A Bayesian Integration Framework for Brand Value Decision-Making and Its Neural Basis

Authors: Rui Ding, Wang Yingying, Luan Mengkai, Chenglin Zhou, Chenglin Zhou

Date: 2026-03-09T11:56:59+00:00

Abstract

Brand value decision-making requires the integration of long-term brand priors with immediate design evidence of the product. From the perspective of Bayesian inference, this review proposes an integrated framework of "Brand Prior—Design Evidence—Value Integration" and outlines its potential neural correspondence mechanisms. Existing research indicates that brand priors may be jointly encoded by the abstract cognitive structures of the medial prefrontal cortex (mPFC) and the mPFC–nucleus accumbens (NAcc) reward pathway. Design evidence undergoes aesthetic and conceptual processing through regions such as the orbitofrontal cortex (OFC), anterior cingulate cortex (ACC), parieto-occipital areas, and the posterior middle temporal gyrus (pMTG). Meanwhile, the ventromedial prefrontal cortex (vmPFC) is responsible for integrating different value cues and representing certainty, while the dorsolateral prefrontal cortex (DLPFC) modulates integration weights during information conflict. These neural processes functionally map onto the prior, likelihood, and posterior structures of the Bayesian framework, providing a new perspective for understanding the computational mechanisms of brand value judgment. Finally, this paper discusses future research directions in quantitative modeling, causal neural validation, and the dynamic learning mechanisms of brand preference.

Full Text

Preamble

A Bayesian Integration Framework for Brand Value Decision-Making and Its Neural Basis

Rui Ding[1], Yingying Wang[1], Mengkai Luan[1], Chenglin Zhou[1**] ([1]School of Psychology, Shanghai University of Sport, Shanghai, 200438)

Brand value decision-making requires the integration of long-term brand priors with immediate product design evidence. From the perspective of Bayesian inference, this review proposes a holistic "Brand Prior–Design Evidence–Value Integration" framework and delineates its underlying neural mechanisms. Existing research suggests that brand priors may be jointly encoded by abstract cognitive structures in the medial prefrontal cortex (mPFC) and the mPFC–nucleus accumbens (NAcc) reward pathway. Design evidence undergoes aesthetic and conceptual processing through the orbitofrontal cortex (OFC), anterior cingulate cortex (ACC), parieto-occipital regions, and the posterior middle temporal gyrus (pMTG). Furthermore, the ventromedial prefrontal cortex (vmPFC) is responsible for integrating diverse value cues and representing certainty, while the dorsolateral prefrontal cortex (DLPFC) modulates integration weights during information conflict. These neural processes functionally map onto the prior, likelihood, and posterior structures of the Bayesian framework, providing a new perspective for understanding the computational mechanisms of brand value judgment. Finally, this paper discusses future research directions concerning quantitative modeling, causal neuroscientific validation, and the dynamic learning mechanisms of brand preference.

Keywords: Brand value decision-making; Bayesian inference; Prior–evidence integration; Neural basis

CLC Number: B849

Funding: General Program of the National Natural Science Foundation of China (32371129).

Corresponding Author: Chenglin Zhou, Professor and Doctoral Supervisor, Shanghai University of Sport. E-mail: chenglin_{600}@126.com.

A Bayesian Integration Framework for Brand Value Decision-Making and Its Neural Basis DING Rui1, WANG Yingying1, LUAN Mengkai1, ZHOU Chenglin1 (1. School of Psychology, Shanghai University of Sport, Shanghai 200438, China)

Abstract

Brand value decision-making requires integrating long-term brand priors with the product's immediate design evidence. From a Bayesian inference perspective, this review proposes an overall framework of "brand priors—design evidence—value integration" and summarizes its potential neural correspondences.

Existing studies suggest that brand priors may be jointly encoded by the abstract cognitive structure of the mPFC and the mPFC–NAcc reward pathway; design evidence is processed through regions such as the OFC, ACC, occipito-parietal areas, and pMTG to support aesthetic and conceptual processing; the vmPFC integrates value signals from different sources and represents certainty, while the DLPFC adjusts integration weights when information conflicts occur. These neural processes functionally map onto the prior, likelihood, and posterior

components of the Bayesian framework, offering a new perspective for understanding the computational mechanisms of brand value judgment. The review concludes by discussing future research directions, including quantitative modeling, causal neural validation, and dynamic learning mechanisms underlying brand preference.

