A Neural Marker for Affective Preference in Young Adults: An ERP Study on Modern Decorative Cabinets

Authors: Fang,Fang, Guan,Huiyuan, Li, Mingzhu, Fang,Fang

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Abstract

Objective: This study is part of a research project on the innovative design of Chinese lacquer furniture. The core objectives are to validate the feasibility of applying event-related potential (ERP) technology to measure emotional responses evoked by the appearance of decorative furniture, and to explore whether ERP components can serve as effective indicators to evaluate preference levels toward images of modern decorative cabinets.Methods: The experiment employed a within-subjects design with young adults as participants. Electroencephalography (EEG) signals were recorded while participants evaluated images of modern decorative cabinets and standardized affective images. For each stimulus, participants indicated their preference level (low, medium, or high) via a keypress response.Results: ERP technology effectively captured emotional responses to cabinet appearances, as reflected in component amplitude variations. Key findings include: (1) The early N100 component served as an effective neural marker for identifying medium preference levels in response to modern decorative cabinet images. (2) A comparison of underlying cognitive mechanisms revealed that preference judgments for cabinet images were primarily driven by early visual features, whereas judgments for standardized affective images relied more heavily on late semantic representations. (3) High-arousal standardized affective images elicited significantly stronger affective brain responses than low-arousal modern decorative cabinet images. These results provide a neurophysiological basis for objectively identifying users' true aesthetic preferences toward furniture.Limitations: This study is limited by its focus on a specific demographic (young adults) and a single category of modern decorative cabinets, which may affect the generalizability of the findings. The laboratory setting might also differ from real-world furniture evaluation contexts.Conclusions: The findings offer practical guidance for lacquer furniture design. In early-stage competitor analysis, measuring user preferences helps identify valuable design references and guides styling improvements. During mid-stage prototype evaluation, this neurophysiological method allows for the objective comparison of design alternatives, supporting the selection of solutions that best match user aesthetic tendencies. Compared to traditional subjective surveys, this work provides a more direct and objective neural measure of aesthetic preference, enhancing both design success and user experience.

Full Text

Preamble

Fang FANG: Conceptualized the specific research idea, designed and conducted the experiment, acquired and analyzed the data, and drafted the manuscript.

Huiyuan GUAN: Proposed the core research topic, guided the research design, and reviewed and revised the final version of the manuscript.

Mingzhu LI: Participated in the design and refinement of the research protocol, assisted in data interpretation, and reviewed and revised the manuscript.

Abstract

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Methods: The experiment employed a within-subjects design with young adults as participants. Electroencephalography (EEG) signals were recorded while participants evaluated images of modern decorative cabinets and standardized affective images. For each stimulus, participants indicated their preference level (low, medium, or high) via a keypress response.

Results: ERP technology effectively captured emotional responses to cabinet appearances, as reflected in component amplitude variations. Key findings include: (1) The early N100 component served as an effective neural marker for identifying medium preference levels in response to modern decorative cabinet images. (2) A comparison of underlying cognitive mechanisms revealed that preference judgments for cabinet images were primarily driven by early visual features, whereas judgments for standardized affective images relied more heavily on late semantic representations. (3) High-arousal standardized affective images elicited significantly stronger affective brain responses than low-arousal modern decorative cabinet images. These results provide a neurophysiological basis for objectively identifying users' true aesthetic preferences toward furniture.

Limitations: This study is limited by its focus on a specific demographic (young adults) and a single category of modern decorative cabinets, which may affect the generalizability of the findings. The laboratory setting might also differ from real-world furniture evaluation contexts.

Conclusions: The findings offer practical guidance for lacquer furniture design. In early-stage competitor analysis, measuring user preferences helps identify valuable design references and guides styling improvements. During mid-stage prototype evaluation, this neurophysiological method allows for the objective comparison of design alternatives, supporting the selection of solutions that best match user aesthetic tendencies. Compared to traditional subjective surveys, this work provides a more direct and objective neural measure of aesthetic preference, enhancing both design success and user experience.

Keywords: young adults; modern decorative cabinet; event-related potential (ERP); affective preference; solid wood furniture design; Chinese lacquer furniture

Introduction

To clarify the origin of this study, four questions must be addressed: Why is it necessary to study the styling innovation design of Chinese lacquer furniture? Why conduct affective preference research? Why use event-related potential (ERP) technology to measure emotions? Why select modern decorative cabinets (hereinafter referred to as MDCs) as the research focus?

