not randomly assigned. The target therefore occupied an equivalent functional area across the six layouts, although its absolute screen position and eccentricity were not identical.

At the beginning of each formal trial, the instructions were displayed at the center of the screen. A fixation point was then presented to guide participants' gaze back to the screen center. Next, a layout sample was presented, and participants were instructed to locate the preset target icon and click it with the mouse, as shown in Figure 4. An

experimenter observed each trial and recorded whether the target was correctly selected, missed, or incorrectly clicked. Participants then entered the PAD evaluation interface and rated the layout in terms of pleasure, arousal, and dominance. The PAD assessment was administered in Chinese using an electronic semantic-differential scale presented in ErgoLAB. Each PAD dimension was measured using a single item on a 9-point horizontal slider. The response anchors were:

- 1 = very unpleasant and 9 = very pleasant for pleasure;
- 1 = very calm and 9 = very excited for arousal;
- 1 = feeling controlled and 9 = feeling in control for dominance.

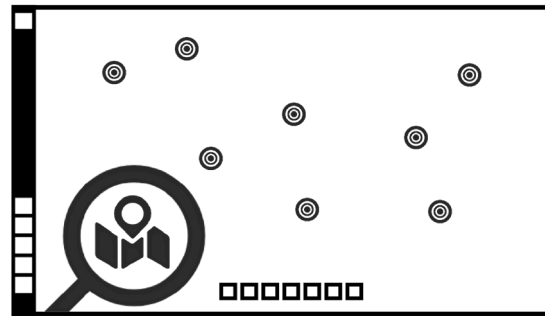


Figure 4. Example stimulus for the visual-search task.

After each rating, a short rest screen was displayed to reduce visual fatigue and potential carryover from the preceding trial. The six layouts were presented in a randomized order for each participant using the random-presentation function in ErgoLAB. No systematic counterbalancing scheme was used. The procedure was repeated until all visual-search tasks and PAD evaluations were completed.

4.4. Data Recording and Preprocessing

Three types of data were recorded: layout aesthetics, visual cognition, and emotional experience. Layout-aesthetics data were calculated from the positions and spatial relationships of modules in the six layouts. Visual-cognition data were recorded using the eye tracker and included total fixation duration, average pupil diameter, and saccade count. Emotional-experience data were obtained using the PAD scale and included pleasure, arousal, and dominance.

For the layout-aesthetics data, the main functional areas of each interface were abstracted into rectangular modules. The horizontal and vertical coordinates, width, height, and area of each module were then extracted. Based on existing interface-aesthetics calculation methods [28], symmetry, density score, and orderliness were calculated separately. To support comparison across these indicators, all values were converted to a 0–1 range, with higher values indicating better performance.

Click accuracy, missed targets, and incorrect clicks were monitored by an experimenter. All formal trials were completed correctly, and the observed click accuracy was therefore 100%. Because these measures showed no variation, they were not included in further analysis. Behavioral response time was not recorded separately, and total fixation duration was interpreted as cumulative fixation time rather than as behavioral task-completion time.

Fixations were identified in ErgoLAB 3.0 using its built-in fixation-detection algorithm, with a minimum fixation duration of 100 ms. Trials were considered invalid when the tracking ratio was below 80%, prolonged gaze loss occurred, gaze points remained outside the stimulus area, or the experimenter recorded obvious distraction. Obvious distractions included looking away from the screen, talking, or interrupting the task. No participants or trials were excluded. Therefore, 32 valid observations were retained for each layout,

resulting in 192 valid observations in total. Ambient lighting, monitor brightness, contrast, and display settings were kept constant throughout the experiment. All layouts used the same black-and-white color scheme and white background. However, the amount and spatial distribution of black areas differed across layouts, so stimulus luminance was not fully matched. Pupil diameter was not baseline-corrected or normalized within participants. The mean pupil diameter recorded during each visual-search trial was used in the subsequent evaluation. Total fixation duration, average pupil diameter, and saccade count were extracted for each participant under each layout. The indicators were calculated for the entire layout stimulus, and no separate areas of interest (AOIs) were defined. The mean of each eye-tracking indicator was then calculated for each layout. Each PAD dimension was measured using one item scored on a 9-point scale. Higher scores indicated higher pleasure, arousal, or dominance, and no reverse scoring was used. Each participant rated the three dimensions once for each layout. The mean scores of the 32 participants were then calculated separately for pleasure, arousal, and dominance under each layout.

