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Design of panoramic virtual museum interactive interface based on entropy weight TOPSIS and PSO-SVR

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This study addresses the neglect of user emotional needs in digital cultural heritage displays by proposing a quantitative methodology to optimize the Panoramic Virtual Museum Interactive Interface (PVMUI). Leveraging Kansei Engineering, we first extracted three core affective dimensions (Technological, Innovative, Fancy) through factor analysis of 45 Kansei terms. Morphological decomposition and entropy-weighted TOPSIS objectively prioritized six critical design features from 14 candidates. A nonlinear mapping model integrating Particle Swarm Optimization Support Vector Regression (PSO-SVR) was developed to correlate these features with user emotions, validated empirically via 100 participants. Results identified an optimal configuration: top-bottom layout (A1-1), 30% screen occupancy (A2-3), transparent navigation icons (A5-5), planar maps (A7-3), arrow-shaped movement icons (A9-7), and no scene interaction (A10-6). The framework advances virtual museum design by establishing emotion-driven optimization principles, bridging theoretical gaps in affective computing for PVMUI while offering actionable guidelines for enhancing user immersion and heritage dissemination.

With the passage of time, the function of museums has gradually shifted from collecting and storing artifacts to engaging in a unique form of cultural exchange with society. This transformation has made museums one of the most popular scientific institutions outside of schools, and such cultural exchanges can bring positive benefits to society, economy, education, and other aspects[1]. With the continuous development of the so-called "Experience Economy," technological innovation and the widespread use of the internet have made people more eager to obtain novel museum experiences. Traditional museum visiting methods can no longer satisfy the emotional needs of users[2]. There is an urgent need for more innovative, high-tech, and interactive museum visiting methods to facilitate cultural exchange with museums. In this context, the digitization of museum experiences is considered a highly anticipated solution[3].

Accompanied by continuous exploration of digital technologies such as VR, AR, MR, panoramic photography, mobile platforms, and interactive animations in the field of museum exhibitions, scholars have combined technologies like computer graphics[4] and artificial intelligence[5]. Starting from two approaches—improving offline and online museums—they have integrated digital technologies into museum exhibitions, promoting the frontier development of cross-disciplinary research in museum digital exhibitions. In the direction of improving offline museums, these technologies and methods have been widely applied in forms such as immersive museum VR installations[6], AR-assisted museum experiences[7,8], and personalized museum experiences[9]. These forms are all considered helpful in enhancing public satisfaction with offline museum exhibitions. In the direction of online museums, these technologies and methods have been applied in forms such as virtual exhibition systems[10–12], serious games[13,14], and Panoramic Virtual Museums (PVMs)[15]. These forms can all provide the public with more convenient, interesting, and immersive online museum experiences.

As digital museum exhibition technologies continue to mature, museums are increasingly integrating diverse digital methods into their exhibitions—ranging from offline AR and VR interactions to interactive touchscreen digital displays, as well as online panoramic virtual museums and gamified virtual museums. These technologies hold the potential to profoundly shape the future of museum experiences. Virtual digital museums provide the public with more immersive and convenient museum viewing experiences, meeting the public's diverse cultural, educational, and emotional experience needs for museum visits, and promoting sustainable social and economic development.

As museum digitization projects continue to advance, online virtual museums - which include immersive virtual reality exhibitions and interactive online platforms - are receiving increasing attention and recognition from the public and museum institutions. However, in academia, there is still no unified definition of "virtual museum," but it is

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generally agreed that its main feature is to provide the public with a three-dimensional virtual museum experience through an interactive interface on the internet. The advantages of Virtual Museums can be summarized as:

(a) Visiting without leaving home: Visitors can enjoy museum exhibitions and services without being physically present, saving time and economic costs.
(b) Simple and easy interactive operation: A user-friendly interactive interface and intuitive operation methods allow users to get started easily, enhancing the convenience of the visiting experience.
(c) Relatively low construction cost: Compared with physical museums, Virtual Museums have lower construction and maintenance costs, higher resource utilization efficiency, and are conducive to the widespread dissemination of museum resources.

The Panoramic Virtual Museum (PVM) is a representative project among Virtual Museums and has been widely applied in various museums around the world, such as cultural museums[16], and science museums[17]. It uses three-dimensional panoramic technology to scan and stitch real museum exhibitions into a large number of high-definition panoramic images, transmits them to the internet through web plugins, and generates PVM scenes. The public can enter the interactive interface via web links[18] to realize functions such as roaming exhibitions, point-to-point movement, voice explanations, and VR tours. Previous studies have shown that visitors regard panoramic virtual museums as a form of leisure activity, finding them both interesting and memorable. Zhang[19] pointed out that virtual museums employ 3D panoramic, VR, and AR technologies to provide immersive experiences, allowing audiences to visit exhibitions without spatial constraints. In addition, as an innovative medium for knowledge dissemination, panoramic virtual museums can offer off-campus educational services for students. Aylana and Gökb's research on Turkey's Panorama 1453 Historical Museum indicated that its three-dimensional narrative mode facilitates the transmission of historical and cultural content while enhancing students' interest in learning[20].

Meanwhile, panoramic virtual museums can serve as specialized exhibition platforms for artifacts limited by real-world conditions, thereby generating cultural tourism benefits for local regions. In a VR game study involving the Terracotta Warriors, Zhang et al.[21] noted that the combination of 360° panoramic photography and 3D modeling enables participants to gain deeper insights into the Mausoleum of the First Qin Emperor, while simultaneously promoting cultural tourism. Moreover, this form of presentation aids museums in preserving, restoring, and displaying ancient cultural heritage while allowing for public oversight. Doulamis et al.[22] proposed that serious games enhance the dissemination of cultural heritage by providing interactive experiences through which audiences can better understand historical cultures.

Interaction between the public and virtual spaces remains a critical focus in VR research. Liarokapis et al.[23] summarized six types of interfaces in AR, VR, and MR systems, suggesting that technological advancements in panoramic virtual museums optimize user experience and offer substantial prospects for cultural education and entertainment. However, Past research on PVMs often focused on how to create an online PVM but did not conduct related design research on the PVM Interactive Interface (PVMUI), ignoring users' emotional needs. To bridge this gap, this study aims to develop a PVMUI design framework to enhance user interaction during exhibitions and promote the advancement and adoption of PVM technology.

In the study of users' emotional design, KE is used as an effective translation method to convert users' Kansei perceptions of products into design specifications that can be used by designers, thereby solving the imbalance between product output strategies and market input strategies caused by the increase in users' Kansei needs. KE originated in the automotive industry and was first applied by Mazda in the production of its "Persona" model[24], which was released in November 1988 and achieved excellent sales. In the subsequent nearly 40 years of development, KE has been applied in various design fields, such as logistics service design[25], space design[26], community service design[27], clothing design[28], and numerous industrial product design fields[29–31]. As a rigorous design framework, KE can be divided into three stages: (1) determining users' perception of the design object, (2) determining key design elements, and (3) constructing a mapping model between user perception and key design elements. In this process, researchers can use various types of mathematical models and computer reasoning systems to make the final design specifications more in line with users' Kansei needs.

For the first stage, most researchers choose to provide product samples to users in the form of product pictures or sketches and obtain Kansei feedback[32]. Some researchers complete this step using new technologies such as virtual reality[33]. For the second stage, methods such as Analytic Hierarchy Process (AHP)[34], Kano model[35], Rough Set Theory (RST)[36,37], Grey Relational Analysis (GRA)[38], etc., are applied. These methods can be used to determine the design elements with higher weights among the design elements, which helps researchers reduce the computational cost of the subsequent mapping model. For the third stage, since the relationship between users' Kansei perception and design elements is often a nonlinear function, traditional linear statistical analysis (such as factor analysis) cannot perform this task. Therefore, artificial intelligence technologies such as Backpropagation Neural Network (BPNN)[39] and Genetic Algorithm (GA)[40] are widely used in this stage.

This study proposes a systematic PVMUI design method based on the Kansei Engineering framework, integrating the entropy weight method, TOPSIS, and PSO-SVR to enhance users' emotional experience and sense of immersion. With the rapid digitization of cultural heritage and museums, PVMs have become an essential avenue for cultural transmission. However, existing research on PVMUIs primarily focuses on technological implementation while overlooking users' emotional experiences, leading to lower user engagement and weaker emotional connection with online museums. To date, no studies have applied the Kansei Engineering framework to optimize PVMUI design. Therefore, the core objective of this research is to establish a scientific approach capable of quantifying users' emotional needs and optimizing PVMUI design, thereby improving the user experience of virtual museums and filling a gap in the literature.

Following the Kansei Engineering approach, the study first identifies core user emotions and then employs the entropy-weighted TOPSIS method to determine key design features. Next, a PSO-SVR model is used to construct a nonlinear mapping between user emotions and these key features, enabling accurate predictions of optimal interface designs. Experimental results confirm the effectiveness of this method for enhancing users' emotional experience and informing PVMUI design decisions.

By providing scientific decision support for virtual museum designers, the findings of this research can optimize PVMUI to boost immersive online viewing and interactive experiences. Additionally, this study expands virtual museums' display forms, attracting the public to explore museums online and improving digital dissemination. It also meets the public's emotional needs for PVMs, enriches the visual experience of virtual exhibitions, and facilitates the continued development and innovation of cultural heritage digitization, promoting broader dissemination and inheritance of cultural heritage.

The innovations of this paper can be summarized as follows:

(a) Combining the Entropy Weight TOPSIS and PSO-SVR methods for design research. The integration of these two methods provides a new approach for the nonlinear mapping between user emotions and design elements.
(b) Offering new perspectives and methods for the field, contributing to the advancement of theory and practice in virtual museum interactive interface design.
(c) Using the Entropy Weight TOPSIS method to screen interactive interface design elements, determining key design elements, and reducing research costs. Through an objective weighting method, the design elements that have the most significant impact on user emotions

are precisely extracted, improving the efficiency and effectiveness of the research.

(d) Employing PSO-SVR to replace traditional linear statistical analysis, establishing a nonlinear mapping model between user perceptions and design elements. By optimizing the parameters of the SVR model using the PSO algorithm, the prediction accuracy of the model is enhanced, overcoming the limitations of traditional methods in nonlinear relationship modeling.

