Behavioral and Neural Mechanisms Underlying the Influence of Plating Aesthetics on Healthy Eating Decisions

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Abstract

Previous research has demonstrated that the aesthetic level of food plating can influence individuals' food choices; however, no studies have further investigated the mechanisms through which different aesthetic features with equivalent aesthetic levels impact healthy eating decisions. The present study recruited 34 participants and employed a value-based food decision-making paradigm, utilizing a 2 (aesthetic features: classical beauty, expressive beauty) × 2 (food caloric content: high, low) within-subjects design. By dissociating computational model parameters and electroencephalographic (EEG) indices, we examined the differential aesthetic values conferred by distinct aesthetic features, as well as the moderating effect of aesthetic value on caloric influence and its underlying cognitive neural basis. The results revealed: (1) Classical beauty (vs. expressive beauty) exhibited higher aesthetic value, resulting in elevated food choice rates and drift rates (v), along with reduced N400 amplitudes; (2) Aesthetic value moderated caloric value, yet the salience of caloric value was greater than that of aesthetic value, with neural processing of caloric information occurring earlier in time (240–320 ms); (3) The moderating effect of aesthetic value transpired during the decision evidence accumulation process, influencing both the drift rate (v) and the centro-parietal positivity (CPP). This study elucidates, at the theoretical level, the moderating effect of aesthetic value and its cognitive neural foundation in healthy eating decision-making, while offering practical aesthetic design guidelines for food plating to nudge healthy food selection.

Classical or Expressive Aesthetics: Computational and Neural Mechanisms by Which Plating Aesthetics Influence Healthy Eating Decisions

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Abstract

Previous research has found that the aesthetic level of food plating influences individuals' food choices, yet no studies have further examined the mechanisms by which different aesthetic characteristics—despite equal aesthetic appeal—affect healthy eating decisions. This study recruited 34 participants and employed a value-based food decision-making paradigm using a 2 (aesthetic characteristics: classical beauty, expressive beauty) × 2 (food calories: high, low) within-subjects design. By isolating computational model parameters and EEG metrics, we examined the differential aesthetic values evoked by different aesthetic characteristics and the moderating effect of aesthetic value on caloric influence, along with its cognitive-neural basis. Results showed: (1) Classical beauty (vs. expressive beauty) carried higher aesthetic value, yielding higher food choice rates and drift rates (v) and lower N400 amplitudes; (2) Aesthetic value moderated caloric value, but caloric value showed higher salience than aesthetics, with neural processing of caloric information occurring earlier (240–320 ms); (3) The moderating effect of aesthetic value occurred during the decision evidence accumulation process, influencing drift rate (v) and centroparietal positivity (CPP). This study reveals, at the theoretical level, the moderating effect of aesthetic value in healthy eating decisions and its cognitive-neural basis, while providing practical guidance for aesthetic design in food plating to nudge healthy eating choices.

Keywords: healthy eating, value-based decision-making, aesthetic characteristics, computational modeling, event-related potentials

Introduction

Over recent decades, changes in food supply systems and dietary environments have exacerbated unhealthy eating patterns in modern society. As overweight and obese populations continue to grow, the burden on healthcare systems and medical resources has risen steadily (Popkin et al., 2012). Consequently, implementing appropriate intervention strategies to reduce caloric cravings and promote healthy eating in modern dietary environments—where high-calorie foods are abundant and easily accessible—has become a critical issue for governments and health departments (Cadario & Chandon, 2020).

Humans' innate preference for high-calorie foods and high taste-hedonic expectations pose the primary challenge to the effectiveness of healthy eating interventions. Research indicates that the approach motivation toward high-calorie foods is an evolutionary adaptation (Hall, 2016). In food-scarce environments, rapid identification and approach to high-calorie foods provided survival advantages; thus, high-calorie foods tend to generate greater intrinsic pleasure and satisfaction than low-calorie foods (Berthoud, 2012). Additionally, caloric information influences expectations of food palatability and hedonic experience, with low-calorie foods consistently associated with relatively inferior taste, lower deliciousness, and reduced hedonic value compared to high-calorie foods (Zheng et al., 2022). This lower hedonic value of low-calorie foods may conflict with modern society' s hedonic eating patterns, potentially explaining why cognitive intervention strategies emphasizing only the health benefits of low-calorie foods have shown limited effectiveness (Cadario & Chandon, 2020). Therefore, researchers have recently begun exploring the effectiveness of affective intervention strategies, including using visual presentation aesthetics to enhance the hedonic value of low-calorie foods and promote healthier choices (e.g., Cornil & Chandon, 2016; Peng & Jemmott, 2018). Indeed, the effect of aesthetic enhancement is significant. People tend to believe that more attractive-looking fruits and vegetables taste better, while oddly shaped or unattractive foods increase perceived consumption risk (Qi et al., 2022). Artistic plating and aesthetically pleasing meals also lead to higher taste evaluations and willingness to pay (Michel et al., 2014, 2015), demonstrating that visual aesthetic pleasure can positively influence hedonic expectations of food.

However, beauty is not merely different levels on a single continuum; aesthetic characteristics also influence perception and judgment of aesthetic objects (e.g., the Forbidden City vs. the Louvre). According to Lavie and Tractinsky' s (2004) aesthetic dimensions theory, visual aesthetics can be divided into two dimensions based on design characteristics and perceivers' subjective perception: classical aesthetics and expressive aesthetics. Classical aesthetics comprises many general principles of good design, emphasizing clarity, symmetry, balance, order, unity, and harmony in visual element organization, closely related to traditional aesthetic concepts. Examples include the highly balanced and orderly Forbidden City and pyramid complexes, or bilateral symmetry in butterflies and flowers. Expressive aesthetics represents design novelty and complexity, emphasizing creativity, fascination, sophistication, and uniqueness, focusing on design creativity and expressiveness. In classical designs, various visual elements cohere and organize clearly, forming a harmonious and unified whole, allowing people to rapidly identify and understand these visual objects with relatively little cognitive effort (Hoffmann & Krauss, 2004). Unlike classical beauty, expressive beauty is characterized by breaking general design conventions to evoke emotional arousal and engagement, providing hedonic value and aesthetic interest

(Lavie & Tractinsky, 2004). Complex and sophisticated game interfaces and abstract art can be considered high expressive beauty designs. Expressive designs often feature rich and diverse visual elements that attract attention and mobilize perceivers' energy and cognitive resource investment (Chang et al., 2014). Generally, in aesthetic design, when orderly or complex aesthetic characteristics dominate visually and overall create a sense of harmonious unity or complex novelty, classical or expressive beauty is formed (Deng & Poole, 2012).