Keywords: brand value decision-making; Bayesian inference; prior–evidence integration; neural basis

Value-based decision-making is a fundamental pillar of the human cognitive system, spanning a wide range of behavioral contexts from daily dietary choices to complex financial investments [?]. Such decisions are rarely simple reactions to a single piece of information; rather, they are built upon the synthesis of multi-source information. Specifically, individuals typically need to integrate two key types of information: first, prior beliefs formed through the accumulation of long-term experience, which reflect an individual' s stable preferences, knowledge, and expectations; and second, immediate sensory evidence from the current environment, which consists of directly accessible external cues such as product features and visual stimuli. Understanding how the brain effectively integrates multi-source information from past experience and current perception is a critical issue in the study of value-based decision-making.

In modern consumer contexts, brand choice constitutes a representative decision-making scenario for studying the integration of value information. When consumers encounter products from familiar brands, their decisions often rely on two types of information simultaneously. On one hand, there are prior beliefs composed of long-term accumulated trust, expectations, and evaluations of the brand; on the other hand, there is sensory evidence provided by current stimuli, such as product design, color schemes, or texture. When these two types of information are congruent, value judgments are typically rapid and stable. However, when the brand image and product design are mismatched, the brain must coordinate and integrate these two sources of information under conditions of uncertainty to form a final value judgment and select the corresponding behavior. From this perspective, a brand is not merely an abstract emotional label or cultural symbol, but can be understood as a structured cognitive prior that guides perception and judgment. It provides a stable frame of reference for individuals to interpret subsequent product features and external cues, enabling consumers to form relatively coherent value judgments even when faced with complex or inconsistent information. Consequently, brand decision-making scenarios clearly illustrate the interaction between prior beliefs and immediate sensory information, providing an important foundation for further exploring the information integration process in value judgment.

In more fundamental research on perceptual decision-making, substantial evidence suggests that the brain tends to dynamically adjust when integrating information from different sources based on their reliability—that is, assigning higher weight to more credible inputs to achieve more stable judgments [?, ?]. This phenomenon reflects a universal principle of information integration in complex environments and has received extensive theoretical and empirical support at the neural level [?, ?]. However, unlike multisensory integration where reliability is determined by physical properties, the reliability of high-level value judgments typically stems from individual experience, preferences, or long-standing cognitive structures. For instance, in brand-related decisions, the "reliability" of prior beliefs reflects subjective certainty, while the effectiveness of current product cues depends on the specific context [?, ?]. Although existing studies have separately examined the influence of brand preference [?, ?] and product features [?] on value judgment, there remains a lack of an integrated theoretical framework regarding how these two are synthesized and what information-processing principles this integration follows. Furthermore, the neural basis of value judgment has been explored in several directions.

Existing research indicates that regions such as the ventromedial prefrontal cortex (vmPFC), anterior cingulate cortex (ACC), and nucleus accumbens (NAcc) are closely associated with subjective value computation, outcome anticipation, and reward processing [?, ?].

However, much of this work treats brand information or product features as independent variables. There is still a lack of a unified theoretical perspective on how prior beliefs and current cues are respectively represented and updated in the brain, and how they are ultimately integrated during value judgment.

In summary, while existing research has revealed the respective influences of brand priors and product design features on value judgment and identified key brain regions involved in value computation, a systematic explanation is still missing regarding how these two types of information interact cognitively, how they are represented and updated in the brain, and whether their integration follows consistent information-processing principles. To address this gap, this paper proposes a brand–design integration framework based on Bayesian inference to characterize the dynamic weighting process of prior beliefs and sensory evidence in value judgment and to explore its potential neural basis. This framework aims to provide a more structured theoretical perspective for understanding brand-related value decisions and to offer systematically testable hypotheses for future research.

2 品牌与设计信息整合的贝叶斯框架

Although brand priors and the immediate information provided by product design jointly influence value judgments at the behavioral level, explaining how these two elements form a unified value representation requires an information integration perspective. During the value assessment process, individuals rely on long-term accumulated brand cognition while also updating their judgments of the target based on currently presented product features. Together, these constitute the critical sources of information in value judgment. Under this framework, brand value judgment can be viewed as an inference process involving the integration of multi-source information. Its core lies in how to form a more stable and consistent estimate of overall value based on the relative certainty of different information sources.

At this level, Bayesian inference provides a clear normative framework. The Bayesian perspective emphasizes that the weights in information integration are not fixed but are determined by the relative uncertainty of different information sources; in other words, more reliable signals should exert a higher degree of influence.

Conceptualizing brand-design integration as a Bayesian information updating process allows us to mathematically and precisely characterize the relationship between the prior, evidence, and posterior. This approach enables us to understand the fundamental principles of information weighting in value judgment (Knill & Pouget, 2004; Ma & Jazayeri, 2014).