The structure of the paper is as follows: "Methods" provides an overview of the main methods used in this paper; "Research Framework and Process" elaborates on the research framework of the PVMUI design proposed in this paper and introduces the specific research process; "Results and Discussion" analyzes and discusses the research results; "Conclusion and Future Work" summarizes the content of this paper and proposes future research prospects.

Methods

A: Application of KE in interactive interfaces

With the continuous improvement of public living standards, consumer demands have shifted from merely functional value to emotional value. In 1986, Mazda first introduced the term "Kansei Engineering," which was further developed in 1995 by Mitsuo Nagamachi at Hiroshima University into a concrete product development technique[24]. Kansei Engineering aims to explore the relationship between consumers' intangible emotional needs and the tangible elements of product design[41].

In recent years, KE has been widely applied in interactive interface research, particularly in evaluating and optimizing user experience. Table 1 clearly summarizes the research methods, techniques, and outcomes related to applying KE in interactive interface design. Despite various existing KE-based studies on interface evaluation or design, no scholars have paid attention to the field of PVM, and there is a lack of design studies on the use of complex integrated models to build mapping models between user perceptual factors and interactive interface design elements. To address this gap, this study selects a web-based PVMUI as the research object and constructs a scientific and rational KE-TOPSIS-SVR integrated model to optimize existing PVMUIs. This approach aims to strengthen digital museum exhibitions and further promote PVM in the field of cultural heritage protection.

B: Entropy weight TOPSIS

To determine the weight of each design feature in PVMUI, we apply the Entropy Weight TOPSIS method. The Entropy Weight Method (EWM) is an objective weighting approach based on information theory, which calculates entropy values to measure the amount of information in the dataset. By avoiding subjective bias, EWM effectively reflects the weighting of user perceptions[42,43]. In Kansei Engineering research, EWM is often used to determine the weights of design elements. For example, Zou et al. employed EWM to assign weights to lychee quality indicators and used a linear weighted sum method to evaluate changes in overall shelf-life quality[42]. Wang et al. integrated EWM with an improved TOPSIS approach, constructing a decision-making system that combines subjective and objective evaluations to provide ergonomic optimization solutions[44].

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the multi-criteria decision-making (MCDM) methods, which ranks alternatives by calculating their distances to an ideal solution[45,46]. Its advantages include intuitive logic, computational efficiency, and suitability for multi-attribute decision-making[47,48]. This method has been extensively applied in industry and design. For instance, Lin et al. combined neural networks with TOPSIS to develop a Kansei Engineering decision support model for optimizing toy designs[49,50]. Wang et al. introduced a KE-TOPSIS-AISM method that uses TOPSIS for partial-order comparisons of product styles and incorporates AISM to establish a topological hierarchy,

Table 1 | Applications of KE in interactive design research

Author	Application	Objective	Methods	Finding
Chen[39]	Autonomous vehicle HMI	Develop senior-friendly interface	Kansei analysis, Factor Analysis, Rough Set, BPNN	Established a KE-driven HMI model to enhance accessibility for elderly users
Tharangie et al.[66]	Interface color design	Assess color impact on UI esthetics	KE Assessment System, Color Analysis	Identified affective color preferences to improve interface design
Deng & Wang[67]	HMI layout	Optimize UI esthetics	Kansei Engineering, Factor Analysis, TOPSIS	Developed an evaluation system for layout esthetics
Naim & Hwang[68]	Interactive video learning	Analyze emotional responses	KE, Emotional Correlation	Identified gender differences in emotional
Qu[69]	E-commerce websites	Enhance visual design for better user experience	Kansei extraction, SEM, Neural Networks	Optimized esthetics using genetic algorithms to align with user preferences
Gretalita et al.[70]	Financial assistant apps	Improve UI design for usability	KE, Data Mining, Persona Approach	KE-based optimization increased interface appeal and functionality

This table summarizes the applications of Kansei Engineering (KE) in interactive design research, highlighting key studies across various domains. Each entry includes the application context, research objectives, applied KE methodologies, and findings.

enhancing the optimization of product appearance design[51]. Furthermore, Quan et al. fused EWM, the Analytic Hierarchy Process (AHP), game theory, and Grey Relational Analysis (GRA) to propose a KE-GRA-TOPSIS approach, demonstrating its unique advantages in Kansei evaluation[52].

In summary, the Entropy Weight TOPSIS method can objectively determine the weights of design elements in multi-criteria decision scenarios. It extracts key features, discards low-weight factors, reduces computational costs, and provides robust support in Kansei Engineering for identifying essential design elements.

The calculation process of the Entropy Weight TOPSIS is as follows.

The EWM is an objective weighting method. It uses the information entropy of the data itself to calculate weights and obtain objective weighting results. The calculation process is as follows:

Step 1: Construct the decision matrix. Suppose there are m elements and n expert scores, the evaluation decision matrix is as in Eq. (1):

$$\boldsymbol{X}_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Calculate the normalized standardized matrix. The normalized matrix $\boldsymbol{Q}$ is formed by taking the ratio of each element in the standardized matrix to the sum of all elements in its column vector. The calculation process is as shown in Eqs. (2) and (3):

$$x_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, j = 1, 2, \cdots n \tag{2}$$

$$\boldsymbol{Q} = (q_{ij}), i = 1, 2, \cdots, m, j = 1, 2, \cdots, n \tag{3}$$

where $q_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij}^2$

Step 3: Calculate the information entropy and weights of each risk evaluation indicator. Use Eq. (4) to obtain the information entropy E_j of NO j, and use Eq. (5) to obtain the weight w_j of NO j:

$$E_j = -\lambda \sum_{i=1}^{n} p_{ij} \ln \mathrm{p_{ij}} \tag{4}$$

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{m} (1 - E_j)} \tag{5}$$

where $\lambda = \frac{1}{\ln \mathrm{n}}$, $p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}$, $i = 1, 2, \cdots, n, j = 1, 2, \cdots, m$, Where $0 \leq w_j \leq 1$ and $\sum_{j=1}^{m} w_j = 1$。

TOPSIS is a decision-making method widely used for multi-attribute problems across various industries. The calculation process is as follows:

Step 1: Construct the weighted decision matrix $\boldsymbol{B}$ based on the indicator weights.

$$\boldsymbol{B} = (b_{ij})$$

where (b_{ij}) is calculated according to Eq. (6):

$$b_{ij} = w_j \cdot q_{ij} \tag{6}$$

Step 2: Determine the positive ideal solution $\boldsymbol{U}^+$ and the negative ideal solution $\boldsymbol{U}^-$ based on the weighted decision matrix $\boldsymbol{B}$, as shown in Eqs. (7) and (8):

$$\boldsymbol{U}^+ = \{ \max_{1 \leqslant i \leqslant m} \{b_{ij}\} | j = 1, 2, \cdots, n\} = \{U_1^+, U_2^+, \cdots U_n^+\} \tag{7}$$

$$\boldsymbol{U}^- = \{ \min_{1 \leqslant i \leqslant m} \{b_{ij}\} | j = 1, 2, \cdots, n\} = \{U_1^-, U_2^-, \cdots U_{\mathrm{n}}^-\} \tag{8}$$

Step 3: Based on the positive and negative ideal solutions, determine the weighted Euclidean distances between the PVM design features and the ideal solutions, as shown in Eqs. (9) and (10):

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (b_{ij} - U_j^+)^2}, \ i = 1, 2, \cdots m \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (b_{ij} - U_j^-)^2}, \ i = 1, 2, \cdots m \tag{10}$$

Step 4: Calculate the relative closeness coefficient of each target and rank them, as shown in Eq. (11):

$$v_i = \frac{D_i^-}{D_i^- + D_i^+}, 0 \leqslant v_i \leqslant 1, i = 1, 2, \cdots m \tag{11}$$

By sorting the v_i values in descending order, a larger v_i indicates a higher importance of the evaluation indicator. Based on the decision results, the design features are ranked according to their importance. Several PVM design features with high importance are selected, effectively extracting design features that have a significant impact on users' Kansei needs.

C: PSO-SVR Particle Swarm Optimization Support Vector Regression method

In Kansei Engineering research, the relationship between Kansei words and design elements is often nonlinear, making it difficult for traditional linear methods to accurately map these associations. Consequently, neural network techniques have been widely adopted for constructing such mapping models. Among them, Support Vector Machine (SVM) has gained attention for its "kernel" technology, which effectively addresses nonlinear problems[53]. Support Vector Regression (SVR), an extension of SVM, performs nonlinear regression analysis for optimizing function estimation[54,55]. Studies have shown that SVR outperforms traditional neural networks in various applications. For instance, Yang et al. demonstrated that SVR yielded better predictive performance than BPNN in experiments involving mobile phone and electric vehicle datasets[56].

Particle Swarm Optimization (PSO) is a global optimization algorithm that simulates the search behavior of particle swarms to find optimal solutions in a given search space[57]. In this research, we employ PSO to optimize SVR parameters, thereby constructing a mapping model between the core design features of the PVMUI and user perceptual needs. This approach enhances both the accuracy and efficiency of design optimization.

SVR has also been widely used in previous design studies. For example, Yang et al. combined SVR with a multi-objective genetic algorithm (MOGA) to develop a hybrid Kansei Engineering system (HKES)[58]. Yuan et al. integrated LDA (Latent Dirichlet Allocation) and rough set theory (RST) to optimize medical care bed design[59]. Shieh et al. proposed a method merging SVR with a multi-objective evolutionary algorithm (MOEA), which they validated in a vase design context[60]. Although SVR has been applied in industrial and product design, it has yet to be adopted for interface design. Therefore, this study utilizes PSO-SVR to build a mapping model that links the core design features of the PVMUI to users' perceptual needs.

The following content briefly introduces the basic principles and calculation methods of PSO-SVR.

