

Article

Visual Fixation Does Not Equal Perceptual Salience: Eye-Tracking-Based Kansei Evaluation of Ming-Style Chair Form

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Abstract

This study addresses a limitation of the assumption in Kansei Engineering (KE) that morphological features contribute equally to affective evaluation by developing a KE framework based on the Feature Integration Theory (FIT). Specifically, eye-tracking data based on Areas of Interest (AOI) are used to calculate the coefficient of variation (CV) of fixation duration between stimuli, which is then applied to rescale morphological features before modeling. In practice, ten Ming-style chairs were encoded with 30 morphological features, and Kansei ratings were collected from 389 participants, along with eye-tracking data from 30 participants. Accordingly, six Partial Least Squares (PLS) models constructed based on the rescaled features demonstrated robust performance ($Q^2 = 0.544\text{--}0.885$), supported by LOOCV, bootstrap, and permutation tests, with external validation further confirming their generalizability. Notably, the results revealed a dissociation between fixation distribution and dispersion-based scaling, indicating that stable gaze concentration does not translate into higher predictive contributions in Kansei responses. This framework provides a repeatable method for incorporating visual attention variability into feature-based KE for product evaluation.

Keywords: eye-tracking; feature integration theory; Kansei engineering; form–emotion; Ming-style chair



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1. Introduction

Understanding how product form evokes affective responses is a core issue in design research, as product experience relies not only on functionality but also on perception, meaning attribution, and emotional response [1,2]. KE has become a widely used framework aimed at converting subjective affective impressions into analyzable design parameters and supporting evidence-based form development [3–5].

A fundamental assumption underlying the conventional KE is that once morphological features are identified and encoded, their contributions to affective evaluation can be directly inferred from their formal representations [6]. This assumption is primarily based on subjective evaluation methods, including semantic differential (SD) scales and questionnaire ratings, which capture explicit affective responses but provide limited insights into the perceptual processes that form these responses [7,8]. In particular, they do

not reveal how observers allocate visual attention among morphological features before forming an overall impression. If visual attention is selectively allocated rather than evenly distributed, then relying solely on morphological coding may not fully represent the perceptual processes underlying affective evaluation, potentially introducing systematic biases in form–emotion modeling.

Eye-tracking research provides empirical evidence that visual attention is selectively allocated among product components. Gaze-based measures, such as fixation duration and fixation count, have been shown to correlate with evaluative responses [9,10], suggesting that affective judgments are influenced not only by the presence of morphological features but also by the manner in which visual attention is allocated during perceptual processing. From this perspective, the CV of fixation reflects the degree of heterogeneity in attention allocation among design alternatives, capturing the uneven distribution of visual attention across morphological components [11]. This should not be interpreted as an indicator of the perceptual importance of individual features, but rather as a description of attention allocation patterns. Failing to distinguish between attention allocation and perceptual interpretation may lead conventional KE models to implicitly conflate attention direction with the formation of affective evaluations, thereby obscuring the role of holistic perceptual integration in form–emotion modeling [12].

The Ming-style chair provides a theoretically appropriate context to study this issue. Unlike many products that rely on color, surface decoration, or material novelty, the visual characteristics of the Ming-style chair are almost entirely defined by proportion, restraint, and the spatial organization of structural components [13–15]. Since the affective changes in this product category are primarily expressed through form, the question of which structural components actually attract visual attention [16]—and whether attention predicts affective evaluation—is particularly important. Previous research has confirmed that the evaluation of Ming-style chairs is closely related to responses to specific structural elements [12,17], yet whether these elements receive sufficient perceptual attention has not been tested.

This gap points to a broader methodological limitation in the field of KE research [18]. Although fixation-based evidence can complement subjective ratings by providing visual-cognitive information on morphological perception [19], such evidence has rarely been systematically incorporated into KE modeling. Importantly, fixation-based measurements indicate the allocation of visual attention in the perceptual process, rather than the perceptual significance of individual morphological feature. Accordingly, fixation should be interpreted as evidence of selective attention allocation, rather than a direct indicator of perceptual significance. To address this limitation, this study integrates KE with AOI-based eye-tracking within an attention-based modeling framework grounded in FIT. FIT conceptualizes perception as a process in which visual features are first selectively attended to and then integrated into coherent object representations [20]. From this perspective, visual attention reflects the allocation of perceptual resources, while perceptual significance emerges at the level of overall object representation, rather than from any single attended component. This distinction provides a conceptual foundation for the proposed modeling framework.

In this context, the study pursues three objectives: (1) to describe how visual attention is distributed among the structural components of Ming-style chairs; (2) to examine the relationship between fixation-based attention indicators and affective evaluations; and (3) to assess how incorporating attention-informed information affects the results of form–emotion modeling.

2. Literature Review

2.1. Limitations of Morphological Coding in Form–Emotion Research

Product form is widely conceptualized in design research as a perceptual stimulus capable of eliciting evaluations and affective responses [21,22]. Based on this premise, KE supports the modeling of affective perception by transforming users' implicit evaluations into measurable design variables, making form–emotion modeling and design decision-making possible [23–25]. In furniture research, this paradigm has been widely adopted to associate morphological changes with perceptual outcomes [26–29]. Recent studies have expanded this paradigm in Chinese furniture design by integrating KE frameworks with decision-making and statistical modeling techniques [30,31], reinforcing a key assumption of KE research: style perception can be decomposed into quantifiable morphological attributes.

However, once morphological attributes are identified and coded, KE often treats their evaluative relevance as directly stemming from their formal existence. This assumption may be less appropriate for crafts whose meanings depend on the relationships between multiple components rather than isolated features [32]. The Ming-style chair clearly illustrates this limitation. Its aesthetic characteristics are expressed through the orderly relationship among the head-rail, backrest, armrests, seat, and supporting components, where proportion, structural order, and compositional harmony operate at the level of overall configuration rather than a single feature [33,34].

From the perspective of perceptual theory, the significance of this limitation becomes clearer. FIT posits that visual perception relies not only on the registration of discrete features but also on the attention-guided integration to form coherent object representations [35,36]. Eye-tracking studies in furniture research support this view, indicating that different components receive varying visual attention and fixation patterns during viewing [16,17,37,38]. Research on chair forms further indicates that structural and decorative regions often dominate viewing patterns [39,40], while studies on Ming-style furniture suggest that attention is focused on the main compositional regions, with aesthetic judgement relying on whole-form integration rather than local feature accumulation [36,41].

Taken together, these studies suggest that the encoded morphological variables should not be assumed to have equal perceptual relevance. In the context of the Ming-style chair, this necessitates clarifying how visual attention is distributed among the morphological elements before examining its role in affective evaluation.

RQ1. How is visual attention distributed among the morphological elements of the Ming-style chair?

2.2. Visual Attention and Differential Attentional Allocation Across Form Components

If the perception of morphological components is not uniform, a core issue is whether the variation in visual attention is systematically related to affective evaluation. Eye-tracking studies consistently show that attention is selectively allocated among product components; such allocation, however, reflects visual priority in the perceptual processing rather than perceptual importance or evaluative contribution [42].

This distinction is particularly important in the perception of furniture, as structural elements simultaneously serve functional, spatial, and symbolic roles [10,17,43]. Empirical studies on Chinese-style furniture have shown stable patterns of non-uniform fixation among various components [44], with regions such as the backrests, armrests, bases, and decorative elements frequently receiving higher fixation density [45]. These findings should be interpreted as evidence of structured attention allocation during viewing, rather than indicators of component-level evaluative dominance. Accordingly, fixation-based metrics (e.g., latency,

count, revisit frequency, dwell time) capture the temporal and spatial characteristics of visual exploration, rather than the perceptual weight of morphological features [46].

From the perspective of FIT, affective evaluation arises from the holistic integration of attended information, forming coherent perceptual representations, rather than from isolated or additive contributions of individual components. Previous research has indicated that aesthetic judgements are inherently non-linear among morphological features [47], and the significance of highly attended components is determined by their role in the overall configuration, not merely by visual salience [48]. The differences in attentional engagement between different materials and structural elements further suggest that visual processing occurs through multiple pathways rather than a single weighted mechanism [49,50].

In summary, the literature supports two propositions: (1) during the perceptual process, visual attention is distributed systematically but unevenly among morphological components, and (2) affective evaluation is based on holistic perceptual integration rather than component-level attentional magnitude. However, how to operationalize attention allocation in form–emotion modeling without confusing it with perceptual importance remains an open methodological question, prompting the second research question:

RQ2. What relationships exist between visual attention distribution and affective evaluation in Kansei-based form perception?

2.3. Attention-Informed Scaling of Morphological Variables in KE

Although conventional KE provides a systematic framework for morphological decomposition and form–emotion modeling, once incorporated into the model, the encoded morphological variables are often treated as analytically equivalent [51,52]. Existing research on Ming-style furniture has established mature procedures for perceptual-word extraction, morphological parameterization, and affective modeling [36,53], while recent work has further explored feature-selection and attribute-reduction strategies to improve model efficiency [54]. These methods collectively enhance the analytical processing of morphological variables, but they rarely incorporate perceptual evidence into their numerical representations.

Eye-tracking studies consistently indicate that visual attention is consistently distributed among furniture components rather than evenly across the overall form [17,19,38]. However, fixation-based metric features describe the patterns of attention allocation during perceptual processing rather than perceptual significance or evaluative contribution. Although several studies have incorporated physiological evidence into Kansei modeling by assigning attention-based weights to design elements [55–61], such methods often interpret fixation-based measures as indicators of perceptual significance.

This study adopts a different modeling strategy. Instead of viewing fixation-based measures as perceptual weights, it uses the CV of fixation duration to quantify the degree of discrete attention allocation between design stimuli [11]. The resulting normalized attention-informed scaling coefficients are used to rescale the numerical representations of morphological variables prior to modeling, without altering their morphological definition or implying perceptual significance [54]. In this way, eye-tracking evidence is incorporated as an operational descriptor of attention distribution rather than as a direct measure of evaluative importance [42,46].

Accordingly, the methodological issue is not whether visual attention determines the importance of perception, but how to incorporate the dispersive nature of attention into the numerical representation of morphological variables within a KE framework. Thus, this study examines how attention-informed scaling can be integrated into the numerical representation of morphological variables for subsequent form–emotion modeling.

RQ3. How does attention-informed scaling represent the representation of morphological variables in Kansei form–emotion modeling?

3. Method

3.1. Research Design

This study employs a sequential mixed-methods design to investigate how Ming-style chair form attributes relate to affective evaluation, and how eye-tracking data can inform the representation of those relationships within the KE framework. The methodological logic follows the Type I KE sequence proposed by Schütte et al. [4]: defining the product domain, covering the semantic space, encompassing product property space, constructing form–image mappings, and validating the resulting model. In this structure, the study integrates three related components—semantic evaluation, eye-tracking measurements, and attention-based weighting—into a unified empirical process.

The study proceeded in four stages (Figure 1). First, through a structured multi-stage screening, representative samples of Ming-style chairs and Kansei descriptors are identified. Second, the selected chair samples are decomposed morphologically into nine main structural components and encoded as binary form variables. Third, the same set of ten sample stimuli is used to conduct a SD survey and eye-tracking experiment simultaneously, capturing subjective Kansei ratings and objective gaze data within a shared measurement context. Fourth, before stepwise regression modeling and predictive validation, the attention weights derived from eye-tracking are applied to the morphological variables. This four-stage sequence aligns the empirical design with the theoretical arguments presented in the previous section: since perceptual attention is not evenly distributed among morphological components, the representation states of those components in the KE models should be adjusted accordingly.

3.2. Semantic Space Construction

3.2.1. Kansei Word Collection and Screening

Kansei words—affective descriptors that capture users’ perceptions and emotional responses to product forms—were sourced from academic literature, furniture market publications, design magazines, and direct user reports elicited through structured interviews. This multi-source approach reflects standard KE practices, prioritizing comprehensive semantic coverage in the target product domain [3]. A preliminary collection of 132 Chinese adjectives was gathered.

The pool was reduced in two steps. First, semantic screening removed synonyms and descriptors with overlapping meaning, retaining 69 representative adjectives. Then, these adjectives were applied in a pilot questionnaire to five participants (three with design training and two without) to assess their clarity and cognitive load; ultimately, 34 adjectives were retained. Subsequently, 62 Generation Y participants in Shenzhen completed a formal screening survey. Descriptors chosen by more than one-third of respondents were retained for dimensional analysis. This process is illustrated in Figure 2.

3.2.2. Kansei Word Dimensional Reduction

The retained Kansei words underwent two stages of dimensional reduction. Participants rated the perceived similarity of all word pairs on a five-point scale, generating a symmetric similarity matrix. Multidimensional scaling (MDS) was applied to this matrix to map semantic proximity into a low-dimensional coordinate space; model fit was assessed using stress and RSQ statistics [62]. Then, Ward’s hierarchical clustering was performed on the MDS coordinates, and the resulting dendrogram was checked alongside the agglomeration coefficient to determine a stable clustering solution. K-means clustering was

subsequently applied to optimize cluster membership, using a predetermined number of clusters. From each cluster, the word pairs closest to their centroids were selected as representative Kansei dimensions.