4.5. Statistical Analysis

Descriptive statistics were used to summarize the eye-tracking and PAD data. Participant-level measurements were reported as mean $\pm$ standard deviation for each layout, and the corresponding layout-level means were used to construct the MCDM decision matrix. Ranking robustness was examined through 54 weight-perturbation scenarios. Agreement between the rankings obtained from the perturbed weights or alternative MCDM procedures and the baseline ranking was assessed using Spearman's rank correlation coefficient, Kendall's rank correlation coefficient, and mean absolute ranking deviation. No inferential statistical tests were conducted to compare the layouts; therefore, the eye-tracking and PAD results were interpreted descriptively.

5. Results

5.1. Results of Layout Aesthetics Evaluation

Based on the computational layout-aesthetics method, symmetry (C1), density score (C2), and orderliness (C3) were quantified for the six smart digital museum interface layouts. The results are presented in Table 2. For symmetry, L6 obtained the highest score (0.93), followed by L1 (0.91) and L2 (0.86), whereas L4 obtained the lowest score (0.44). For density score, L5 achieved the highest value (0.87), followed by L1 and L3 (both 0.82). These layouts therefore showed relatively small deviations from the optimal screen coverage of 50%. L6 recorded the lowest density score (0.61), indicating the largest deviation from the optimal density level among the six layouts. For orderliness, L5 obtained the highest score (0.91), followed by L1 (0.86) and L2 (0.83), while L4 obtained the lowest score (0.53).

Table 2. Results of interface layout aesthetics evaluation.

Interface Sample	Symmetry C1	Density Score C2	Orderliness C3
L1	0.91	0.82	0.86
L2	0.86	0.68	0.83
L3	0.62	0.82	0.64
L4	0.44	0.76	0.53
L5	0.72	0.87	0.91
L6	0.93	0.61	0.72

Overall, L1 maintained relatively high values across all three layout-aesthetics indicators. L5 showed advantages in density score and orderliness, although its symmetry score

was lower than those of L1, L2, and L6. L4 received relatively low scores for symmetry and orderliness. At the descriptive level, layouts with a stable spatial distribution, continuous functional modules, and clear primary–secondary relationships tended to obtain higher layout-aesthetics scores. Layouts with unevenly distributed elements, suboptimal space utilization, or weak visual guidance tended to obtain lower scores.

5.2. Results of the Visual Cognition Experiment

The eye-tracking data were processed using SPSS, and the mean values of total fixation duration (C4), average pupil diameter (C5), and saccade count (C6) were calculated for the six layouts. The results are presented in Table 3. These indicators describe cumulative fixation activity, pupil response, and gaze shifts during the target-search task. Average pupil diameter was treated as a supplementary indicator because it may also be affected by luminance, fatigue, individual differences, and emotional activation.

Table 3. Results of visual cognition evaluation.

Sample	Total Fixation Duration (s) C4	Average Pupil Diameter (mm) C5	Saccade Count (N) C6
L1	1.58 ± 0.31	3.47 ± 0.40	11.70 ± 3.89
L2	1.69 ± 0.36	3.90 ± 0.53	14.62 ± 4.31
L3	1.80 ± 0.52	4.25 ± 0.44	18.10 ± 4.55
L4	1.94 ± 0.47	4.39 ± 0.62	21.55 ± 5.19
L5	1.73 ± 0.46	3.73 ± 0.51	12.30 ± 3.45
L6	1.36 ± 0.28	3.33 ± 0.57	15.95 ± 4.31

Among the six layouts, L6 showed the lowest total fixation duration (1.36 s) and average pupil diameter (3.33 mm), followed by L1. These values indicate less cumulative fixation and a smaller pupil response during the visual-search trial. They should not be interpreted as evidence of faster behavioral task completion because response time was not recorded separately. For saccade count, L1 had the lowest value (11.70), followed by L5 (12.30) and L2 (14.62), indicating relatively concentrated gaze-shift patterns. L4 showed relatively high values for all three indicators: a total fixation duration of 1.94 s, an average pupil diameter of 4.39 mm, and a saccade count of 21.55. Under the present experimental conditions, this pattern represents longer cumulative fixation, a larger pupil response, and more frequent gaze shifts.

Overall, L6 showed relatively low total fixation duration and average pupil diameter, but its saccade count was not the lowest. This pattern may reflect the concentration of interface elements in the lower portion of the layout, which required gaze shifts between the main area and the bottom modules. L1 showed relatively low values across the three indicators, including the lowest saccade count. The descriptive results showed that layouts with clearer spatial organization, continuous functional modules, and explicit visual paths tended to have lower total fixation duration and fewer gaze shifts. Layouts with uneven element distribution or weaker target guidance tended to show higher eye-tracking values.