SVR maps the input sample vectors into a high-dimensional feature space using a nonlinear function $\phi(x)$, thereby approximating a linear function in that feature space. The linear regression function of SVR can be expressed as Eq. (12):

$$f(x_i) = \omega \cdot \phi(x_i) + b \tag{12}$$

In Eq. (12), $\phi(x_i)$ is the nonlinear mapping function that maps the sample data into the feature space, ω is the coefficient of the independent variable, and b is the bias term. ω and b are obtained by minimizing the following Eq. (13):

$$\min f(\omega, \xi_i^*, \xi_i) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i^* + \xi_i) \tag{13}$$

$$s.t.\begin{cases} y_i - \omega \cdot \phi(x_i) - b \leqslant \varepsilon + \xi_i^* \\ \omega \cdot \phi(x_i) + b - y_i \leqslant \varepsilon + \xi_i \\ \xi_i^*, \xi_i \geqslant 0, (i = 1, 2, \ldots, n) \end{cases} \tag{14}$$

In Eq. (13), $\min f(\omega, \xi_i^*, \xi_i)$ is the generalized optimal classification hyperplane function that considers the minimum misclassified samples and the maximum classification margin; $\frac{1}{2}\|\omega\|^2$ is the regularization term; n is the total number of samples; C is the penalty factor; and $\mathcal{E}$ is the insensitive loss function (error control function). To find suitable constraint conditions, the original problem can be minimized by introducing the upper and lower slack variables. By introducing the upper and lower slack variables ξ_i^* and ξ_i, the original problem is minimized.

Using the Lagrangian equation and dual theory, by setting the partial derivatives of ω, b, ξ_i^* and ξ_i to zero respectively, the dual form is obtained, as shown in Eq. (15):

$$\begin{aligned} \max\ W(a, a^*) = &-\frac{1}{2}\sum_{i=1}^{n}(a_i^* - a_i)(a_j^* - a_j)K(x_i, x_j) \\ &+ \sum_{i=1}^{n} y_i(a_i^* - a_i) - \sum_{i} \varepsilon(a_i^* + a_i) \end{aligned} \tag{15}$$

$$s.t.\begin{cases} \sum\limits_{i=1}^{m}(\alpha_i{}^* - \alpha_i) = 0 \\ 0 \leqslant \alpha_i \leqslant C \\ 0 \leqslant \alpha_i^* \leqslant C \end{cases} \tag{16}$$

Where $K(x_i, x_j)$ represents the kernel function, and a, a^* denotes the Lagrange multipliers. Based on the above dual calculation equation, the regression function can be obtained as shown in Eq. (17):

$$f(x) = \sum_{i}^{n}(a_i^* - a_i)K(x_i, x_j) + b\sqrt{2} \tag{17}$$

The basic concept of PSO can be summarized as particles moving continuously in an n-dimensional space, where each particle continuously adjusts its position and velocity based on its own experience or that of neighboring particles. The functional equations can be expressed as Eqs. (18) and (19):

$$v_{ij}(t+1) = wv_{ij}(t) + c_1R_1(p_{ij}(t) - x_{ij}(t)) + c_2R_2(p_{gj}(t) - x_{ij}(t)) \tag{18}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{19}$$

where $i = (1, 2, \cdots, n)j = (1, 2, \cdots, D),n$ represent the number of particles; D represents the dimension of the search space; x_{ij} represents the position of the particles; v_{ij} represents the velocity of the particles; w represents the inertia weight; c_1 and c_2 represent the learning factors; R_1 and R_2 are random numbers between [0, 1]; p_i represents the best position of particle i; and p_g represents the best position among all particles i in the entire group.

Research Framework and Process

The purpose of this study is to develop an interactive interface design model for PVMs under the global background of the virtualization and digitization of museums and cultural heritage. The research method combines qualitative and quantitative approaches. First, PVM websites were retrieved through web searches to screen and obtain a sample set of PVM interactive interfaces. By releasing an online interactive interface survey questionnaire, 45 Kansei words targeting PVMs were obtained, and 10 Kansei words representing user perceptions were identified through the KJ method (Affinity Diagram Method). After an initial sorting of the sample set, 12 PVM interactive interface design elements were derived, which were reduced to 6 key design elements based on the Entropy Weight TOPSIS method. An SVR model was used to establish a mapping between user perceptions and key design elements, ultimately obtaining the optimal design combination for PVMs. Based on this result, a design practice was conducted, and a satisfaction evaluation of the practice results was performed to verify the feasibility of the design process. Figure 1 shows the specific research steps.

Determining the design sample set

This study selects the content of the interactive interface that first appears after entering the web link of a PVM as the design sample. By accessing the official websites of various provinces, cities, and specific cultural relic museums, more than 90 interactive interface design samples that meet the research content were extensively collected. To avoid the influence of different exhibited artifacts within PVMs on user decisions, the viewpoints are oriented as much as possible towards non-exhibition areas (such as walls, corridors, etc.). Through expert group interviews, issues that may affect user perception, such as duplicate sample forms and blurred interactive interfaces, were resolved. Representative PVM interactive interfaces were selected from the original sample set, and an interactive interface sample set containing 60 design samples was established (see Fig. 2) for subsequent analysis.

Establishing the Kansei vocabulary set for the PVMUI

During the Kansei vocabulary collection phase, based on the previously constructed set of 60 design samples, a user perception evaluation questionnaire targeting the PVMUI was distributed to focus groups, collecting a total of 1120 Kansei evaluations. At the same time, a panel of six experts was established, consisting of two designers, two experts in Kansei Engineering, and two representative users with experience in virtual museum interaction. After removing evaluations that did not conform to the form of Kansei words, were repetitive, or had significant semantic errors, 45 qualified Kansei words were selected. Using the KJ method (Affinity Diagram), these 45 Kansei words were organized and summarized into ten Kansei word groups. After discussion within the expert panel, a Kansei word that matched the content of each group was assigned, ultimately resulting in ten of the most representative Kansei words (see Table 2).

Subsequently, questionnaires were administered to 20 design students, 20 designers, and 20 potential users of PVMs. They rated all 60 design samples using the ten categories of Kansei words. The questionnaire employed a five-point Likert scale, where 5 represented “highly consistent,” 3 represented “moderately consistent,” and 1 represented “not consistent.” A total of 53 valid questionnaires were collected. To ensure the objectivity of the questionnaire, the average result corresponding to each sample and the ten Kansei words were calculated, constructing a Kansei semantic evaluation matrix (see Table 3 and Supplementary Data 1). This paper uses factor analysis to reduce the dimensionality of the Kansei semantic evaluation matrix. The matrix was imported into IBM SPSS Statistics 27, and the structural reliability and validity of the factor analysis scale were verified through KMO and Bartlett’s tests. The experimental results showed that the

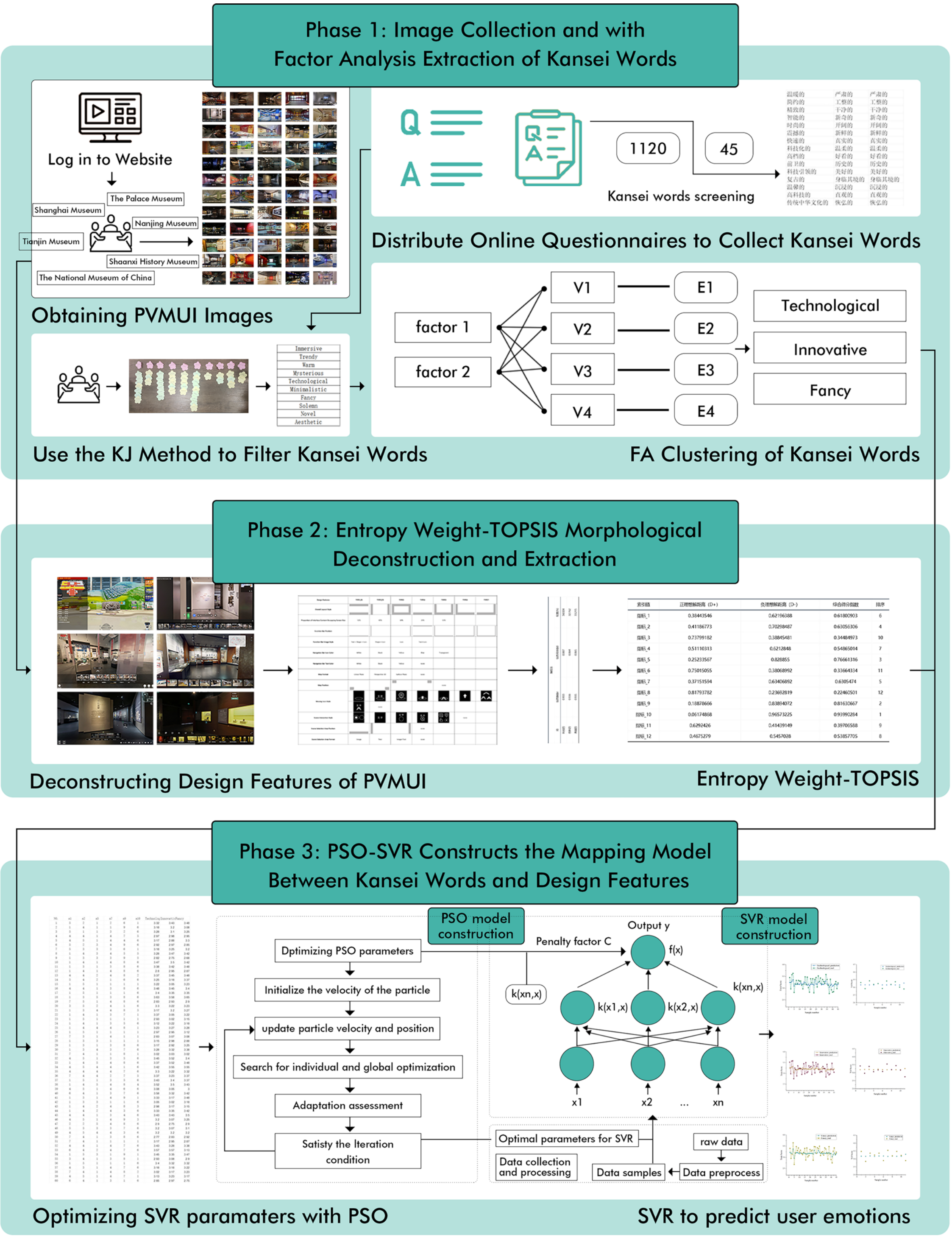


Fig. 1 | The proposed research framework. This figure presents the proposed research framework for optimizing the Panoramic Virtual Museum Interactive Interface (PVMUI). The framework consists of three phases: **Phase 1:** Image Collection and Factor Analysis Extraction of Kansei Words • PVMUI images are gathered from various online sources. • Kansei words are collected through online questionnaires and screened. • The KJ Method is used to filter Kansei words, followed by Factor Analysis (FA) Clustering to extract core emotional dimensions (Technological, Innovative, and Fancy). **Phase 2:** Entropy Weight-TOPSIS Morphological Deconstruction and Extraction. • The design features of PVMUI are deconstructed. • The Entropy Weight-TOPSIS method is applied to identify and extract critical interface design features based on user perception. **Phase 3:** PSO-SVR Mapping of Kansei Words and Design Features. • Particle Swarm Optimization (PSO) is used to optimize Support Vector Regression (SVR) parameters. • The SVR model is then used to predict the mapping between user emotions and design features, refining the optimal PVMUI configuration.

