Attention-Weighted Kansei Engineering: Ming-Style Armchair

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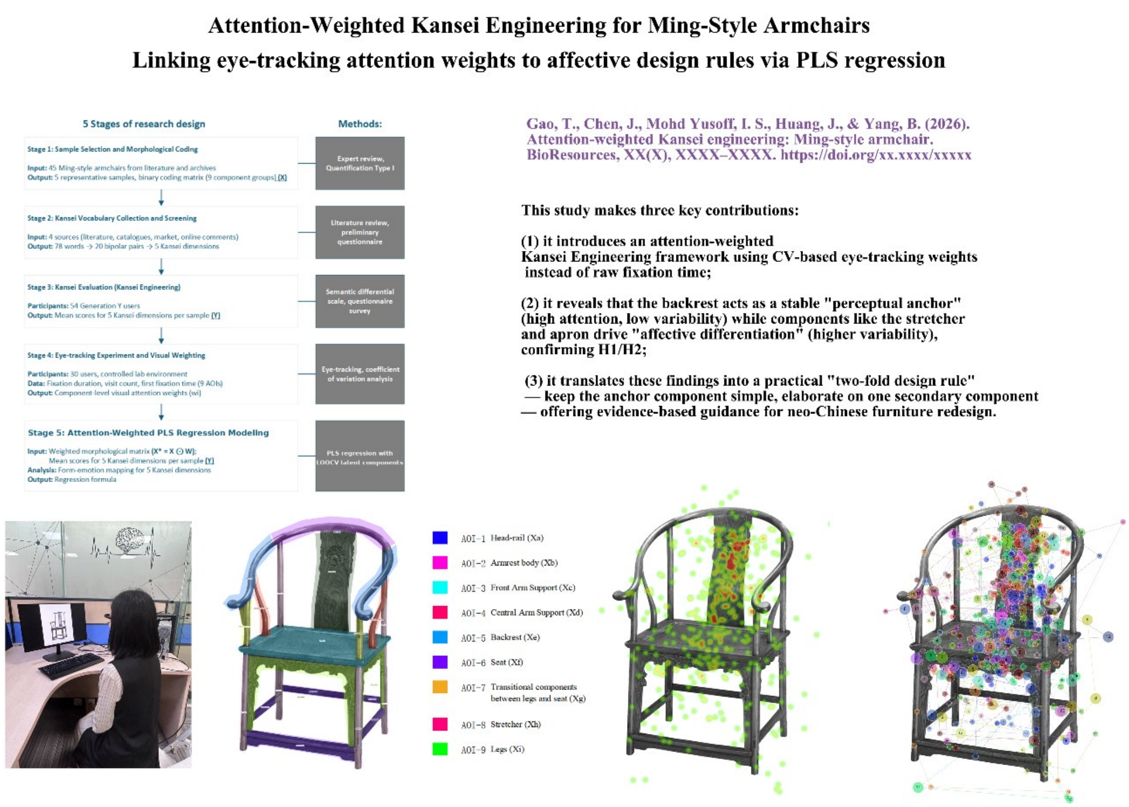
GRAPHICAL ABSTRACT



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Ming-style armchairs represent a distinctive form of Chinese classical furniture, yet systematic methods for linking their morphological features to users' affective responses remain limited. Conventional Kansei Engineering (KE) models treat design components as equally weighted, neglecting differences in visual attention. This study proposes an attention-weighted KE framework that integrates eye-tracking data with partial least squares (PLS) regression modelling. Five representative Ming-style armchairs were evaluated by 200 Generation Y participants across five Kansei dimensions using semantic differential scales. A subsequent eye-tracking experiment with 30 participants derived visual attention weights for nine morphological components *via* the coefficient of variation of total fixation duration. These weights were embedded into binary morphological coding and analysed using partial least squares (PLS) regression. Results indicated that the stretcher, apron, and spindle showed stronger associations with affective differentiation than the dominant backrest, which served as a stable perceptual anchor. Plain aprons and slightly curved spindles enhanced perceptions of simplicity and naturalness, while step-by-step stretchers and carved aprons were associated with complexity. The regression coefficients were translated into preference-avoidance design rules, suggesting that redesign may benefit from a two-fold strategy of preserving simple, recognisable treatment of the dominant category-defining component while concentrating tasteful elaboration on one selected secondary feature.

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Keywords: Ming-style armchair; Eye-tracking; Kansei engineering; Partial least squares; PLS regression; Contemporary design

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INTRODUCTION

Ming-style armchairs are among the most recognized forms of Chinese classical furniture. They are distinguished by circular top rails, square seat frames, and mortise-and-tenon joinery. Their design philosophy derives aesthetic expression from structural logic (Wang 2016). With growing interest in cultural revival and consumption upgrading among contemporary consumers, redesigning these chairs requires translating structural form into user perception while balancing cultural continuity with modern usability.

Previous studies have examined structural logic, craftsmanship traditions, and literati aesthetics of Ming furniture (Wang 2016; Xue *et al*. 2024). However, this body of work adopts a predominantly historical-technical perspective, emphasizing what traditional furniture represents rather than how contemporary users perceive it. In modern living environments characterized by spatial constraints and shifting aesthetic preferences, users evaluate furniture through expectations of simplicity, visual lightness, and spatial compatibility. The central question is thus how specific morphological components can be selectively retained, simplified, or reorganized on the basis of empirical perceptual evidence rather than designer intuition.

Kansei Engineering (KE) offers a structured way to link product form to affective response through semantic evaluation and quantitative modelling (Nagamachi 1995; Schütte and Eklund 2005). Conventional KE assigns equal weight to all design elements, disregarding hierarchical differences in visual attention. For multi-component furniture in which backrests, armrests, seats, stretchers, and aprons interact within integrated compositions, this equal-weight assumption may distort form-emotion relationships.

Eye-tracking technology captures implicit visual behavior and reveals attention distribution across components (Wedel and Pieters 2008; Duchowski 2017; Fu *et al*. 2024). Recent work has incorporated attention-based weighting into KE (Chen *et al*. 2009; Deng and Wang 2020; Sun and Jiang 2025), typically using raw fixation duration as the weighting criterion. This approach overlooks a key distinction: Components that attract consistent attention may function as perceptual anchors for recognition, whereas components with variable attention patterns may be more strongly associated with affective discrimination despite lower absolute viewing time. The difference between perceptual stability and perceptual differentiation has not been adequately addressed.

Additionally, translating KE outputs into actionable design guidance remains underexplored. Regression coefficients reveal statistical associations but do not specify how to synthesize components into coherent designs that respect proportional systems and cultural authenticity. A structured pathway is needed to convert modelling results into component-level design rules applicable by designers while preserving structural and cultural integrity. Three research gaps persist: (1) insufficient empirical evidence on component-level perceptual contributions to affective evaluation; (2) inadequate distinction between perceptual stability and differentiation in attention-based weighting; and (3) lack of systematic pathways from modelling outputs to structured design guidance.