5.3. Emotional Experience Evaluation

The PAD scale was used to evaluate pleasure (C7), arousal (C8), and dominance (C9) for the six layouts. The results are presented in Table 4. L1 obtained the highest pleasure and dominance scores, at 8.20 and 8.34, respectively. L5 and L6 also showed relatively high pleasure and dominance scores. L4 obtained the lowest pleasure and dominance scores, at 4.05 and 3.15, respectively. For arousal, L4 obtained the highest score (8.18), followed by L3

(7.55). L1, L5, and L6 showed arousal scores closer to the moderate level, at 5.10, 5.35, and 5.20, respectively.

Table 4. Results of emotional experience evaluation.

Sample	Pleasure C7	Arousal C8	Dominance C9
L1	8.20 ± 1.19	5.10 ± 0.91	8.34 ± 0.82
L2	6.60 ± 1.01	5.62 ± 0.95	6.85 ± 1.03
L3	5.57 ± 0.90	7.55 ± 0.86	4.63 ± 0.84
L4	4.05 ± 0.98	8.18 ± 1.12	3.15 ± 1.02
L5	7.85 ± 1.12	5.35 ± 1.05	7.29 ± 1.29
L6	7.56 ± 1.34	5.20 ± 1.10	7.70 ± 1.21

Overall, L1 combined relatively high pleasure and dominance scores with a moderate arousal score. L4 showed low pleasure and dominance scores together with high arousal. These results are descriptive and should not be interpreted as evidence that a particular layout caused the observed emotional responses. Across the six layouts, clearer spatial structures and more stable visual order tended to occur together with higher pleasure and dominance scores, whereas less stable visual focus and higher visual-search indicators tended to occur together with higher arousal and less favorable emotional ratings.

5.4. Results of Comprehensive Evaluation

To compare the descriptive performance of the six layouts across the three evaluation dimensions, all indicator values were normalized to the range of 0–1. Benefit criteria were normalized using Equation (7), whereas cost criteria were reverse-normalized using Equation (6). Arousal (C8) was first converted into closeness to the ideal value of 5 using Equation (18) and was then normalized as a benefit criterion. To obtain a descriptive score for each dimension, the three normalized indicators within that dimension were combined using an equally weighted arithmetic mean, as defined in Equation (19):

$$S_{ik} = \frac{1}{3} \sum_{j \in G_k} r_{ij} \quad (19)$$

where S_{ik} denotes the score of layout i for dimension k , r_{ij} represents the normalized value of indicator j for layout i , and G_k indicates the three indicators included in dimension k . The final MCDM weights reported in Table 5 were not used in Figure 5. Therefore, Figure 5 provides a descriptive comparison across the three dimensions and does not affect the subsequent TOPSIS ranking. As shown in Figure 5, L1, L5, and L6 performed relatively well across the three dimensions, while L4 showed relatively low scores.

Table 5. Results of subjective, objective, and combined weights.

Indicator	Subjective Weight	Objective Weight	Combined Weight
C1	0.125	0.119	0.122
C2	0.045	0.113	0.079
C3	0.185	0.111	0.148
C4	0.095	0.094	0.095
C5	0.060	0.094	0.077
C6	0.105	0.117	0.111
C7	0.145	0.122	0.134
C8	0.075	0.111	0.093
C9	0.165	0.118	0.142

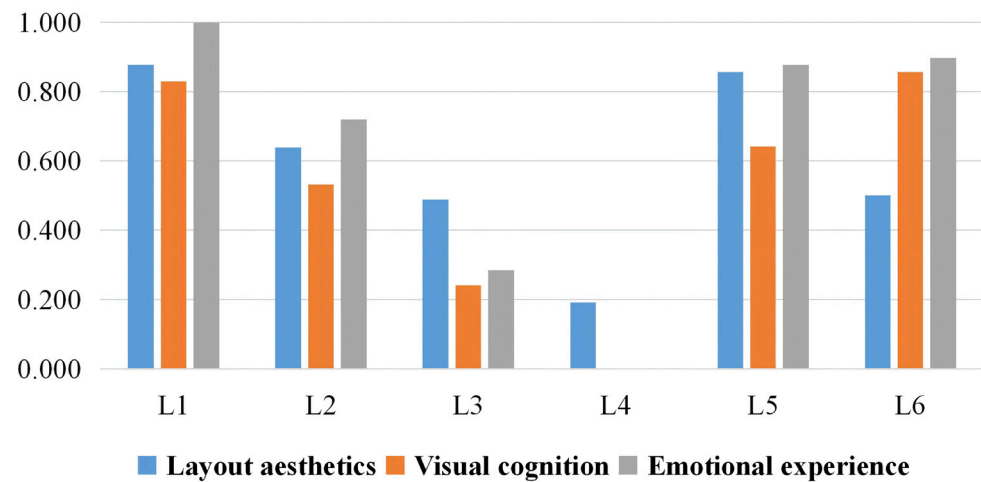


Figure 5. Comparison of equally averaged normalized scores across the three dimensions.