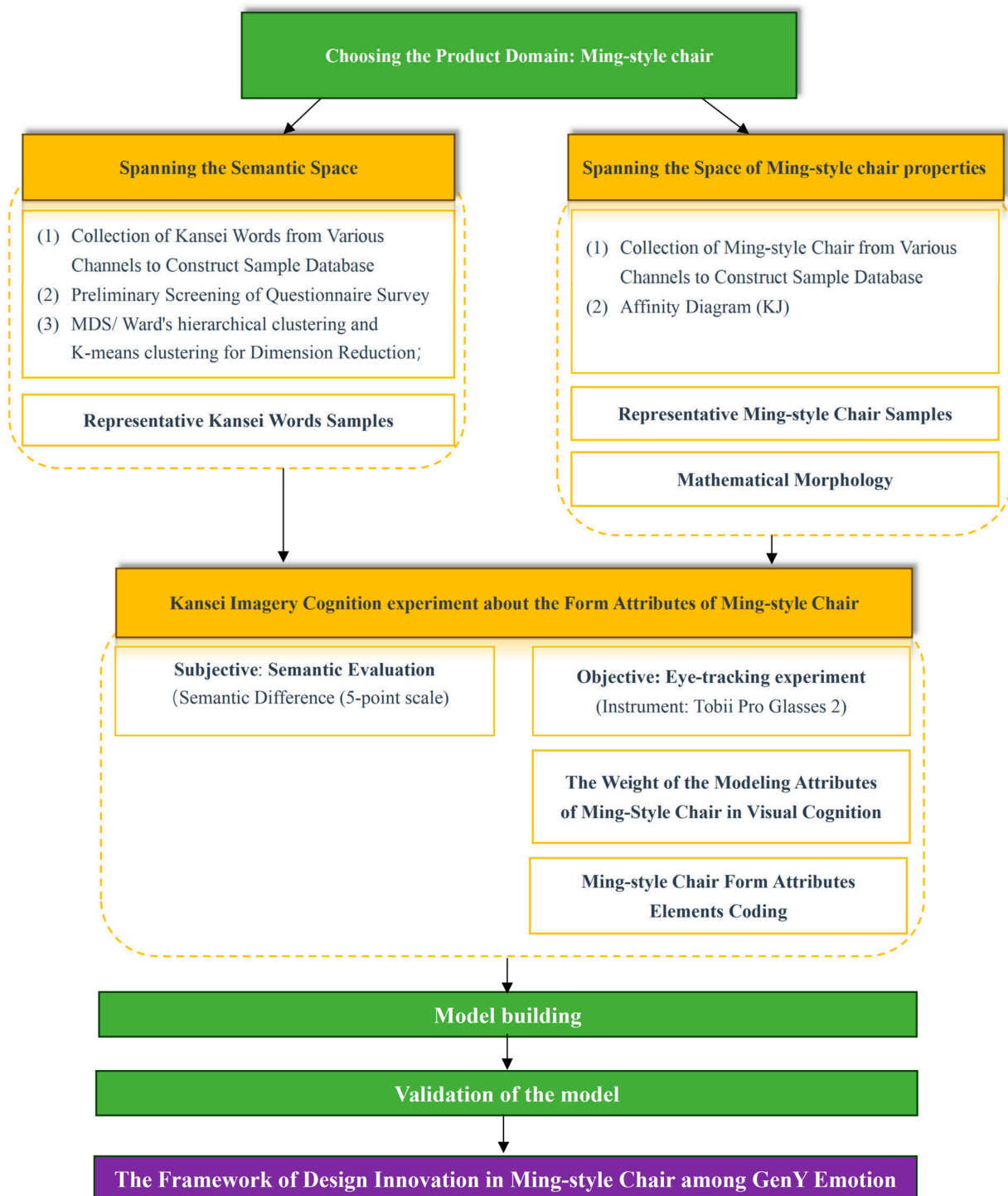


Figure 1. Overall Research Procedure for Attention-weighted KE Modeling of Ming-Style Chairs.

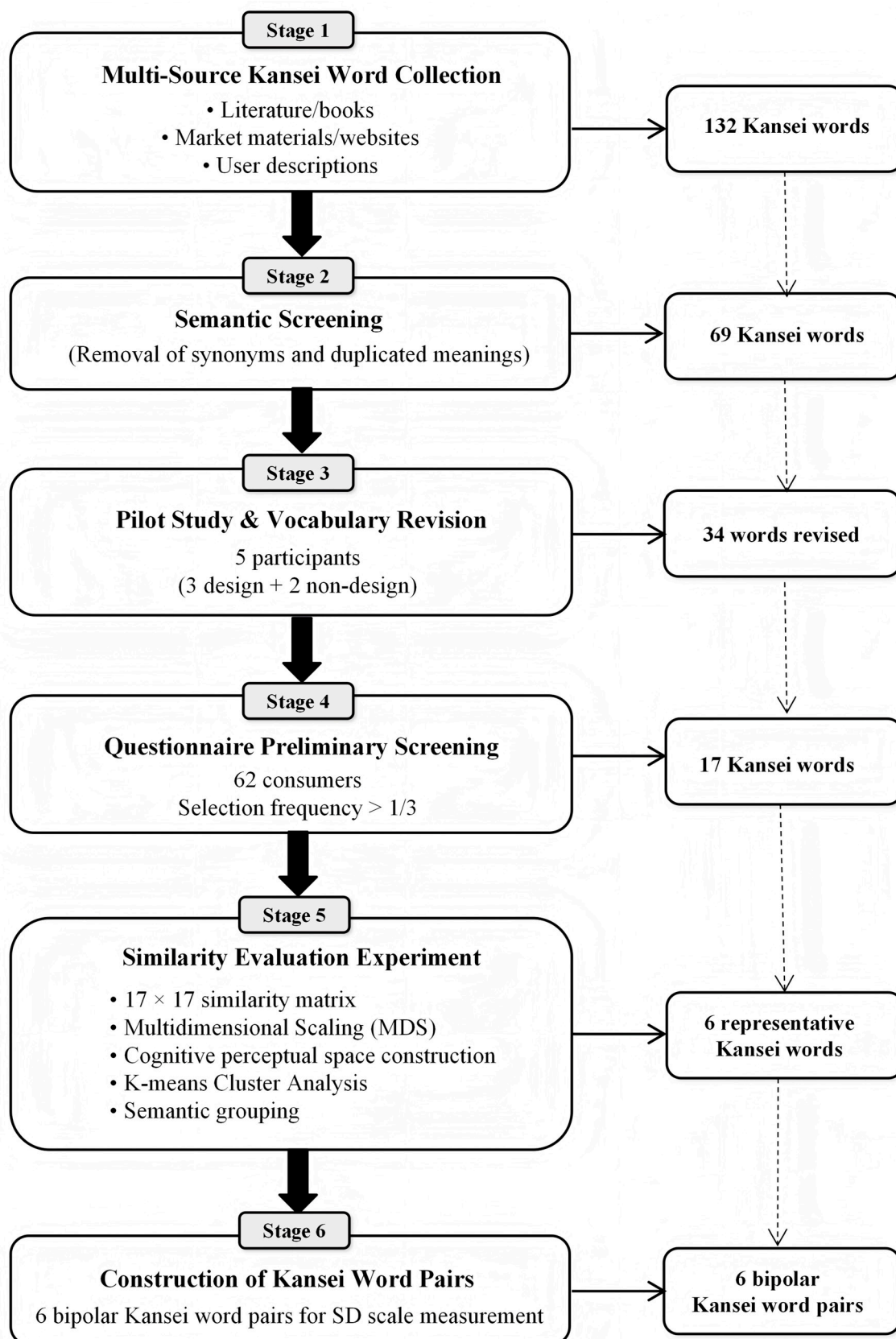


Figure 2. Research Flow for Kansei Word Selection and Dimensional Reduction.

The program produced six bipolar Kansei dimensions (Table 1): Traditional–Fashionable, Practical–Decorative, Unique–Ordinary, Concise–Complicated, Natural–

Artificial, and Graceful–Clumsy. These six dimensions form the semantic basis for the questionnaire and eye-tracking experiments.

Table 1. Six Bipolar Kansei Dimensions Derived from MDS and Cluster Analysis.

Dim.	Bipolar Pair
Y1	Traditional ↔ Fashionable
Y2	Practical ↔ Decorative
Y3	Unique ↔ Ordinary
Y4	Concise ↔ Complicated
Y5	Natural ↔ Artificial
Y6	Graceful ↔ Clumsy

3.3. Stimuli and Morphological Coding

3.3.1. Sample Collection and Selection

The product domain covers all major types of Ming-style chairs: round-backed chairs, hanging-lamp chairs, Northern and Southern official-hat chairs, rose chairs, Zen chairs, and folding armchairs. Representative samples were sourced from academic literature, museum websites, art archives, antique furniture stores, and auction databases. After redundancy screening, 159 candidate images were retained, each standardized to a 45° viewing angle.

To reduce this set to a manageable size for the experiment, a structured expert panel consisting of ten experts (six furniture designers and four academic researchers in the field of furniture design; combined experience range: 13–44 years) conducted a KJ method meeting (Table 2). The experts independently classified all images into morphologically coherent groups and identified the most representative samples within each group. This process ultimately produced ten samples of Ming-style chairs spanning five major form categories.

Table 2. Composition of the Expert Panel Using the KJ Method.

Name	Age	Organization	Position	Professional Knowledge	Work Experience (Years)
Lv Jufang	54	Nanjing Forestry University	Director (Institute of Classical Furniture and Mahogany Technology)	Furniture Design and Engineering	31
Liu Xinyou	42	Nanjing Forestry University	Head of Furniture Design Department	Furniture Design and Engineering	15
Huang Huifang	35	Chuanshilong Chinese Classical Furniture Co., Ltd.	Design Director	Ming-style Furniture Design and Manufacturing	13
He Pengsheng	37	San Fu	Designer of the Research Center for New Chinese Furniture Design	Furniture Design	13
Gao Weixia	35	Changshu University	Lecturer	Furniture Culture	14
Qian Xiaojin	59	San Fu	Factory Director and Design Director	Traditional Chinese Furniture Carpentry, Mortise and Tenon Structure, Shape, and Craftsmanship	38
Wen Ming	40	Youxiang Chinese Classical Furniture Co., Ltd.	Design Director	Furniture Design	14

Table 2. Cont.

Name	Age	Organization	Position	Professional Knowledge	Work Experience (Years)
Ni Jianping	62	Yulinshijia Premium Hardwood Furniture	Boss and Designer Director	Ming-style Furniture Design and Manufacturing, Classical Furniture Restoration	44
Song Weidong	54	Sufu Hardwood Furniture Co., Ltd.	National Intangible Cultural Heritage Project Representative Inheritor of Ming-style Furniture (City-level), Jiangsu Provincial Craft Master, Senior Craft Artist	Ming-style Furniture Manufacturing Skills	34
Zhang Tianxing	42	Wuyi University	Lecturer	traditional furniture theory research and the restoration of antique lacquer furniture	14

3.3.2. Image Standardization

All stimuli are processed using the same standardized procedure in Adobe Photoshop. Background and shadow pixels are removed, each chair is centered in the frame, the image is converted to grayscale (saturation = −100) to eliminate color-driven perceptual effects, and logos are removed. The output file is standardized to 30 cm × 35 cm on a white background, with a resolution of 300 PPI, maintaining morphological forms as the primary source of visual variation (Figure 3).

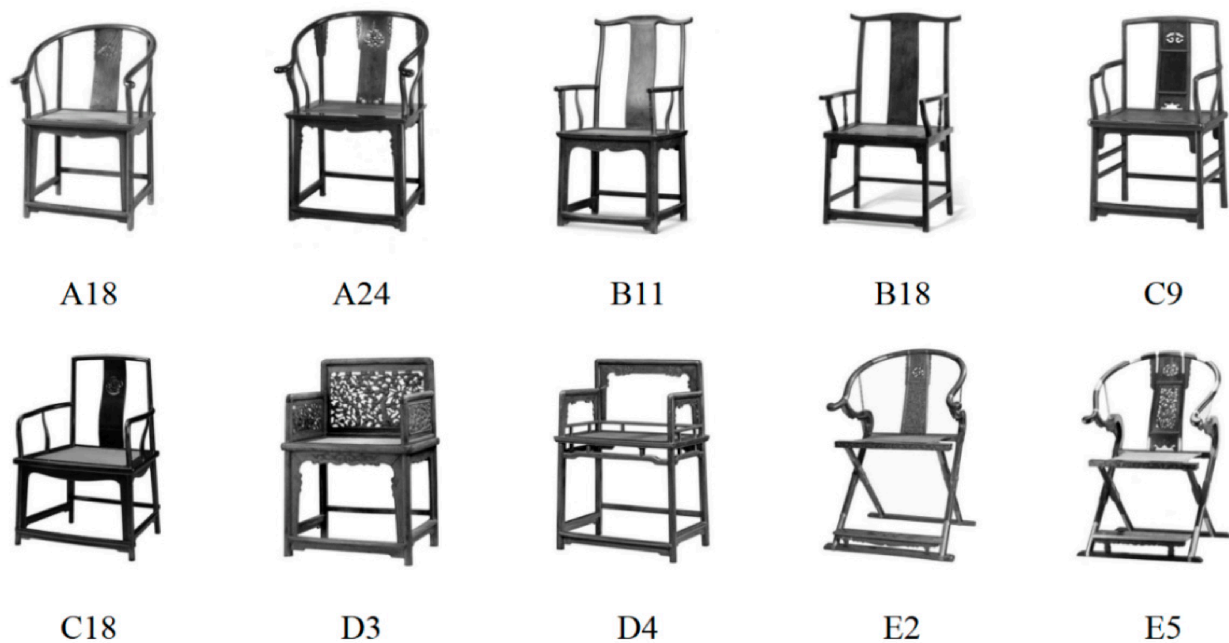


Figure 3. Ten Standardized Ming-Style Chair Stimuli Used Consistently Across Both Experiments.

3.3.3. Morphological Encoding

Each chair is decomposed into nine main structural elements through mathematical morphological analysis [63]: head-rail (Xa), armrest body (Xb), front arm support (Xc), central arm support (Xd), backrest (Xe), seat (Xf), seat–leg transition (Xg), stretcher (Xh), and legs (Xi) (Table 3). The number of morphological types within each element ranges from two

to six (Table 3). Each morphological category is encoded as a binary variable (1 = present, 0 = absent), resulting in a 30-parameter morphological vector for each chair (Table 4).

Table 3. Morphological Coding Scheme for Ten Ming-Style Chair Form Attributes Analysis.

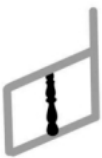
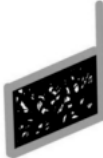
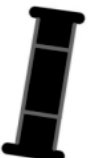
Items	Categories				
Head-rail (X_a)					
	Straight type (X_{a1})	Convex type (X_{a2})	Bow-shaped type (X_{a3})	Circular type (X_{a4})	
Armrest body (X_b)					
	Protruding (X_{aa})	Non-protruding (X_{ab})			
Front Arm Support (X_c)					
	Straight type (X_{b1})	Curved type (X_{b2})			
Central Arm Support (X_d)					
	Plain type (X_{ca})	Apron-present type (X_{cb})			
Backrest (X_e)					
	Turned type (X_{da})	Sickle-shaped spindle (X_{db})	Carved panel (X_{dc})		
Seat (X_f)					
	Plain type (X_{ea})	Carved type (X_{eb})	Pierced type (X_{ec})	Framework Panel (X_{ed})	Windowed type (X_{ee})
Seat (X_f)					
	Rectangular seat (X_{f1})	Fan-shaped seat (X_{f2})	II type (X_{f3})		

Table 3. Cont.