Classical and expressive beauty exert different influences on attribute perception of visual objects (Casey & Poropat, 2014). Generally, classical beauty in design can enhance inferences about product utilitarian value (i.e., practical qualities such as efficiency, usefulness, ease of use, and predictability) (Casey & Poropat, 2014; Robins & Holmes, 2008). Additionally, marketing research aimed at improving perceived health and safety of food has revealed potential benefits of classical beauty in food visual presentation (Hagen, 2021). In contrast, hedonic products (e.g., gaming products, cultural products) typically use expressive beauty design to increase emotional arousal and enhance interesting, novel, and stimulating experiences (Hassenzahl et al., 2010). In food sensory marketing, expressive beauty has also been shown to enhance dietary pleasure, as Michel et al. (2014, 2015) demonstrated through laboratory and field studies that artistic plating of salads led to higher taste evaluations and willingness to pay.

Food is a stimulus object with complex attributes: it provides energy for normal bodily function, giving it utilitarian properties, while also providing delicious taste experiences and sensory pleasure, endowing it with hedonic properties. So in food plating visual design, do people prefer classical or expressive beauty? In other words, under equal aesthetic appeal, which aesthetic design characteristic can maximize food' s aesthetic value and thereby moderate the influence of calories on food choice? Distinguishing appetite values evoked by different aesthetic characteristics without changing visual aesthetics is important. For the food service industry, while enhancing visual aesthetics of healthy foods to improve eating experiences is a common nudging strategy (Cadario & Chandon, 2020; Cornil & Chandon, 2016), few restaurants use low-visual-aesthetics presentation of unhealthy foods to reduce consumer selection of unhealthy options. Since visual aesthetics often influence product quality perception (Pombo & Velasco, 2021), low-aesthetics food presentation may threaten brand image (Jin et al., 2015). However, identifying plating aesthetic characteristics with equal aesthetics but different aesthetic values could provide food service businesses with two parallel pathways to nudge healthy choices—presenting healthy foods with high-appetite-value aesthetic characteristics while presenting unhealthy foods with low-appetite-value aesthetic characteristics—without affecting brand image or food quality perception.

This study used a value-based dietary decision-making paradigm (Hajihosseini & Hutcherson, 2021; Harris et al., 2013) to examine the computational basis and intrinsic mechanisms of people' s visual aesthetic valuation of food, and to explore how aesthetics moderate caloric reward value and how this moderation unfolds in cognitive and neural processes. Decision neuroscience theory indicates that value-based decisions follow sequential sampling models (SSM), where people gradually accumulate noisy information until reaching an evidence threshold for decision-making (Forstmann et al., 2016). Drift-diffusion models (DDM), as effective standard models, have been widely applied to process construction in food value decisions (Krajbich et al., 2015). Specifically, DDM decomposes decisions into latent processes based on RT and accuracy metrics, including information processing quality (evidence accumulation speed, drift rate, v), response caution (information amount needed for decision, threshold/boundary, a), prior bias (bias, z), and time unrelated to decision processing—such as motor preparation and execution (non-decision time, t). Therefore, this study used DDM to explore the process mechanisms of aesthetic moderation of caloric reward value. Additionally, to provide multimodal evidence for aesthetic value computation and moderating effects, beyond objective behavioral metrics, we utilized EEG event-related potentials (ERP) with high temporal resolution to disentangle the cognitive-neural determinants of aesthetic value and dietary decision formation. First, we hypothesized that stimulus-locked EEG would allow detection of neural signals for aesthetic value processing (i.e., N300/N400, see EEG recording and processing section for component details). Second, by response-locked EEG localization of decision points, we hypothesized that the centroparietal positivity (CPP) ERP component, associated with decision sensory signal accumulation, could reflect the synergy and competition between aesthetic and caloric values in dietary decisions.

2.1 Participants

Using G*Power 3.17 with a medium effect size of f = 0.25, statistical power of 0.9, and α level of 0.05, the required sample size was calculated as 30 participants. We recruited 34 students from Soochow University (9 males, 25 females; 20 humanities majors, 14 science majors; mean age = 21.1 ± 1.86 years). The mean BMI was 21.82 ± 3.65, all within the normal range. Pre-experiment hunger levels averaged 4.00 ± 0.34, indicating participants were neither hungry nor satiated. All participants were right-handed, had normal or corrected-to-normal vision, no eating disorders, were not vegetarians, and had never participated in similar experiments. The study was approved by the Soochow University Ethics Committee and conducted according to the ethical standards of the Declaration of Helsinki. All participants provided informed consent before the experiment.

2.2 Apparatus and Materials

BMI was calculated using the standard formula: weight (kg) divided by height (m) squared (BMI = weight/height^2). Hunger status was measured using a single-item 7-point scale: “Please rate your current hunger level” (1 = very hungry, 7 = very full).

Experimental materials were selected from online image databases, comprising 53 common Asian meals categorized into 25 low-calorie and 28 high-calorie foods based on main ingredient caloric content. Adobe Photoshop CC 2019 was used for post-processing and design, presenting all food images at a 45° angle on identical white plates. Based on the two-dimensional aesthetic concept, classical beauty plating was manipulated for balance, symmetry, and order; expressive beauty plating was manipulated for creativity, interest, and complexity (Hagen, 2021). A pre-experiment with 30 participants evaluated the food materials. Based on pre-experiment results, we selected food stimuli where the two plating styles showed no significant difference in overall aesthetic ratings, yet classical beauty plating scored significantly higher on classical aesthetics and expressive beauty plating scored significantly higher on expressive aesthetics. Additionally, high- and low-calorie food groups showed significant differences in subjective caloric ratings; the same food with two plating designs could be identified as the same food (pre-experiment procedures and data see Appendix 1). The final selection included 36 foods (18 high-calorie, 18 low-calorie), yielding 72 stimulus images (36 foods × 2 plating styles). All images were standardized to 397 × 307 pixels (visual angle: 4.36° × 3.37°). Example experimental materials are shown in Figure 1 [Figure 1: see original paper].