5.4.1. Indicator Weight Results

To incorporate both expert judgment and data characteristics, the RANCOM–LOPCOW combined-weighting approach was used to determine the criterion weights. The results are presented in Table 5. The subjective weights were derived from the rankings provided by the five experts described in Section 3.3.1. The experts assessed the relative importance of the nine indicators for layout quality, visual cognition, and emotional experience in smart digital museum interface evaluation. Orderliness (C3, 0.185), dominance (C9, 0.165), pleasure (C7, 0.145), and symmetry (C1, 0.125) received relatively high subjective weights. For the objective weights, the raw data for the six layouts and nine indicators were used to construct the initial decision matrix. Arousal (C8) was converted into closeness to the ideal arousal level before calculation. Pleasure (C7, 0.122), symmetry (C1, 0.119), dominance (C9, 0.118), and saccade count (C6, 0.117) received relatively high objective weights, indicating relatively strong discrimination among the six layouts in the current dataset.

The combined-weight results show that orderliness (C3, 0.148), dominance (C9, 0.142), and pleasure (C7, 0.134) received relatively high weights in the current evaluation model. Density score (C2, 0.079) and average pupil diameter (C5, 0.077) received relatively low combined weights. These values describe the contribution of each indicator to the selected MCDM procedure under the current dataset and should not be interpreted as universal importance levels.

5.4.2. TOPSIS Comprehensive Evaluation

After the RANCOM–LOPCOW combined weights were obtained, TOPSIS was used to evaluate the six layouts. Symmetry (C1), density score (C2), orderliness (C3), pleasure (C7), and dominance (C9) were treated as benefit criteria. Total fixation duration (C4), average pupil diameter (C5), and saccade count (C6) were treated as cost criteria. These directions were defined specifically for correctly completed target-search trials: lower C4 and C6 values indicated less cumulative fixation and fewer gaze shifts, while C5 was used only as a supplementary pupil-response indicator. Density score was treated as a benefit criterion because the raw density ratio had already been transformed relative to the optimal value of 50%; therefore, a higher C2 value indicates closer proximity to the optimal density level rather than a greater amount of interface content. Arousal (C8) was treated as a moderate criterion and was converted into closeness to the ideal arousal level before calculation. The raw values in Tables 2–4 jointly formed the initial decision matrix, while Table 5 reports the subjective, objective, and combined weights. Table 6 presents the normalized decision

matrix, weighted TOPSIS matrix, and ideal solutions. Table 7 presents the distances, relative closeness coefficients, and final rankings.

Table 6. Normalized decision matrix, weighted TOPSIS matrix, and ideal solutions.

(a) Normalized decision matrix.									
Sample	C1	C2	C3	C4	C5	C6	C7	C8	C9
L1	0.9592	0.8077	0.8684	0.6207	0.8679	1.0000	1.0000	1.0000	1.0000
L2	0.8571	0.2692	0.7895	0.4310	0.4623	0.7036	0.6145	0.8312	0.7129
L3	0.3673	0.8077	0.2895	0.2414	0.1321	0.3503	0.3663	0.2045	0.2852
L4	0	0.5769	0	0	0	0	0	0	0
L5	0.5714	1.0000	1.0000	0.3621	0.6226	0.9391	0.9157	0.9188	0.7977
L6	1.0000	0	0.5000	1.0000	1.0000	0.5685	0.8458	0.9675	0.8767
(b) Weighted TOPSIS matrix and ideal solutions.									
Sample	C1	C2	C3	C4	C5	C6	C7	C8	C9
L1	0.1170	0.0638	0.1285	0.0590	0.0668	0.1110	0.1340	0.0930	0.1420
L2	0.1046	0.0213	0.1168	0.0409	0.0356	0.0781	0.0823	0.0773	0.1012
L3	0.0448	0.0638	0.0428	0.0229	0.0102	0.0389	0.0491	0.0190	0.0405
L4	0	0.0456	0	0	0	0	0	0	0
L5	0.0697	0.0790	0.1480	0.0344	0.0479	0.1042	0.1227	0.0855	0.1133
L6	0.1220	0	0.0740	0.0950	0.0770	0.0631	0.1133	0.0900	0.1245
A ⁺	0.1220	0.0790	0.1480	0.0950	0.0770	0.1110	0.1340	0.0930	0.1420
A [−]	0	0	0	0	0	0	0	0	0

Table 7. TOPSIS comprehensive evaluation results.