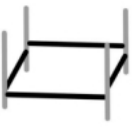
Items	Categories		
Transitional components between legs and seat (Xg)			
	Camel's hump type (Xg1)	Apron type (Xg2)	Kūn mén type (Xg3)
			
	Plain type (Xga)	Carved type (Xgb)	
Stretcher (Xh)			
	Flat stretcher (Xh1)	Step-by-step rising stretcher (Xh2)	
Legs (Xi)			
	H-shaped (Xi1)	X-shaped (Xi2)	

Table 4. Binary Coding Matrix of 10 Representative Ming-Style Chair Samples.

NO.	Xa1	Xa2	Xa3	Xa4	Xaa	Xab	Xb1	Xb2	Xca	Xcb	Xda	Xdb	Xdc	Xea	Xeb	Xec	Xed	Xee	Xf1	Xf2	Xf3	Xg1	Xg2	Xg3	Xga	Xgb	Xh1	Xh2	Xi1	Xi2
A18	0	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	0	1	1	0	0	1	1	0
A24	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	0	0	1	1	0	0	1	1	0
B11	0	1	0	0	1	0	0	1	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	1	1	0
B18	0	1	0	0	1	0	0	1	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	0	1	1	0
C09	0	0	1	0	0	1	0	1	1	0	0	1	0	0	0	1	1	0	1	0	0	0	1	0	1	0	0	1	1	0
C18	0	0	1	0	0	1	0	1	1	0	0	1	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	1	0	
D03	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	1	0	1	1	0	0	0	0	1	0	1	0	1	1	0
D04	1	0	0	0	0	1	1	0	1	0	0	0	1	0	1	0	0	1	1	0	0	1	0	0	1	0	0	1	1	0
E02	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	1	1	0	0	1
E05	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	1	1	0	0	1

3.4. Kansei Evaluation Survey

3.4.1. Participants

The target population comprised Generation Y consumers (aged 25–44) in Shenzhen, China. Based on the finite population proportion formula, using a conservative maximum-variability estimate ($p = 0.5$, confidence level = 95%, margin of error = 5%), the minimum required sample size is 384 valid responses; the target is set at 403 to facilitate quality-control loss. The survey was conducted online through the Credamo platform, restricted to four economically developed districts (Nanshan, Futian, Bao'an, and Longgang) with inclusion criteria: (1) continuous six-month residence, (2) familiarity with Ming-style furniture, and (3) residential addresses at least 1 km apart to prevent neighborhood clustering (Table 5).

Table 5. Sample Demographic Characteristics (N = 389).

Item	Frequency	Percent(%)	Mean	Median	Std. Deviation	Minimum	Maximum
Age Group (years old)			31.77	31	4.836	23	42
25–26	11	2.8					
26–30	172	44.2					
31–35	120	30.8					
36–40	65	16.7					
40–44	21	5.4					
Gender							
Male	152	39.1					
Female	237	60.9					
Education							
Junior high school or below	2	0.5					
General high school/Technical secondary school/Technical school/Vocational high school	13	3.3					
Junior college	43	11.1					
Undergraduate	259	66.6					
Master	66	17					
Doctor	6	1.5					
Occupation							
Engineer	84	21.6					
Sales and Marketing Professional	71	18.3					
Designer/Artist	62	15.9					
Self-employed/Freelance Professional	40	10.3					
Educator/Teaching Professional	27	6.9					
Government Employee/Public Sector Worker	22	5.7					
Corporate/Institutional Staff	21	5.4					
Service Sector Employee	17	4.4					
Administrative/Management Personnel	17	4.4					
Manufacturing Sector Worker	11	2.8					
Healthcare Practitioner and Technician	9	2.3					
Finance and Accounting Professional	8	2.1					
Design Field							
Yes	136	35					
No	253	65					
Monthly Income (RMB)			12,811.05	10,000	12,559.648	0	180,000
<5001	28	7.19					
5001–10,000	182	46.8					
10,001–15,000	96	24.7					
15,001–20,000	58	14.9					
>20,001	25	6.4					
Family Structure							
Single	110	28.3					
Unmarried couple/In a relationship	55	14.1					
Married without children	18	4.6					
Married with children	205	52.7					
Divorced with children	1	0.3					
Family Number							
1	37	9.5					
2	51	13.1					
3	124	31.9					
4	96	24.7					
5	59	15.2					
6	16	4.1					
7	6	1.5					
House Type							
Commercial housing/Standard residential apartment	245	63.1					
Apartment/Condominium	74	19					
Self-built rural house/Village house	34	8.7					
Staff dormitory/Student dormitory	24	6.2					
Villa/Detached house	6	1.5					
Rental/Rented accommodation	6	1.5					

Table 5. Cont.

Item	Frequency	Percent(%)	Mean	Median	Std. Deviation	Minimum	Maximum
Decoration Type							
Modern Minimalist Style	283	72.8					
Traditional Chinese Style	72	18.5					
Contemporary European Style	18	4.6					
Rustic/Country Style	5	1.3					
Industrial Style	4	1					
Basic Functional Style	3	0.8					
Luxury/Opulent Style	2	0.5					
American Style	1	0.3					
Japanese/Zen Style	1	0.3					
Housing Area (m²)			90.29	90	47.546	7	400
<51	91	23.4					
51–100	161	41.4					
101–150	118	30.3					
151–200	12	3.1					
>200	7	1.8					

3.4.2. Procedure and Instrument

A pilot survey ($n = 30$) was conducted to verify the clarity and internal consistency of the items. In the main survey, participants viewed ten standardized images of chairs and rated them on six bipolar Kansei dimensions using a five-point SD scale [64], with -2 anchored at the left pole and 2 at the right pole. Stimuli were presented in randomized order. The average SD score for each dimension and each chair constitutes the dependent variable in subsequent regression modeling.

3.5. Eye-Tracking Experiment

3.5.1. Participants

A total of 48 participants 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 ($M = 32.7$) (Table 6). All participants had normal or corrected-to-normal vision with no color deficiencies. Written informed consent was obtained before participation (Figure 4), and each participant received RMB 20 on completion.

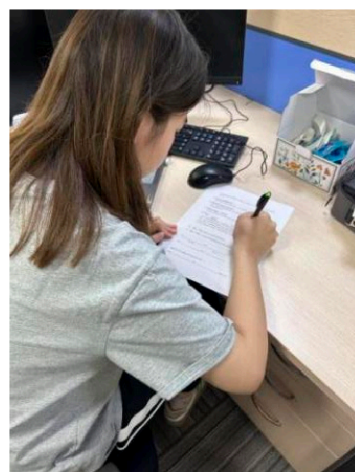


Figure 4. Participants Signed the Informed Consent Form before the Eye-Tracking Experiment.

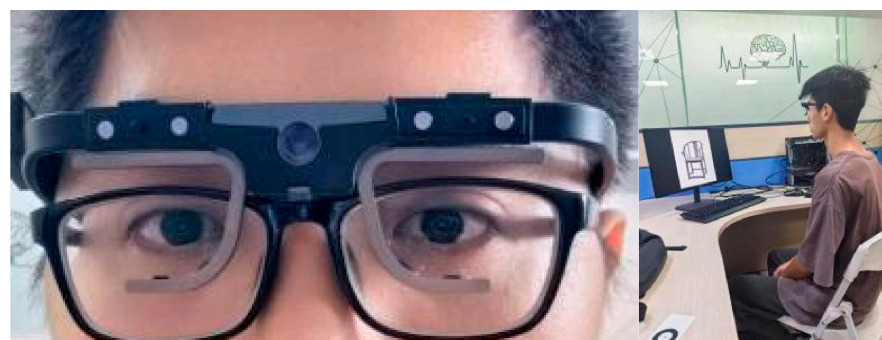
Table 6. Demographic Characteristics of Final Participant Samples of Eye-Tracking Experiment (N = 30).

No.	Initials	Gender	Age	Design Field	No.	Initials	Gender	Age	Design Field
106	CXY	Female	25	Yes	201	TX	Male	39	No
109	LJM	Male	26	Yes	205	HDJ	Female	30	No
110	FWY	Female	24	Yes	206	LRT	Male	32	No
112	LHP	Male	31	Yes	207	YEY	Female	26	No
113	HSW	Female	27	Yes	208	FHL	Male	42	No
114	ZDH	Male	30	Yes	213	HJB	Male	38	No
115	LZJ	Male	27	Yes	214	JGQ	Male	36	No
117	MZH	Female	32	Yes	215	YZJ	Male	34	No
118	HXY	Female	38	Yes	217	LY	Female	37	No
119	LQJ	Male	35	Yes	218	HZY	Male	27	No
122	CMZ	Male	32	Yes	219	CCM	Male	25	No
123	OYWN	Female	37	Yes	221	LLM	Female	26	No
124	XY	Male	41	Yes	222	WSM	Male	39	No
126	SYN	Female	33	Yes	223	DRH	Female	37	No
130	LYC	Male	36	Yes	225	WXL	Female	43	No

Note: Participant identifiers are anonymized codes assigned to ensure confidentiality.

3.5.2. Apparatus and Environment

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. The stimuli were displayed on a 25-inch monitor (16:9) under uniform LED lighting in a controlled laboratory at Wuyi University. Participants were seated 40–90 cm away from the monitor; curtains were drawn to exclude external light; only one participant was present in each session (Figure 5).

**Figure 5.** Tobii Pro Glasses 2 Eye-Tracking System (Left) and Experimental Setup (Right).

3.5.3. Experimental Procedure

Each participant first wore the Tobii Pro Glasses 2 head-mounted eye tracker with the assistance of the researchers; participants were instructed to remain relaxed and not to adjust the device after positioning (Figure 3). After the device was set up, the manufacturer's calibration procedure was conducted, followed by a pilot validation trial to confirm gaze stability (tolerance: ≤ 3 mm drift on the display surface). Participants then completed 2–3 practice trials to familiarize themselves with the sequence structure of the image-viewing procedure and were encouraged to ask any questions before the formal experiment; practice data were excluded from all analyses. Once the researchers confirmed that the device status and calibration results met the requirements, participants viewed the on-screen experimental instructions and clicked the "Start Experiment" button to enter the formal phase.

The formal experiment adopted a structured trial-based paradigm [65,66]. Each trial consisted of four sequential stages (Figure 6): an instruction screen, where participants continued after confirming by clicking, followed by a 2-s transition; an 8-s stimulus presentation (the 8-s stimulus presentation time was determined through a pilot study and participant interviews, which indicated that this duration was sufficient for visual inspection while avoiding fatigue or loss of interest.), during which a standardized grayscale chair image was displayed on the 25-inch monitor, and gaze points were continuously recorded at a frequency of 50 Hz; an unrestricted semantic evaluation phase, where participants rated the previous stimulus on six Kansei dimensions using a 5-point SD scale (−2 to +2); and a 3-s blank screen buffer to attenuate visual carryover effects before starting the next trial. This four-stage sequence was repeated for each stimulus, and the presentation order of the chair images was fully randomized among participants to control for order and fatigue effects.

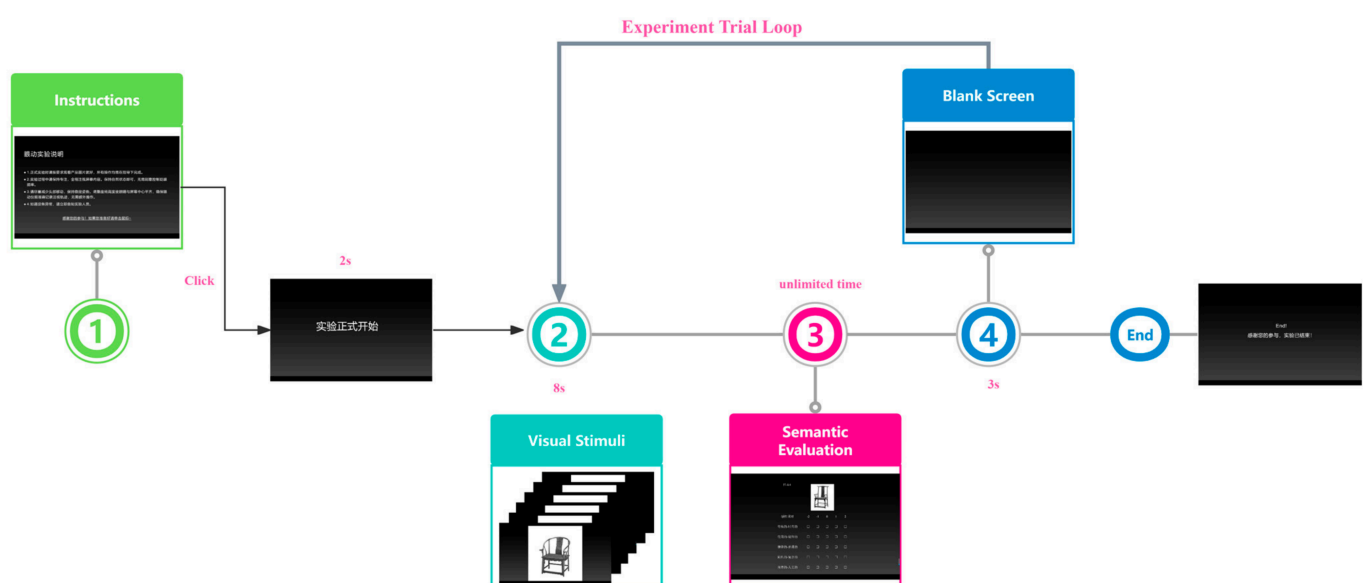


Figure 6. Trial Sequence Structure Showing the Four Stages of Each Experimental Trial.

3.5.4. AOI Definition and Gaze Measures

Nine AOIs were defined for ten chair stimuli in Tobii Pro Lab, directly corresponding to the nine morphological elements in the coding scheme (Xa–Xi). The AOI boundaries for each image were drawn individually to accommodate morphological variations between samples [67]. This element-level alignment ensures that perceptual data and the formal coding system operate at the same analytical granularity (Figures 7 and 8).