Rationale for Conducting Studies on Styling Innovation Design of Chinese Lacquer Furniture

Lacquer furniture is a significant category in the Chinese furniture system and the earliest embodiment of traditional Chinese style [?, ?, ?]. Before the emergence of hardwood furniture, lacquer furniture dominated traditional Chinese furniture, and even afterward, both have coexisted. However, current lacquer furniture design faces significant issues: its traditional decorative features no longer align with modern living aesthetics, making it difficult to integrate into contemporary interiors [?, ?, ?, ?, ?, ?, ?, ?, ?]. Traditional styling outweighs innovation, leading to outdated designs. Additionally, long production cycles and high maintenance costs erode market share, and consumer demand is shrinking. Therefore, innovating and improving the styling of Chinese lacquer furniture is urgently needed.

Rationale for Conducting Studies on Affective Preference

Given the inevitable innovation and reform of Chinese lacquer furniture, how should this be guided? Previous scholars have considered the innovation and evolution of Chinese lacquer furniture from a styling design perspective. They suggest future designs should balance tradition and modernity by combining traditional lacquer-painting techniques with modern design concepts and production technologies to meet consumers' affective preference [?, ?, ?, ?, ?, ?, ?, ?, ?].

In other words, future lacquer furniture styling should not only reflect national cultural characteristics but also be improved and optimized based on target users' affective preference. This viewpoint suggests that the styling evolution of lacquer furniture should shift from technique-centered to human-centered and user-affective preference-oriented. Based on this viewpoint, the study of affective preference in design is introduced into the styling innovation of Chinese lacquer furniture. This aims to help designers identify and select furniture styles that align with target users' aesthetic expectations, define the future direction of lacquer furniture creation and reform, and promote innovation and evolution of Chinese lacquer furniture within modern design contexts.

Rationale for Employing ERP Technology as a Method for Affective Measurement

Product-induced affective preference is like a black box, often difficult to express accurately [?, ?, ?, ?, ?, ?, ?]. Existing methods for measuring affective responses to product appearance include both psychological and physiological approaches [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?]. Psychological methods, like the semantic differential method used in Kansei Engineering, are subjective. While adaptable, they risk subject inhibition and may not accurately capture emotional data [?, ?, ?, ?, ?, ?, ?]. In contrast, physiological measurements provide objective data, effectively avoiding the problem of subject inhibition and accurately reflecting user preferences [?, ?, ?, ?, ?, ?, ?]. Common physiological measurements include electroencephalography (EEG), electrodermography (EDG), electromyography (EMG), blood pressure (BP), and heart rate (HR) [?, ?, ?, ?, ?, ?, ?]. ERP in EEG technology is a widely used tool in cognitive psychology. It induces emotional experiences and reflects cognitive processes with advantages like non-invasiveness and high temporal resolution [?, ?, ?, ?, ?, ?, ?]. ERPs have gained increasing attention from product design researchers. Studies show that differences in product appearance can induce variations in ERP components. Wang Xueshuang et al. [?, ?, ?, ?, ?, ?, ?] used a humidifier and found N100, P200, and LPP components reflect emotional changes. Yang Yuan et al. [?, ?, ?, ?, ?, ?] used office chairs as stimulus and found P300 can be a screening indicator for product-induced perceptual-emotional cognition. Shi Aiqin et al. [?, ?, ?, ?, ?, ?] investigated the differences in neural response during high- and low-design-aesthetic product perception, and indicated that the N400 component can be used as an indicator for measuring the perceived value of a product in a future product design study. Pšurný et al. [?, ?, ?, ?, ?, ?] demonstrated that P200 and LPP components reflect early attentional and affective responses to product appearance and decision factors. Guo Fu et al. [?, ?, ?, ?, ?, ?, ?] revealed that humanoid robot appearances elicited variations in ERP components (enhanced N1, P2, and LPP), uncovering the neural dynamics of user preference formation.

Rationale for Choosing MDCs as the Research Object

On the one hand, from a perspective of comprehensiveness and accuracy, the research object should not be limited to traditional lacquer furniture but should include furniture from various geographical backgrounds, styles, genres, and forms of expression. Including various furniture styles in the study reveals the diversity of the current design context and facilitates accurate screening of target user preferences. Since ornamentation is a key styling feature of lacquer furniture, the study includes modern decorative furniture with surface decorations and craftsmanship, including but not limited to traditional lacquer-painting techniques. On the other hand, both traditional lacquer and modern decorative furniture include various categories such as beds, sofas, chairs, stools, tables, chests, cabinets, pedestals, and screen seats [?, ?, ?]. For practical and theoretical guidance, the research object needs focus. Research shows that cabinets can incorporate diverse lacquer-painting techniques, offer more decorative area compared to chairs, stools, and shelves, and are more adaptable to modern living environments compared to beds, tables, and other types of furniture. Therefore, cabinets are indispensable in modern living spaces and are better suited for diverse craftsmanship and adapting to modern living environments. Considering decorative and practical aspects, the research focuses on individual cabinets (e.g., bookcases, wardrobes, chests, TV cabinets, dining cabinets) with movable tops or doors. Non-movable whole cabinets, wall cabinets, or cabinet combinations are excluded.