KMO measure of sampling adequacy was 0.890, and Bartlett's test of sphericity yielded an approximate chi-square value of 464.327, degrees of freedom of 45, and a significance less than 0.001, meeting the standards for data suitability for factor analysis (KMO value greater than 0.5, Bartlett's test of sphericity less than 0.05). Therefore, it was determined that the data have statistical significance and are suitable for factor analysis (see Table 4). In the total variance explained obtained by principal component analysis, the cumulative contribution rate of the first three factors was 79.805%, close to

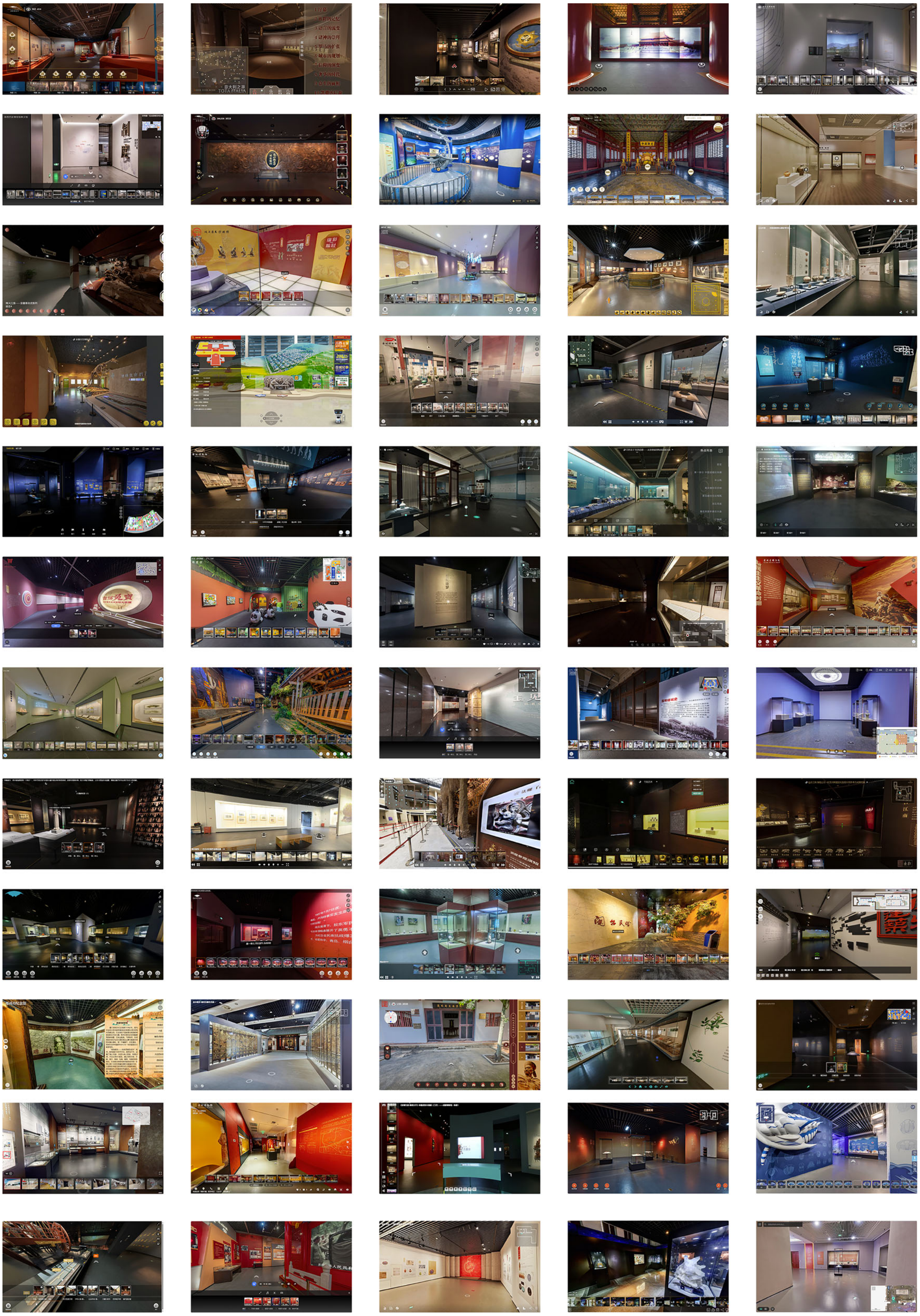


Fig. 2 | 60 representative PVMUIs. This figure displays 60 representative Panoramic Virtual Museum Interactive Interfaces (PVMUI) collected from various online sources. These samples include diverse interface layouts, color schemes, navigation styles, and interaction elements, reflecting a broad spectrum of virtual museum design approaches. The dataset was curated by ensuring: • A variety of museum types (e.g., historical, cultural, science museums). • Standardized perspectives that minimize content bias and focus on interface design.

Table 2 | Ten representative Kansei words

Immersive	Trendy	Warm	Mysterious	Technological
Minimalistic	Fancy	Solemn	Novel	Esthetic

This table presents the ten representative Kansei words identified through factor analysis and expert evaluation. These words reflect key emotional perceptions associated with Panoramic Virtual Museum Interactive Interfaces (PVMUI) and serve as the basis for subsequent design optimization and user experience modeling.

80%, proving that the ten Kansei words can be reduced to three representative Kansei words (see Table 5). The ten Kansei words were orthogonally rotated using the Kaiser normalization maximum variance method. To reduce interference, factor loadings with absolute values less than 0.5 were not displayed (see Table 6).

Finally, the component score coefficient matrix was obtained (see Table 7). Three Kansei word groups were derived from the ones targeting the PVMUI and were named based on the rotated component matrix scores.

Table 3 | Kansei semantic evaluation matrix data

NO.	Immersive	Trendy	Mysterious	Warm	Technological	Minimalistic	Fancy	Solemn	Novel	Esthetic
1	3.83	3.92	4.08	4.02	3.87	4.08	3.96	4.06	4.02	3.96
2	3.91	3.87	4.06	3.74	3.96	3.79	3.85	3.74	3.85	3.77
3	3.75	4.00	3.83	3.89	3.98	3.83	3.87	3.68	3.92	3.91
4	3.89	4.06	3.98	4.04	4.11	3.96	4.04	3.96	4.00	4.02
5	3.79	3.83	3.92	3.53	4.04	3.81	3.91	3.87	3.72	3.77
6	3.70	3.70	3.81	3.70	3.68	3.70	3.92	3.70	3.85	3.81
7	3.91	4.15	4.04	3.96	3.98	4.00	4.13	3.96	3.85	4.11
8	3.66	3.87	3.85	3.75	3.94	3.72	3.92	3.77	3.81	3.83
9	3.89	3.91	4.02	3.89	3.96	3.75	4.04	3.79	3.85	4.02
10	3.98	3.96	4.06	3.85	4.08	3.96	4.15	3.92	3.75	4.08
11	3.83	3.94	4.08	3.91	4.06	3.91	3.92	3.98	3.91	3.98
12	4.15	3.98	4.04	4.08	3.96	3.96	4.19	3.92	4.06	4.19
13	4.11	3.96	4.08	3.81	4.17	3.98	3.96	3.89	3.87	4.08
14	3.98	3.91	4.00	3.92	3.96	3.94	4.17	3.87	3.91	4.04
15	3.87	3.91	4.04	3.91	3.81	3.94	3.74	3.89	3.74	4.00
16	3.66	3.91	3.85	3.83	3.83	3.75	3.81	3.79	3.98	3.87
17	3.89	3.96	3.98	3.98	4.08	3.94	3.89	3.83	3.96	3.91
18	3.51	3.53	3.60	3.70	3.70	3.58	3.74	3.43	3.51	3.64
19	4.26	4.02	4.23	4.21	4.08	4.21	4.09	3.94	4.11	3.92
20	3.89	3.92	3.96	3.91	3.98	3.87	3.98	3.98	3.92	3.98
21	3.53	3.83	3.83	3.70	3.75	3.62	3.96	3.66	3.70	3.83
22	4.17	4.26	4.19	4.09	4.21	4.11	4.17	4.06	4.23	4.06
23	3.60	3.96	3.85	3.79	3.94	4.00	3.75	3.77	3.68	3.81
24	4.02	4.09	4.11	3.92	4.21	4.13	4.19	3.87	4.02	4.02
25	4.00	3.91	3.91	3.94	3.96	4.02	4.06	4.02	3.96	3.98
26	3.91	3.89	4.08	4.13	4.02	4.04	4.11	4.13	4.11	4.02
27	3.91	4.04	3.92	3.89	3.98	3.87	3.92	3.83	3.91	3.92
28	3.98	3.83	3.89	3.85	3.96	3.85	3.92	3.85	3.81	4.06
29	3.68	3.47	3.68	3.72	3.57	3.77	3.85	3.45	3.47	3.72
30	3.94	4.06	4.08	4.09	4.15	4.00	4.00	3.87	4.08	3.98
31	3.89	4.09	3.96	3.83	3.98	3.91	3.89	3.92	3.98	4.00
32	4.06	4.04	3.98	3.96	4.02	3.85	4.06	3.89	4.02	4.15
33	3.98	4.00	4.15	3.89	4.11	3.94	3.94	3.81	3.94	4.02
34	3.89	3.94	3.98	3.70	4.13	3.89	3.89	3.92	3.89	4.11
35	3.87	3.87	3.92	3.77	3.87	3.83	4.08	3.83	3.77	4.08
36	4.21	4.09	4.08	4.08	4.09	4.11	4.04	4.11	4.11	4.09
37	3.75	3.85	4.09	3.81	3.98	3.75	4.06	3.98	3.79	3.92
38	3.72	3.70	3.83	3.57	3.83	3.72	3.58	3.81	3.72	3.83
39	3.87	3.94	3.81	3.79	4.04	3.83	3.91	4.02	3.83	4.06
40	4.06	4.08	4.21	3.94	3.98	4.02	3.98	3.91	4.09	4.08
41	3.72	4.06	3.85	3.91	3.94	3.96	3.94	3.91	3.85	3.92
42	4.04	4.09	4.09	4.09	4.23	4.21	4.19	4.08	3.85	3.98
43	4.13	4.21	4.21	4.32	4.28	4.08	4.19	4.19	4.11	4.00