Sample	D_i^+	D_i^-	C_i^*	Ranking
L1	0.045	0.318	0.876	1
L5	0.091	0.287	0.759	2
L6	0.122	0.275	0.693	3
L2	0.122	0.239	0.662	4
L3	0.234	0.120	0.339	5
L4	0.334	0.046	0.120	6

Based on the selected TOPSIS procedure, L1 had the highest relative closeness coefficient (0.876) and ranked first. L5 and L6 ranked second and third, respectively. L5 showed relatively high density-score and orderliness values, while L6 showed relatively low total fixation duration and average pupil diameter. L4 had the lowest relative closeness coefficient (0.120) and ranked last. The TOPSIS ranking was generally consistent with the descriptive patterns in the individual indicators. Under the current layouts, indicators, and weighting procedure, layouts with balanced spatial organization, clear visual paths, and higher perceived control tended to receive higher comprehensive evaluation scores.

5.5. Robustness and Method-Comparison Analysis

5.5.1. Weight Sensitivity and Ranking Robustness Analysis

To examine the sensitivity of the RANCOM–LOPCOW–TOPSIS ranking to changes in indicator weights, a weight-perturbation analysis was conducted using the combined weights as the baseline. Each indicator from C1 to C9 was selected in turn, and its weight was reduced by 15%, 30%, 45%, 60%, 75%, and 90%. After each perturbation, the remaining weights were proportionally renormalized so that the total remained 1. This procedure generated 54 weight-perturbation scenarios. For each scenario, the TOPSIS relative closeness coefficients and rankings of the six layouts were recalculated.

The baseline ranking was $L1 > L5 > L6 > L2 > L3 > L4$. Figure 6 presents the rankings under the different perturbation scenarios, where a smaller rank value indicates a higher-ranked layout. Of the 54 scenarios, 51 retained the baseline ranking, corresponding to a consistency rate of 94.44%. The ranking therefore remained unchanged under most of the tested weight variations.

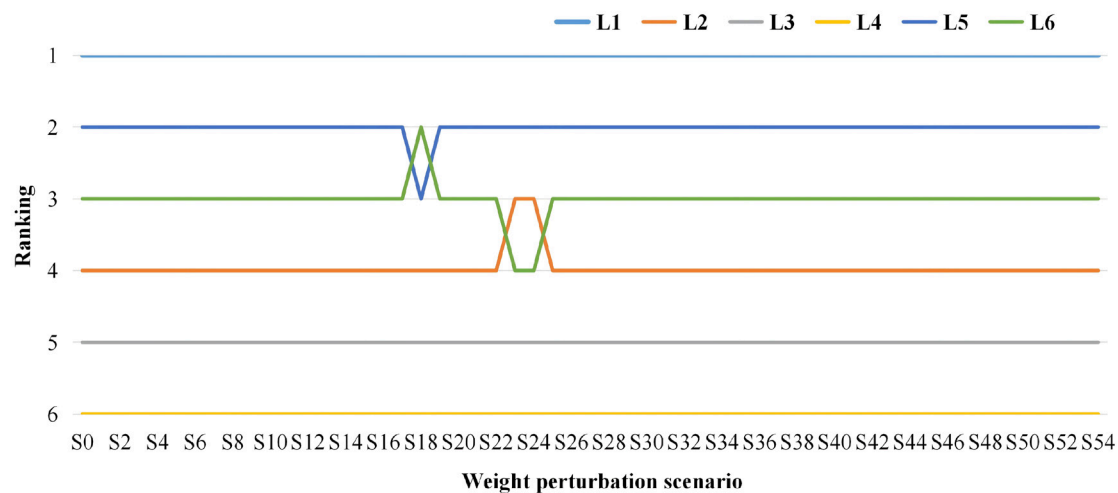


Figure 6. Ranking changes under different weight perturbation scenarios.

Ranking changes occurred only under three extreme perturbation scenarios and were limited to adjacent alternatives. When the weight of orderliness (C3) was reduced by 90%, L5 and L6 exchanged positions. When the weight of total fixation duration (C4) was reduced by 75% or 90%, L2 and L6 exchanged positions. These changes did not alter the overall ranking pattern. L1 remained first and L4 remained sixth in all scenarios.

Agreement between the perturbed rankings and the baseline ranking was further assessed using Spearman's rank correlation coefficient, Kendall's rank correlation coefficient, and mean absolute ranking deviation. Spearman's coefficients ranged from 0.943 to 1.000, Kendall's coefficients ranged from 0.867 to 1.000, and mean absolute ranking deviation ranged from 0 to 0.333. These results indicate high agreement with the baseline ranking and relatively low sensitivity to the tested changes in indicator weights.