Building on this distinction, the present study advances two guiding hypotheses. H1: Structurally dominant components that establish a furniture piece's categorical identity — such as the backrest of a Ming-style armchair — will attract the greatest absolute visual attention across viewers and samples. H2: Because the coefficient of variation directly indexes how consistently a component is fixated across differently-styled samples, components with higher attention variability by this measure will show a stronger association with affective differentiation between designs, regardless of their absolute share of viewing time. If supported, these hypotheses would imply that redesign strategies can decouple the treatment of category-defining features, which may be simplified without eroding stylistic identity, from the treatment of secondary features, whose careful elaboration offers a more efficient route to shaping user perception; this implication is examined directly in the Results and Discussion.

This study proposes an attention-weighted KE framework for multi-component traditional furniture. Using Ming-style armchairs as a case, the framework identifies affective dimensions through semantic evaluation, derives component-level weights *via* eye-tracking using coefficient-of-variation metrics that capture attention variability, integrates these weights into PLS regression modelling, and translates the results into preference-avoidance design rules. These rules provide structured guidance for selectively retaining, simplifying, or reorganizing traditional components based on empirical perceptual evidence. The framework offers a reproducible methodology transferable to other artefacts exhibiting clear component structures and form-driven aesthetics.

METHODOLOGY

Research Design

A sequential mixed-method design was adopted, comprising five stages: Sample selection and morphological coding, Kansei vocabulary collection and screening, Kansei evaluation, eye-tracking experiment with visual weighting, and attention-weighted PLS regression modelling. This sequence ensured that the final design proposal traced a documented chain from user evaluation through visual behavior analysis, statistical modelling, and design translation.

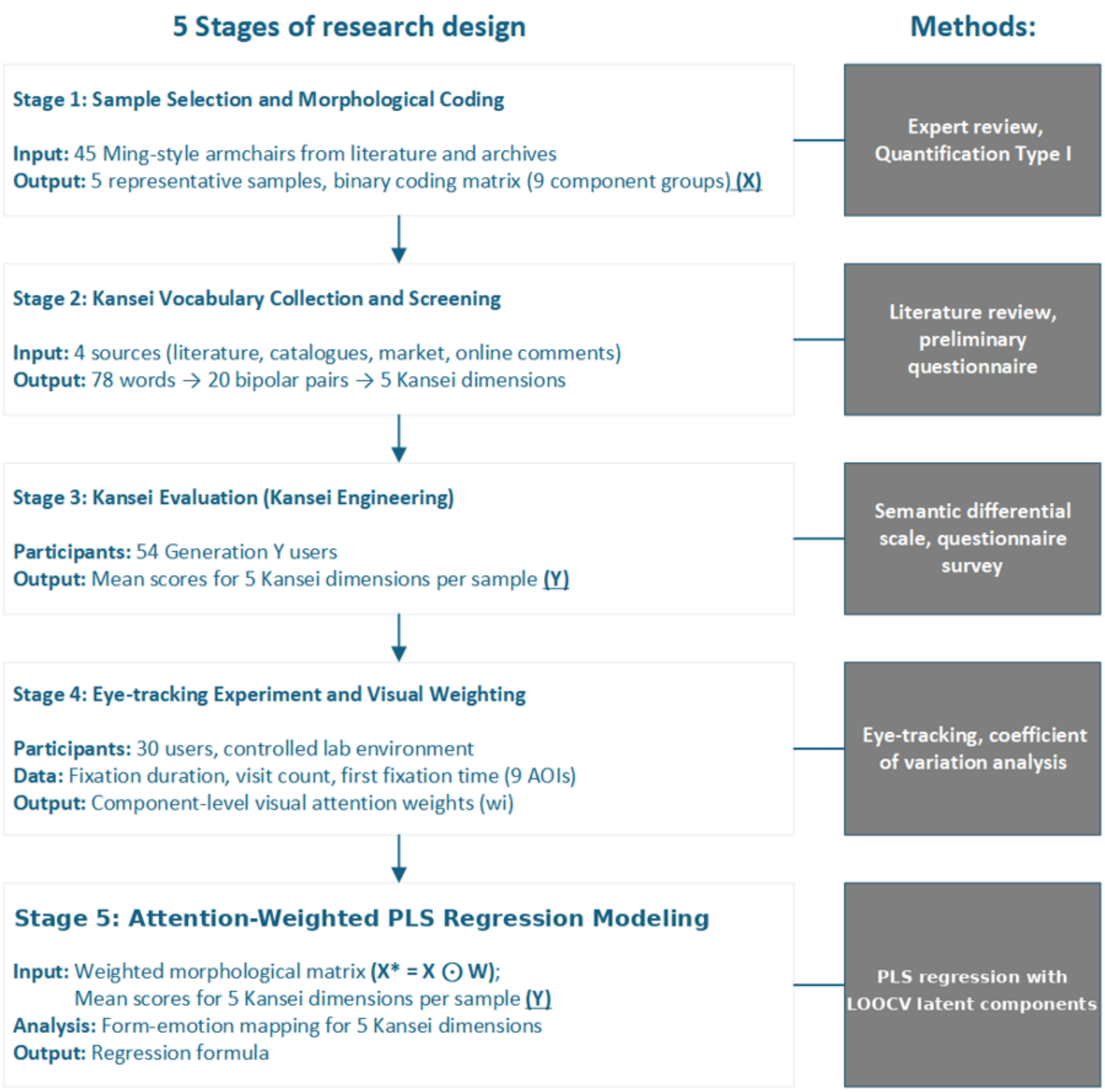


Fig. 1. Five-stage attention-weighted KE framework

Sample Selection and Morphological Coding

Sample selection

A sample pool of 45 Ming-style armchairs was collected from academic literature, museum collections, antique furniture stores, auction records, and online image archives. Three experts in furniture design and traditional furniture studies reviewed the pool and selected five representative samples for subsequent evaluation. The selection considered overall typicality, structural recognizability, component-level variation, and image quality. The five selected samples are shown in Fig. 2.

Fig. 2. Five representative Ming-style armchair samples

Morphological coding

After sample selection, morphological coding was conducted for the five representative chairs. Each chair was decomposed into eight component groups: Top rail, armrest, gooseneck post, spindle, backrest, apron, stretcher, and legs. These components were encoded as mutually exclusive binary categories, where "1" indicates the presence of a feature and "0" its absence.

The seat was excluded from morphological coding due to its consistency across samples but was retained in the eye-tracking stimuli. For attention-weighting, the backrest was further divided into two Areas of Interest (AOIs) — backrest contour and backrest carving—because their visual processing differed. The coding scheme is presented in Table 1.