Table 3 (continued) | Kansei semantic evaluation matrix data

NO.	Immersive	Trendy	Mysterious	Warm	Technological	Minimalistic	Fancy	Solemn	Novel	Esthetic
44	3.91	4.13	4.15	4.02	3.98	3.92	4.06	3.89	4.04	4.08
45	4.23	4.11	4.08	3.96	4.17	4.08	4.04	3.94	4.09	4.26
46	3.89	4.04	4.21	3.75	3.89	3.98	4.04	3.92	3.89	4.11
47	3.81	3.85	3.85	3.87	4.04	3.87	3.92	4.04	3.74	4.02
48	3.75	3.91	3.98	3.79	3.92	3.77	3.85	3.74	3.87	3.92
49	3.75	3.91	3.89	3.68	3.81	3.87	3.75	3.62	3.60	3.79
50	3.75	3.83	4.00	4.00	3.83	3.70	3.92	3.81	3.89	3.87
51	3.77	4.02	3.94	3.92	3.92	3.91	4.02	3.92	3.92	3.96
52	3.74	3.83	3.91	3.81	3.75	3.96	4.09	3.81	3.92	3.91
53	3.85	3.87	3.91	3.96	3.81	3.94	3.92	3.83	3.70	4.09
54	3.62	3.77	3.77	3.77	3.74	3.75	3.81	3.58	3.72	3.58
55	3.85	4.04	3.81	3.98	4.00	4.15	4.08	3.87	3.81	4.00
56	4.30	4.08	4.19	4.13	4.04	4.11	3.91	3.98	3.96	3.98
57	3.81	3.91	3.91	3.96	3.89	4.04	3.98	3.96	3.87	3.98
58	3.94	4.19	4.23	3.91	4.23	4.08	4.06	4.19	3.96	4.19
59	4.09	4.02	4.06	3.89	3.96	3.87	4.15	4.06	3.92	4.06
60	3.70	3.75	3.81	3.81	3.87	3.64	3.66	3.66	3.72	3.79

This table presents the Kansei semantic evaluation matrix, containing user ratings for ten Kansei words across 60 samples. The scores reflect users' perceived emotional responses to different Panoramic Virtual Museum Interactive Interface (PVMUI) designs. These data serve as the input for Entropy Weight-TOPSIS and PSO-SVR modeling, enabling the construction of a mapping model between design features and user emotions.

Table 4 | KMO and Bartlett's Test

KMO Measure of Sampling Adequacy		0.890
Bartlett's Test of Sphericity	Approximate Chi-Square	464.327
	Degrees of Freedom	45
	Significance	<0.001

This table presents the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity, which assess the suitability of the dataset for factor analysis. The KMO value (0.890) indicates strong sampling adequacy, and the Bartlett's test ($p < 0.001$) confirms that the dataset is appropriate for factor extraction, supporting the validity of the Kansei word clustering process.

The first word group was defined as "Technological," consisting of five words: "immersive", "Trendy", "mysterious", "technological", and "solemn", with "technological" having the highest score of 0.843. The second word group consisted of "warm," "Minimalistic," and "novel," with "warm" having the highest score of 0.878. Since "warm" as a Kansei word is too broad in meaning, after expert panel discussion, this word group was named "Innovative." The third word group consisted of two Kansei words: "Fancy" and "esthetic," with "Fancy" having a higher score of 0.792. Therefore, this word group was defined as "Fancy."

Identifying key design elements of the PVMUI using the entropy weight TOPSIS method

We extracted design elements from the 60 design samples in the sample set. To ensure the representativeness and objectivity of the extraction results, a panel of four experts in the field of interaction design was invited to form an expert group. After group discussions and morphological analysis, the PVMUI was decomposed into 12 design elements: overall layout style, interface content occupying screen size, function bar position, function bar image style, navigation bar icon color, navigation bar text color, map form, map position, movement icon style, scene interaction style, scene selection area position, and scene selection area form. Each design element can be further subdivided, totaling 64 types (see Fig. 3).

Since different design elements in the PVMUI have different perceptual weights for users, design features with lower or even no influence may lead to inaccurate subsequent results. Therefore, this paper uses the Entropy Weight TOPSIS method to perform dimensionality reduction and screening on the 12 design elements to determine the design elements with higher weights among them.

First, we recruited an expert group consisting of five design students, two Kansei Engineering experts, and two designers, all of whom hold master's or doctoral degrees in design. Using a combination of online and offline questionnaire evaluations, the 12 design elements were compared in detail with the three representative Kansei words selected earlier for evaluation and scoring. A five-point Likert scale was used, where 5 represented "very important for this word," 3 represented "generally important for this word," and 1 represented "very unimportant for this word." A total of 9 questionnaires were collected. By calculating the average value of each target, a mean matrix of design elements corresponding to the representative Kansei words was constructed(Supplementary Data 2). According to Eq. (1), the mean matrix was normalized to obtain the standardized matrix. Using Eqs. (2)–(5), we calculated the entropy values and weight coefficients of the three Kansei words, obtaining the information entropy values, information utility values, and weight values of the Kansei words (see Table 8).

By integrating the weight coefficients of the Kansei words for the PVMUI into TOPSIS, there were 12 evaluation objects, each with 3 Kansei evaluation attributes. According to Eq. (6), each attribute of the morphological components was vector normalized to form a decision matrix. Using Eqs. (7)–(11), we calculated the positive ideal solution (D+) and negative ideal solution (D-) for the 12 design elements, as well as the distance between each indicator and the best and worst situations (see Table 9) and obtained the comprehensive score index. We selected design elements with a comprehensive score index greater than 0.6 as key design elements. Therefore, through the Entropy Weight TOPSIS method, we identified 6 key design elements that have a significant impact on user perception of the PVMUI: overall layout style, interface content occupying screen size, navigation bar icon color, map form, movement icon style, and scene interaction style.

Constructing a mapping model between representative Kansei words and key design elements using PSO-SVR

After performing factor analysis for dimensionality reduction on the Kansei words in the earlier stage, the three representative Kansei words

Table 5 | Total variance explained

NO.	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Sum	Var%	Cum%	Sum	Var%	Cum%	Sum	Var%	Cum%
1	6.788	67.884	67.884	6.788	67.884	67.884	3.529	35.292	35.292
2	0.623	6.231	74.115	0.623	6.231	74.115	2.485	24.855	60.146
3	0.569	5.690	79.805	0.569	5.690	79.805	1.966	19.659	79.805
4	0.432	4.321	84.126						
5	0.397	3.974	88.100						
6	0.338	3.384	91.483						
7	0.293	2.930	94.413						
8	0.273	2.727	97.140						
9	0.184	1.836	98.975						
10	0.102	1.025	100.000						

This table presents the results of principal component analysis (PCA), showing the initial eigenvalues, extracted sums of squared loadings, and rotation sums of squared loadings. The first three components account for 79.805% of the total variance, indicating that they effectively represent the underlying structure of the Kansei word dataset, supporting dimensionality reduction in the analysis.

Table 6 | Rotated component matrix

Kansei word	component		
	1	2	3
Immersive	0.593		
Trendy	0.757		
Warm		0.878	
Mysterious	0.696		
Technological	0.843		
Minimalistic	0.510	0.608	
Fancy			0.792
Solemn	0.644		
Novel	0.558	0.621	
Esthetic	0.563		0.737

This table presents the rotated component matrix from factor analysis, showing the loadings of Kansei words onto three principal components. The clustering indicates that:

- Component 1 is strongly associated with Technological, Immersive, Trendy, and Mysterious perceptions.
- Component 2 aligns with Warm, Minimalistic, and Novel attributes.
- Component 3 corresponds to Fancy, Esthetic, and Minimalistic elements.

Table 7 | Component score coefficient matrix

Kansei word	Component		
	1	2	3
Immersive	0.089	0.063	0.065
Trendy	0.355	−0.038	−0.201
Warm	−0.342	0.782	−0.166
Mysterious	0.281	−0.006	−0.138
Technological	0.555	−0.251	−0.261
Minimalistic	−0.010	0.312	−0.089
Fancy	−0.525	0.149	0.825
Solemn	0.183	−0.158	0.180
Novel	0.064	0.325	−0.209
Esthetic	0.089	−0.486	0.679

This table presents the component score coefficients derived from factor analysis, indicating the contribution of each Kansei word to the three principal components.