Accordingly, the research is limited to MDCs, including but not limited to lacquer cabinets, primarily focusing on solid wood, monolithic cabinets with decorative images available on the market.

In conclusion, lacquer furniture faces a consumption dilemma as its styling deviates from modern aesthetic interests. This study uses EEG technology to investigate affective preference for MDCs, deciphering the aesthetic mechanisms and laying the foundation for driving the styling innovation of lacquer furniture to align with target users' evolving affective preference. This paper is conducted in this context.

2.1 Stimuli

The stimuli were divided into two categories. This division was motivated by two factors: First, affective research on product appearance, which predominantly relies on case studies [?, ?, ?, ?], often yields findings that are difficult to generalize. Second, product-evoked responses are documented to be subtler than those elicited by standardized affective pictures or interactive experiences [?, ?, ?, ?]. To address this, a comparative design was employed, utilizing MDC images and standardized affective pictures.

The first stimulus set comprised 36 representative MDCs exhibiting significant morphological variations. An initial collection of 426 commercially available MDC samples was gathered from corporate, independent designer, and online sources to cover mainstream stylistic trends. To ensure a non-arbitrary selection, a rigorous screening protocol was implemented: (1) Preliminary filtering of the 426 samples via the Delphi expert survey method yielded 90 candidates;

(2) Similarity assessment was performed using a dichotomous card sorting procedure, with data processed through EZSort clustering algorithms; (3) A final panel of industrial designers selected the 36 most representative prototypes (Fig. 1 [Figure 1: see original paper]).

The second stimulus set comprised 36 standardized affective pictures from the China Affective Picture System (CAPS). Three image categories were used differing in affective valence: positive, neutral, and negative. Twelve positive images (CAPS IDs: 012, 014, 018, 045, 102, 121, 437, 478, 488, 640, 780, 781) had mean valence and arousal ratings of 7.38 and 6.61. Twelve neutral images (CAPS IDs: 234, 258, 318, 320, 355, 386, 451, 469, 521, 724, 763, 767) showed mean valence and arousal values of 5.04 and 4.54. Twelve negative images (CAPS IDs: 146, 152, 196, 205, 218, 244, 246, 522, 540, 555, 577, 580) had mean valence and arousal scores of 2.23 and 5.47. This selection ensured significant differences in emotional valence across images.

All stimuli were standardized as 1280$×$1024 pixel JPEG files (500KB). Stimulus presentation was controlled via E-Prime 2.0.

2.2 Participants

Affective preference was measured among young adults, who were defined prior to participant selection.

The definition of "young adults" varies across different fields and regions. In this study, referring to the age definitions of young people by the United Nations World Health Organization and the National Bureau of Statistics of China, and considering the convenience of participant selection, "young adults" was defined as highly educated individuals (undergraduates, master' s and doctoral students, and young teachers) aged 18 to 35. This group is open-minded, highly receptive to new ideas, knowledgeable about traditional culture and non-genetic heritage, and serves as a typical representation of young adults.

The sample size was calculated using G*Power software (α = 0.05, power = 0.95) based on methods described by Faul, Erdfelder, Buchner, & Lang [**?**, **?**, **?**, **?**, **?**, **?**, **?**]. The experiment employed a 2 (image type: CAPS vs. modern decorative cabinet) × 3 (preference level: high/medium/low) within-subjects factorial design. With an assumed effect size of 0.25, G*Power analysis indicated a minimum required sample size of 28 participants. Thirty-seven participants were recruited from Nanjing Forestry University, including undergraduate and graduate students majoring in furniture design, industrial design, law, and engineering. Data from one participant were excluded due to behavioral data loss, and five additional participants were excluded because their artifact rejection rates exceeded acceptable thresholds. The final dataset included 31 participants (14 female, 17 male; age range 19-30 years, M = 21.71, SD = 2.57). All participants had normal or corrected-to-normal vision with no history of ocular or neurological disorders.

Participants were instructed to: (1) abstain from smoking and caffeine consumption for at least 2 hours before the experiment; (2) avoid strenuous physical/mental activities; (3) obtain adequate rest to maintain alertness during testing. All participants were right-handed and volunteered for the study after being fully informed of the procedures. The experimental sessions were conducted in the Human-Computer Interaction Laboratory at Nanjing Forestry University under controlled environmental conditions.