Table 1. Morphological Coding Scheme for Ming-Style Armchair Components

Component Group	Code	Binary Coding Categories
Top Rail	X_a	X_{a1} Large-Arc Top Rail; X_{a2} Slight-Arc Top Rail
Armrest	X_b	X_{b1} Rounded terminal; X_{b2} Raised terminal
Gooseneck Post	X_c	X_{c1} Slightly curved; X_{c2} Clearly curved; X_{c3} Straight
Spindle	X_d	X_{d1} slightly curved; X_{d2} clearly curved
Backrest Carving / Panel Treatment	X_e	X_{e1} Shallow-relief backrest; X_{e2} Openwork backrest
Backrest Contour	X_f	X_{f1} Slight S-shaped backrest; X_{f2} Slight C-shaped backrest
Apron	X_g	X_{g1} Plain apron; X_{g2} Simplified shallow-relief apron; X_{g3} Heavily carved apron
Stretcher	X_h	X_{h1} Step-by-step stretcher; X_{h2} Double-foot-tube stretcher
Leg	X_i	X_{i1} Circular-section leg; X_{i2} Irregular-section leg

Each sample was thus represented as a binary vector, in which only one category within each component group was assigned a value of 1. The resulting coding matrix is shown in Table 2. In the subsequent modelling stage, these binary values were weighted by the corresponding AOI-based visual attention, allowing morphological features to reflect both structural presence and perceptual salience.

Table 2. Binary Morphological Coding Matrix of the Five Representative Chair Samples

Code	Component	Morphological category	S1	S2	S3	S4	S5
X_{a1}	Top rail	Large-arc top rail	1	1	1	0	1
X_{a2}	Top rail	Slight-arc top rail	0	0	0	1	0
X_{b1}	Armrest	Rounded armrest end	1	0	0	1	0
X_{b2}	Armrest	Raised armrest end	0	1	1	0	1
X_{c1}	Gooseneck post	Slightly curved gooseneck post	0	1	1	0	1
X_{c2}	Gooseneck post	Clearly curved gooseneck post	0	0	0	1	0
X_{c3}	Gooseneck post	Straight gooseneck post	1	0	0	0	0
X_{d1}	Spindle	Slightly curved spindle	0	0	1	0	0
X_{d2}	Spindle	Clearly curved spindle	1	1	0	1	1
X_{e1}	Backrest carving	Shallow-relief backrest	1	1	1	0	1
X_{e2}	Backrest carving	Openwork backrest	0	0	0	1	0
X_{f1}	Backrest contour	Slight S-shaped backrest	1	0	0	0	1
X_{f2}	Backrest contour	Slight C-shaped backrest	0	1	1	1	0
X_{g1}	Apron	Plain apron	0	0	1	1	0
X_{g2}	Apron	Simplified shallow-relief apron	0	1	0	0	1
X_{g3}	Apron	Heavily carved apron	1	0	0	0	0
X_{h1}	Stretcher	step-by-step stretcher	1	0	1	1	1
X_{h2}	Stretcher	Double-foot-tube stretcher	0	1	0	0	0
X_{i1}	Leg	Circular-section leg	0	1	1	0	0
X_{i2}	Leg	Irregular-section leg	1	0	0	1	1

Kansei Vocabulary Collection and Screening

Kansei vocabulary was collected prior to the semantic differential evaluation from four sources: Academic literature on Ming-style furniture, furniture catalogues and design books, market and auction product descriptions, and online consumer comments. Terms related to visual style, structural impression, cultural recognition, and use-related affect were manually extracted. After removing duplicates, merging synonyms and excluding overly abstract or irrelevant terms, 78 Kansei words were retained.

These terms were organized into bipolar semantic pairs based on semantic opposition and design relevance, resulting in 20 candidate pairs covering dimensions such as tradition, decoration, simplicity, naturalness, rhythm, lightness, and comfort. A preliminary screening questionnaire was conducted with 44 participants, who selected the most representative pairs for evaluating Ming-style armchairs. Word pairs chosen by more than one third of participants and confirmed for semantic clarity were retained.

This process resulted in five representative Kansei dimensions: Traditional–Fashionable, Practical–Decorative, Unique–Ordinary, Simple–Complex, and Natural–Artificial. The final selection and screening results are presented in Table 3.

Table 3. Representative Kansei Word Pairs Retained for Semantic Differential Evaluation

Codes	Selected Kansei Word Pair	Screening Value
K1	Traditional–Fashionable	0.64
K2	Practical–Decorative	0.55
K3	Unique–Ordinary	0.48
K4	Simple–Complex	0.64
K5	Natural–Artificial	0.45

Semantic Differential Evaluation

The formal Kansei evaluation was conducted using the five retained bipolar word pairs shown in Table 3. Generation Y was operationally defined, following Gurău (2012), as individuals born between 1980 and 2000. Participants were recruited using simple random sampling via a snowball procedure implemented through Google Forms, targeting individuals belonging to Generation Y. A total of 276 individuals completed the survey; after excluding respondents younger than 23 years or older than 42 years, 200 valid questionnaires were retained for analysis. Demographic characteristics of the valid sample are summarized in Table 4.

Table 4. Demographic Characteristics of the Semantic Differential Evaluation Sample (N = 200)

Variable	Category	N	Percentage (%)
Gender	Male	89	44.5
	Female	111	55.5
Age	23-32 years	169	84.5
	33-42 years	31	15.5
Education	High school or below	4	2.0
	Bachelor's degree	141	70.5
	Master's degree	36	18.0
	Doctoral degree	19	9.5
Professional Field	Furniture, art, design, or collection-related occupations	113	56.5
	Not related to furniture, art, design, or collection	87	43.5

Two hundred Generation Y participants evaluated the five representative chair samples using a five-point semantic differential scale ranging from -2 to +2. On this scale, -2 represented the left-side adjective pole, +2 represented the right-side adjective pole, and 0 represented a neutral perception. The scores of each sample on the five Kansei dimensions were averaged at the sample level and used as the baseline subjective evaluation values for the subsequent form-emotion modelling.

Eye-Tracking Experiment and Visual Weighting

The five chair samples were converted into standardized black-and-white front-view images with a resolution of 2360 × 2950 pixels. This treatment was used to reduce interference from material, color, and background differences, allowing the experiment to focus on structural form. A total of 48 participants who had not taken part in the earlier evaluation were recruited through online postings and word-of-mouth referral. After calibration and technical screening, 30 participants were retained for analysis; 8 participants were excluded due to calibration failure caused by contact lens reflections or uncorrected astigmatism. The final sample comprised 17 males and 13 females, aged between 25 and 44 years (M = 32.7). All participants had normal or corrected-to-normal vision with no color deficiencies. Written informed consent was obtained before participation, and each participant received RMB 20 upon completion.