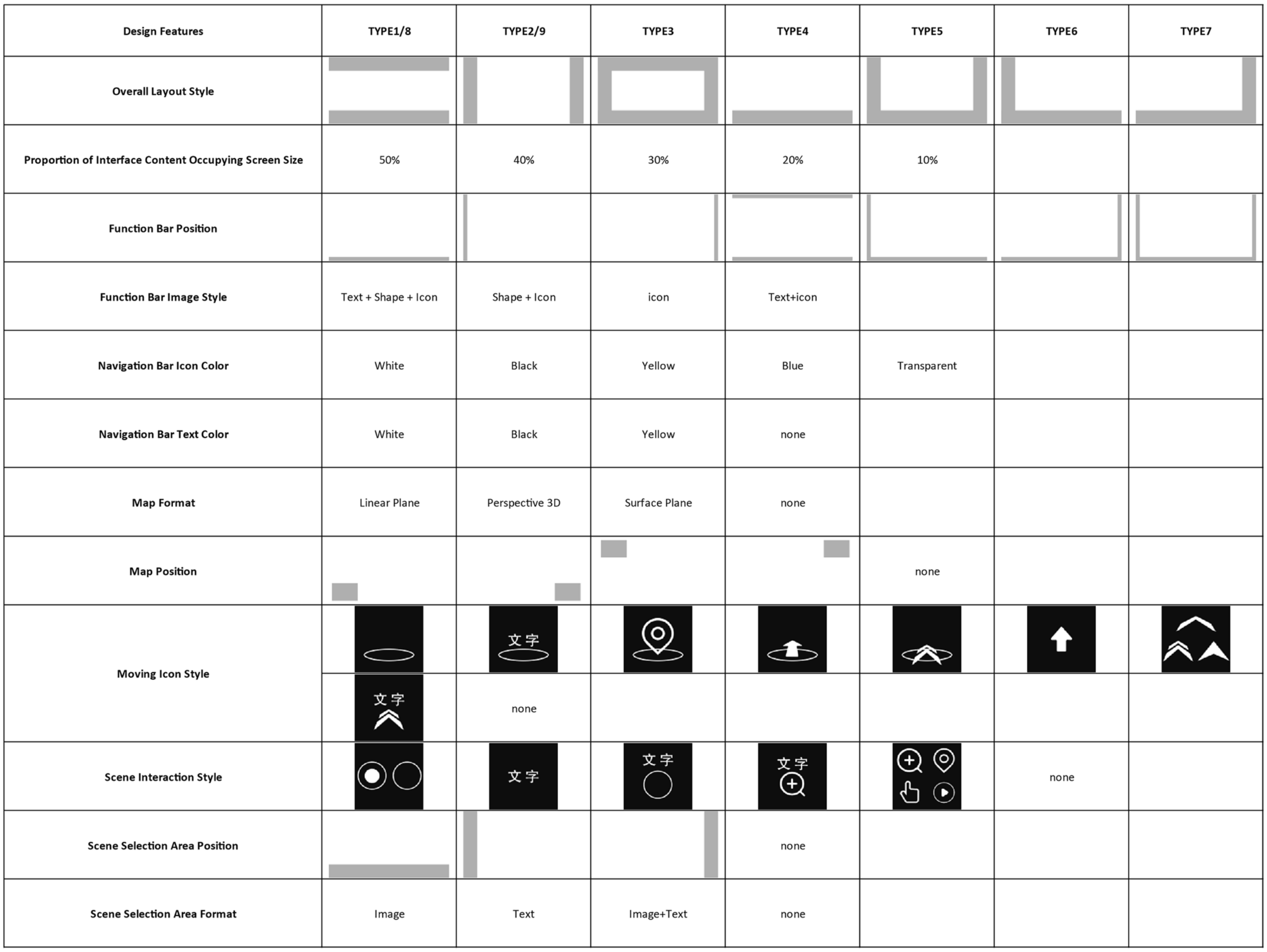
("Technological," "Innovative," and "Fancy") were introduced into 60 PVMUI samples. A 5-point Likert scale was constructed, and a total of 100 subjects were recruited to participate in the evaluation. The subjects included a small number of designers with a background in design studies and users with experience using virtual museum interactive interfaces. Combined with the key interactive interface design features obtained from the Entropy Weight TOPSIS ranking, a sample-key design feature-representative Kansei word matrix was constructed, as shown in Table 10 and Supplementary Data 3.

At this stage, we used the PSO-SVR model to construct a mapping model between Kansei words and design features. By using the Matlab® software package, PSO-SVR was used to learn the matrix data in Table 10. Randomly selected 48 samples were used as the model's training set, and the remaining 12 samples were used as the test set. The key design features were used as input of feature values, and the evaluation values from 100 participants were used as outputs. According to Eqs. (18) and (19), the PSO settings were determined. The PSO size was set to 20, the learning factors were both set to 2, and the number of iterations was set to 20 to optimize the SVR accordingly. The optimized SVR was used to establish the mapping relationship between Kansei words and design elements, as per Eqs. (12)–(17). Both the test set and the training set showed strong convergence, and the fitting graphs of the Kansei words are shown in Fig. 4. Good parameter results were obtained (training set: $R^2 = 0.243$, $MSE = 0.035$; test set: $R^2 = -0.140$, $MSE = 0.056$) (see Table 11, Supplementary Data 5 and Supplementary Data 6), indicating that the model used in this study has good predictive ability and high fitting degree, and can be used to establish the mapping relationship between user emotions and PVMUI design elements.

In order to obtain the combination of PVMUI features with the highest user recognition, this study used the KJ method and factor analysis to collect and reduce the dimensionality of users' perception needs Kansei words, obtaining the three reduced Kansei words: "Technological," "Innovative," and "Fancy." Through the Entropy Weight TOPSIS method, 12 design features were extracted to 5 key design features. Each design feature has 7, 5, 5, 4, 9, 6 categories respectively, and their combinations can yield $7 \times 5 \times 5 \times 4 \times 9 \times 6 = 37{,}800$ design combination schemes (Supplementary Data 4). The PSO-SVR algorithm was used to calculate the corresponding values of the three Kansei words for each design combination scheme. The three corresponding values were summed to obtain the corresponding value of each design combination scheme as the user perception evaluation standard. Through calculation of the results, the maximum corresponding value of the design combination scheme was 10.0457, corresponding to the design feature categories of 1, 3, 5, 3, 7, 6. This is the optimal PVMUI design scheme.

Results and Discussion

To demonstrate the applicability of the method proposed in this paper, the author used the optimal PVMUI design scheme obtained from the experiment as a reference. Specifically, the design features selected were a1-1



Design Features	TYPE1/8	TYPE2/9	TYPE3	TYPE4	TYPE5	TYPE6	TYPE7
Overall Layout Style							
Proportion of Interface Content Occupying Screen Size	50%	40%	30%	20%	10%		
Function Bar Position							
Function Bar Image Style	Text + Shape + Icon	Shape + Icon	icon	Text+icon			
Navigation Bar Icon Color	White	Black	Yellow	Blue	Transparent		
Navigation Bar Text Color	White	Black	Yellow	none			
Map Format	Linear Plane	Perspective 3D	Surface Plane	none			
Map Position					none		
Moving Icon Style	 文字	文字 none					
Scene Interaction Style		文字	文字	文字		none	
Scene Selection Area Position				none			
Scene Selection Area Format	Image	Text	Image+Text	none			

Fig. 3 | From the deconstruction table. This figure presents the morphological deconstruction of Panoramic Virtual Museum Interactive Interface (PVMUI) design features. The table categorizes different design elements and their corresponding types, which serve as the basis for feature extraction in the Entropy Weight-TOPSIS analysis. Key design features include: • Overall Layout Style. • Proportion of Interface Content on Screen. • Function Bar and Navigation Bar. • Map Format and Position. • Moving Icon Styles. • Scene Interaction and Selection Area.

Table 8 | Information entropy and weight coefficient

Item	Information Entropy (e)	Information Utility Value (d)	Weight (%)
Technological	0.933	0.067	34.024
Innovative	0.936	0.064	32.762
Fancy	0.935	0.065	33.215

This table presents the information entropy, utility value, and weight coefficient for the three Kansei dimensions: Technological, Innovative, and Fancy. The entropy values (e) indicate the distribution uncertainty, while the utility values (d) represent the information contribution. The weight coefficients reflect the relative importance of each Kansei dimension in the Entropy Weight-TOPSIS model, with Technological (34.024%) being the most influential.

(overall layout style with upper and lower distribution), a2-3 (interface content occupying 30% of the screen), a5-5 (transparent navigation bar icon color), a7-3 (plane-type map style), a9-7 (arrow-shaped movement icon style), and a10-6 (no scene interaction style added). Using 2D and 3D design software such as Adobe Photoshop 2020, Adobe Illustrator 2020, SketchUp Pro 2022, and Enscape 3.2, the rendering images and interactive interface of the PVM were obtained, as shown in Fig. 5, and placed into usage scenarios as shown in Fig. 6.

This paper adopts the KE-Entropy Weight TOPSIS-SVR research method to determine the optimal PVMUI design combination scheme that meets users' perceptual needs. Using Chinese PVMs as the sample set, ten

Table 9 | Relative proximity and ranking of design elements

Design Elements	Positive ideal solution distance (D +)	Negative ideal solution distance (D-)	Comprehensive Score Index	Ranking
A1	0.384	0.622	0.618	6
A2	0.412	0.703	0.631	4
A3	0.738	0.388	0.345	10
A4	0.511	0.621	0.549	7
A5	0.252	0.829	0.767	3
A6	0.750	0.381	0.337	11
A7	0.372	0.634	0.631	5
A8	0.818	0.237	0.225	12
A9	0.189	0.839	0.816	2
A10	0.062	0.966	0.940	1
A11	0.629	0.414	0.397	9
A12	0.468	0.546	0.539	8

This table presents the Entropy Weight-TOPSIS evaluation results for different PVMUI design elements, showing their relative proximity to the ideal solution and final ranking.

- D^{+} (Positive Ideal Solution Distance): The distance from the optimal solution.
- D^{-} (Negative Ideal Solution Distance): The distance from the least favorable solution.
- Comprehensive Score Index: A higher score indicates a stronger alignment with user preferences.
- Ranking: A10 (0.940) achieved the highest score, while A8 (0.225) ranked lowest.
- These results guide the selection of key design features for optimizing PVMUI.