For each AOI, seven gaze indicators were extracted (Table 7). For attention-weight calculation, total fixation duration was used as the primary metric, as sustained fixation is the most established indicator of effortful perceptual processing in applied eye-tracking research [68].

3.6. Data Analysis and Model Development

3.6.1. Kansei Word Dimensionality Reduction

Kansei word data were reduced through a four-stage procedure described in Section 3.2.2: frequency screening (retention threshold: selecting items that exceed 1/3 of respondents), similarity matrix construction, MDS analysis, and two-stage Ward’s/K-means clustering. The final six representative bipolar dimensions (Table 1) formed the semantic basis for all subsequent modeling. All analyses were conducted in SPSS 26.0.



Figure 7. AOI Definition for Component-based Eye-Tracking Analysis (sample A18).



Figure 8. AOI Divisions Applied to All Ten Ming-Style Chair Stimuli.

Table 7. Key Performance Indicators Extracted per AOI from the Eye-Tracking Experiment.

No.	Indicator	Description
1	Sequence	Order in which the participant's gaze first visited each AOI
2	Time to first fixation	Time elapsed from stimulus onset to the first fixation within the AOI (ms)
3	Total visit duration	Total time spent in a single continuous visit to the AOI, including all fixations (ms)
4	Visit count	Number of separate entries into the AOI across the trial
5	Total fixation duration	Sum of all fixation durations within the AOI across the entire trial (ms)—primary weighting metric
6	Average fixation duration	Mean duration of individual fixations within the AOI (ms)
7	Fixation count	Total number of fixations recorded within the AOI

3.6.2. Form Attribute Parameterization

Each chair sample is represented as a binary parameter vector based on the coding scheme in Table 4. The encoding rules are as follows:

$$x_{ij} = \begin{cases} 1, & \text{if sample } m \text{ possesses type } j \text{ of attribute } i \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

This resulted in a structured form matrix (10 samples $\times$ 30 binary parameters) for subsequent modeling.

3.6.3. Attention-Informed Scaling of Morphological Parameters

The CV is used to derive an attention-informed scaling coefficient for each morphological element based on AOI fixation data. For element i , the CV is defined as:

$$V_{bi} = \frac{\sigma_{bi}}{\bar{X}_{bi}} \quad (2)$$

σ_{bi} is the standard deviation, and $\bar{X}_{bi}$ is the mean fixation duration of participants and stimuli.

A higher CV indicates greater between-stimulus dispersion in fixation allocation, reflecting less stable and more variable attentional distribution under designed conditions, rather than greater perceptual significance.

Then, the raw CV values are normalized to obtain a set of attention coefficients for modeling purposes:

$$w_{bi} = \frac{V_{bi}}{\sum_{i=1}^n V_{bi}} \quad (3)$$

where w_{bi} represents the normalized dispersion-based attention coefficient, used as a scaling parameter in subsequent form–emotion modeling.

$$x_{ij}^* = w_{bi} \cdot x_{ij} \quad (4)$$

This means that the original binary morphological variables are rescaled (rather than redefined) using the CV-based coefficients derived from eye-tracking data. Specifically:

x_{ij} : Original binary morphological coding (0 = absent, 1 = present) for feature i in stimulus j

w_{bi} : Normalized dispersion-based attention coefficient derived from the CV of fixation data

x_{ij}^* : Attention-informed (scaled) morphological variable used as input in the PLS model

3.6.4. Form–Emotion Regression Modeling

PLS regression is used to model the relationship between morphological variables and Kansei ratings, as it is well-suited for high-dimensional datasets with correlated predictors and limited sample sizes [69]. Compared with conventional multiple regression, PLS projects the predictors into a reduced latent-variable space while retaining their covariance with the response variable, thereby improving model stability under multicollinearity.

Six independent PLS models were constructed, one for each Kansei dimension, using the attention-informed scaled morphological variables (x_{ij}^* ; Equation (4)) as predictors, with the corresponding mean SD scores as the dependent variable.

The optimal number of latent components was determined by minimizing the prediction residual error sum of squares (PRESS) under leave-one-chair-out cross-validation (LOOCV). The predictive performance of the model is evaluated using the coefficient of

determination (Q^2) from cross-validation, leave-one-out root mean square error ($RMSE_{LOO}$), and leave-one-out mean absolute error (MAE_{LOO}). The conventional coefficient of determination (R^2) is reported as a descriptive measure of model fit.

To assess coefficient stability, non-parametric bootstrap resampling ($B = 1000$) is employed, evaluating by repeatedly sampling observations (with replacement) [70]. Empirical 95% confidence intervals are calculated for each regression coefficient, and predictors whose confidence intervals do not include zero are considered statistically robust.

3.6.5. Predictive Validity Assessment

Predictive validity is assessed using a two-level validation strategy, combining LOOCV on the calibration dataset ($n = 10$) with external validation based on five additional Ming-style chair samples excluded from model development (Figure 9). The validation samples are parameterized using the dispersion-scaled morphological coding procedure described in Sections 3.6.2 and 3.6.3. All validation stimuli are processed using the same image-standardization pipeline and experimental protocol and evaluated by 30 participants under the same SD procedure.



Figure 9. Five New Ming-Style Chair Samples Used for Model Validation.

Predictive validity is assessed using a set of complementary criteria [71], including prediction errors (RMSE, MAE), association strength (Pearson r , Spearman ρ), agreement (Bland–Altman analysis), equivalence testing (TOST), and calibration analysis. These metrics quantify absolute error, statistical association, systematic bias, practical equivalence, and model calibration quality, respectively. Prediction validity is evaluated through converging evidence from these criteria rather than relying on any single statistical indicator.

3.6.6. AI Assistance Declaration

During the manuscript preparation process, only ChatGPT (OpenAI) and Claude (Anthropic) were used to support the literature synthesis phase. All primary literature was independently collected and thoroughly reviewed by the author(s), who constructed a structured literature matrix summarizing bibliographic information, research objectives, methods, and key findings. Only this author-curated matrix was used as input to AI.

The AI-assisted workflow consisted of two structured operations. First, the literature matrix provides prompts for thematic clustering based on shared methodologies and conceptual characteristics (e.g., eye-tracking-based attention modeling methods, Kansei evaluation strategies, or weighting schemes). Second, the resulting clusters are used as input for paragraph-level synthesis, where the AI generates draft summaries for each thematic group.

Typical prompts include instructions such as: “Cluster these studies based on the operationalization of visual attention in KE and summarize the methodology of each group”. The output includes (i) grouped research clusters with brief labels and (ii) draft narrative summaries for each cluster.

All AI-generated content was subsequently cross-checked with original sources and underwent substantial revisions by the author(s) to ensure accuracy, interpretive validity, and alignment with the manuscript’s analytical framework. AI tools were not involved in data collection, statistical analysis, modeling, or interpretation.

4. Results

4.1. Kansei Word Screening and Dimensional Reduction

Kansei word collection yielded an initial pool of 132 Chinese adjectives drawn from academic literature, market publications, design magazines, and structured user interviews. Semantic screening removed synonyms and descriptors with overlapping meanings, reducing the vocabulary pool to 69 representative adjectives. A pilot questionnaire conducted with five participants further narrowed the vocabulary set to 34 adjectives based on clarity and cognitive load. A formal frequency screening of these 34 adjectives, compared with feedback from 62 Generation Y consumers, retained 17 Kansei words, each selected by more than one-third of respondents (Table 8).

Table 8. Kansei Words Retained After Frequency Screening (N = 62; threshold > 1/3).

Kansei Word	n	%	Kansei Word	n	%
Classic	49	79.0	Rhythmic	29	46.8
Stable	47	75.8	Traditional	42	67.7
Elegant	44	71.0	Poetic	33	53.2
Exquisite	33	53.2	Durable	33	53.2
Smooth	31	50.0	Solid	27	43.5
Practical	29	46.8	Noble	25	40.3
Concise	29	46.8	Unadorned	25	40.3
Unique	25	40.3	Graceful	21	33.9
Natural	24	38.7			

MDS of the 17×17 pairwise similarity matrix resulted in a six-dimensional solution (Stress = 0.014, RSQ = 0.998). K-means clustering on the MDS coordinates identified six stable clusters, with the centroid-nearest word pair selected as the representative bipolar label for each cluster. The final six Kansei dimensions are: Traditional–Fashionable (Y1), Practical–Decorative (Y2), Unique–Ordinary (Y3), Concise–Complicated (Y4), Natural–Artificial (Y5), and Graceful–Clumsy (Y6).

4.2. Kansei Evaluation

Mean SD ratings for the ten chair stimuli are reported in Table 9 (N = 389; Cronbach’s $\alpha = 0.907$). In Y1, eight of ten stimuli scored negatively, indicating a dominant traditional association; E02 (M = 0.16) and E05 (M = 0.36)—these two folding chairs—were the only stimuli that shifted towards fashion. All ten stimuli scored negatively in Y3, confirming a consistent unique characteristic perception across the entire series. Official-hat chairs B11 and B18 exhibited the strongest concise associations (Y4 ≈ -0.99), while the rose chair D03 received the highest complexity rating (Y4 = 1.24) and the strongest artificial association (Y5 = 1.08). Nine of ten stimuli fell in the graceful direction in Y6, with A18 showing the strongest graceful rating (M = -0.73).

The two-dimensional perception map confirms that the chair category occupies different semantic quadrants (Figure 10). In Y1 $\times$ Y2, the official-hat chair and the Southern official-hat chair cluster in the Traditional–Practical quadrant, the rose chair in Traditional–Decorative, and the folding chairs in Fashionable–Decorative; the Fashionable–Practical quadrant is unoccupied. All stimuli are in the Unique half in Y3 $\times$ Y4; six occupy Unique–

Concise and four Unique–Complicated. In $Y5 \times Y6$, nine of ten stimuli occupy Artificial–Graceful, with only D03 in Artificial–Clumsy.

Table 9. Mean SD Ratings for Ten Ming-Style Chair Stimuli (N = 389).

Stimulus	Y1 Trad.–Fash.	Y2 Prac.–Dec.	Y3 Uniq.–Ord.	Y4 Con.–Comp.	Y5 Nat.–Art.	Y6 Grac.–Clum.
A18	−1.028	−0.411	−0.370	−0.650	0.226	−0.733
A24	−0.722	−0.108	−0.578	−0.033	0.530	−0.711
B11	−0.997	−0.763	−0.098	−0.992	0.067	−0.378
B18	−0.995	−0.815	0.067	−0.990	0.026	0.000
C09	−0.638	−0.285	−0.506	−0.319	0.357	−0.133
C18	−0.473	−0.478	−0.260	−0.563	0.229	−0.067
D03	−0.653	0.753	−1.013	1.244	1.080	0.200
D04	−0.512	0.517	−0.748	0.270	0.725	−0.111
E02	0.162	0.686	−1.057	0.409	0.869	−0.644
E05	0.357	0.833	−1.039	0.828	1.023	−0.422

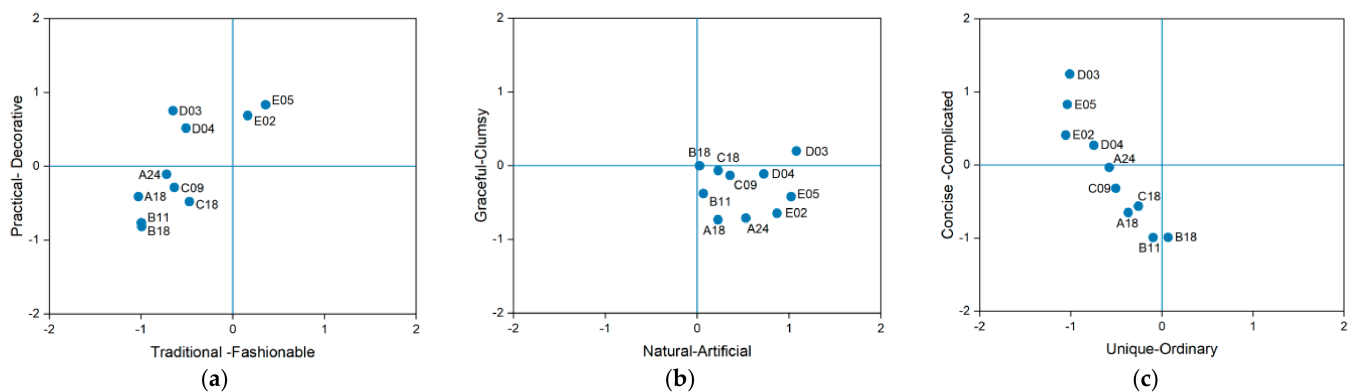


Figure 10. Two-dimensional Perception Map: (a) $Y1 \times Y2$, (b) $Y3 \times Y4$, (c) $Y5 \times Y6$.

4.3. Visual Attention Distribution

Total fixation duration per AOI across all ten stimuli is reported in Table 10. AOI-5 (backrest, X_e) dominated the fixation allocation, accounting for 50.01% of the total fixation time, and attracted the first fixation at 320 ms (D03, E05). AOI-6 (seat, X_f) ranked second, accounting for 15.59%, followed by AOI-7 (seat–leg transition, 9.12%) and AOI-9 (legs, 7.70%). AOI-4 (central arm support) had the lowest total fixation share (2.39%), while AOI-8 (stretcher) was below 5% in each stimulus.

Table 10. Total Fixation Duration (ms) Per AOI Across Ten Stimuli, and Element-level Fixation Weight (%).