Table 5. Demographic Characteristics of the Eye-Tracking Experiment Participant Sample (N = 30)

No.	Initials	Gender	Age	No.	Initials	Gender	Age
1	CXY	Female	25	16	TX	Male	39
2	LJM	Male	26	17	HDJ	Female	30
3	FWY	Female	24	18	LRT	Male	32
4	LHP	Male	31	19	YEY	Female	26
5	HSW	Female	27	20	FHL	Male	42
6	ZDH	Male	30	21	HJB	Male	38
7	LZJ	Male	27	22	JGQ	Male	36
8	MZH	Female	32	23	YZJ	Male	34
9	HXY	Female	38	24	LY	Female	37
10	LQJ	Male	35	25	HZY	Male	27
11	CMZ	Male	32	26	CCM	Male	25
12	OYWN	Female	37	27	LLM	Female	26
13	XY	Male	41	28	WSM	Male	39
14	SYN	Female	33	29	DRH	Female	37
15	LYC	Male	36	30	WXL	Female	43

Gaze data were recorded using the Tobii Pro Glasses 2 head-mounted eye tracker (sampling rate: 50 Hz; gaze accuracy: approximately 0.5° visual angle; system latency: <35 ms), connected to the Tobii Pro Glasses Controller and Tobii Pro Lab for data collection and AOI-based analysis. Tests were performed in a controlled laboratory environment under uniform LED lighting with curtains drawn to exclude external light; only one participant was present in each session. Each participant first wore the eye tracker with the assistance of the researchers, followed by the manufacturer's calibration procedure and a pilot validation trial to confirm gaze stability (tolerance: ≤3 mm drift on the display surface). Each participant completed 2 to 3 practice trials before the formal experiment; practice data were excluded from all analyses.

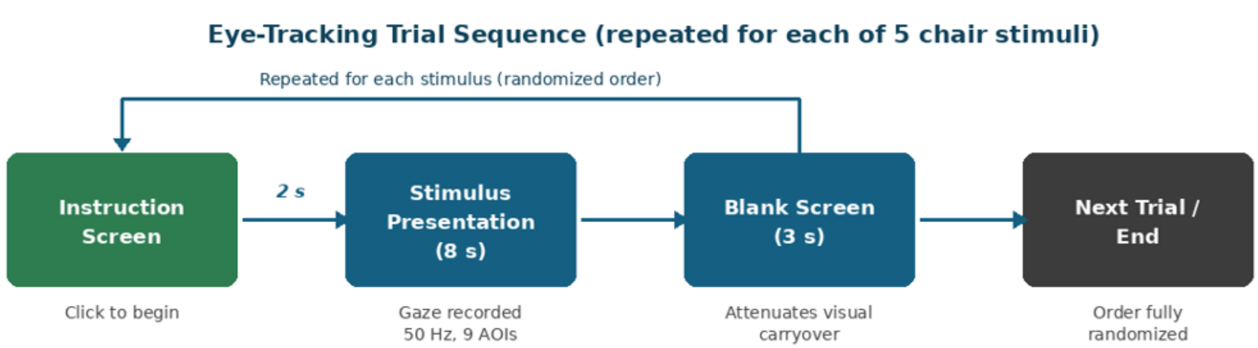


Fig. 3. Eye-tracking trial sequence showing the four stages of each experimental trial

Each trial consisted of an instruction screen followed by a 2-s transition, an 8-s (8000 ms) stimulus presentation during which gaze points were continuously recorded, and a 3-s blank-screen buffer to attenuate visual carryover effects before the next trial; the presentation order of the chair images was fully randomized among participants. The recorded indicators included first fixation time, visit count, total fixation duration, average fixation duration and fixation count.

Areas of interest were defined according to the component system described above. The backrest was divided into backrest shape and backrest carving AOIs, resulting in nine AOIs for visual-weight calculation. Eye-tracking analysis (Table 6) included five indicators: First fixation time, visit count, total fixation duration, average fixation duration, and fixation count. Total fixation duration was used as the primary weighting indicator because it directly reflects the accumulated visual processing allocated to each component, while the remaining indicators were used to describe the overall viewing behavior and to support data screening.

Table 6. Eye-Tracking Indicators Used in the Visual Attention Analysis

Indicator	Abbreviation	Role in the Analysis
First Fixation Time	FFT	Time required before a component was first fixated; used to describe early visual entry.
Visit Count	VC	Number of revisits to an AOI; used to describe repeated attention.
Total Fixation Duration	TFD	Accumulated fixation duration within an AOI; used as the basis for CV-derived weighting.
Average Fixation Duration	AFD	Mean duration of fixations within an AOI; used to describe processing depth.
Fixation Count	FC	Number of fixations within an AOI; used to describe attention frequency.

To transform users' implicit visual attention to the components of Ming-style armchairs into quantifiable and comparable design-element weights, this study adopted the coefficient-of-variation (CV) method to analyze and weight the eye-tracking data. The procedure consisted of three steps.

Data extraction and descriptive statistics

For the core morphological components other than the seat, total fixation duration was extracted for each component across the five representative chair samples. The analyzed components included the top rail, armrest, gooseneck post, spindle, backrest shape, backrest carving, apron, stretcher, and legs. For each component, the mean and standard deviation of total fixation duration across the five samples were calculated.

Coefficient of variation

The CV value was used to represent the relative fluctuation of visual attention attracted by each component across different samples. It was calculated as follows:

$$CV_i = \sigma_i / \mu_i \tag{1}$$

where μ_i denotes the mean total fixation duration of component i across the five chair samples, and σ_i denotes the corresponding standard deviation. A larger CV indicates stronger variation in the component's ability to attract visual attention across samples. In this study, such variation was treated as an empirical weighting criterion — an index of attention variability across the sampled chairs — rather than a direct measure of the component's overall design importance; the relationship between this attention-variability index and affective differentiation was subsequently tested empirically through the PLS regression models reported in the Results.

Weight normalization

The CV values of all components were then normalized so that the sum of component weights equaled to 1. The normalized visual weight was calculated as follows,

$$w_i = CV_i \,/\, \Sigma_{i=1}^{n} CV_i \tag{2}$$

where w_i represents the normalized visual weight of component i, CV_i is the coefficient of variation of component i, and n is the total number of analyzed components.

Attention-Weighted Morphological Coding

To convert qualitative morphological features into numerical independent variables suitable for regression analysis, and to integrate the visual cognitive weights obtained in the previous step, the following parameterization procedure was conducted.