2.3 Apparatus and Data Acquisition

EEG data were acquired using the Brain Vision Recorder system (Brain Products GmbH, Germany) with a standard 10-20 electrode configuration. A 32-channel electrode cap was used to record signals from 30 scalp electrodes: Fp1, Fp2, F7, F3, Fz, F4, F8, T8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, O1, Oz, O2 (Fig. 2 [Figure 2: see original paper]). Additional electrodes monitored horizontal (HEOG) and vertical (VEOG) electrooculograms. The recording setup used FCz as the online reference, with ground electrode positioned between FPz and Fz. HEOG electrodes were placed 1cm lateral to the outer canthus of the right eye, and VEOG electrodes 1cm below the left infraorbital ridge. All electrode impedances were maintained below 10 kΩ. The signals were amplified using a band-pass of 0.05-100Hz and a sampling rate of 500Hz.

2.4 Procedure

After obtaining consent, participants received detailed instructions about the experimental procedures before electrode cap placement and impedance calibration. Participants adjusted their seating for comfort and remained still while seated 0.6-0.7 m from the stimulus display (Fig. 3 [Figure 3: see original paper]). They were instructed to maintain central fixation on a crosshair during the experiment. The experimental stimuli were presented using E-Prime 2.0. Participants rated picture appearance preference using a 5-point Likert scale via keypress responses: key 1 for strongly dislike, key 2 for dislike, key 3 for neutral, key 4 for like, and key 5 for strongly like. Responses were categorized into three preference levels: low (keys 1-2), medium (key 3), and high (keys 4-5).

The study employed a within-subjects design where participants sequentially completed two experimental conditions: (1) MDC images and (2) CAPS images. Each condition contained 36 unique stimuli that were each repeated 12 times, resulting in 432 trials per participant (36 stimuli $\times$ 12 repetitions) to ensure adequate signal-to-noise ratio for ERP averaging [?, ?, ?]. Stimulus duration was participant-controlled through keypress responses, with each trial advancing immediately after rating submission. Following each response, a central fixation cross (+) appeared for 500-800 ms (randomized inter-trial interval) to dissipate visual persistence and reset ocular focus before subsequent stimulus onset (Fig.

4 [Figure 4: see original paper]). Three scheduled breaks were implemented between experimental blocks. Participants initiated the resumption of trials by pressing any key, with total session duration ranging 30-45 minutes.

2.5.1 Subjective Data Analysis

Subjective evaluation data for the MDCs were processed. Each participant provided 12 ratings for each MDC sample. To mitigate the impact of random errors, the modal (most frequent) response for each participant-stimulus pair was selected as the final preference score. Preferences were quantified on a 5-point Likert scale (1 = "Strongly Dislike" to 5 = "Strongly Like"), with higher scores indicating a stronger preference. The statistical results of the subjective data are presented in Table 1 .

2.5.2 Behavioral Data Analysis

Response times (RTs) were aggregated by stimulus category (CAPS vs. MDC) and preference level (high/medium/low) using participants' subjective ratings. Mean RTs were calculated per participant for each combination of factors.

2.5.3 Electrophysiological Data Analysis

EEG data were processed offline using MATLAB R2013a and SPSS Statistics 26.0. Continuous data were segmented into epochs from -200 to 800ms relative to stimulus onset, with the -200 to 0ms interval serving as the baseline for correction. The epoched data were then band-pass filtered at 0.1–30 Hz. Ocular artifacts (HEOG and VEOG) were corrected, and other artifacts were thoroughly removed by automatically rejecting trials with voltage amplitudes exceeding $±$70 V. Finally, for each participant, ERP waveforms were generated by averaging the trials separately for each experimental condition, defined by image type and preference level.

3.1 Subjective Preference Results

Clustering analysis was conducted on the MDC samples to examine whether the experimental materials could elicit differentiated preferences among participants. The subjective preference rating matrix from Table 1 was imported into SPSS 19.0. Hierarchical cluster analysis using Ward' s method with squared Euclidean distance indicated three clusters as the optimal solution. This determined the cluster number (k=3) for the subsequent K-means clustering analysis, with detailed membership results shown in Table 2 .

Based on Table 2, participants with similar preferences were assigned to one of three clusters, labeled as C1, C2, and C3. The mean preference ratings of each cluster toward the 36 MDC samples were calculated, resulting in Table 3 and Figure 5 [Figure 5: see original paper].

Cluster-specific preference profiles showed significant between-cluster differences (Table 3, Figure 5). These results confirm that: (1) genuine preference heterogeneity exists among young adults; and (2) the stimulus materials effectively elicited distinct affective responses, validating the ecological validity of the MDC samples for neurocognitive research. Accordingly, the subjective data provide a justified basis for subsequent ERP statistical analysis.