Figure 1 Example of experimental materials

The entire experiment was conducted in a soundproof, dimly lit room. All stimuli were presented on a 27-inch ASUS GTX1060 monitor with 1920$×$1080 resolution and 60 Hz refresh rate. Participants' eyes were maintained approximately 75 cm from the screen center. EEG signals were recorded and analyzed using a Brain Products ERP system, collected through a 64-channel EasyCap electrode cap extended from the international 10-20 system. Reference and ground electrodes were located at FCz and AFz, respectively. Horizontal electrooculogram (HEOG) was recorded from electrodes at the outer canthi, and vertical electrooculogram (VEOG) from electrodes above and below the left eye. The original sampling rate was 5000 Hz, with scalp impedance below 5 kΩ. Lab Stream Layer was used to synchronize behavioral and EEG data during the experiment. The experiment was programmed, presented, and recorded using MATLAB PsychToolbox.

2.3 Procedure

The experiment employed a 2 (plating aesthetic characteristics: classical beauty, expressive beauty) × 2 (food calories: high, low) within-subjects design. Dependent variables included food choice rate, HDDM decision parameters, and ERP indices related to meaning processing and decision signal accumulation. The experimental paradigm was adapted from Hajihosseini and Hutcherson (2021) and Harris et al. (2013), capturing participants' value-based food choices through willingness-to-eat ratings for each food stimulus. For standardization, participants were instructed to abstain from eating or drinking (except water) for 2 hours before the experiment. Upon arrival, participants read the experimental introduction, signed informed consent, and rated their hunger level on a 1-7 scale.

Before the experiment, participants were informed they needed to evaluate food images on screen as "want" or "don' t want" quickly and accurately. Each food image was presented three times, totaling 216 trials, with random presentation order across consecutive trials. In each trial, a fixation cross appeared for 500 ms, followed by a food image at screen center. Participants indicated their preference using keys (d, f, j, k) for "really don' t want," "don' t want," "want," and "really want," with key order counterbalanced across participants. This rating method distinguished both willingness to choose food (yes/no) and choice preference intensity (strong/weak). After participant response (or no response within 4 s), a blank screen appeared for 1-2 s before the next trial. The trial procedure is shown in Figure 2 [Figure 2: see original paper]. The experiment comprised 15 blocks of 15 trials each, with the final block containing 6 trials. Participants could rest after each block. Before the formal experiment, participants completed 6 practice trials to understand requirements and familiarize themselves with key positions.

Figure 2 Schematic diagram of experimental procedure

2.4 Data Analysis

2.4.1 EEG Recording and Processing

Offline EEG data were analyzed using the MATLAB EEGLAB toolbox (Delorme & Makeig, 2004). Data were first downsampled to 500 Hz, then high-pass filtered at 0.5 Hz and low-pass filtered at 35 Hz. Bad channels were identified and interpolated based on experimental records and visual inspection of continuous data. After excluding bad channels and EOG channels, continuous data were converted to average reference. Following removal of trials with high-frequency EMG and ECG artifacts, independent component analysis (ICA) was used to correct ocular artifacts. Two segmentation approaches were employed: stimulus-locked segmentation from 200 ms pre-stimulus to 2000 ms post-stimulus with baseline correction from -200 ms to 0 ms; and response-locked segmentation from 1500 ms pre-response to 700 ms post-response with baseline correction from 500 ms to 700 ms. Segmented data were automatically denoised using an absolute threshold of $±$80 V. Participants with trial rejection rates exceeding 30% were excluded (n = 3), leaving 31 participants (8 males, 23 females; mean age = 21.2 ± 1.92 years; mean BMI = 21.70 ± 3.44; mean hunger level = 4.03 ± 0.31).

This study focused on three ERP components: N300, N400, and CPP. Given that aesthetic experience typically involves meaning extraction from the environment (Bara et al., 2022), we examined aesthetic meaning accumulation in dietary decisions within a semantic cognition framework. Previous research shows that the N400 component is sensitive to violation effects in both linguistic and non-linguistic stimuli, including object perception (Lauer et al., 2021).

For example, when actual food taste is inconsistent (vs. consistent) with taste expectations evoked by visual presentation, a significantly larger negative deflection N400 occurs (Domracheva & Kulikova, 2020), validating N400’ s potential in representing cross-modal conceptual information about food. Additionally, in recognition tasks for other meaningful stimuli, N400 amplitude is lower when prior repeated exposure facilitates semantic processing, indicating N400’ s sensitivity to conceptual processing fluency (Voss & Paller, 2006, 2007). Therefore, N400 is associated with meaning processing, conceptual representation, and context-based information retrieval, with amplitude modulated by processing fluency. N300 partially overlaps functionally with N400 as an earlier negative deflection related to semantic expectation and recognition processes, sensitive to recognition difficulty of meaningful stimuli (Lauer et al., 2018). A recent study suggests N300 and N400 may reflect different cognitive computational time periods mapped onto the same cortical substrate representing continuous processes (Draschkow et al., 2018). Based on previous research, object recognition N300 and meaning processing/integration N400 show more occipital distributions (Huang et al., 2010; Kutas & Federmeier, 2011; Truman & Mudrik, 2018). Therefore, based on existing literature and topographic distributions from grand-averaged waveforms, N400 mean amplitude was extracted from the occipital electrode cluster (PO3, PO4, POz, O1, O2, Oz) between 380–500 ms post-stimulus. Additionally, N300 mean amplitude was extracted from the same region in an earlier time window (240–320 ms). N300/N400 whole-head envelope plots are shown in Figure 3 [Figure 3: see original paper]A.