Original feature coding. Based on the morphological decomposition described in Table 2, the morphological features of each sample were represented as a binary (0/1) vector, forming the original morphological feature matrix X_{raw}. If a sample contained a given feature category, such as a large-arc top rail (X_{a1}), the corresponding position was coded as 1; otherwise, it was coded as 0.

Feature weighting. Each value in the original binary coding matrix was multiplied by the weight of its corresponding morphological component to generate the attention-weighted morphological feature matrix. The weighted feature value was calculated as follows,

$$x^*_{ij} = x_{ij} \cdot wi \tag{3}$$

where x^*_{ij} denotes the weighted value of feature j in component i, x_{ij} is the original binary encoding, and wi is the normalized visual attention weight of component i in nine AOI (Fig. 4).

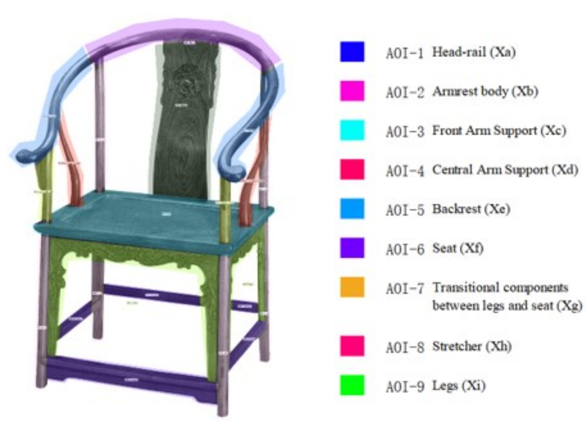


Fig. 4. AOI definition for the component-based eye-tracking analysis (sample 1)

This operation incorporates perceptual salience derived from eye-tracking into the feature representation. The resulting weighted feature matrix can be expressed as,

$$X^* = X \odot W \tag{4}$$

where X is the original binary morphological coding matrix, W is the AOI-weight matrix expanded to match the dimensions of X, and $\odot$ denotes element-wise multiplication.

Attention-Weighted PLS Regression Modelling

Based on the attention-weighted feature matrix X^*, partial least squares (PLS) regression models were constructed for the five Kansei dimensions: Traditional-Fashionable, Practical-Decorative, Unique-Ordinary, SimpleComplex, and Natural-Artificial. Each model is defined as:

$$Y_m = \beta_{0m} + \sum_{j=1}^{p} \beta_{jm} x_j^* + \varepsilon_m \tag{5}$$

where Y_m is the mean semantic differential score of dimensions m, β_{0m} is the intercept, β_{jm} are regression coefficients, p is the number of features, and ε_m is the error term.

PLS regression was adopted, rather than ordinary least squares or ridge regression, because it is specifically suited to conditions in which the number of predictors greatly exceeds the number of observations ($p = 20$, $n = 5$) and predictors are highly collinear, as is the case for the mutually-exclusive binary morphological codes used here. Rather than estimating a coefficient for every predictor directly, PLS regression constructs a small number of latent components from X^* that maximise covariance with each Kansei dimension Y_m, and expresses Y_m as a linear combination of these components.

$$X^* = TP^T + E, \quad Y_m = TQ_m^T + F_m \tag{6}$$

In Eq. 6, T is the matrix of latent-variable scores common to both X^* and Y_m, P, and Q_m are the corresponding loading matrices, and E and F_m are residuals. Because the latent components are themselves linear combinations of the original predictors, the fitted model can be re-expressed in the original predictor space in the same form as Eq. (5), with β_{jm} now denoting the PLS regression coefficients. The number of latent components retained for each Kansei dimension is a complexity-control parameter analogous to the ridge penalty λ, and was selected via the nested leave-one-out cross-validation procedure described below.

Model Validation

Given the small calibration sample ($n = 5$), conventional k-fold cross-validation was not considered informative because partitioning the data into multiple folds would result in extremely small validation subsets and highly unstable performance estimates. Leave-one-out cross-validation (LOOCV) was therefore adopted to evaluate the out-of-sample predictive performance of each PLS regression model and to assess overfitting under the high predictor-to-sample ratio (20 coded features for 5 calibration samples). For each Kansei dimension, LOOCV was implemented using a nested procedure. In each of the five outer iterations, one sample was held out as the test case, while the PLS regression model was fitted using the remaining four samples. Within each outer training set, the number of latent components k (ranging from 1 to 4, *i.e.* up to $n - 1$ for the four-sample training set) was independently selected through an inner LOOCV procedure that minimized RMSE, ensuring that the held-out sample was not used in either model fitting or component-count selection. The model fitted with the selected number of components was then used to predict the Kansei score of the held-out sample. This procedure was repeated until all five samples had served once as the test case, producing a complete set of leave-one-out predictions, $\hat{y}_{-i}$.

Predictive performance was assessed using the LOOCV root mean square error (RMSE) and predictive Q^2:

$$RMSE_{\text{LOOCV}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_{-i})^2} \tag{7}$$

$$Q^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_{-i})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{8}$$

where y_i is the observed Kansei score of sample *i*, $\hat{y}_{-i}$ is the predicted score for sample *i* obtained from the model fitted without sample *i*, $\bar{y}$ is the mean observed Kansei score across the five calibration samples, and *n* is the total number of calibration samples. Unlike the in-sample R^2, predictive Q^2 directly reflects out-of-sample prediction and may take negative values when the cross-validated prediction error exceeds that of the mean-based null model. Thus, a negative Q^2 indicates that the model does not provide useful predictive performance for unseen samples despite potentially exhibiting a high apparent in-sample fit.

In addition, a sensitivity analysis was performed across component counts of $k = 1$ to 4 to examine the relationship between model complexity, in-sample fit, and LOOCV predictive performance. This analysis was used to characterize the extent to which additional latent components may improve apparent model fit while simultaneously increasing out-of-sample prediction error, thereby providing an additional assessment of overfitting risk under the limited calibration sample size.

RESULTS

Semantic Differential Results

Using the five Kansei dimensions defined in the Methods section, semantic differential evaluation generated the subjective scores for each representative chair sample. The mean values across the five samples are reported in Table 7. All samples were positioned toward the traditional end of the Traditional–Fashionable dimension, indicating a consistent preservation of Ming-style identity. These five dimensions served as the dependent variables in the subsequent PLS regression modelling.