3.2 Behavioral Results

Based on the preference ratings, a repeated-measures ANOVA with image type (CAPS vs. MDC) × preference level (high/medium/low) was conducted on response times. Results showed a significant main effect of image type, $F(1, 30) = 9.525$, $p = .004$, $^2 = 0.241$, with faster responses to CAPS images ($M = 953.63$ ms, $SD = 39.20$) than to MDC images ($M = 1114.26$ ms, $SD = 74.45$), $p = .004$. A significant main effect of preference level was also found, $F(2, 60) = 7.516$, $p = .001$, $^2 = 0.200$. Pairwise comparisons indicated that for MDCs, response times were shorter for both high- and low-preference images compared to medium-preference images (all $ps < .05$), with low-preference images also eliciting faster responses than high-preference ones ($p = .028$). For CAPS images, response times to low-preference images were shorter than to medium-preference images ($p = .007$), while high-preference images showed no significant differences from the other levels (all $ps > .05$). The image type × preference level interaction was not significant, $F(2, 60) = 1.933$, $p = .154$, $^2 = 0.061$.

The analysis of reaction times demonstrated distinct effects of preference level and image type. Response times were longest for medium-preference images and shortest for low-preference images, indicating faster evaluation of stimuli with clear affective valence compared to ambiguous neutral stimuli requiring extended processing. MDC images elicited significantly longer response times than CAPS images, indicating that processing low-arousal furniture stimuli requires more attentional resources due to their subtler affective cues.

3.3.1 ERP Component Selection

Grand average ERPs were derived by averaging EEG signals according to participants' affective preference ratings, generating distinct waveforms for MDC and CAPS images across preference levels (Figures 6 and 7). Analysis revealed two key components: the N100 (110–160 ms) localized to the frontal area (F3, Fz, F4) and frontal–central area (FC1, FC2), and the late positive potential (LPP, 450–750 ms) prominent in the central area (C3, Cz, C4), centroparietal area (CP1, CP2), and parietal area (P3, Pz, P4). Topographic mapping confirmed these spatiotemporal patterns. During the N100 time window (110–160 ms), maximal activation was observed over the frontal area and frontal–central area electrodes (Figure 8 [Figure 8: see original paper]), whereas the LPP exhibited peak amplitudes in the parietal area between 450–750 ms (Figure 9 [Figure 9: see original paper]).

Based on these observations, statistical analyses focused on the N100 (frontal/frontal-central area) and LPP (parietal area) components within their respective time windows.

3.3.2 Statistical Analysis of ERP Components

A 2 (image type: CAPS vs. MDC) × 3 (preference level: high/medium/low) within-subjects repeated-measures ANOVA was conducted on mean component amplitudes. Greenhouse-Geisser corrections were applied when Mauchly' s test indicated violation of sphericity. Table 5 presents the mean amplitudes of the ERP components across their respective time windows and brain areas.

(1) N100: N100 amplitudes (110-160 ms) were quantified in the frontal and frontal-central areas.

In the frontal area, a significant main effect of image type was observed ($F(1, 30) = 74.853$, $p < .001$, $^2 = 0.714$), with CAPS images eliciting substantially larger N100 amplitudes (M = -3.946 µV, SD = 0.432) compared to MDC images (M = -1.586 µV, SD = 0.418), $p < .001$. No significant main effect of preference level emerged ($F(2, 60) = 0.982$, $p = .380$, $^2 = 0.032$). A significant image type × preference level interaction was detected ($F(2, 60) = 5.325$, $p = .007$, $^2 = 0.151$). Pairwise comparisons revealed that for MDC images, medium-preference stimuli evoked larger N100 amplitudes than both high- ($p = .049$) and low-preference stimuli ($p = .003$), while high- and low-preference stimuli showed comparable amplitudes ($p = .585$). For CAPS images, no significant differences emerged across preference levels (all ps > .05).

In the frontal–central area, a significant main effect of image type was observed ($F(1, 30) = 76.628$, $p < .001$, $^2 = 0.719$), with CAPS images eliciting substantially larger N100 amplitudes (M = -3.813 µV, SD = 0.424) compared to MDC images (M = -1.422 µV, SD = 0.406), $p < .001$. No significant main effect of preference level emerged ($F(2, 60) = 0.518$, $p = .568$, $^2 = 0.017$). A significant image type × preference level interaction was detected ($F(2, 60) = 4.154$, $p = .020$, $^2 = 0.122$). Pairwise comparisons revealed that for MDC images, medium-preference stimuli evoked larger N100 amplitudes than low-preference stimuli ($p = .003$), but showed no difference from high-preference stimuli ($p = .135$). High- and low-preference stimuli were statistically equivalent ($p = .693$). For CAPS images, no significant differences in N100 amplitude were observed across preference levels (all ps > .05).