Table 10 | Kansei evaluation matrix

NO.	a1	a2	a5	a7	a9	a10	Technological	Innovative	Fancy
1	5	2	1	2	6	1	3.32	3.43	3.48
2	1	4	1	1	9	6	3.18	3.2	3.08
3	5	1	1	3	2	6	3.28	3.1	3.25
4	4	4	1	4	7	5	2.97	2.98	2.95
5	4	5	1	4	4	6	3.17	2.88	3.3
6	5	2	3	4	9	6	2.92	2.97	2.85
7	5	3	3	3	6	1	3.18	3.25	3.2
8	1	4	3	4	5	5	3.28	3.47	3.42
9	1	3	3	3	9	5	2.82	2.75	2.68
10	1	4	1	4	8	6	3.47	3.5	3.42
11	1	3	1	3	8	6	3.38	3.42	3.48
12	1	4	1	4	8	6	2.8	2.95	2.87
13	4	4	2	4	8	2	3.37	3.45	3.48
14	5	4	2	1	6	6	3.25	3.18	3.37
15	1	5	1	1	1	1	3.22	3.05	3.23
16	4	4	1	3	8	6	3.48	3.45	3.4
17	1	5	1	1	1	6	3.4	3.35	3.35
18	1	3	5	3	8	6	3.63	3.58	3.65
19	7	5	1	4	8	6	2.83	2.93	2.9
20	3	5	2	4	1	6	3.3	3.22	3.23
21	1	3	4	4	8	3	3.17	3.2	3.27
22	1	4	1	3	7	1	3.37	3.05	3.22
23	1	5	1	1	1	1	2.93	3.02	3.15
24	1	4	1	3	5	6	3.12	3.22	3.18
25	1	4	4	4	8	1	3.23	3.27	3.28
26	1	5	1	1	1	1	2.97	2.95	3.12
27	7	3	1	4	1	1	2.83	3.07	3.08
28	1	3	3	1	1	1	3.15	2.98	2.88
29	1	3	1	3	8	6	3.17	2.92	3.25
30	1	3	4	3	7	6	3.28	3.32	3.38
31	7	4	1	1	8	1	3.02	3.03	3.02
32	4	5	1	3	5	6	3.45	3.52	3.4
33	1	4	5	4	8	6	3.37	3.52	3.48
34	4	5	4	4	1	6	3.42	3.55	3.55
35	4	4	4	4	7	6	3.3	3.22	3.32
36	7	4	4	2	7	5	3.37	3.23	3.37
37	1	5	1	3	5	6	3.43	3.4	3.37
38	1	4	5	4	8	4	3.52	3.5	3.43
39	4	5	1	4	6	6	3.08	3.05	3
40	6	4	1	3	7	6	3.58	3.32	3.42
41	1	3	1	4	9	1	3.33	3.17	3.48
42	1	3	3	1	1	6	3.05	3.02	3.18
43	1	4	2	4	8	3	2.98	3.17	3.15
44	1	4	2	4	3	6	3.33	3.35	3.42
45	4	4	1	3	4	6	3.43	3.43	3.5
46	4	5	1	4	9	3	3.2	3.07	3.25
47	2	2	5	4	8	6	2.9	2.75	2.9
48	5	3	3	3	7	6	3.2	3.07	3.1
49	4	5	4	4	3	6	3.2	3.2	3.2
50	7	4	1	3	8	6	2.77	2.83	2.92
51	7	4	1	1	1	1	3.17	2.95	2.87

Table 10 (continued) | Kansei evaluation matrix

NO.	a1	a2	a5	a7	a9	a10	Technological	Innovative	Fancy
52	4	4	1	4	7	6	3.43	3.28	3.38
53	6	4	2	4	7	6	3.57	3.57	3.13
54	1	5	3	1	9	1	3.45	3.35	3.47
55	3	4	1	3	8	1	2.93	3.08	2.9
56	1	5	1	1	1	6	3.4	3.32	3.32
57	4	3	1	4	7	6	3.18	3.18	3.22
58	7	4	1	4	8	2	3.02	3.17	3.23
59	4	5	1	4	7	1	3.13	3.23	3.17
60	6	4	1	3	1	6	2.85	2.97	2.75

This table presents the Kansei evaluation matrix, which maps PVMUI design elements (A1, A2, A5, A7, A9, A10) to user-perceived emotional dimensions (Technological, Innovative, Fancy).

- Design Elements (A1–A10): Represent different PVMUI configuration features.
- Kansei Scores: Indicate user evaluations of the interface design's emotional impact.

These data serve as the input for PSO-SVR modeling, enabling the prediction of optimal PVMUI configurations based on user emotional preferences.

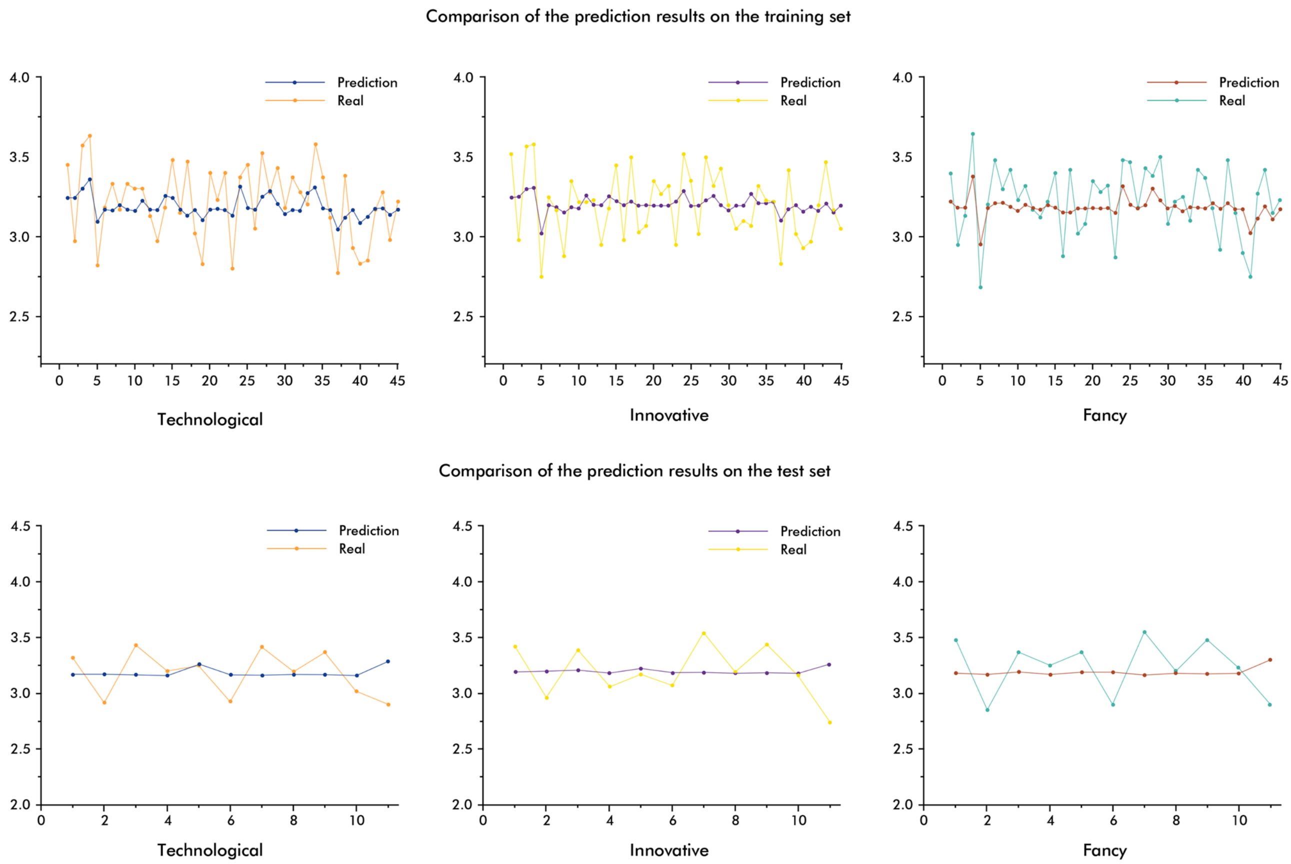


Fig. 4 | Fitting graph of the training set and the test set. This figure presents the comparison between predicted and actual values of the PSO-SVR model for the three Kansei dimensions: Technological, Innovative, and Fancy. The evaluation is conducted on both the training set (top row) and the test set (bottom row). **Training Set (Top Row):** • Each graph compares the predicted (solid lines) and real (dotted lines) values across 45 samples. • The model shows varying accuracy across the three Kansei dimensions, with Fancy having the closest alignment between predicted and actual values. **Test Set (Bottom Row):** • Predictions for the Technological and Innovative dimensions show a small deviation from actual values, while the Fancy dimension maintains a relatively stable fit. • These results demonstrate the model's capability in predicting user emotional responses to PVMUI design features, validating its effectiveness for design optimization.

Kansei words were collected and screened through questionnaires and the KJ method. Factor analysis was used for dimensionality reduction to obtain three key Kansei words: "Technological," "Innovative," and "Fancy." By decomposing the morphology of 60 PVM samples, 12 design features and a total of 64 corresponding types were obtained. The Entropy Weight TOPSIS method was used to screen the design features, resulting in six high-weight design features: overall layout style, interface content occupying screen size, navigation bar icon color, map form, movement icon style, and scene interaction style. It was found that users pay more attention to interface layout, interactive icons, and map forms when experiencing PVMs. The six design features corresponded to the 60 design samples. Finally, the three Kansei words were introduced into the SVM to predict the design combinations that would obtain higher Kansei weights for users. The results showed that selecting types 1, 3, 5, 3, 7, and 6 in the six design features could obtain the optimal design combination scheme. The comprehensive Kansei score of this scheme was 10.0457, higher than the other 37,799 schemes.

Based on the key design features identified from the optimal design combination, this study refined the Panoramic Virtual Museum Interactive Interface (PVMUI) by emphasizing user interaction behavior and interface simplicity, thereby more effectively enhancing the user experience. To evaluate acceptance of the optimized interface, 100 participants were recruited, and a 7-point Likert scale was used to rate the interface shown in Fig. 5. The results indicate that the interface's average rating is 5.19, which is significantly higher than the theoretical midpoint of 4.00 on the 7-point scale, suggesting a high level of user recognition for the optimized PVMUI.

These findings validate the effectiveness of the proposed approach in quantifying online museum users' emotional needs and demonstrate that the optimized PVMUI aligns more closely with user preferences. Looking ahead, museum authorities or interface designers can refer to the optimal design solution proposed in this study to improve online museum interactive interfaces, thereby increasing user satisfaction and retention. This, in turn, will help advance the digital display and dissemination of museum cultural heritage.

Table 11 | The parameter results

The predicted results on the training set		The predicted results on the testing set	
R2	MSE	R2	MSE
0.243	0.035	-0.140	0.056

This table presents the performance metrics of the PSO-SVR model, comparing the training and testing results.

- Training Set: The model achieved an R^2 of 0.243 and an MSE of 0.035, indicating moderate predictive accuracy.
- Testing Set: The model achieved an R^2 of -0.140 and an MSE of 0.056,

In the field of Kansei Engineering, establishing a mapping model between user emotional preferences and design features is one of the core research areas. Traditional linear statistical methods, such as Quantification Theory Type I (QT-I)[61] and Principal Component Analysis (PCA)[62], exhibit significant limitations when dealing with highly subjective and uncertain emotional data. These methods cannot directly measure and quantify user emotional experiences and struggle to accurately capture the nonlinear characteristics of user emotional needs, thereby limiting their application in complex design tasks.