Unlike typical ERP components, CPP represents gradual signals that increase with cumulative sensory evidence input and peak near decision execution. This gradually rising threshold activity is independent of stimulus features and motor preparation (O’ Connell et al., 2012) but similar to drift rate v in DDM, thus tracking the decision evidence accumulation process (Steinemann et al., 2018). Additionally, response-locked CPP activity relates to decision evidence strength, with larger CPP activity when decision-relevant evidence is weaker, making CPP a potential indicator of value-based decision difficulty (Frömer et al., 2023). Following O’ Connell et al. (2012), CPP time windows were determined data-driven: starting 1000 ms pre-response and ending at response execution (0 ms), calculating the temporal slope of average waveform activity at Pz electrode for each participant in 100 ms moving windows in 10 ms steps. Signal accumulation rate was the linear slope of unfiltered signals captured at Pz in each sliding window. Single-tailed permutation t-tests were then implemented via mne.stats.permutation_t_{test} with 5000 iterations to identify signal accumulation rates significantly different from zero across all participants, indicating accelerating CPP activity. The resulting accelerated CPP signal began 450 ms pre-response and ended 10 ms pre-response, with CPP time windows not identical across conditions. Accumulated signal accumulation rates were used as CPP values in this study (Steinemann et al., 2018). CPP whole-head envelope plots are shown in Figure 3B.

Figure 3 Grand-averaged waveforms for all trials and all participants (n =

31). A) Stimulus-locked; B) Response-locked. Line colors represent different electrode sites. Scalp topographies at peak activity time points are plotted above waveforms.

2.4.2 Modeling Data Preprocessing

Three participants with excessive EEG artifacts were excluded (after ICA correction, rejection rates still exceeded 30% using 80 V absolute threshold). Response time and choice data from the remaining 31 participants were included in decision modeling. Since DDM only accepts binary response variables, choice data were dichotomized: 1 = want/really want; 0 = don’ t want/really don’ t want. We used the Bayesian variant of the drift-diffusion model—Hierarchical Drift-Diffusion Model (HDDM)—for decision modeling. HDDM employs Bayesian algorithms for parameter estimation, offering higher reliability (Vandekerckhove et al., 2011). Additionally, HDDM constrains individual differences’ impact on decision parameter estimation by computing group-level hyperparameters (Regenbogen et al., 2016). Moreover, to control noise, HDDM integrates variability in drift rate, non-decision time, and response bias separately via likelihood functions based on parameter characteristics, making decision parameter estimates more precise and stable (Ratcliff & Tuerlinckx, 2002). Given the subjectivity of aesthetic experience, HDDM was selected to control additional impacts of individual differences on parameter estimation. Finally, HDDMs were constructed with no variables, calories, aesthetic characteristics, and calories × aesthetic characteristics as dependent conditions for parameter estimation to determine the most explanatory variable combination for dietary decision processes through model comparison. Specifically, Deviance Information Criterion (DIC) was used to compare fitted models. Generally, lower DIC indicates better model fit; when DIC differences exceed 10, model fit differences are considered significant (Spiegelhalter et al., 2002). Model data analysis was completed using Python 3.8 HDDM 0.8 package (Wiecki et al., 2013). “Want”was set as the upper boundary (positive drift rate) and “don’ t want” as the lower boundary (negative drift rate). Since stimuli were randomly presented across trials, participants could not predict or establish response preferences beforehand, so response bias z was set at 0.5 (midpoint between decision boundaries). Monte-Carlo Markov Chain simulation (MCMC) with gradient ascent optimization estimated model posterior distributions a-posteriori. 11,000 samples were drawn, with the first 1000 discarded for model stabilization (Hajihosseini & Hutcherson, 2021). For model convergence analysis, each model was fitted five times, with final fitted values included in analysis (Wiecki et al., 2013). Gelman-Rubin R values were selected as quantitative convergence indicators (Gelman & Rubin, 1992). R values closer to 1 indicate smaller differences between sample estimates from different distributions and more reliable models.

2.4.3 Behavioral Data Preprocessing

Consistent with decision modeling, three participants with excessive EEG artifacts were excluded, leaving 31 participants. Behavioral data exclusion criteria were: (1) no response; (2) RT below 0.15 s or above M + 3SD; (3) choice data beyond M ± 3SD. After preprocessing, 6,657 valid trials remained.

2.5 Statistical Methods

Using food calories (high, low) and aesthetic characteristics (classical beauty, expressive beauty) as independent variables, two-way repeated-measures ANOVAs were conducted on behavioral performance metrics (choice rate), ERP components (N300, N400 mean amplitudes, CPP), and decision parameters (drift rate v, decision threshold a, non-decision time t), with significance level at 0.05 and ^{2} as effect size measure. Post-hoc comparisons reported Bonferroni-corrected values. To determine relative contributions of calories and aesthetics to food choice rates, a generalized linear mixed model (GLMM) was constructed with calories and aesthetics as fixed factors, participant ID as random factor, and binary food choice (0,1) as predictor. Wald tests further analyzed β coefficient differences between caloric and aesthetic values. Finally, to evaluate evidence accumulation direction under each condition, posterior distribution probabilities of drift rates being greater or less than zero were calculated (Wiecki et al., 2013). Positive drift rates indicated stable accumulation of "accept" decision evidence; negative rates indicated "reject" decision evidence. If posterior probability differed from zero by >95%, participants were considered to stably accumulate evidence toward a decision direction. All statistical analyses were performed in SPSS 27.0, Python 3.8 HDDM 0.8, and R OSF (https://osf.io/7vjfp/).

3.1 Behavioral Results

Trial-by-trial analysis of choice patterns revealed that high-calorie classical beauty consistently corresponded to more positive choice intentions, while low-calorie expressive beauty showed the lowest choice intentions (see Figure 4 [Figure 4: see original paper]A). Further two-way repeated-measures ANOVA on food choice rates showed a significant main effect of aesthetic characteristics, F(1,30) = 18.55, $p < 0.001$, $^{2} = 0.38$, with higher choice rates for classical beauty than expressive beauty (M_{classical} = 0.59 vs. M_{expressive} = 0.52). The main effect of calories was also significant, F(1,30) = 25.90, $p < 0.001$, $^{2} = 0.46$, with significantly higher choice rates for high-calorie than low-calorie foods (M_{high}-calorie = 0.63 vs. M_{low}-calorie = 0.48). Additionally, the interaction between calories and aesthetic characteristics was significant (see Figure 4B), F(1,30) = 6.37, p = 0.017, $^{2}p = 0.108$. *Simple effects analysis showed that classical beauty plating induced more food choices for both high- and low-calorie foods (i.e., food approach responses). Specifically, for high-calorie foods, participants preferred classical beauty (vs. expressive beauty) plating (M*{classical} = 0.68; M_{expressive} = 0.58), t(30) = 5.29,

$p < 0.001$, Cohen’ s d = 0.95, 95% CI = [0.52, 1.37]. For low-calorie foods, classical beauty plating also showed significantly higher choice rates than expressive beauty (M_{classical} = 0.50; M_{expressive} = 0.46), t(30) = 2.29, p = 0.029, Cohen’ s d = 0.41, 95% CI = [0.04, 0.78].