(2) LPP: LPP amplitudes (450-750 ms) were analyzed in the parietal area.

In the parietal area, a significant main effect of image type was observed ($F(1, 30) = 7.249$, $p = .011$, $^2 = 0.195$), with CAPS images eliciting substantially larger LPP amplitudes (M = 5.003 µV, SD = 0.609) compared to MDC images (M = 4.234 µV, SD = 0.639), $p = .011$. A significant main effect of preference level was found ($F(2, 60) = 5.671$, $p = .006$, $^2 = 0.159$), showing that high-preference stimuli evoked significantly smaller LPP amplitudes (M = 4.135 µV, SD = 0.602) than both medium-preference (M = 4.895 µV, SD = 0.693) and low-preference stimuli (M = 4.826 µV, SD = 0.572), all ps < .05. The image type × preference level interaction was not significant ($F(2, 60) = 1.010$, $p = .370$, $^2 = 0.033$). Pairwise comparisons revealed that for MDC images, no significant differences in LPP amplitude were observed across preference levels (all ps > .05). For CAPS images, high-preference stimuli evoked significantly smaller LPP amplitudes than both low-preference ($p = .004$) and medium-preference stimuli ($p = .018$).

4.1 Preference-Level Effects on the N100 Component

The N100 components in frontal and frontal-central areas showed distinct response patterns across preference levels. As shown in Figures 6-7, N100 components evoked by different preference-level stimuli demonstrated broad spatial distribution, with earlier emergence in anterior regions (frontal/frontal-central) than posterior occipital areas, replicating established spatiotemporal patterns [?, ?, ?, ?, ?, ?, ?].

The N100 component reflects discriminative processing of external stimuli under attentional conditions [?, ?, ?, ?]. This component demonstrates sensitivity to physical stimulus attributes (color, size, spatial location) through automatic sensory processing, indicating early-stage attentional resource allocation [?, ?, ?, ?, ?, ?]. Enhanced N100 amplitudes typically indicate intensified attentional engagement with visual stimuli [?, ?, ?, ?, ?, ?, ?, ?, ?].

Using International Affective Picture System (IAPS) stimuli, Keil et al. [?, ?, ?, ?, ?, ?, ?] demonstrated enhanced N100 amplitudes to emotional compared to neutral stimuli. In this study, for CAPS images, while no significant N100 amplitude differences emerged across preference levels (Table 5), medium-preference stimuli consistently showed reduced amplitudes compared to high- and low-preference stimuli. This pattern aligns with Keil et al. [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?] findings, suggesting attenuated attentional allocation to moderately preferred stimuli during early visual processing. The absence of significant N100 differences across preference levels may be attributed to methodological considerations in stimulus selection. To accommodate ethical concerns and minimize participant discomfort, high-arousal negative stimuli (e.g., corpses #629/282, wreckage #222, car accidents #280/281) were excluded; instead, moderately negative images (e.g., beggar children, self-immolation) were selected as negative emotional stimuli. Similarly, extreme positive stimuli (e.g., sexual content #472/132) were excluded from the positive stimulus set. This conservative approach likely attenuated emotional intensity gradients between preference categories, resulting in nonsignificant N100 variations.

In contrast, for MDC images, medium-preference stimuli evoked significantly larger N100 amplitudes in frontal and frontal-central areas compared to both high- and low-preference stimuli. This pattern suggests enhanced attentional allocation to medium-preference cabinets during early perceptual discrimination, reflecting stimulus-driven cognitive demands in evaluating complex aesthetic stimuli. These results diverged from Keil et al.' s findings but aligned with Guo Fu et al. [?, ?, ?, ?, ?, ?, ?]. A plausible explanation, consistent with Guo et al.' s interpretation, is that the divergence resulted from the use of different types of visual stimuli. Furthermore, unlike the standardized stimuli (e.g., IAPS images, geometric icons, or uniformly designed products) commonly used in prior research [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?], the MDCs in our study incorporated multi-dimensional design elements (e.g., patterns, colors, textures, layouts, materials), resulting in greater visual complexity and perceptual load. This heightened complexity likely required increased attentional investment to extract task-relevant features from stimuli that lacked strong inherent affective valence.