5.5.2. Method-Comparison Analysis

To compare the rankings produced by different MCDM procedures, four alternative hybrid approaches were constructed with reference to related studies [45–48]: AHP–CRITIC–TOPSIS, BWM–EWM–TOPSIS, BWM–LOPCOW–TOPSIS, and RANCOM–CRITIC–TOPSIS. EWM refers to the Entropy Weight Method. All approaches used the same six layouts, nine indicators, and dataset; they differed mainly in their subjective and objective weighting methods. The analysis examined the level of ranking agreement among the different weighting procedures. Since all methods used the same layouts, indicators, and dataset, this comparison was used to assess ranking consistency rather than to provide independent model validation.

Figure 7 presents the rankings obtained using the five MCDM procedures. All procedures ranked L1 first and L4 last. RANCOM–LOPCOW–TOPSIS, BWM–EWM–TOPSIS, and BWM–LOPCOW–TOPSIS produced the same ranking: $L1 > L5 > L6 > L2 > L3 > L4$. AHP–CRITIC–TOPSIS and RANCOM–CRITIC–TOPSIS produced only adjacent exchanges between L2 and L6 and did not substantially change the overall ranking pattern.

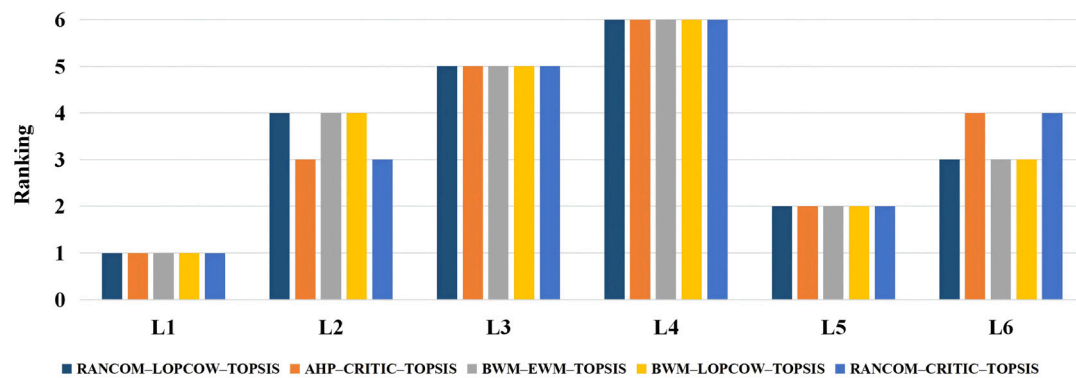


Figure 7. Ranking comparison of layout samples under different multi-criteria decision-making methods.

BWM-EWM-TOPSIS and BWM-LOPCOW-TOPSIS had Spearman's and Kendall's coefficients of 1.000 relative to the proposed procedure, with a mean absolute ranking deviation of 0. For AHP-CRITIC-TOPSIS and RANCOM-CRITIC-TOPSIS, Spearman's coefficient was 0.943, Kendall's coefficient was 0.867, and mean absolute ranking deviation was 0.333. These results indicate high agreement among the rankings, with the observed differences limited to adjacent layouts.

The small ranking differences can be interpreted in relation to the characteristics of the weighting methods. AHP relies on pairwise comparisons, while BWM requires identification of the best and worst criteria. RANCOM derives subjective weights from criterion rankings and adjacent differences. For objective weighting, CRITIC emphasizes criterion variability and conflict, EWM focuses on data dispersion, and LOPCOW uses logarithmic percentage changes. Under the current dataset, RANCOM-LOPCOW-TOPSIS produced a ranking that was highly consistent with those obtained using the alternative procedures. However, this comparison does not show that the proposed procedure is more accurate or superior. It indicates only ranking agreement among the examined methods under the same layouts, indicators, and dataset.

6. Discussion

6.1. Analysis of Differences in the Comprehensive Performance of Layout Schemes

The selected TOPSIS procedure generated the ranking $L1 > L5 > L6 > L2 > L3 > L4$. This result shows that the model-based evaluation was determined by the combined performance of the layouts across spatial organization, visual-search indicators, and emotional ratings rather than by any single indicator. Because no inferential statistical comparison was conducted, the ranking should not be interpreted as evidence of statistically significant differences among the layouts.