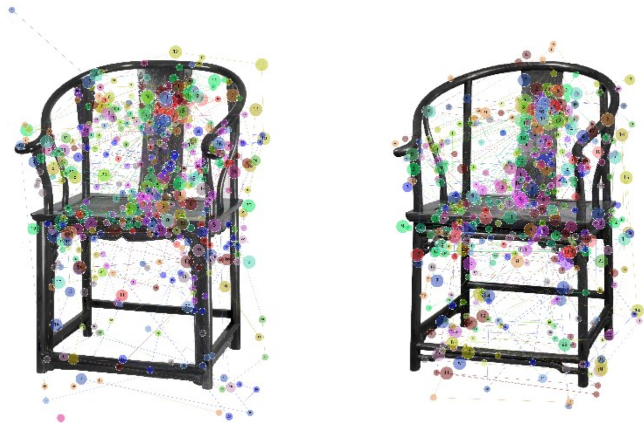
Table 7. Mean Semantic Differential Scores of the Five Representative Chair Samples

Sample	Traditional - Fashionable	Practical - Decorative	Unique - Ordinary	Simple - Complex	Natural - Artificial
Sample 1	-1.45	0.11	-0.64	0.06	0.85
Sample 2	-1.15	-0.11	-0.40	-0.43	0.43
Sample 3	-1.11	-0.23	-0.32	-0.60	0.43
Sample 4	-1.06	0.09	-0.74	0.19	0.72
Sample 5	-0.96	-0.23	-0.40	-0.34	0.49

Heatmap and Gaze Scanpath

To further illustrate the distribution of visual attention across chair components, representative heatmaps and gaze scanpath maps from the eye-tracking experiment are presented (Figs. 5 and 6).

Fig. 5. Eye-tracking experiment setting and representative heatmaps



Sample 4 Sample 5

Fig. 6. Representative gaze scanpath maps of participants viewing Ming-style chair samples

The heatmaps display the cumulative fixation distribution across the five chair samples, while the scanpath maps reveal the sequential viewing patterns of participants. The results indicate that participants focused primarily on the carved-backed surfaces and textured seat surfaces, followed by the viewing panel positioned lower in the center, with structural connectors and joints appearing last.

On the scanpath maps, most observers began their observation at the headrail and backrests, then followed their visual attention downward sequentially. However, half of the participants initiated their observation from more visually appealing decorative areas with larger surface areas.

Visual Cognitive Weights of Morphological Components

Table 8 presents the visual cognitive weights, recalculated from a follow-up eye-tracking measurement on the same five representative samples using the same nine-component AOI scheme, derived from the coefficient of variation of total fixation duration. The top rail obtained the highest weight (0.205), closely followed by the stretcher (0.203), the gooseneck post (0.125), and the armrest (0.122).

The backrest carving / panel treatment (*X*e) and backrest contour (*X*f) had the longest absolute fixation duration, but they exhibited the lowest weight (0.040 each; because the follow-up eye-tracking measurement recorded backrest attention as a single undivided AOI, the same coefficient of variation was assigned to both backrest sub-components). This indicates that the backrest functioned as a stable visual centre, while the top rail, stretcher, gooseneck post and armrest showed stronger perceptual differentiation across samples.

Table 8. Visual Cognitive Weights of Morphological Components

Component	Mean Fixation Duration (ms)	SD	CV	Weight (w_i)
Top Rail (Xa)	33.71	19.73	0.585	0.205
Armrest (Xb)	155.64	53.95	0.347	0.122
Gooseneck Post (Xc)	109.00	38.68	0.355	0.125
Spindle (Xd)	135.92	32.18	0.237	0.083
Backrest Carving or Panel Treatment (Xe)	2580.22	295.67	0.115	0.040
Backrest Contour (Xf)	2580.22	295.67	0.115	0.040
Apron (Xg)	465.99	129.48	0.278	0.097
Stretcher (Xh)	142.92	82.65	0.578	0.203
Leg（Xi）	213.94	51.75	0.242	0.085
Total			2.852	1.000

Each value in the original feature matrix (Table 2) was multiplied by the visual attention weight of its corresponding component, generating a weighted morphological feature matrix from formula 3. The resulting weighted encoding matrix for the five samples is presented in Table 9.

Table 9. Attention-Weighted Morphological Coding Matrix of the Five Representative Samples

Code	Component	S1	S2	S3	S4	S5
X_{a1}	Top Rail	0.205	0.205	0.205	0.000	0.205
X_{a2}	Top Rail	0.000	0.000	0.000	0.205	0.000
X_{b1}	Armrest	0.122	0.000	0.000	0.122	0.000
X_{b2}	Armrest	0.000	0.122	0.122	0.000	0.122
X_{c1}	Gooseneck Post	0.000	0.125	0.125	0.000	0.125
X_{c2}	Gooseneck Post	0.000	0.000	0.000	0.125	0.000
X_{c3}	Gooseneck Post	0.125	0.000	0.000	0.000	0.000
X_{d1}	Spindle	0.000	0.000	0.083	0.000	0.000
X_{d2}	Spindle	0.083	0.083	0.000	0.083	0.083
X_{e1}	Backrest Carving	0.040	0.040	0.040	0.000	0.040
X_{e2}	Backrest Carving	0.000	0.000	0.000	0.040	0.000
X_{f1}	Backrest Contour	0.040	0.000	0.000	0.000	0.040
X_{f2}	Backrest Contour	0.000	0.040	0.040	0.040	0.000
X_{g1}	Apron	0.000	0.000	0.097	0.097	0.000
X_{g2}	Apron	0.000	0.097	0.000	0.000	0.097
X_{g3}	Apron	0.097	0.000	0.000	0.000	0.000
X_{h1}	Stretcher	0.203	0.000	0.203	0.203	0.203
X_{h2}	Stretcher	0.000	0.203	0.000	0.000	0.000
X_{i1}	Leg	0.000	0.085	0.085	0.000	0.000
X_{i2}	Leg	0.085	0.000	0.000	0.085	0.085

Form–Emotion Mapping and Design Rules

PLS regression was conducted for all five Kansei dimensions using the attention-weighted morphological coding matrix as the predictor matrix, with the number of latent components selected independently for each dimension via the nested LOOCV procedure described in the Methods section (n = 5, *P* = 20). The resulting model equations, expressed in the original predictor space, were as follows:

$$Y1_{\text{Traditional–Fashionable}} = -1.0573 - 0.6821X_{c3} - 0.5293X_{g3} - 0.5142X_{b1} - 0.4713X_{a1} + 0.3947X_{c1} + 0.3852X_{b2} + 0.2546X_{a2} + 0.2454X_{g1} - 0.1947X_{d2} + 0.1813X_{g2} - 0.1756X_{i2} - 0.1578X_{h1} + 0.1552X_{c2} - 0.1323X_{f1} + 0.1069X_{d1} - 0.0920X_{e1} + 0.0900X_{f2} + 0.0857X_{i1} - 0.0568X_{h2} + 0.0497X_{e2} \quad (9)\ [k = 1]$$