Stimulus	AOI-1 X_a	AOI-2 X_b	AOI-3 X_c	AOI-4 X_d	AOI-5 X_e	AOI-6 X_f	AOI-7 X_g	AOI-8 X_h	AOI-9 X_i
A18	740	5367	3418	4038	78,724	18,819	10,574	4927	6426
A24	1769	3308	2549	2289	72,078	27,044	11,133	2908	7885
B11	10,044	3228	7136	2828	56,857	21,957	11,084	3918	10,444
B18	2958	1739	6057	5837	47,262	21,397	7126	4537	15,331
C09	1659	1629	4298	2139	86,520	20,108	7256	6426	8545
C18	1049	5887	2579	3238	53,089	29,463	8895	3758	8895
D03	1859	1179	16,041	2728	59,915	11,753	24,955	3138	6576
D04	8375	1509	15,081	4897	61,884	21,897	20,548	4587	11,583
E02	3798	4927	5687	0	53,878	12,183	7226	9025	12,283
E05	3318	7646	3228	2439	67,290	14,032	7426	12,433	10,144
Weight (%)	2.79	2.86	5.18	2.39	50.01	15.59	9.12	4.37	7.70

The heatmap (Figure 11) reveals three fixation density patterns within AOI-5: concentrated (red-zone intensity, 15–40% of backrest area: A24, D03, C09), characterized by stimuli with focal carved motifs; distributed (yellow-green coverage spanning 50–70%: A18, C18, E02, B18), characterized by a uniformly structured backrest; and hierarchical (multiple discrete density tiers: A24, C09). AOI-8 and AOI-9 showed the lowest density (blue-green) across all stimuli. Gaze plots (Figure 12) shows that the fixation proportion in AOI-5 varied from 35–45% (E05, D04) to 70–80% (B18, D03). Cross-participant fixation convergence was strongest in AOI-5 for stimuli with central carved motifs (D03, A18, B18).



Figure 11. Heatmap for Ten Chair Stimuli (A18, A24, B11, B18; C09, C18, D03, D04; E02, E05). Red-orange = high fixation density; blue-green = low density.

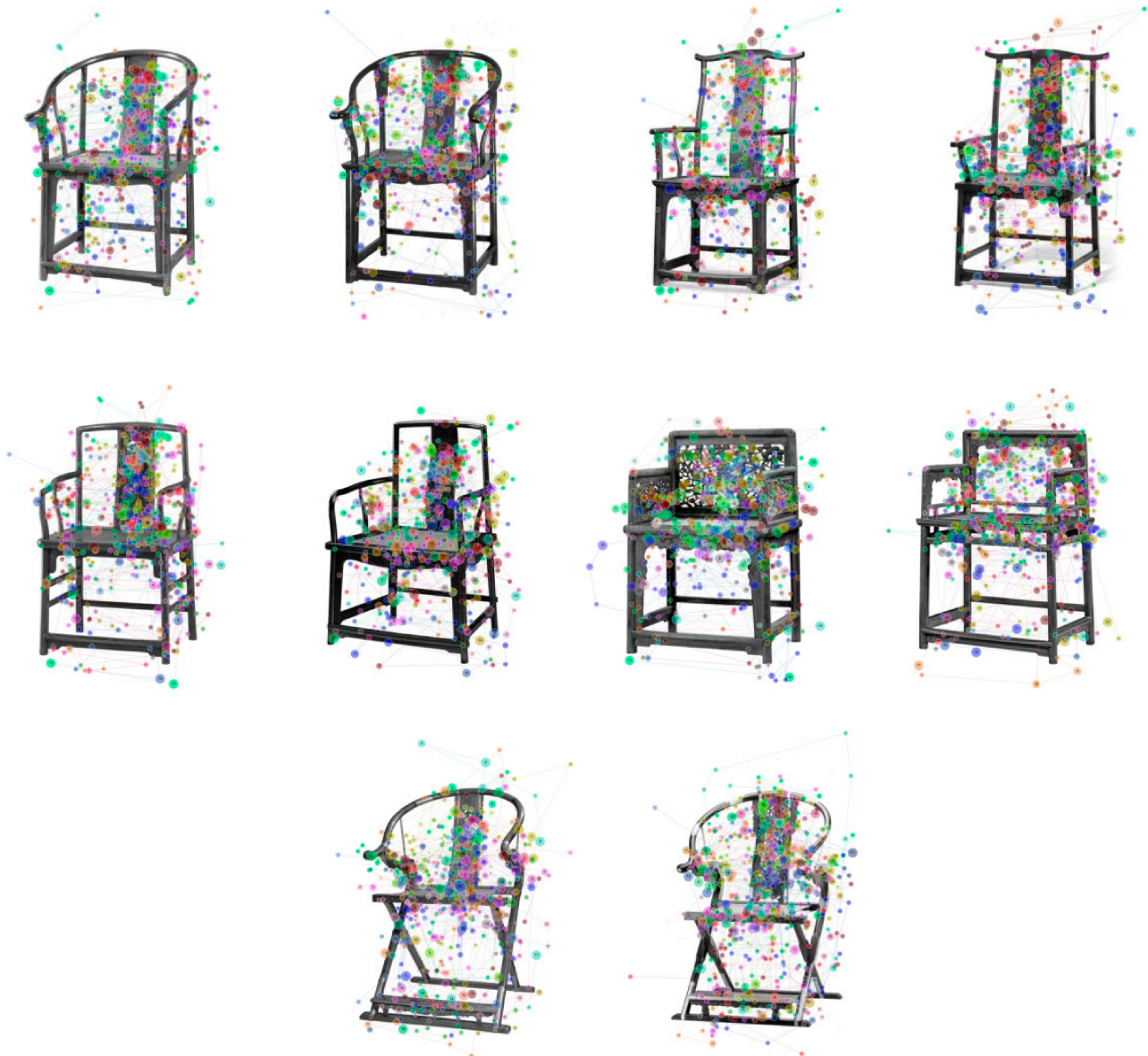


Figure 12. Gaze Plots for Ten Chair Stimuli (same order as Figure 2). Circle size = fixation duration; number = fixation sequence; lines = saccadic paths.

4.4. Attention-Derived Element Coefficients

The normalized attention coefficient (w_{bi}) is derived from the CV of the total fixation duration for each AOI of the stimuli (Table 11). These coefficients represent between-stimulus dispersion in attentional allocation, rather than perceptual importance. Although AOI-5 (backrest, X_e) accounts for 50.01% of the total fixation duration, it exhibits the lowest dispersion-based coefficient ($w_{bi} = 0.042$), reflecting a high consistency in fixation allocation among observers ($V_{bi} = 0.184$). In contrast, AOI-1 (head-rail, X_a ; $w_{bi} = 0.192$) and AOI-3 (front arm support, X_c ; $w_{bi} = 0.163$) show the highest coefficients, indicating greater variability in attention allocation between the stimuli and participants. Despite AOI-6 (seat, X_f ; $w_{bi} = 0.064$) having relatively low original fixation share, it displays a moderate dispersion-based coefficient, suggesting that the fixation distribution for this element is not uniform among observers.

Table 11. CV for Each AOI Per Stimulus, Mean CV (V_{bi}), and Corresponding Normalized Dispersion-based Attention Coefficients (w_{bi}).

Sample	AOI-1 Xa	AOI-2 Xb	AOI-3 Xc	AOI-4 Xd	AOI-5 Xe	AOI-6 Xf	AOI-7 Xg	AOI-8 Xh	AOI-9 Xi
A18	0.941	0.820	0.677	0.650	1.278	0.187	0.179	0.224	1.295
A24	0.597	0.159	0.862	0.493	0.711	1.280	0.083	0.932	0.737
B11	2.166	0.197	0.112	0.140	0.588	0.373	0.092	0.578	0.242
B18	0.200	0.904	0.117	1.825	1.407	0.273	0.768	0.361	2.112
C09	0.634	0.957	0.490	0.591	1.943	0.043	0.746	0.302	0.484
C18	0.837	1.067	0.855	0.127	0.910	1.711	0.466	0.634	0.351
D03	0.567	1.170	2.003	0.206	0.327	1.447	2.277	0.852	1.238
D04	1.609	1.014	1.799	1.211	0.159	0.362	1.525	0.343	0.678
E02	0.080	0.611	0.195	1.938	0.842	1.370	0.751	1.214	0.946
E05	0.080	1.903	0.717	0.395	0.302	1.040	0.717	2.410	0.127
V_{bi}	0.842	0.578	0.713	0.503	0.184	0.282	0.504	0.512	0.266
w_{bi}	0.192	0.132	0.163	0.115	0.042	0.064	0.115	0.117	0.061

4.5. Ming-Style Chair Form Attribute Scaling Based on Attention-Informed Coefficients

This section applies the dispersion-based attention coefficients (w_{bi}) derived from eye-tracking data (Section 3.6.3) to rescale the original binary morphological parameters of Ming-style chair forms. For each morphological feature, the binary coding x_{ij} is multiplied by the corresponding normalized dispersion coefficient w_{bi} to obtain the attention-informed scaled parameters x_{ij}^* . This process does not redefine the categorical structure of the original form coding; rather, it adjusts the numerical representation of each feature to reflect the variability in attention allocation between stimuli. The resulting scaled form attribute matrix (x_{ij}^*) is used as input for subsequent form–emotion modeling, as shown in Table 12.

Table 12. Form Attribute Coding Matrix for Samples.

NO.	$Xa1$	$Xa2$	$Xa3$	$Xa4$	$Xb1$	$Xb2$	$Xc1$	$Xc2$	$Xd1$	$Xd2$	$Xe1$	$Xe2$	$Xe3$
A18	0	0	0	0.192	0	0.132	0	0.163	0.115	0	0	0.042	0
A24	0	0	0	0.192	0	0.132	0	0.163	0.115	0	0	0.042	0
B11	0	0.192	0	0	0	0.132	0	0.163	0.115	0	0	0	0.042
B18	0	0.192	0	0	0	0.132	0	0.163	0.115	0	0	0	0.042
C09	0	0	0.192	0	0	0.132	0	0.163	0.115	0	0	0.042	0
C18	0	0	0.192	0	0	0.132	0	0.163	0.115	0	0	0	0.042
D03	0.192	0	0	0	0.132	0	0.163	0	0	0	0.042	0	0
D04	0.192	0	0	0	0.132	0	0.163	0	0	0	0.042	0	0
E02	0	0	0	0.192	0	0	0	0	0	0	0	0.042	0
E05	0	0	0	0.192	0	0	0	0	0	0	0	0	0.042
NO.	$Xf1$	$Xf2$	$Xf3$	$Xg1$	$Xg2$	$Xg3$	$Xg4$	$Xh1$	$Xh2$	$Xi1$	$Xi2$		
A18	0.064	0	0	0	0	0	0.115	0	0.117	0.061	0		
A24	0.064	0	0	0	0	0	0.115	0	0.117	0.061	0		
B11	0.064	0	0	0	0	0	0.115	0	0.117	0.061	0		
B18	0.064	0	0	0	0	0	0.115	0	0.117	0.061	0		
C09	0.064	0	0	0	0	0.115	0	0	0.117	0.061	0		
C18	0	0.064	0	0	0	0	0.115	0	0.117	0.061	0		
D03	0.064	0	0	0	0	0	0.115	0	0.117	0.061	0		
D04	0.064	0	0	0	0.115	0	0	0	0.117	0.061	0		
E02	0.064	0	0	0	0	0	0	0.117	0	0	0.061		
E05	0.064	0	0	0	0	0	0	0.117	0	0	0.061		

Table 12. Cont.

NO.	Xaa	Xab	Xca	Xcb	Xda	Xdb	Xdc	Xea	Xeb	Xec	Xed	Xee	Xga	Xgb
A18	0	0.192	0	0.163	0	0.115	0	0	0.042	0	0	0	0.115	0
A24	0	0.192	0	0.163	0	0.115	0	0	0	0.042	0	0	0.115	0
B11	0.192	0	0	0.163	0	0.115	0	0.042	0	0	0	0	0	0.115
B18	0.192	0	0	0.163	0.115	0	0	0.042	0	0	0	0	0.115	0
C09	0	0.192	0.163	0	0	0.115	0	0	0	0	0.042	0	0.115	0
C18	0	0.192	0.163	0	0	0.115	0	0	0.042	0	0	0	0.115	0
D03	0	0.192	0.163	0	0	0	0.115	0	0	0	0	0.042	0	0.115
D04	0	0.192	0.163	0	0	0	0.115	0	0	0	0	0.042	0.115	0
E02	0	0.192	0	0.163	0	0.115	0	0	0.042	0.042	0.042	0	0	0.115
E05	0	0.192	0	0.163	0	0.115	0	0	0	0.042	0.042	0	0	0.115

4.6. Predictive Performance and Design-Attribute Effects Across Kansei Dimensions

The six PLS models, fitted with 2–3 latent variables selected by LOOCV, achieved cross-validated Q^2 values ranging from 0.544 (Y6, Graceful–Clumsy) to 0.885 (Y2, Practical–Decorative) (Table 13). Calibration fit ($R^2Y = 0.951$ – 0.995) consistently exceeded cross-validated fit, with the largest R^2Y – Q^2 gap observed for Y4 (Concise–Complicated; $R^2Y = 0.981$, $Q^2 = 0.670$) and the smallest for Y2 ($R^2Y = 0.993$, $Q^2 = 0.885$) (Figure 13). Cross-validated prediction error (RMSECV) ranged from 0.138 (Y3, Unique–Ordinary) to 0.415 (Y4, Concise–Complicated), with MAECV showing a matching ordering across dimensions (Figure 14).

Table 13. Calibration and Cross-validation Performance of the PLS Models for the Six Kansei Image Dimensions.

Response	LVs	R^2Y	Q^2	RMSEC	RMSECV	MAEC	MAECV
Y1 (Traditional–Fashionable)	2	0.951	0.745	0.099	0.227	0.089	0.195
Y2 (Practical–Decorative)	3	0.993	0.885	0.051	0.207	0.043	0.191
Y3 (Unique–Ordinary)	3	0.995	0.868	0.027	0.138	0.024	0.112
Y4 (Concise–Complicated)	3	0.981	0.670	0.098	0.415	0.076	0.347
Y5 (Natural–Artificial)	3	0.985	0.791	0.045	0.170	0.036	0.147
Y6 (Graceful–Clumsy)	3	0.971	0.544	0.052	0.209	0.044	0.183

Note: R^2Y = calibration goodness-of-fit; Q^2 = LOCO-CV coefficient of determination; RMSEC/MAEC = calibration error; RMSECV/MAECV = cross-validated error; LVs = number of latent variables (selected within 1–3 by maximizing Q^2).