4.2 Preference-Level Effects on the LPP Component

The LPP components in parietal area showed distinct response patterns across preference levels. The LPP has been associated with both sustained attentional engagement and categorical processing mechanisms during stimulus evaluation [?, ?, ?, ?, ?, ?]. It has also been shown that the LPP reflects a neural mechanism of categorical processing, with its average amplitude increasing as more attentional resources are devoted [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?].

Prior research using standardized stimuli (International Affective Picture System, IAPS) and product images consistently shows enhanced LPP amplitudes for emotional versus neutral stimuli [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?], with positive stimuli generally evoking larger responses than negative counterparts [?, ?, ?, ?, ?, ?, ?]. The analysis of MDC images revealed no significant differences in LPP amplitudes across preference levels. This suggests comparable motivated attention allocation during evaluation of cabinets with varying preference levels. These null effects may stem from both stimulus-specific characteristics and task demands. Guo et al. [?, ?, ?, ?, ?, ?] employed a target discrimination task where participants only made keypress responses to smartphone images that evoked a sense of anticipated use. In contrast, the categorical rating task used in this study required graded preference evaluations (on a 1-5 scale) for all MDC stimuli. Unlike prior target detection paradigms, this approach necessitated explicit affective evaluations across all stimuli. Contemporary furniture design philosophy emphasizes eliciting positive emotional responses through three dimensions: visceral (sensory appeal), behavioral (functional utility), and reflective (symbolic significance) [?, ?, ?]. Consequently, commercially launched furniture is inherently designed to gain consumer acceptance, with designers and decision-makers actively avoiding designs that provoke strong negative emotions (e.g., disgust) [?, ?, ?, ?]. It is important to note that the cabinet images used in this experiment were all selected from commercially successful and representative products. As their designs were inherently optimized to evoke positive responses from target consumer groups, this selection may constrain the accuracy and range of negative emotional responses observable in non-target demographics.

Further analysis of the mean amplitudes revealed that the medium-preference cabinets elicited the largest LPP activation. This pattern suggests that stimuli with extreme preferences (high/low) may have been more memorable than those with ambiguous (medium) preferences. Two factors may underlie this phenomenon. First, the limited quantity of these distinct high- and low-preference cabinets enhanced their memorability, while their repeated, randomized presentation facilitated the cognitive stabilization of their preference representations. Second, evaluating medium-preference cabinets demanded greater attentional resources for continuous matching against pre-existing mental representations of cabinet designs and home environments during categorical judgment.

For CAPS images, medium- and low-preference stimuli evoked larger LPP amplitudes compared to high-preference stimuli (Table 5). This pattern suggests an inverse cognitive resource allocation gradient, with high-preference stimuli receiving minimal resources and low-preference stimuli requiring maximal allocation. While diverging from previous findings, these results align with negative bias effect [?, ?, ?, ?]. A plausible explanation for this divergence, as discussed above, may lie in stimulus selection criteria, specifically the deliberate exclusion of high-arousal images from the CAPS database.

Building on the analyses in Sections 4.1-4.2, this study demonstrates the utility of ERP methodology for assessing aesthetic responses to MDCs, though significant differences were confined to N100 amplitude variations between medium-preference stimuli and other categories. During categorical evaluation tasks, participants exhibited rapid physical property detection of cabinet stimuli within 200ms post-stimulus onset. Significant N100 amplitude differences emerged during this early window, revealing immediate preference discrimination at initial processing stages. Medium-preference cabinets elicited enhanced anterior scalp activation, suggesting prioritized resource allocation for ambiguous aesthetic stimuli. Analysis revealed non-significant differences in LPP amplitudes across cabinet preference levels. This null finding suggests limited utility of LPP as a late-stage biomarker for cabinet preference evaluation under current experimental parameters. Collectively, these results indicate that cabinet preference judgments predominantly originate from early-stage unconscious processing (automatic sensory integration) rather than deliberate appraisal. This pattern implies that variations in low-level visual features (e.g., contour complexity, chromatic contrast) predominantly drive initial aesthetic evaluations of cabinet designs [?, ?, ?, ?, ?, ?, ?, ?, ?, ?]. Conversely, CAPS stimuli elicited differential neural responses primarily in later processing stages (450-750ms post-stimulus), suggesting that semantic/conceptual attributes (e.g., symbolic meaning), rather than low-level visual features, mediate preference formation for CAPS stimuli [?, ?, ?, ?, ?, ?, ?, ?].