$$Y2_{\text{Practical–decorative}} = -0.0269 - 0.3784X_{c1} - 0.3693X_{b2} + 0.3660X_{b1} - 0.2535X_{a1} + 0.2480X_{a2} + 0.2238X_{c3} - 0.2137X_{i1} + 0.2114X_{i2} - 0.1898X_{d1} + 0.1876X_{d2} + 0.1737X_{g3} + 0.1512X_{c2} - 0.1045X_{g1} - 0.0718X_{g2} - 0.0522X_{f2} + 0.0511X_{f1} - 0.0495X_{e1} + 0.0484X_{e2} - 0.0461X_{h2} + 0.0406X_{h1} \quad (10)\ [k = 1]$$

$$Y3_{\text{Unique–ordinary}} = -0.5314 - 0.4856X_{b1} + 0.4312X_{c1} + 0.4208X_{b2} - 0.3792X_{a2} - 0.3279X_{d2} - 0.2892X_{i2} + 0.2838X_{d1} + 0.2702X_{a1} - 0.2664X_{c3} + 0.2440X_{i1} - 0.2312X_{c2} - 0.2067X_{g3} + 0.1522X_{g1} - 0.1112X_{h2} - 0.0740X_{e2} - 0.0621X_{f1} + 0.0527X_{e1} + 0.0408X_{f2} + 0.0034X_{h1} + 0.0030X_{g2} \quad (11)\ [k = 2]$$

$$Y4_{\text{Simple–complex}} = -0.1297 - 0.7937X_{c1} - 0.7746X_{b2} + 0.7588X_{b1} - 0.6955X_{i1} + 0.6845X_{i2} - 0.6536X_{d1} + 0.6428X_{d2} - 0.5528X_{a1} + 0.5262X_{a2} - 0.5148X_{g1} + 0.4566X_{c3} + 0.3543X_{g3} + 0.3208X_{c2} - 0.2246X_{f2} + 0.2194X_{f1} + 0.1479X_{g2} - 0.1079X_{e1} + 0.1027X_{e2} - 0.0626X_{h2} + 0.0362X_{h1} \quad (12)\ [k = 2]$$

$$Y5_{\text{Natural–artificial}} = 0.5567 + 0.5536X_{b1} + 0.5349X_{c3} - 0.4976X_{c1} - 0.4857X_{b2} + 0.4151X_{g3} + 0.3317X_{i2} - 0.2843X_{i1} + 0.2818X_{d2} - 0.2503X_{g1} - 0.2356X_{d1} + 0.2158X_{h1} + 0.1457X_{f1} - 0.1235X_{f2} - 0.1108X_{g2} - 0.1028X_{h2} + 0.0611X_{a1} + 0.0530X_{a2} + 0.0323X_{c2} + 0.0119X_{e1} + 0.0103X_{e2} \quad (13)\ [k = 2]$$

Model Validation Results

Following the nested leave-one-out cross-validation (LOOCV) procedure described in the Methods section, each of the five PLS regression models was evaluated for out-of-sample predictive performance. For each outer fold, the number of latent components was re-selected through an inner LOOCV search over the remaining four samples, and the resulting model was used to predict the held-out sample. The LOOCV root mean square error ($RMSE_{loocv}$) and predictive Q^2 for each Kansei dimension are summarized in Table 10.

Table 10. Leave-One-Out Cross-Validation (LOOCV) Predictive Performance of the PLS Regression Models

Kansei Dimension	LOOCV RMSE	Predictive Q²
Traditional–Fashionable	0.285	-1.995
Practical–Decorative	0.162	-0.182
Unique–Ordinary	0.143	0.210
Simple–Complex	0.254	0.283
Natural–Artificial	0.142	0.310

Unlike the ridge regression models reported in earlier analyses, the PLS models improved out-of-sample predictive performance for three of the five Kansei dimensions. Unique–Ordinary, Simple–Complex, and Natural–Artificial all achieved positive predictive Q^2 (0.210, 0.283 and 0.310 respectively), each retaining two latent components (k = 2), indicating that the latent-component structure extracted by PLS generalises, to a modest degree, beyond the five calibration samples for these dimensions. The Traditional–Fashionable and Practical–Decorative dimensions, however, remained poorly predicted out-of-sample (Q^2 = -1.995 and -0.182), with the inner-LOOCV procedure retaining only a single latent component (k = 1) for both — the minimum available model complexity — without this reducing overfitting sufficiently given the severe predictor-to-sample imbalance (n = 5, P = 20). Taken together, these diagnostics indicate that the PLS regression coefficients in Eqs. (9)–(13) should be interpreted with dimension-specific caution: the models for Unique–Ordinary, Simple–Complex and Natural–Artificial provide some genuine out-of-sample generalisation within the sampled morphological space, whereas the models for Traditional–Fashionable and Practical–Decorative remain descriptive, within-sample associations rather than validated predictive models for unseen designs; this limitation is discussed further in the Discussion section.

A consistent pattern emerged across the five equations that speaks directly to hypotheses H1 and H2 proposed in the Introduction. Consistent with H1, Table 8 shows that the backrest received by far the longest absolute fixation duration of any component. Yet consistent with H2, rather than a simple "more attention, more influence" expectation, the backrest carving predictors (X_{e1}, X_{e2}) ranked among the four smallest-magnitude coefficients of the twenty predictors in every one of Eqs. 9 to 13; the backrest contour predictors (X_{f1}, X_{f2}) showed the same pattern in three of the five equations (Y1, Y2, Y3) but reach moderate, mid-range magnitude in Y4 and Y5.

Predictors linked to the top rail, stretcher, gooseneck post, apron and spindle, by contrast, carried the largest-magnitude coefficients for at least one Kansei dimension each. This pattern is consistent with a two-fold design logic, in which the backrest's morphology contributes comparatively little to affective differentiation and can be treated as a stable categorical anchor, while one or more of the smaller components can serve as a deliberate, higher-variance focal point for affective tuning. This interpretation is developed further in the Discussion.

DISCUSSION

Perceptual Hierarchy in Multi-Component Furniture Evaluation

The dissociation between visual dominance and affective contribution revealed a hierarchical processing structure in furniture perception. While the backrest functions as a stable recognition anchor—establishing categorical identity through consistent attention patterns—smaller components with variable attention patterns are more strongly associated with affective discrimination. This finding extends Gestalt psychology's figure-ground organization principles (Wagemans *et al*. 2012) to complex product forms, suggesting that perceptual stability and evaluative sensitivity operate through different attentional mechanisms.

This hierarchy may reflect adaptive perceptual strategies for evaluating multi-component artefacts. Once structural configuration is resolved (*via* dominant forms), cognitive resources shift toward variable features for comparative evaluation. This two-stage processing—categorical recognition followed by fine-grained assessment—offers one possible account of why visually subordinate elements show stronger association with affective responses, challenging the implicit assumption in product design that visual salience predicts emotional impact.