Furthermore, GLMM analysis based on total trial data showed that caloric value significantly affected food choice, with low-calorie significantly reducing choice rates compared to high-calorie, *β{calories} = -0.60, z(6654) = -11.57, $p < 0.001$, 95% CI = [-0.70, -0.50]. Aesthetic value also significantly affected food choice, with expressive beauty significantly reducing choice rates compared to classical beauty, β*{aesthetics} = -0.31, z(6654) = -5.97, $p < 0.001$, 95% CI = [-0.41, -0.21]. Wald test of β coefficient differences between aesthetic and caloric values indicated that caloric value had a significantly greater impact on food choice than aesthetic value, ^{2}(1) = 16.27, $p < 0.001$.

Figure 4 Descriptive statistics for food calories and plating aesthetics. A) Total trial distribution of different food choice patterns across conditions; B) Mean food choice rates across conditions; C) Median RTs for different food choice patterns across conditions; D) Mean RTs across conditions. Note: Error bars represent SE, ***$p < 0.001$,*** *$p < 0.01$,* $p < 0.05$

RT median analysis across choice patterns showed lower RTs for extreme choice intentions (really don’ t want/really want) (see Figure 4C). Further repeated-measures ANOVA on RT data revealed a significant main effect of aesthetic characteristics, F(1,30) = 18.41, $p < 0.001$, ^{2} = 0.38, with faster responses for classical beauty than expressive beauty (M_{classical} = 1.19 vs. M_{expressive} = 1.27). The main effect of calories was also significant, F(1,30) = 9.04, p = 0.005, ^{2} = 0.23, with significantly faster responses to high-calorie than low-calorie foods (M_{high}-calorie = 1.19 vs. M_{low}-calorie = 1.24). Additionally, the interaction between calories and aesthetic characteristics was significant (see Figure 4D), F(1,30) = 7.99, p = 0.008, ^{2}*p = 0.21. Simple effects analysis showed that for high-calorie foods, RTs were significantly faster for classical beauty than expressive beauty plating (M*{classical} = 1.15; M_{expressive} = 1.23), t(30) = -4.95, $p < 0.001$, Cohen’ s d = -0.89, 95% CI = [-0.30, -0.47]. For low-calorie foods, RT differences were not significant (M_{classical} = 1.22; M_{expressive} = 1.23), t(30) = -1.62, p = 0.70.

3.2 Model Results

3.2.1 Model Convergence and Comparison

Visual inspection of convergence plots for decision threshold parameter a indicated good model convergence. Autocorrelation in the last 100 trials approached zero (see Figure 5 [Figure 5: see original paper]B), indicating independent sampling from posterior distributions. For 10,000 iterations, a estimates did not deviate excessively from the overall distribution mean (i.e., posterior highest probability point: 1.6–1.7, see Figure 5A). Consistent with Figure 5A, the threshold estimate histogram (see Figure 5C) showed highest probability at 1.6–1.7 and lower probabilities at other points, indicating good convergence. Additionally, Gelman-Rubin $\mathbb{R}$ values for all four models were close to 1 (M = 1.000006), indicating robust estimates and good convergence. Model comparison of the four HDDMs (model1: calories × aesthetic characteristics; model2: calories; model3: aesthetic characteristics; model4: none) showed that the calories × aesthetic characteristics model was most reliable, indicating both calories and aesthetic characteristics influenced food choice (see Table 1).

Figure 5 Convergence plots for threshold a parameter in decision model. A) Trace plot for all iterations (10,000 iterations, first 1100 discarded); B) Autocorrelation of last 100 fitted iterations; C) Estimated histogram of threshold showing normal distribution around converged values. Histogram shows estimate frequency per iteration

Table 1 DIC values for four HDDMs

Model	DIC
Calories × Aesthetic characteristics	
Calories	
Aesthetic characteristics	
None	

Note: Lower values indicate better fit. "Calories × Aesthetic characteristics" = model dependent on both calories and aesthetic characteristics; "Calories" = model dependent only on calories; "Aesthetic characteristics"= model dependent only on aesthetic characteristics

3.2.2 Model Results

(1) Decision Threshold

Repeated-measures ANOVA on decision threshold (a) revealed no significant main effects or interaction. Specifically, the main effect of calories was not significant, F(1,30) = 0.3, p = 0.59, ^{2} = 0.01; the main effect of aesthetic characteristics was not significant, F(1,30) = 2.68, p = 0.11, ^{2} = 0.08; and the interaction between calories and aesthetic characteristics was not significant, F(1,30) = 0.05, p = 0.82, ^{2} = 0.00. Posterior distributions for parameter estimates are shown in Figure 6 [Figure 6: see original paper]A. Bayesian estimate distributions for decision thresholds across four conditions almost overlapped, indicating statistically equivalent effects of calories, aesthetic characteristics, and their interaction on decision threshold.

(2) Non-decision Time

Mean non-decision time (t) was 0.572, with posterior distributions shown in Figure 6B. Repeated-measures ANOVA showed no significant between-condition differences. Specifically, the main effect of calories was not significant, F(1,30)

= 1.67, p = 0.21, ^{2} = 0.05; the main effect of aesthetic characteristics was not significant, F(1,30) = 1.49, p = 0.23, ^{2} = 0.05; and the interaction between calories and aesthetic characteristics was not significant, F(1,30) = 0.95, p = 0.34, ^{2} = 0.03. Since non-decision time differences across conditions were minimal, they were not considered linked to potential psychological process differences between conditions.