4.3 Stimulus-Type Effects on ERP Components

Comparative N100/LPP analyses revealed systematic divergences between CAPS stimuli and MDC stimuli. Across all preference levels, CAPS stimuli elicited stronger N100 negativity and LPP positivity compared to cabinet stimuli. This aligns with established IAPS findings, where high-arousal stimuli evoke amplified emotional reactions relative to low-arousal counterparts [?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?, ?]. This effect is particularly pronounced in human-focused images, which surpass animal/object/scene depictions in emotional potency [?, ?, ?, ?]. Consistent with these mechanisms, the attenuated emotional salience of cabinet stimuli in this study stems from their categorical constraint as object-type stimuli, fundamentally contrasting with CAPS' multimodal spectrum (humans, animals, scenes, etc.). Mirroring the behavioral data, low-arousal cabinet evaluations required prolonged reaction times, confirming higher cognitive load for low-arousal stimuli.

5 Conclusion

The present study systematically validated the utility of ERP techniques in quantifying affective responses to modern cabinet designs through affective preference measurements. Behavioral and neurophysiological measures revealed robust differentiation in both reaction times (RTs) and ERP component amplitudes (N100 and LPP) when participants evaluated stimuli with varying preference levels, as evidenced by the following observations:

1. Conscious evaluation elicits differential reaction times. Participants responded faster to high-arousal stimuli with negative emotional valence, whereas low-arousal neutral cabinet stimuli required prolonged reaction times for preference judgments.

2. The early marker utility of N100 is constrained by categorical limitations. The frontal N100 component effectively differentiated cabinet stimuli with moderate preference levels but failed to distinguish high/low preference levels. The LPP showed no significant discriminative capacity for cabinet preference classification.

3. Arousal levels modulate neurophysiological responses. High-arousal CAPS stimuli elicited significantly larger N100 negativity and LPP positivity than low-arousal cabinet stimuli across all preference levels.

4. Frontal N100 components exhibit earlier peak latencies. Frontal N100 components peaked earlier than occipital counterparts, suggesting prioritized engagement of anterior regions during initial stimulus appraisal.

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Figure Legends

Fig. 1 The 36 Representative Samples of MDCs

Fig. 2 Electrode location of brain regions

Fig. 3 Experimental scene

Fig. 4 Experimental process

Fig. 5 Line chart of preference mean (Legend: Blue diamonds denote Cluster 1; red squares denote Cluster 2; green triangles denote Cluster 3)

Fig. 6 [Figure 6: see original paper] Grand-average ERP waveforms for MDC images across preference levels (Legend: Blue curve -High preference; red curve -Medium preference; black curve -Low preference)

Fig. 7 [Figure 7: see original paper] Grand-average ERP waveforms for CAPS images across preference levels (Legend: Blue curve -High preference; red curve

–Medium preference; black curve –Low preference)

Fig. 8 Scalp topographies of the N100 (110-160 ms) for MDC and CAPS stimuli

Fig. 9 Scalp topographies of the LPP (450-750 ms) for MDC and CAPS stimuli

Figures

Fig. 1 The 36 Representative Samples of MDCs

Fig. 2 Electrode location of brain regions

Fig. 3 Experimental scene

Fig. 4 Experimental process

Fig. 5 Line chart of preference mean

Fig. 6 Grand-average ERP waveforms for MDC images across preference levels (horizontal axis: time(ms); vertical axis: amplitude(V))

Fig. 7 Grand-average ERP waveforms for CAPS images across preference levels (horizontal axis: time(ms); vertical axis: amplitude(V))

Fig. 8 Scalp topographies of the N100 (110-160 ms) for MDC and CAPS stimuli

Fig. 9 Scalp topographies of the LPP (450-750 ms) for MDC and CAPS stimuli

Tables

Tab. 1 Preference evaluation matrix

Sample ID	Participant ID	Preference Score

Tab. 2 Result of K-means clustering analysis for participants

Cluster	Euclidean Distance
Cluster	Euclidean Distance
Cluster	Euclidean Distance
Cluster	Euclidean Distance
Sample	Sample

Tab. 3 Preference means of the three clusters

Note. Means greater than 3 are highlighted in bold.

1C	2C	3C
1C	2C	3C

Tab. 4 Mean reaction time (Unit: ms)

Image type	Preference level	Standard Error
Medium	Medium	

Tab. 5 Mean amplitude of different brain area in different time windows (Unit: V)

Image	Preference level	110-160ms (N100)	450-750ms (LPP)
		Frontal area	Frontal–central area
		-1.461 (2.592)	-1.322 (2.559)
Medium	Medium	-1.972 (2.452)	-1.724 (2.422)
		-1.222 (2.180)	-4.066 (2.662)
Medium	Medium	-3.784 (2.309)	-3.603 (2.280)
		-3.815 (2.408)	3.869 (3.388)
		4.318 (3.557)	4.402 (3.607)
		5.332 (3.107)	

Note. Values in parentheses are standard deviations

Note: Figure translations are in progress. See original paper for figures.