With the rapid development of artificial intelligence technologies, nonlinear modeling techniques such as Neural Networks (NN)[63], Genetic Algorithms (GA)[64], and Support Vector Regression (SVR) have been gradually introduced into KE to establish nonlinear mapping relationships between emotions and design features. Among them, Deep Convolutional Neural Networks (DCNN)[65] perform excellently in image processing and pattern recognition but have high requirements for input image sizes and certain limitations in handling non-image data. Genetic Algorithms have been widely and successfully applied in engineering optimization problems, but their search efficiency significantly decreases when facing high-

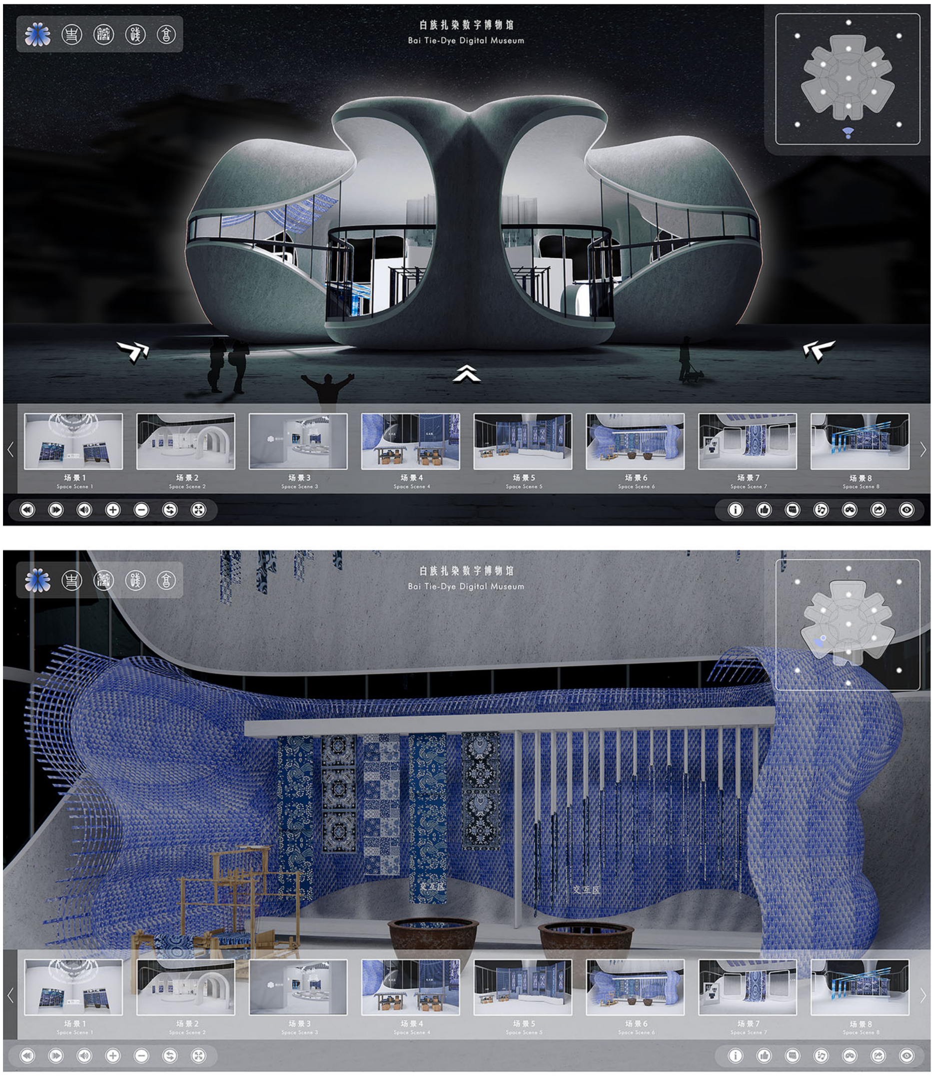


Fig. 5 | PVMUI scheme design. This figure presents the interactive interface design for the Bai Tie-Dye Digital Museum, developed based on the optimized Panoramic Virtual Museum Interactive Interface (PVMUI) configuration identified in this study. The design integrates the optimal interface elements derived from Entropy Weight-TOPSIS and PSO-SVR analysis to enhance user engagement and emotional resonance. **Top Image (Exterior View):** Implements the top-bottom layout style (A1-1), ensuring a clear hierarchical interface structure. The interface content occupies 30% of the screen space (A2-3), providing a balanced visual experience. Transparent navigation bar icons (A5-5) and a planar-style map (A7-3) are employed to reduce cognitive load while maintaining effective wayfinding. **Bottom Image (Interior View):** The movement interaction follows the arrow-shaped movement icon style (A9-7), facilitating intuitive navigation. The scene maintains a non-interactive environmental setting (A10-6), reducing unnecessary distractions and improving focus on exhibition content.

Fig. 6 | The design effect of PVMUI. This figure showcases the optimized Panoramic Virtual Museum Interactive Interface (PVMUI) in different usage environments, illustrating its visual adaptability across various settings. The interface maintains consistent usability and esthetic coherence, ensuring an engaging experience in diverse contexts.

Table 12 | Comparison of different sentimental mapping algorithms

Algorithms	Data representation	Fuzzy expression	Reasoning complexity	Loss rate	Decision result
SVR	Moderate	High	Moderate	Low	High
SVM	Moderate	Low	Moderate	Moderate	Low
GA	Non	High	Moderate	High	Low
DCNN	High	Moderate	Moderate	Low	High
NN	Low	Moderate	Moderate	Low	Low
ARM	Low	Low	Low	High	High
QT-1	High	Low	Low	Low	Non
PCA	Low	Low	Low	Moderate	Non

This table compares various sentimental mapping algorithms in terms of data representation, fuzzy expression, reasoning complexity, loss rate, and decision result.

- SVR (Support Vector Regression) stands out as the best-performing algorithm, offering high decision accuracy, strong fuzzy expression capability, and low loss rate, making it the most suitable choice for sentiment mapping in PVMUI design optimization.
- DCNN (Deep Convolutional Neural Networks) also demonstrates high decision accuracy but with increased reasoning complexity.
- Other methods, such as NN (Neural Networks), GA (Genetic Algorithm), and PCA (Principal Component Analysis), show limitations in accuracy or high loss rates, reducing their effectiveness in sentiment analysis tasks.

dimensional spaces and complex fitness functions, and they can only solve a limited number of optimal solutions.

In contrast, SVR performs exceptionally well in handling small samples, high-dimensional data, and nonlinear problems. Compared to traditional parametric statistical methods and neural network methods, SVR has stronger generalization ability and data adaptability. By finding the optimal hyperplane in a high-dimensional feature space, it can directly learn complex nonlinear relationships from known data and make accurate predictions. Therefore, when constructing mapping models between emotions and design features, SVR is more suitable for various types of data. Relevant studies have shown that SVR outperforms other methods in Kansei mapping performance, as detailed in Table 12.

Conclusion and Future Work

Despite the demonstrated effectiveness of the proposed Kansei Engineering–based PVMUI design framework in terms of user ratings, several limitations remain in practical applications. These should be addressed in future work:

(a) Real-World Constraints: The implementation of the PSO-SVR model requires technical support from trained professionals, which may be challenging for local museums with limited resources. In addition, existing digital infrastructure in museums may not fully support the proposed optimized interface design, thus preventing it from achieving its intended effectiveness when presented to users. Future studies could explore lighter-weight algorithmic designs and collaborate with museums to validate these approaches across different scenarios.

(b) User Group Constraints: Although digital museum platforms are becoming more widespread, certain user segments—particularly the elderly and other populations affected by the digital divide—may be unfamiliar or uncomfortable with digital tools. Even though the optimized PVMUI prioritizes ease of use and user-friendly interactions, these groups might still encounter usage barriers, negatively affecting their engagement and recognition of virtual museum experiences. In the future, usability testing should be conducted to collect objective data (e.g., task completion time, error rates, navigation paths) and subjective feedback (e.g., satisfaction, immersion, perceived workload) to fully assess how well the interface design meets the needs of different user groups.

(c) Design Details Constraints: The current PVMUI design primarily focuses on the visual and functional layout of the interactive interface. However, a more holistic enhancement of user interactions within PVM requires improvements in functionality, service quality, and feedback mechanisms to address diverse user needs.

(d) Methodological Constraints: This study employed a mixed qualitative–quantitative approach, which may inevitably be influenced by subjective factors. Future research could incorporate high-precision affective computing tools, such as electroencephalography (EEG), galvanic skin response (GSR), and eye-tracking devices, to capture and analyze users' emotional feedback more accurately.

To further refine the PVMUI design framework, this study addresses both user experience enhancement and the broader dissemination of cultural heritage in virtual environments. By integrating the Kansei Engineering (KE) framework, factor analysis was applied to extract representative Kansei words, and the Entropy Weight TOPSIS method was employed to identify key design features that significantly impact user experience. Subsequently, a PSO-SVR model was constructed to establish a mapping between user Kansei words and key design features. The validation study, involving 100 participants, confirmed that the optimized design combination aligns with users' emotional preferences.

Building on these findings, this study makes several key contributions:

(a) Under the research framework of KE, a design process based on KE-Entropy Weight TOPSIS-PSO-SVR is proposed. This method integrates Kansei Engineering, Entropy Weight TOPSIS and PSO-SVR, providing a new methodology for design research.

(b) Currently, there is no design research on the PVMUI based on the KE framework. This paper fills the research gap in this field and offers a new perspective for the interactive interface design of virtual museums.

(c) The Entropy Weight TOPSIS method was used to more objectively identify key design features that strongly affect user emotions. By objective weighting, the accuracy and reliability of key design feature extraction were improved.

(d) SVR was adopted to replace traditional linear analysis methods, establishing a mapping model between Kansei words and key design features. By determining the optimal hyperplane, the optimal design combination scheme of the PVMUI was obtained, satisfying user experience needs and promoting the display and dissemination of museum cultural heritage.

Data availability

All datasets generated and/or analyzed during the current study are included in the manuscript and its supplementary files. The full raw dataset necessary for interpreting, replicating, and building upon the findings reported in this article is available in the supplementary materials. These datasets can be accessed directly in the supplementary files section of the manuscript. For any further inquiries or access to additional data, please contact the corresponding author.

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Author contributions

Z.K.W. conducted the main research, data collection, and manuscript writing. F.L. supervised the entire study, provided guidance on research design and analysis, and critically reviewed and revised the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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