(3) Drift Rate

Repeated-measures ANOVA on drift rate revealed a significant main effect of calories, with faster decision evidence accumulation for high-calorie than low-calorie foods (M_{high}-calorie = 0.37 vs. M_{low}-calorie = -0.11), F(1,30) = 33.65, $p < 0.001$, ^{2} = 0.53. The main effect of aesthetic characteristics was also significant, with faster decision speed for classical beauty than expressive beauty plating (M_{classical} = 0.25 vs. M_{expressive} = 0.01), F(1,30) = 32.34, $p < 0.001$, ^{2} = 0.52. Additionally, the interaction between aesthetic characteristics and calories was significant, F(1,30) = 10.11, p = 0.003, ^{2}*p = 0.26. Simple effects analysis (see Figure 6D) showed that for high-calorie foods, decision speed was faster for classical beauty (vs. expressive beauty) plating (M*{classical} = 0.53; M_{expressive} = 0.20), t(30) = 6.27, $p < 0.001$, Cohen’ s d = 1.14, 95% CI = [0.22, 0.43]. Conversely, for low-calorie foods, decision speed was faster for expressive beauty (vs. classical beauty) plating (M_{classical} = -0.04; M_{expressive} = -0.19), t(30) = 2.98, p = 0.03, Cohen’ s d = 0.54, 95% CI = [0.05, 0.25].

Bayesian posterior estimate distributions for drift rate v are shown in Figure 6C. Table 2 shows posterior distribution probability comparisons across conditions. Regarding decision evidence accumulation direction, participants stably accumulated “accept” decision evidence for high-calorie foods regardless of plating style, P(HC > 0) = 100%, P(HE > 0) = 98.88%. However, expressive beauty significantly reduced the speed of accumulating “accept”evidence for high-calorie foods compared to classical beauty, P(HC > HE) = 99.56%. Aesthetic value had greater impact on evidence accumulation direction for low-calorie foods: when low-calorie foods were expressively plated, participants stably accumulated “reject” evidence, P(LE < 0) = 98.36%; when classically plated, the probability of accumulating “reject” evidence was no longer significant, P(LC < 0) = 65.66%. This indicates classical beauty has a certain enhancing effect on appetite value of low-calorie foods.

Figure 6 Posterior distributions of decision parameter estimates. A) Decision threshold a; B) Non-decision time t; C) Drift rate v; D) Means and data distributions of drift rate v across conditions. Note: HC = high-calorie classical beauty; HE = high-calorie expressive beauty; LC = low-calorie classical beauty; LE = low-calorie expressive beauty. Error bars represent SE, *$\mathbf{p < 0.001,}$ $p < 0.01$

Table 2 Posterior distribution probability comparisons

Comparison	P (%)
P(HC > LC)	
P(HE > LE)	
P(HC > HE)	
P(LC > LE)	
P(HC > LE)	
P(HE > LC)	
P(HE > 0)	
P(HC > 0)	
P(LE < 0)	
P(LC < 0)	

Note: HC = high-calorie classical beauty; HE = high-calorie expressive beauty; LC = low-calorie classical beauty; LE = low-calorie expressive beauty; P = posterior distribution probability difference. Differences are significant when P > 95%.

3.3 EEG Results

(1) N300

The main effect of calories on N300 was significant, with low-calorie foods eliciting larger N300 amplitudes than high-calorie foods (M_{high}-calorie = -0.91 vs. M_{low}-calorie = -1.16), F(1,30) = 9.64, p = 0.004, ^{2}_p = 0.24 (see Figure 7 [Figure 7: see original paper]A). However, the main effect of aesthetic characteristics was not significant, F(1,30) = 1.43, p = 0.242, ^{2}_p = 0.05, nor was the interaction between calories and aesthetic characteristics, F(1,30) = 0.21, p = 0.651, ^{2}_p = 0.01.

(2) N400

Repeated-measures ANOVA showed a significant main effect of aesthetic characteristics on N400, with expressive beauty plating eliciting larger N400 amplitudes than classical beauty (M_{classical} = -2.11 vs. M_{expressive} = -2.31), F(1,30) = 8.17, p = 0.008, ^{2}_p = 0.21 (see Figure 7B). However, the main effect of calories was not significant, F(1,30) = 1.28, p = 0.27, ^{2} = 0.04, nor was the interaction between calories and aesthetic characteristics, F(1,30) = 0.27, p = 0.61, ^{2}_p = 0.01.

(3) CPP

Neither calories nor aesthetic characteristics showed significant main effects on CPP, F_{calories}(1,30) = 1.25, p = 0.27, ^{2} = 0.04; F_{aesthetics}(1,30) = 0.01, p = 0.92, ^{2} = 0.00. However, the interaction between calories and aesthetic characteristics on CPP was significant (see Figure 7C), F(1,30) = 9.38, p = 0.005, ^{2} = 0.24. Simple effects analysis (see Figure 7D) showed that for high-calorie foods, decision signal accumulation rate was lower for classical beauty (vs. expressive beauty) plating (M_{classical} = 70.37; M_{expressive} = 179.69), t(30) = -3.2, p = 0.003, Cohen' s d = -0.58, 95% CI = [-0.95, -0.19]. Conversely, for low-calorie foods, signal accumulation rates for classical and expressive beauty plating did not differ significantly (M_{classical} = 222.84; M_{expressive} = 120.66), t(30) = 1.73, p = 0.09, Cohen' s d = 0.31, 95% CI = [-0.05, 0.67].