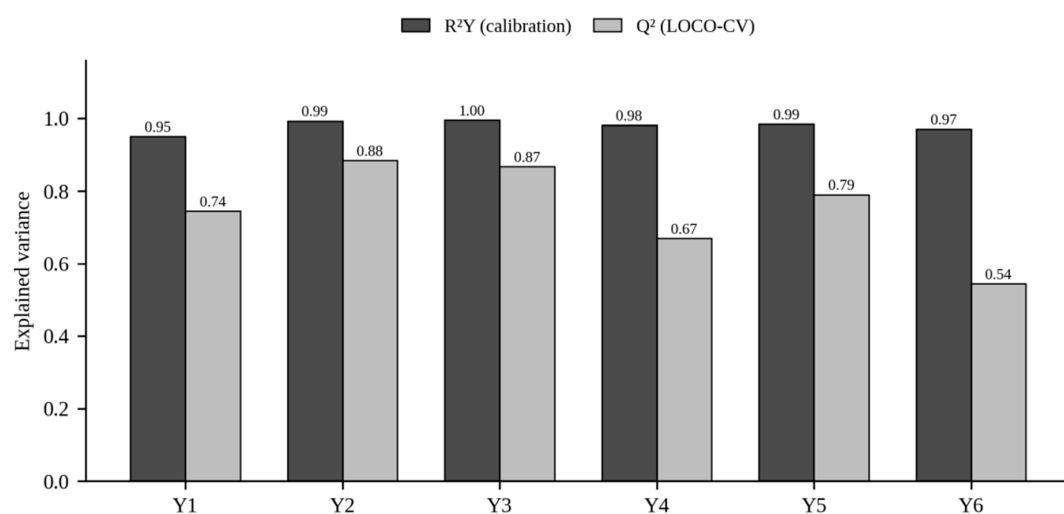


Figure 13. Calibration Goodness-of-fit (R^2Y) Versus Cross-validated Predictive Power (Q^2) for the Six Kansei Image Dimensions.

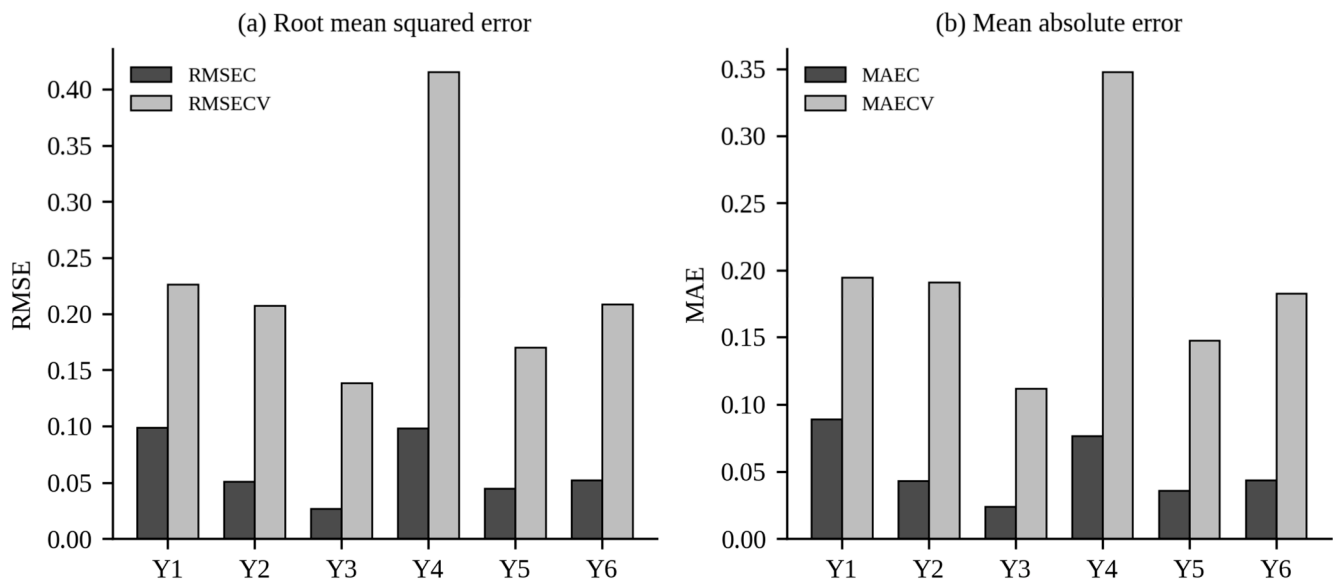


Figure 14. Calibration Versus Cross-validated Error for the Six Kansei Image Dimensions: (a) RMSE; (b) MAE.

The VIP scores identify a small subset of overlapping design attributes as the main contributors to each dimension (Figure 15), and the standardized regression coefficients show a mix of dimension-specific and cross-dimension effects, with several signs reversing between dimensions (Figure 16). Table 14 summarizes the design attributes with standardized coefficients whose 95% bootstrap confidence intervals exclude zero, indicating statistically significant effects for each dimension.

Table 14. Statistically Robust Design-attribute Effects (95% bootstrap CI excluding zero) by Kansei Dimension.

Response	Attribute	Standardized β (95% CI)	VIP
Y1 (Traditional–Fashionable)	Xg3	−0.105 [−0.126, −0.017]	1.30
Y2 (Practical–Decorative)	Xdb	−0.124 [−0.171, −0.023]	1.29
Y2 (Practical–Decorative)	Xec	0.104 [0.015, 0.162]	1.19
Y3 (Unique–Ordinary)	Xec	−0.139 [−0.181, −0.048]	1.38
Y4 (Concise–Complicated)	Xec	0.184 [0.038, 0.293]	1.47
Y4 (Concise–Complicated)	Xdb	−0.122 [−0.161, −0.007]	1.22
Y5 (Natural–Artificial)	Xec	0.155 [0.031, 0.261]	1.38
Y5 (Natural–Artificial)	Xdb	−0.121 [−0.164, −0.011]	1.23
Y6 (Graceful–Clumsy)	Xca	0.183 [0.088, 0.210]	1.76
Y6 (Graceful–Clumsy)	Xcb	−0.183 [−0.210, −0.088]	1.76
Y6 (Graceful–Clumsy)	Xa4	−0.150 [−0.177, −0.040]	1.66
Y6 (Graceful–Clumsy)	Xb1	0.150 [0.040, 0.177]	1.66
Y6 (Graceful–Clumsy)	Xb2	−0.150 [−0.177, −0.040]	1.66
Y6 (Graceful–Clumsy)	Xdb	−0.119 [−0.179, −0.003]	1.01

Note: only attributes whose standardized-coefficient 95% bootstrap CI excludes zero are listed.

Attribute *Xdb* shows statistically significant negative effects in four of the six dimensions (Y2, Y4, Y5, Y6; $\beta = -0.119$ to -0.124) and is the only attribute with significant effects and consistent signs across multiple dimensions. Attribute *Xec* shows significant effects in four dimensions, but the signs reverse: Y2, Y4, and Y5 are positive ($\beta = 0.104$ – 0.184), while Y3 is negative ($\beta = -0.139$), indicating that this attribute increases Practical–Decorative, Concise–Complicated, and Natural–Artificial ratings, while simultaneously decreasing Unique–Ordinary ratings. Y6 (Graceful–Clumsy) has the most statistically significant drivers (six

attributes: Xca , Xcb , $Xa4$, $Xb1$, $Xb2$, Xdb ; $|\beta| = 0.119\text{--}0.183$), consistent with its relatively high VIP concentration (Figure 15f), although its cross-validated Q^2 is lower (0.544).

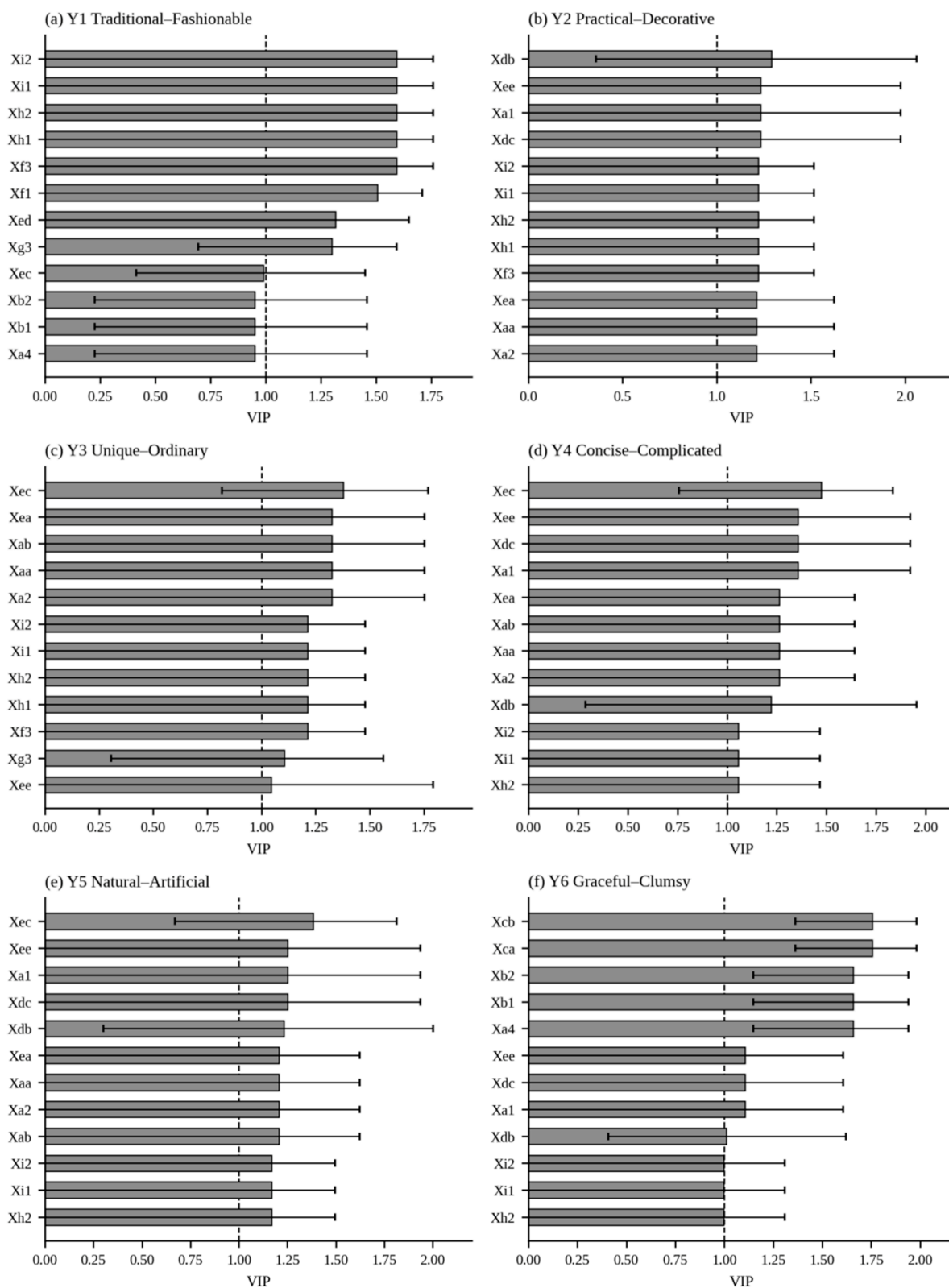


Figure 15. Top-12 Design Attributes Ranked by Variable Importance in Projection (VIP) with 95% Bootstrap Confidence Intervals for Each Kansei Dimension (dashed line: VIP = 1 reference).

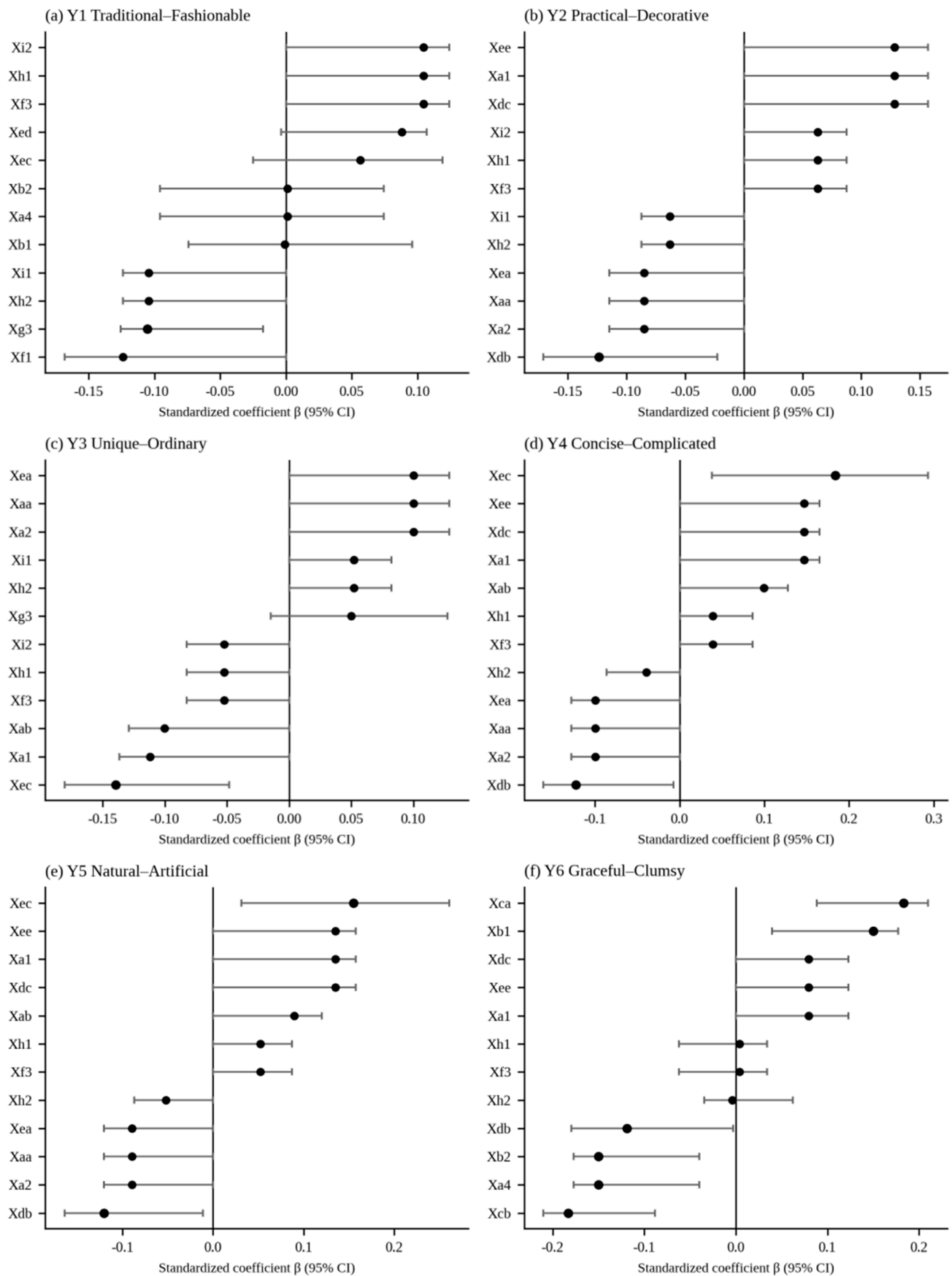


Figure 16. Forest Plot of Standardized Regression Coefficients for the Top-12 Contributing Design Attributes in Each Kansei Dimension (filled markers denote attributes whose 95% CI excludes zero).