The higher ranking of L1 was associated with its relatively balanced values across the three evaluation dimensions. L1 did not obtain the best value for every indicator, but it maintained relatively favorable values for layout aesthetics, visual cognition, and emotional experience. This pattern suggests that interface layout evaluation should consider the coordination of spatial structure, information guidance, and user perception rather than optimize a single indicator such as symmetry or total fixation duration. This interpretation is consistent with previous studies showing that information layout and spatial arrangement can influence visual-search performance and subjective evaluation [49,50]. In the present study, L1 combined continuous functional modules and a stable spatial structure with fewer gaze shifts and a higher dominance score. This represents a descriptive association rather than evidence of a causal relationship.

L5 and L6 also ranked relatively high, but their strengths differed. L5 showed high orderliness and module continuity. L6 showed the shortest total fixation duration and the

smallest average pupil diameter, indicating less cumulative fixation and a smaller pupil response under the present task conditions. However, its elements were concentrated mainly in the lower portion of the layout, and its density score and orderliness were lower than those of L5. L6 therefore ranked slightly below L5. This result indicates that low eye-tracking values alone did not determine the overall ranking; spatial distribution and functional organization also contributed to the selected MCDM evaluation.

L3 and L4 showed weaker comprehensive performance. L3 had a relatively high density score but lower symmetry and orderliness values, indicating that proximity to the optimal density level alone did not ensure a high overall ranking. L4 had low layout-aesthetics scores, high eye-tracking values, low pleasure and dominance scores, and the highest arousal score. In the current dataset, this combination of unclear module distribution and unstable visual focus occurred together with higher visual-search indicators and lower perceived control. Previous research has shown that website and task complexity can affect visual attention and cognitive load [10]. However, the present findings should be interpreted as descriptive differences among the layouts rather than as direct evidence that unclear spatial organization caused greater cognitive processing demands or poorer emotional experience.

Overall, the rankings reflect the integration of multiple dimensions rather than a comparison of isolated indicators. In the descriptive results, layouts with balanced spatial relationships, continuous functional modules, and clear visual paths tended to show lower visual-search indicators and higher pleasure and dominance scores. Layouts with local imbalance, unclear module relationships, or weak visual guidance tended to show higher visual-search indicators and less favorable emotional ratings.

6.2. Descriptive Comparison of Patterns Across the Three Evaluation Dimensions

The three evaluation dimensions showed similar descriptive patterns across the six layouts. Layouts with higher aesthetics scores generally had more balanced spatial structures and clearer visual order. Under the target-search task used in this study, these characteristics appeared together with lower visual-search indicators and higher emotional ratings. This pattern is consistent with previous research on interface layout and visual-search performance [49,50]. However, the current findings represent only descriptive comparisons among the evaluated layouts. They do not provide statistical evidence of relationships or causal effects among the three dimensions. Lower eye-tracking values should also not be regarded as inherently better in every interface context. In open-ended museum browsing, lower values may reflect limited engagement or incomplete information exploration. Their treatment as cost criteria in this study was therefore restricted to correctly completed preset target-search trials.

Across the six layouts, L1, L5, and L6 showed relatively favorable spatial organization and visual guidance together with lower visual-search indicators, higher pleasure and dominance scores, and arousal values closer to the moderate level. L3 and L4 showed higher visual-search indicators. In particular, L4 had the longest total fixation duration, the largest average pupil diameter, and the highest saccade count, together with low pleasure and dominance scores and high arousal. In this context, high arousal should not be interpreted automatically as positive engagement; it may also be associated with tension or uncertainty during visual search.

This pattern supports the treatment of arousal as a moderate indicator in the comprehensive evaluation. A higher arousal score does not necessarily represent a better interface experience. Moderate arousal may help maintain attention, whereas excessive arousal may occur together with visual pressure, uncertainty, and reduced perceived control. Layout

evaluation should therefore consider whether emotional activation is accompanied by pleasure and dominance rather than interpret arousal independently.

The descriptive pattern is consistent with previous studies on the role of perceived visual aesthetics in user evaluation [51]. In smart digital museum interfaces, layout aesthetics is not only a matter of formal visual quality. In the present data, clearer and more balanced structures tended to occur together with lower visual-search indicators, higher perceived control, and more positive emotional ratings. Layout aesthetics, visual cognition, and emotional experience should therefore be considered together in layout evaluation. Future studies should test the statistical relationships among these dimensions using correlation analysis, regression analysis, or structural equation modeling.

6.3. Design Implications and Research Limitations

Based on the model-generated rankings and descriptive results, smart digital museum interface layouts should prioritize balanced spatial organization and continuous visual paths. Higher-ranked layouts generally had stable module relationships and clear browsing sequences. These features may help users identify the relationships among the main display area, functional entries, and auxiliary areas. Layouts should therefore avoid excessive dispersion or localized clustering of functional modules. Continuous navigation areas, a clear primary–secondary hierarchy, and stable spatial boundaries can be used to support coherent visual-search paths.