These results suggest a two-fold strategy for neo-traditional furniture design, directly addressing hypotheses H1 and H2. The first step is to preserve simple, low-variation treatment of the categorical anchor — here, the backrest — so that the chair's Ming-style identity remains immediately and unambiguously legible to viewers; elaborating this component appears to contribute little additional affective differentiation despite commanding the longest absolute fixation duration of any component (Table 8). The second step is to concentrate stylistic elaboration on a single secondary component with high attention variability, such as the stretcher, apron, gooseneck post, or top rail, as the deliberate focus of embellishment. The coefficients in Eqs. 9 to 13 indicate that variation in these smaller components — plain versus carved aprons, slightly versus clearly curved spindles, step-by-step versus double-foot-tube stretchers — is what most strongly shifts perceived simplicity, naturalness, and stylistic character across samples. Rather than distributing embellishment evenly across all components, designers may therefore achieve stronger affective differentiation while preserving recognisability by combining restrained treatment of the primary recognition anchor with focused, tasteful detailing of one selected secondary feature. This proposal is consistent with the association-level evidence reported here but has not been tested experimentally; confirming it would require systematically varying the treatment of a single secondary component while holding the backrest constant and measuring the resulting affective ratings.

Rethinking Weight Assignment in Kansei Engineering

Traditional Kansei Engineering's equal-weight morphological coding (Nagamachi 1995) assumes design elements contribute independently to affective responses. For multi-component products where elements interact perceptually, this assumption overlooks hierarchical salience structures. The coefficient-of-variation weighting method addresses this by distinguishing stable visual anchors from differentiating cues, operationalizing what we term "evaluative attention"—attention patterns that vary systematically with changing affective contexts.

However, attention-weighting represents perceptual processing under specific viewing conditions, not comprehensive design importance. Eye-tracking captures where users look and how viewing patterns differ across stimuli. However, eye-tracking cannot directly measure why components matter aesthetically. The method identifies which features warrant empirical investigation in design decisions, rather than prescribing component importance rankings. This dissociation between fixation magnitude and attention-variability weighting has since been corroborated in a larger-scale related study on Ming-style chairs (Gao *et al.* 2026).

Component Quantification within Integrated Design Systems

Regression analysis necessarily decomposes holistic forms into analytical components, creating tension with design practice where elements exist only within relational structures. Chinese furniture aesthetics' principle of "qi yun sheng dong" (rhythmic vitality through structural logic) emphasizes that components derive meaning from compositional relationships, not isolated forms—a perspective aligned with Gestalt relational determination (Li 2010; Wagemans *et al*. 2012).

This epistemological challenge distinguishes design science from design practice. Quantitative models identify statistical associations between morphological features and affective responses, providing empirical grounding for design critique (Cross 2011). However, synthesizing components into coherent wholes requires tacit knowledge of proportional systems and stylistic conventions that resist formalization (Schön 1983). The regression coefficients serve as directional signals within expert judgement, not autonomous design specifications.

Methodological Contributions and Boundaries

This study demonstrates how behavioral data (eye-tracking) can inform weight assignment in morphological coding, addressing a specific limitation when products consist of interdependent components with unknown relative contributions. PLS regression handles multicollinearity inherent in stylistic coherence by projecting the predictors onto a small number of latent components that maximise covariance with the response (Wold *et al.* 2001), though effect sizes should be interpreted as conditional associations within the sampled morphological space.

The workflow's applicability depends on whether design traditions articulate component-level variations that are perceptually distinguishable and affectively meaningful. Traditional artefacts often satisfy these conditions, but the method's transferability requires careful consideration of what constitutes a meaningful "component" within each design domain structural and cultural logic.

Sample size limitations (five representative chairs) enabled controlled exploration of component-level relationships but preclude universal claims. The regression coefficients represent design tendencies within this morphological subspace. Controlled viewing conditions (static images, frontal views) isolated visual-affective relationships but excluded tactile experience and ergonomic dimensions (Zhang *et al*. 2025). Cultural specificity (Chinese participants evaluating Chinese furniture) may reflect learned aesthetic frameworks rather than universal perceptual principles (Chuang *et al*. 2001).

CONCLUSION

1. This study revealed that visual attention dominance and affective contribution operate through distinct perceptual mechanisms in multi-component furniture evaluation, consistent with hypotheses H1 and H2 proposed in the Introduction. Attention-weighted morphological coding, based on coefficient-of-variation weighting, is intended to capture perceptual hierarchy that equal-weight approaches overlook, offering a more differentiated basis for morphological weighting than uniform schemes; whether it yields a measurable improvement in Kansei Engineering model performance was not directly tested here and remains a question for future comparative work. PLS regression is well suited to the multicollinearity among binary morphological codes in furniture morphology, yielding coefficients that are interpretable as within-sample associations rather than confirmed design effects.
2. The findings advance both methodology and practice. Methodologically, the integration of eye-tracking behavior with affective modelling provides an empirical approach to determine component salience. Practically, the quantified component-affective relationships support evidence-informed design decisions within holistic reasoning, where aesthetic coherence, cultural continuity, and structural integrity remain essential considerations beyond statistical coefficients.
3. The dissociation between attention magnitude and affective differentiation further points to a two-fold design heuristic for neo-traditional furniture: preserve simple, low-

variation treatment of the categorical anchor (the backrest) so that stylistic identity remains unambiguous, while concentrating tasteful elaboration on one selected secondary component (*e.g.*, the stretcher, apron, gooseneck post, or top rail) as the component most strongly associated with affective differentiation. This heuristic follows from the observed association pattern rather than from a causal or experimentally validated test and should be treated as a hypothesis for future design and validation studies.

4. Limitations of the present work include small sample size, controlled viewing conditions, and focus on visual-affective relationships. Future research should expand sample diversity, test ecological validity through physical prototypes, incorporate multi-sensory evaluation, and explore cross-cultural generalizability.

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Conflict of Interest

The authors declare no conflict of interest.

Institutional Review Board Statement

The studies involving human participants were reviewed and approved by Universiti Putra Malaysia Institutional Review Board (JKEUPM-2025-170, date of approval: 30 April 2025).

Use of Generative AI

During the preparation of this work, the author(s) used ChatGPT (OpenAI) and Claude (Anthropic) to assist in two stages of the writing process. First, in the literature review section, the author(s) independently collected all primary data and constructed a structured literature matrix, which was subsequently submitted to the aforementioned AI tools to facilitate the extraction and thematic summarization of key findings. Second, in the discussion section, the author(s) provided selected published literature to these AI tools to support comparative analysis. All data collection, research design, experimental analysis, interpretation of results, and conclusions presented in this article were conducted independently by the author(s) without AI assistance. After using these tools, the author(s) thoroughly reviewed and edited all AI-assisted content and take(s) full responsibility for the accuracy, originality, and integrity of the content of the published article.

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