4.7. Robustness Validation: Bootstrap and Permutation Testing

Given the small sample size ($n = 10$) relative to the number of predictors ($p = 30$), the credibility of the fitted models depends on evidence beyond in-sample fitting. Therefore, two complementary diagnostics were conducted: (i) bootstrap resampling to assess the stability of the standardized regression coefficients (Section 4.6, Tables 13 and 14), and (ii) permutation tests to evaluate whether the cross-validated predictive relevance reported in Table 13 might have occurred by chance due to the high predictor-to-sample ratio. Leave-one-chair-out predictions also showed strong linear agreement with the observed Kansei scores across all six dimensions (Pearson $r = 0.75$ – 0.96), consistent with the Q^2 values reported in Table 13; a comprehensive assessment of the predictive validity for chairs not involved in model calibration is reported separately in Section 4.8.

Permutation Tests for Overfitting Risk

Permutation tests were conducted (1000 iterations per dimension, response randomly shuffled between chairs, and the full LOCO-CV component-selection procedure re-applied at each iteration) to test whether the observed Q^2 values could have occurred by chance given $p = 30$ predictors and $n = 10$ (Table 15, Figure 17). The observed Q^2 exceeded the corresponding permutation null distribution across all six dimensions, with empirical p -values ranging from $p < 0.001$ (Y3) to $p = 0.020$ (Y6), all below $\alpha = 0.05$. The center of the permutation null distribution was close to or below zero (mean permuted $Q^2 = -0.69$ to -0.60), consistent with the expected behavior of an uninformative model under LOCO-CV at this predictor-to-sample ratio.

Table 15. Permutation Test (1000 iterations) of Cross-validated Predictive Relevance (Q^2) for the Six Kansei Dimensions.

Response	Observed Q^2	Permuted Q^2 (Mean $\pm$ SD)	Permuted Q^2 95% Range	p -Value
Y1 (Traditional–Fashionable)	0.745	-0.663 ± 0.679	$[-2.014, 0.664]$	0.014
Y2 (Practical–Decorative)	0.885	-0.603 ± 0.824	$[-2.500, 0.688]$	0.002
Y3 (Unique–Ordinary)	0.868	-0.627 ± 0.820	$[-2.518, 0.571]$	<0.001
Y4 (Concise–Complicated)	0.670	-0.691 ± 0.805	$[-2.512, 0.540]$	0.011
Y5 (Natural–Artificial)	0.791	-0.637 ± 0.796	$[-2.515, 0.563]$	0.004
Y6 (Graceful–Clumsy)	0.544	-0.637 ± 0.811	$[-2.659, 0.515]$	0.020

Note: p -value = proportion of 1000 permuted Q^2 values $\geq$ the observed Q^2 , computed with the response randomly shuffled across chairs and the full component-selection LOCO-CV procedure re-applied at each iteration.

4.8. External Validation Performance

4.8.1. Model-Calculated and Observed Kansei Scores

The dispersion-scaled morphological parameters of each validation sample are summarized in Table 16. These parameters were substituted into the calibrated PLS regression models (Section 4) to obtain the model-calculated Kansei scores (Y_{cv}). The resulting predicted scores, together with the observed SD scores (Y_{sv}) for the five validation chairs, are presented in Table 17. The observed scores represent the average SD ratings collected from 30 participants, using the same experimental protocol as in the calibration phase.

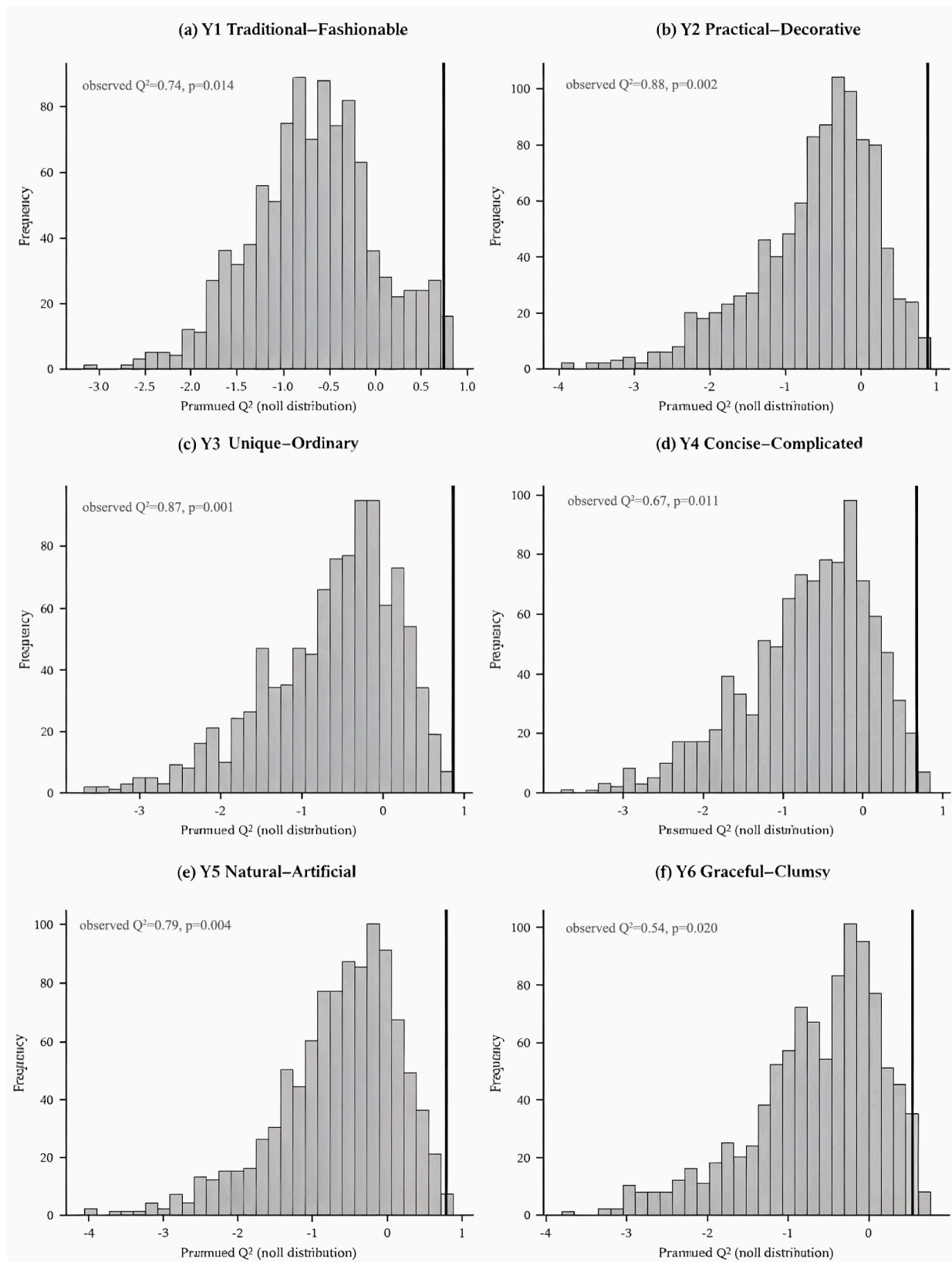


Figure 17. Null Distributions of Cross-validated Q^2 under 1000 Response Permutations for the Six Kansei Dimensions. Solid vertical line: observed Q^2 from the unpermuted model. The clear separation between the observed model and its respective null distribution indicates that the predictive relationships identified in Table 13 are unlikely to be artifacts of the high predictor-to-sample ratio, but rather reflect a true, non-random covariance structure between design attributes and each Kansei dimension.

Table 16. The Form Attribute Element Parameters for Five Validation Samples.

NO.	<i>Xa1</i>	<i>Xa2</i>	<i>Xa3</i>	<i>Xa4</i>	<i>Xaa</i>	<i>Xab</i>	<i>Xb1</i>	<i>Xb2</i>	<i>Xca</i>	<i>Xcb</i>	<i>Xda</i>	<i>Xdb</i>	<i>Xdc</i>	<i>Xea</i>	<i>Xeb</i>
A04	0	0	0	0.192	0	0.192	0	0.132	0	0.163	0	0.115	0	0	0.041
B10	0	0.192	0	0	0.187	0	0	0.132	0	0.163	0	0	0	0.042	0
C14	0	0	0.192	0	0	0.192	0	0.132	0.163	0	0	0	0	0	0.042
D01	0.192	0	0	0	0	0.192	0.132	0	0.163	0	0	0	0.115	0	0
E03	0	0	0	0.192	0	0.192	0	0.128	0	0.163	0	0.115	0	0	0.042
NO.	<i>Xec</i>	<i>Xed</i>	<i>Xee</i>	<i>Xf1</i>	<i>Xf2</i>	<i>Xf3</i>	<i>Xg1</i>	<i>Xg2</i>	<i>Xg3</i>	<i>Xga</i>	<i>Xgb</i>	<i>Xh1</i>	<i>Xh2</i>	<i>Xi1</i>	<i>Xi2</i>
A04	0	0	0	0.064	0	0	0	0	0.115	0.115	0	0	0.117	0.061	0
B10	0	0	0	0.064	0	0	0	0.115	0	0.115	0	0	0.117	0.061	0
C14	0.042	0.042	0	0.064	0	0	0	0	0.115	0.115	0	0	0.117	0.061	0
D01	0.042	0.042	0.042	0.064	0	0	0	0	0.115	0	0.115	0	0.117	0.061	0
E03	0	0	0	0	0	0.064	0	0	0	0	0.115	0.117	0	0	0.061

Table 17. Model-calculated (Y_{cv}) and Observed (Y_{sv}) Kansei Scores for the Five External Validation Samples.

Chair	$Y1_{cv}$	$Y2_{cv}$	$Y3_{cv}$	$Y4_{cv}$	$Y5_{sv}$	$Y6_{sv}$	$Y1_{sv}$	$Y2_{sv}$	$Y3_{sv}$	$Y4_{sv}$	$Y5_{sv}$	$Y6_{sv}$
A04	−0.863	−0.359	−0.397	−0.607	0.270	−0.792	−1.149	−0.106	−0.404	−0.426	0.426	−0.833
B10	−0.970	−0.722	−0.121	−1.101	0.042	−0.484	−1.085	−0.851	−0.021	−1.213	−0.043	−0.278
C14	−0.560	−0.112	−0.541	−0.169	0.446	−0.299	−0.894	−0.043	−0.681	−0.362	0.340	−0.111
D01	−0.448	0.772	−1.035	1.255	1.091	0.151	−1.064	0.915	−1.234	1.340	1.362	0.085
E03	0.031	0.436	−0.834	0.085	0.700	−0.664	−0.298	0.255	−1.043	0.021	0.830	−1.056

Note. Y1–Y6 correspond to the six Kansei dimensions: Y1 Traditional–Fashionable, Y2 Practical–Decorative, Y3 Unique–Ordinary, Y4 Concise–Complicated, Y5 Natural–Artificial, Y6 Graceful–Clumsy.

4.8.2. External Validation Performance

The agreement between model-calculated (Y_{cv}) and observed (Y_{sv}) Kansei scores was assessed using Pearson correlation coefficients, RMSE, MAE, and mean prediction bias (Table 18; Figure 18). The Pearson correlation coefficients ranged from 0.874 (Y6) to 0.995 (Y3), indicating a strong agreement among the six Kansei dimensions. The RMSE values ranged from 0.137 to 0.373, and the MAE values ranged from 0.127 to 0.336. The average prediction bias for five of the six dimensions was small ($|\text{bias}| \leq 0.091$), while the Traditional–Fashionable dimension (Y1) showed a larger positive bias (0.336), indicating a systematic overestimation relative to the observed ratings. Considering the limited external validation sample size ($n = 5$), these findings provide preliminary evidence that the proposed developed PLS model has satisfactory predictive capability for unseen Ming-style chair designs.

Table 18. External Validation Performance: Agreement between Model-calculated (Y_{cv}) and Observed (Y_{sv}) Kansei Scores for the Five Independent Validation Chairs.

Response	Pearson r	RMSE	MAE	Bias
Y1 (Traditional–Fashionable)	0.890	0.373	0.336	0.336
Y2 (Practical–Decorative)	0.958	0.167	0.155	−0.031
Y3 (Unique–Ordinary)	0.995	0.150	0.131	0.091
Y4 (Concise–Complicated)	0.988	0.137	0.127	0.020
Y5 (Natural–Artificial)	0.978	0.163	0.149	−0.073
Y6 (Graceful–Clumsy)	0.874	0.218	0.178	0.021

Note: RMSE, MAE and bias were computed as $Y_{cv} - Y_{sv}$ across the five validation chairs ($n = 5$); bias = mean ($Y_{cv} - Y_{sv}$).