Layout design should not focus only on formal symmetry or simplicity; it should also consider users' perceived control and emotional experience. In this study, clearer interface structures and easier target identification occurred together with higher pleasure and dominance scores. Less distinct visual focus and poorly defined functional entries occurred together with higher visual-search indicators and less favorable emotional ratings. Smart digital museum interfaces should therefore highlight key interaction entries while maintaining visual order so that users can understand the interface structure and complete target-locating tasks efficiently.

This study has several limitations that may affect the generalizability of the findings. First, the experiment used six representative interface layouts. Although these layouts were selected from digital museum, virtual gallery, and digital exhibition cases using the KJ method, they cannot represent all possible layout types in smart digital museums. The ranking should therefore be interpreted within the scope of the selected layouts rather than as a universal conclusion for all digital museum interfaces. Future studies should include a larger and more diverse set of interface layouts.

Second, the participant sample was relatively small, and no a priori sample-size calculation was conducted. The 32 participants repeatedly evaluated all six layouts and were mainly young adults. The findings may therefore not represent older adults, children, users from different cultural backgrounds, or people with different levels of digital experience. The presentation order was randomized independently for each participant, but no systematic counterbalancing scheme was used. Short rest screens were provided, yet order, learning, and fatigue effects may still have occurred. Future studies should determine the sample size in advance, recruit more diverse participants, use counterbalanced sequences, or include trial order in the analysis.

Third, the experimental stimuli were simplified black-and-white wireframe interfaces rather than fully realistic digital museum interfaces. This design controlled the influence of color, artifact images, textual content, brand identity, and decorative elements so that the experiment could focus on layout structure. However, it also reduced ecological validity and limited the museum-specific context of the stimuli. The wireframes did not represent cultural narratives, exhibit meanings, museum atmosphere, interaction feedback,

or dynamic effects. The findings are therefore more directly applicable to layout-level comparison and should be examined further using realistic prototypes or operational digital museum systems. In addition, although the target icon represented the same function and was visually identical across layouts, its absolute screen position and eccentricity differed according to the original layout structures. The influence of target location could therefore not be separated fully from the overall layout effect. Ambient lighting and display settings were held constant, but the amount and distribution of black areas differed across the layouts. Pupil diameter was not baseline-corrected or normalized within participants. Average pupil diameter was therefore treated as a supplementary pupil-response indicator rather than as a direct measure of cognitive load.

Fourth, emotional experience was measured mainly using the PAD scale. Although PAD captures basic responses in terms of pleasure, arousal, and dominance, it cannot fully explain deeper museum experiences such as cultural engagement, immersion, learning motivation, or narrative involvement. Future studies could combine subjective scales with physiological signals, behavioral data, interviews, or task-performance measures to provide a more comprehensive account of user experience.

Fifth, the final rankings may depend on the selected data-processing and MCDM procedures, including min–max normalization, the transformation of arousal around the ideal value of 5, the RANCOM–LOPCOW weighting combination, and the TOPSIS aggregation rule. The sensitivity and method-comparison analyses showed stable ranking patterns under the tested conditions, but they do not eliminate dependence on these methodological choices. Future studies should compare additional normalization, weighting, and aggregation procedures and test the framework using new datasets or external benchmarks.

7. Conclusions

This study developed a RANCOM–LOPCOW–TOPSIS-based method for evaluating interactive interface layouts in smart digital museums. Based on the selected MCDM procedure, the six layouts were ranked as $L1 > L5 > L6 > L2 > L3 > L4$. $L1$ had the highest relative closeness coefficient (0.876), while $L4$ had the lowest value (0.120). The baseline ranking was retained in 51 of the 54 weight-perturbation scenarios, indicating relative ranking robustness under the tested conditions. However, these results represent the ranking generated by the selected evaluation procedure and do not provide statistical evidence of significant differences among the layouts.

At the descriptive level, the higher-ranked layouts generally showed more balanced spatial relationships, clearer visual paths, lower visual-search indicators, and higher pleasure and dominance scores. These patterns should not be interpreted as causal relationships. From a design perspective, the framework can support the comparison of alternative interface layouts and help identify potential problems related to spatial balance, module continuity, visual guidance, and perceived control.

Future research should test the framework using larger and more diverse participant samples, additional layout types, realistic digital museum interfaces, and independent datasets. Inferential statistical analyses should also be conducted to examine differences among layouts and improve the generalizability and applicability of the method.

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