Figure 7 Stimulus-locked and response-locked ERP waveforms and descriptive statistics for CPP across conditions. A) N300 component waveforms and topographies for occipital electrode cluster, with time window marked below and enlarged N300 window at top right; B) N400 component waveforms and topographies for occipital electrode cluster, with time window marked below and enlarged N400 window at top right; C) Response-locked waveforms at Pz, with time windows of signal accumulation acceleration marked below for each condition; D) CPP means per condition. Note: HC = high-calorie classical beauty; HE = high-calorie expressive beauty; LC = low-calorie classical beauty; LE = low-calorie expressive beauty. Error bars represent SE, **p < 0.01

Discussion

This study used a value-based decision-making paradigm to investigate the intrinsic mechanisms of aesthetic value computation, the moderating effect of aesthetic value on caloric value, and its cognitive and neural process basis by isolating computational model parameters and EEG metrics. Findings revealed that classical beauty (vs. expressive beauty) increased food choice rates, carrying higher aesthetic value. High aesthetic value led to greater decision drift rates (v) and lower N400 amplitudes. Aesthetics moderated food reward value: high aesthetic value enhanced caloric reward value and increased food choice rates, while low aesthetic value caused greater discounting of caloric reward value and decreased choice rates. However, caloric reward value showed higher salience than aesthetics, with earlier cognitive-neural processing of caloric information (240-320 ms). Finally, synergistic and competitive effects between caloric and aesthetic values occurred during decision evidence accumulation, influencing drift rate (v) and decision-related neural signal strength (CPP).

4.1 Computational Basis and Intrinsic Mechanisms of Aesthetic Value

The current study demonstrates that classical beauty (vs. expressive beauty) in food plating led to greater food choice preference, indicating that classical beauty carries higher aesthetic value for food presentation design. Model parameter analysis showed larger drift rates for classical than expressive beauty. Generally, drift rate represents the average evidence accumulated per unit time, serving as an index of task difficulty or individual information processing capacity (Forstmann et al., 2016). Thus, results indicate faster decision evidence accumulation for classical (vs. expressive) beauty designs, meaning participants more easily extracted and processed food value information from classical visual presentations. This parameter result corresponds to the ERP pattern for N400, which showed lower N400 amplitudes for classical beauty, indicating more fluent meaning processing of classically plated foods, while expressive beauty elicited larger semantic violation effects and greater difficulty in computing and processing value information of expressively plated foods. Previous research suggests that aesthetic value assessment is rooted in whether objects can satisfy homeostatic needs, with more useful aesthetic organizational forms implying higher aesthetic value (Brown et al., 2011). In nature, classical design features (i.e., order, symmetry, balance, and pattern repetition) often serve as important indicators of genetic quality, representing physical beauty, developmental stability, and genetic fitness (Thornhill & Møller, 1997). Moreover, food sensory marketing research confirms that classical beauty relates to functional values like food safety, health, and nutrition (Hagen, 2021; Liu et al., 2023). Classical beauty can improve food quality evaluation and satisfy diet-related homeostatic needs by signaling food source safety, thereby acquiring higher aesthetic value. Conversely, expressive beauty as an artificial aesthetic, with art, complexity, and novelty as design principles, primarily gains reward value by satisfying social needs (e.g., self-expression, relationship building) (Brown et al., 2011). Since this study focused on rapid choices of familiar daily meals in non-social eating contexts, expressive beauty may have lower aesthetic value due to its inability to satisfy basic food needs. In summary, the study indicates that food aesthetic value depends on whether the visual organizational form can convey information relevant to dietary need satisfaction.

Furthermore, evolutionary pressures have shaped the brain' s ability to rapidly process survival-advantage-relevant information, with brain networks processing natural scene image information more fluently (Grzywacz & Aleem, 2022). Indeed, rapidly identifying and processing food information in nature minimizes psychological costs of foraging, improves energy acquisition efficiency, and enhances survival adaptability (de Vries et al., 2020). As mentioned, high aesthetic value means the food' s visual organization can satisfy bodily balance needs and convey survival advantage information, leading to fluent neural information processing and decision evidence accumulation—i.e., lower N400 amplitudes and higher decision drift rates. This suggests participants could rapidly accumulate food meaning value signals with low cognitive resource investment. Conversely, low aesthetic value led to relatively higher N400 amplitudes, both because it carries less survival advantage information by failing to meet basic food function needs, and because the visual design' s complexity and novelty increased difficulty in extracting food meaning information, resulting in low conceptual processing fluency. In conclusion, this study demonstrates that aesthetic value computation is based on meaning processing and processing fluency.

4.2 Moderating Effect of Aesthetic Value on Caloric Value and Its Cognitive-Neural Process Basis

This study found that aesthetic value moderates the effect of calories on food choice rates. Specifically, for high-calorie foods, expressive beauty (vs. classical beauty) reduced choice rates; for low-calorie foods, classical beauty (vs. expressive beauty) increased choice rates. Thus, expressive beauty increased discounting of high-calorie food reward value, while classical beauty significantly enhanced value estimation of low-calorie foods. Moreover, posterior distribution probability tests of drift rates showed that for low-calorie foods, classical beauty (vs. expressive beauty) reduced the probability of accumulating "reject" decision evidence; for high-calorie foods, expressive beauty (vs. classical beauty) reduced the speed of accumulating "accept" decision evidence. This further validates the moderating role of aesthetic value in caloric reward value processing. However, although aesthetic value can moderate the impact of calories on food choice and decision processes, this study found that calories had significantly greater influence on dietary decisions than aesthetics, and neural processing of caloric information (240-320 ms) occurred earlier than aesthetic meaning integration (380-500 ms), indicating higher caloric value salience and greater detection sensitivity and value allocation weight for food calories. The cue utilization theory of quality perception (Olson & Jacoby, 1972) posits that people use various intrinsic and extrinsic information cues to evaluate product (here, food) quality. Intrinsic cues are inherent to the evaluation object, e.g., energy, calories, texture; extrinsic cues are elements related but not physically part of the object, e.g., labels, packaging, marketing information, plating design. Both can influence food value expectations and determine quality judgments. However, intrinsic cues are more diagnostic than extrinsic cues, with extrinsic cues moderating value judgments based on intrinsic cues (Chonpracha et al., 2020). Therefore, for food value evaluation, caloric information as an intrinsic cue is more important than aesthetic information as an extrinsic cue, resulting in higher decision weight and earlier meaning processing.