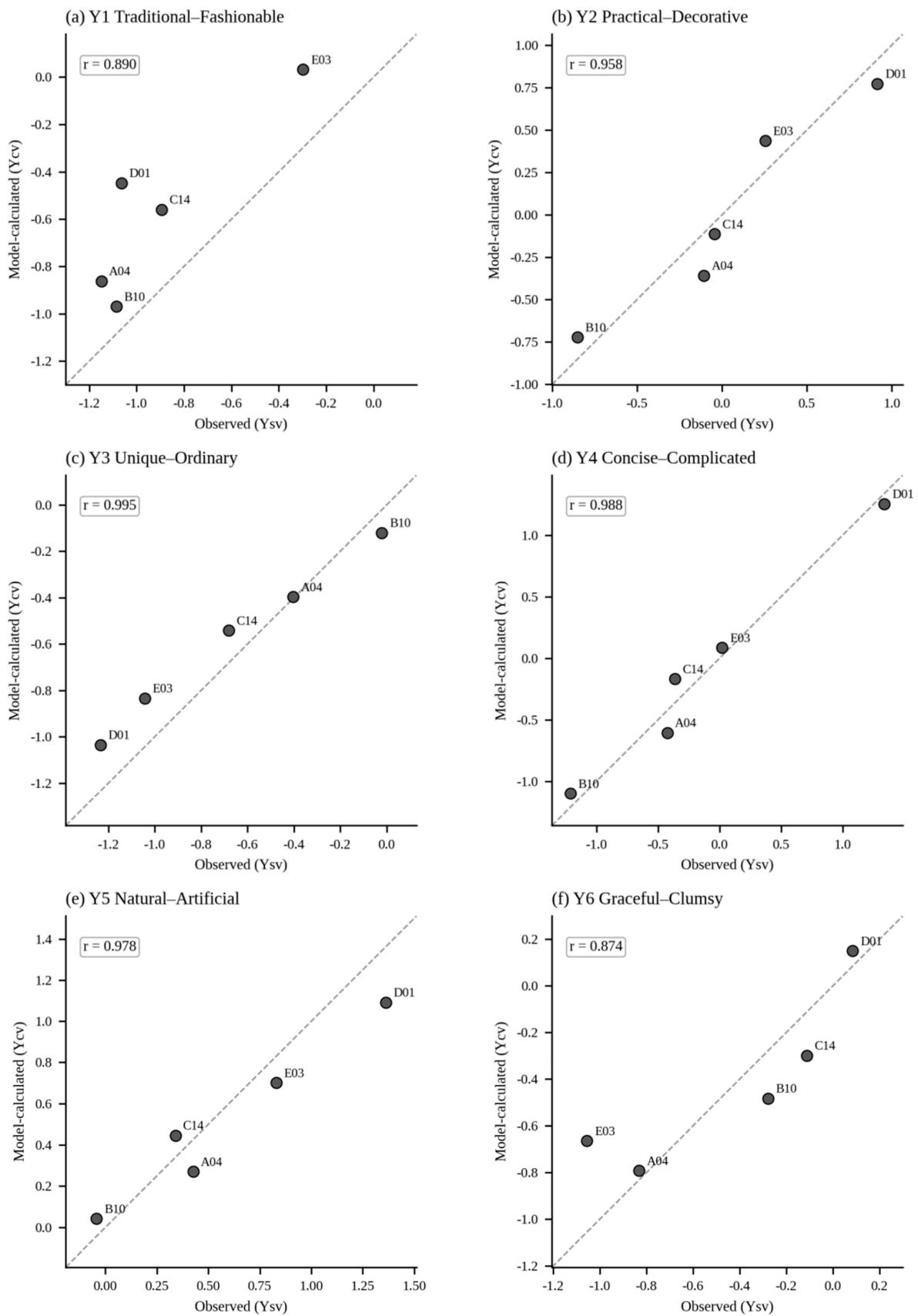


Figure 18. Model-calculated (Y_{cv}) Versus Observed (Y_{sv}) Kansei Scores for the Five External Validation Chairs. Dashed line: identity ($Y_{cv} = Y_{sv}$).

Overall, external validation indicates that the fitted PLS model generalizes well to chairs outside the calibration sample in five of the six Kansei dimensions, with the magnitude of prediction error comparable to the internal LOOCV error reported in Table 13. The systematic positive bias observed for Y1 (Traditional–Fashionable) suggests that this dimension may require recalibration or the use of a larger and more diverse calibration sample in future work, consistent with the limitations discussed in Section 5.

5. Discussion

This study explores whether the visual attention allocated to Ming-style chair forms can be interpreted as a proxy for perceptual importance of morphological components, and whether integrating attention-derived dispersion measures into KE can improve form–emotion modeling. The findings reveal three main results: (1) attention is highly unevenly distributed across structural elements; (2) fixation magnitude and attentional dispersion represent distinct and decoupled constructs; and (3) dispersion-informed scaling enhances the predictive and explanatory performance of KE models. These results are discussed in relation to eye-tracking theory, feature-based perception, and design evaluation.

5.1. Hierarchical Distribution of Visual Attention Across Chair Morphology

Visual attention is highly concentrated on a limited subset of morphological components rather than evenly distributed across the chair structure. The backrest (X_e) dominated viewing behavior, accounting for 50.01% of total fixation duration and attracting the earliest fixations (as early as 320 ms). This was followed by the seat (15.59%), seat–leg transition (9.12%), and legs (7.70%), while the central arm support (2.39%), head-rail (2.79%), and armrest body (2.86%) received only marginal attention (Table 10).

This model replicates and extends previous eye-tracking evidence on Chinese chair designs, consistently reporting a hierarchical distribution of gaze on structurally and ornamentally prominent regions [17,19,42,44]. In particular, the dominance of the backrest aligns with findings that elaborately carved Ming-style backrests function as primary perceptual attractors [38], while also being consistent with broader evidence that visually rich areas disproportionately guide early and sustained fixations [39].

In addition to the overall fixation share, heatmap analysis reveals heterogeneous attention structures within the backrest AOI. Three distinct fixation patterns were identified—concentrated, distributed, and hierarchical—corresponding to variations in carving density and compositional organization. Chairs with salient carved panels (e.g., D03, A18, B18) elicited tightly clustered inter-observer fixation patterns, while structurally uniform backrests produced a more diffused viewing distribution. This indicates that fixation allocation is shaped by both structural saliency and compositional differences, rather than being driven solely by evaluative processing, which is consistent with salience-driven attention capture mechanisms [48].

Overall, visual attention in Ming-style chair perception exhibits a strong hierarchical and structure-dependent distribution, indicating that the contributions of morphological features to perceptual processing are not equal. This finding directly challenges the equal-weight assumption of morphological variables commonly adopted in conventional KE models, including previous implementations in related work [36,52,55].

5.2. Decoupling of Fixation Magnitude and Attentional Dispersion

A key result involves the relationship between fixation magnitude and attention dispersion. When attention is operationalized as between-stimulus dispersion of fixation (CV of fixation duration), the ranking of morphological elements changes significantly. Although the backrest dominates total fixation time, it exhibits the lowest dispersion (V_{bi}

= 0.184; w_{bi} = 0.042). In contrast, the head-rail (w_{bi} = 0.192) and front arm support (w_{bi} = 0.163), despite having low fixation shares, show the highest dispersion values (Table 11). This reversal indicates that fixation magnitude and dispersion capture fundamentally different aspects of perceptual processing. High fixation does not imply high discriminative relevance; rather, uniformly fixated elements serve as perceptual anchors, while elements with higher dispersion are more sensitive to design changes, thus possessing greater discriminative value.

This dissociation is consistent with FIT [20], which distinguishes between the allocation of attention during feature encoding and the integration of features into evaluative representations. In this sense, fixation magnitude reflects the anchoring of attention, while dispersion reflects sensitivity to morphological differences between stimuli.

These findings challenge physiologically based KE approaches that directly convert fixation measures into feature weights [11,56,61]. Such magnitude-based schemes would overemphasize visually dominant elements (e.g., the backrest) while underestimating components that drive perceptual differences. This supports evidence that saliency and evaluative importance are separable constructs in aesthetic perception [46–48], while perceptual relevance arises from variations between stimuli rather than absolute gaze allocation. Since the dispersion metric relies on scale, low-mean fixation elements may exaggerate coefficient values; thus, results should be interpreted as indicative rather than definitive.

5.3. Attention-Informed Scaling and Form–Emotion Modeling

Attention-informed scaling rescales morphological variables using dispersion-derived weights, without redefining their categorical structure. Although the ratio of samples to predictor variables was deliberately limited ($p = 30$, $n = 10$), robust and generalizable PLS models were still produced. The cross-validated Q^2 values ranged from 0.544 (Y6, Graceful–Clumsy) to 0.885 (Y2, Practical–Decorative), with five dimensions exceeding the threshold of 0.67 (Table 13). Permutation tests (1000 iterations) confirmed that all models significantly exceeded chance-level performance ($p \leq 0.020$; Table 15). External validation further supported model stability, with observed–predicted correlations ranging from $r = 0.874$ to $r = 0.995$ (Table 18).

Mechanistically, the scaling procedure aligns morphological feature weights with the covariance structure utilized by PLS by amplifying elements with high dispersion and attenuating visually uniform elements. This provides a functional explanation for why attention-informed scaling enhances predictive performance rather than serving merely as a descriptive adjustment.

At the attribute level, effects are both stable and context-dependent. The sickle-shaped central-arm-support spindle (*Xdb*) exhibits consistent effects across four dimensions ($\beta = -0.119$ to -0.124), serving as a structural cue associated with broad effects related to practical, concise, and graceful evaluations. In contrast, the pierced backrest (*Xec*) shows strong sign reversals across dimensions, shifting evaluations toward opposite affective poles depending on context, highlighting the non-additive nature of morphological semantics, which cannot be captured by equal-weight coding.

The Graceful–Clumsy dimension (Y6) is driven by a set of larger but relatively smaller and partially offset significant effects ($|\beta| = 0.119$ – 0.183), which may contribute to its relatively low predictive stability ($Q^2 = 0.544$). This pattern suggests that distributed affective judgments stem from multiple cues with weak additive effects, which, despite statistical significance, increase the residual variance of the model. Finally, the Traditional–Fashionable dimension (Y1) exhibits moderate internal fit ($Q^2 = 0.745$) but systematic external prediction bias (+0.336), indicating that this evaluative dimension cannot be fully explained by morphological structure alone. Instead, it appears to be influenced

by cultural and semantic associations that extend beyond the encoded form space [1,32]. This boundary condition suggests that attention-informed scaling is most effective for structurally grounded affective dimensions, while its explanatory power diminishes in culturally saturated evaluations.

5.4. Theoretical Implications

Taken together, these findings provide empirical operationalization for the FIT in the context of design evaluation [20]. FIT distinguishes between early-stage selective attention to features and later-stage integration into a unified object representation. In this study, these two stages map to complementary analytical levels: the AOI-based fixation-dispersion index reflects feature-level attentional allocation, whereas the PLS latent constructs represent the integrated perceptual-affective representation.

Therefore, the decoupling of observed fixation magnitude from evaluative contributions is not an anomaly, but rather a phenomenon consistent with a two-stage perceptual architecture, in which behavioral gaze does not directly determine evaluative importance. Instead, importance emerges at the integration stage, where dispersed feature information is combined into an overall judgment.

This perspective reframes a core ambiguity in eye-tracking-based design research—whether gaze intensity can be interpreted as a proxy for what “matters”—by demonstrating that fixation primarily indexes attention allocation, while evaluative relevance is determined at the level of integrated representation.

5.5. Methodological and Design Implications

Methodologically, this study proposes a transferable protocol for integrating visual attention into KE without conflating attention with perceptual importance. Eye-tracking data are incorporated by transforming conventional binary morphological descriptors through attention-informed scaling prior to statistical modeling, while preserving the original coding structure and interpretability. This provides a structured alternative to magnitude-based weighting approaches [11] and highlights the limitations of directly interpreting fixation as importance [48].

From a design perspective, the results identify different functional roles of morphological elements. The head-rail and front arm support serve as key distinguishing features, as variations in these regions most strongly reorganize visual attention and corresponding affective evaluations. In contrast, the backrest primarily acts as a perceptual anchor, having limited distinguishing value despite its visual dominance. This distinction provides actionable guidance for heritage furniture design and broader form-generation processes. Rather than distributing design effort uniformly across all components, interventions can be prioritized toward elements that maximize emotional differentiation while maintaining overall structural coherence.

5.6. Limitations and Future Directions

Several limitations should be acknowledged. First, the sample size (ten calibration chairs and five validation chairs) is relatively small, although cross-validation and permutation tests were used to mitigate overfitting. Larger and more diverse datasets are required to improve the stability of dimension-specific coefficients, particularly for Y1. Second, the use of standardized grayscale images from a fixed perspective isolated form effects but excluded material, color, and tactile information known to affect furniture perception [39]. Consequently, observed attention patterns may change when richer perceptual cues are introduced. Third, attention weighting relies on a single dispersion metric (CV of fixation duration). While this captures between-stimulus variability, it is sensitive to mean fixation levels; elements with lower fixation shares may exhibit inflated variability. Moreover, the

reported w_{bi} and V_{bi} values should be interpreted as point estimates, as no confidence intervals or null-model comparisons were applied to formally assess scale dependence.

Therefore, future research should expand this framework in three directions: (i) methodological validation using bootstrap or null-model approaches and alternative attention metrics (e.g., time-to-first-fixation and revisit frequency), (ii) multimodal integration with neurophysiological measures (e.g., EEG or event-related potentials) and immersive VR environments to better approximate real-world perception, and (iii) cross-cultural and demographic expansion to test the generalizability and boundary conditions of attention-informed KE.

6. Conclusions

This study proposes and validates an attention-informed KE framework that integrates AOI-based eye-tracking data into weighted morphological variables of product form evaluation. By replacing traditional equal-weight methods with attention-derived weights, the framework provides a more objective representation of the relationship between product form and users' affective responses. The findings further indicate that visual fixation does not necessarily reflect the perceptual importance of design elements, suggesting that attention-based weighting provides a more informative basis for modeling users' emotional responses than mere fixation magnitude.

From a methodological perspective, the proposed framework integrates attention-derived weights before regression modeling, allowing eye-tracking data to directly contribute to the performance of morphological variables. This provides a practical procedure for integrating eye-tracking with KE and supports more objective modeling of product form and emotional responses. From a practical standpoint, the framework helps designers identify the morphological features that most significantly impact users' affective responses, providing supporting evidence for product evaluation and design optimization.

Although developed using Ming-style chairs, the proposed method can be transferred to other product categories where subtle form changes affect user perception, including furniture, consumer electronics housings, automotive interiors, and packaging design. It is particularly relevant to heritage and culturally rooted product design, where evidence is needed to support controlled modifications of traditional forms while maintaining perceived stylistic identity. More broadly, the framework provides a reproducible protocol that supports evidence-based decision-making in product development, enabling designers and design teams to prioritize morphological variables based on behavioral data rather than expert intuition.

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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).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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