Model and EEG results provide cognitive and neurophysiological evidence for how dynamic interactions between aesthetic and caloric values unfold in decision processes. This study found that aesthetic moderation of caloric value occurred during decision information processing stages, influencing decision evidence accumulation speed (v) and decision-related brain signal strength (CPP). As mentioned, high-calorie (vs. low-calorie) and classical beauty (vs. expressive beauty) led to higher food choice rates, while low-calorie (vs. high-calorie) and expressive beauty (vs. classical beauty) led to higher food rejection rates. When caloric and aesthetic values aligned in direction (i.e., high-calorie foods with classical beauty plating or low-calorie foods with expressive beauty plating), compared to when they conflicted (i.e., high-calorie foods with expressive beauty plating or low-calorie foods with classical beauty plating), participants showed higher drift rates (v)—i.e., faster evidence accumulation—and larger decision neural signal accumulation (CPP)—i.e., lower decision difficulty. This pattern matches decision processes under approach-avoidance conflict. For example, Garcia-Guerrero et al. (2023) found through two mouse-tracking experiments that greater approach-avoidance conflict led to slower responses, larger trajectory deviations, and more pre-decision vacillation. Additionally, Choi et al. (2022) showed that decision conflict leads to more cautious strategies, sacrificing decision speed for choice safety. Therefore, in dietary decisions, when caloric and aesthetic values conflict (vs. align), participants experience higher approach-avoidance conflict, resulting in higher decision difficulty and slower evidence accumulation. In other words, both high and low caloric/aesthetic values can induce food approach and avoidance motivations; the synergy (alignment) and competition (conflict) between these value directions reflect approach-avoidance conflict intensity, causing dynamic changes in decision speed and difficulty.

4.4 Innovation and Limitations

This study is the first to verify, under equal aesthetic appeal, that different aesthetic characteristics of food plating have different aesthetic values, showing that classical beauty carries higher aesthetic value than expressive beauty for familiar daily food choices, expanding the boundaries of food presentation aesthetics research. Moreover, this study validates the potential of plating aesthetic value as a low-cost, effective healthy eating nudging strategy—moderating caloric reward value to promote healthier choices. Specifically, classical beauty can enhance food value evaluation, thereby increasing low-calorie food choice rates; conversely, expressive beauty can reduce caloric reward value, thereby inhibiting high-calorie food selection. This moderation does not sacrifice visual food aesthetics. Most importantly, this study, through multimodal data combining computational modeling and EEG, is the first to explore aesthetic value computation mechanisms, showing that fluent information processing and meaning integration are the intrinsic basis of aesthetic value assessment. Previous research suggests evolution shaped humans' efficient food search abilities for energy acquisition (de Vries et al., 2020); this study further indicates that visual organizational forms facilitating this food search ability may be the intrinsic prerequisite for preference formation. Future research could explore whether cross-modal information affecting food value processing efficiency or fluency can also modulate food choice preferences, thereby facilitating healthy eating choices. Additionally, this study is the first to examine the mechanism of aesthetic value' s effect on dietary decision processes, showing that aesthetic value moderation occurs during decision information processing stages, affecting decision value computation speed and difficulty. Based on this, this study provides a comprehensive understanding of aesthetic value' s impact on both outcomes and processes of healthy dietary decisions.

This study has several limitations. First, due to practical constraints, no incentive-compatible decision strategy was implemented, which may affect food choice accuracy to some extent. Second, because of difficulty in manipulating aesthetic characteristics, food images were sourced from online rather than standardized databases, lacking actual caloric value measurements. High- and low-calorie groupings were based on subjective ratings from pre-experiment participants; future research should verify the robustness of these conclusions using actual caloric groupings. Third, limited by available experimental materials, the trial count was relatively small. While this does not affect the main findings, it may not fully reveal potential effects of aesthetic value on food choice; future studies should expand material quantity for deeper analysis. Finally, the study did not achieve gender balance, which may affect conclusions to some extent, especially considering gender differences in caloric effects on food choice (Heiman & Lowengart, 2014). Caution is needed when generalizing these conclusions to broader consumer populations.

Conclusion

1. In dietary decisions, classical beauty (vs. expressive beauty) carries relatively higher aesthetic value. The direct basis for aesthetic value computation lies in whether visual organizational forms can satisfy individual dietary needs, with intrinsic cognitive-neural basis in meaning processing fluency.
2. Aesthetic value can moderate caloric reward value. High aesthetic value enhances caloric reward value, while low aesthetic value increases discounting of caloric reward value. Caloric value shows higher salience than aesthetic value, with greater information detection sensitivity and decision value allocation weight.
3. Synergistic and competitive effects between caloric and aesthetic values occur during decision evidence accumulation, reflecting motivational conflict intensity and affecting both decision speed (v) and decision difficulty (CPP).

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Appendix: Pre-experiment Methods and Results

Pre-experiment Methods

The pre-experiment recruited 30 participants (10 males, 20 females) with mean age = 21.27 ± 2.34, mean BMI = 21.30 ± 3.21, and mean hunger level = 3.83 ± 0.69. Independent samples t-tests showed no significant differences between pre-experiment participant characteristics (age, BMI, hunger) and those of final valid participants, all ts > 0.19, ps > 0.16. Pre-experiment data were collected online via questionnaire (Qualtrics) comprising two evaluation parts. First, participants rated 106 food images (53 foods × 2 plating styles) in random order on four items. Subjective caloric rating used the single item “How would you rate this food’ s subjective calories? 1 = very low, 7 = very high.” Food plating overall aesthetics, classical aesthetics, and expressive aesthetics ratings were adapted from Hagen et al. (2022) and Lavie and Tractinsky’ s (2004) definitions. Specifically, overall aesthetics used “Do you think this food plating is beautiful?” , classical aesthetics used “Do you think this food plating looks symmetrical, proportionally balanced, and orderly?” , and expressive aesthetics used “Do you think this food plating looks novel, complex, and creative?” on 7-point Likert scales. In the second part, both plating versions of the same food were presented simultaneously, and participants rated “Do you think the foods in these two images are the same food?” on a single 7-point Likert scale (1 = strongly disagree; 4 = neither agree nor disagree; 7 = strongly agree).

Manipulation Check Results

Table 1 Aesthetic dimension manipulation check

Comparison	95% Confidence Interval	Cohen’ s d
Lower	Upper	

Table 2 Food calorie manipulation check

Comparison	95% Confidence Interval	Cohen’ s d
Lower	Upper	

Table 3 Manipulation check for identifying same food across different plating styles

Comparison	95% Confidence Interval	Cohen’ s d
Lower	Upper	

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

Source: ChinaXiv —Machine translation. Verify with original.