Under the Bayesian framework, information integration can be characterized by the following general form: θ represents the latent feature or state to be estimated, while *data* represents the observable evidence. In the expression $p(\theta|data) \propto p(data|\theta) * p(\theta)$, $p(\theta)$ is the prior distribution, characterizing the individual' s beliefs about θ formed based on past experience and long-term knowledge before encountering the current evidence; $p(data|\theta)$ is the likelihood distribution, describing the probability of observing the data under different latent states of θ; and $p(\theta|data)$ is the posterior distribution, reflecting the individual' s updated estimate of θ after combining the prior belief with the current evidence. Through this update rule, Bayesian theory formally unifies "prior experience," "immediate evidence," and "integrated judgment" within a single probabilistic inference framework.

Applying this general form to the context of brand-design integration allows for a more specific characterization of the information structure in brand value judgment. Let V represent the "overall value" of the product, *brand* represent prior information related to the brand, and *design* represent currently perceivable design cues. The updating process can then be written as:

$p(V|brand, design) \propto p(design|V) * p(V|brand)$ In this expression, $p(V|brand)$ can be regarded as the prior distribution of the overall value, reflecting the long-term value beliefs formed by the individual based on brand reputation, historical experience, and accumulated impressions before observing a specific product. $p(design|V)$ corresponds to the likelihood distribution, used to describe the likelihood of the current design features appearing given a latent value V. The resulting posterior distribution $p(V|brand, design)$ represents the updated judgment of product value after integrating the brand prior and design evidence. Through this formulation, brand-design integration is naturally embedded into a unified "prior-evidence-posterior" inference architecture, laying a formalized foundation for the subsequent construction of specific parametric models. After clarifying that brand-design integration can be viewed as Bayesian inference of the latent value V, the next step is to provide a parametric form that is quantifiable and facilitates the connection between theoretical analysis and empirical testing. Among many possible distributional assumptions, the Gaussian-Gaussian conjugate structure, where both the prior and likelihood follow normal distributions, offers significant advantages. First, this structure allows for a closed-form analytical posterior distribution, enabling the influence of different information sources on the final value estimate to be precisely expressed as a functional relationship between parameters (Griffiths, Kemp, & Tenenbaum, 2008; Lebreton et al., 2015). Second, the Gaussian distribution possesses high interpretability in psychological research, naturally characterizing the central tendency of subjective value ratings, the inherent noise and uncertainty in assessment, and the relative reliability of different information sources (Körding & Wolpert, 2006). Therefore, the Gaussian-Gaussian conjugate model is not only mathematically transparent but also provides an appropriate psychological basis for understanding the structure of uncertainty in value judgment.

Under this Gaussian framework, it can be assumed that a consumer' s long-term belief regarding brand value follows a normal distribution: $V|brand \sim N(\mu_{brand}, \sigma^2_{brand})$. Here, μ_{brand} represents the average value evaluation of the brand from past experience, while σ^2_{brand} reflects the subjective uncertainty of that judgment. Similarly, the design features of the current product can be viewed as a noisy observation of the same latent value, which can be written as a conditional distribution: $V_{design}|V \sim N(V, \sigma^2_{design})$. Here, V_{design} is the subjective value estimate induced by design cues, and its variance σ^2_{design} describes the degree of noise or reliability of the design cues themselves: when the design style is clear and cues are consistent, σ^2_{design} is small; when the design is ambiguous or information is insufficient, this variance increases. Under this Gaussian-Gaussian conjugacy, the posterior distribution $p(V|brand, design)$ remains normal, $N(\mu_{posterior}, \sigma^2_{posterior})$. Its posterior variance is determined by the sum of the prior precision and likelihood precision: $1/\sigma^2_{posterior} = 1/\sigma^2_{brand} + 1/\sigma^2_{design}$. The posterior mean is the precision-weighted average of the two types of information: $\mu_{posterior} = \frac{1/\sigma^2_{brand}}{1/\sigma^2_{brand}+1/\sigma^2_{design}}\mu_{brand} + \frac{1/\sigma^2_{design}}{1/\sigma^2_{brand}+1/\sigma^2_{design}}V_{design}$. This update form reveals the core mechanism of value integration. First, the posterior mean $\mu_{posterior}$ represents the integrated subjective value estimate, with weights determined by the relative precision of the brand prior and design evidence: when the brand prior variance σ^2_{brand} is small, representing a highly stable brand belief, the brand signal exerts higher influence during integration, and the posterior mean is closer to the brand evaluation μ_{brand}. Conversely, when the design cue variance σ^2_{design} is small, implying that the current visual and product attributes are more clear and credible, the integration result will lean toward the value estimate brought by the design. The posterior variance $\sigma^2_{posterior}$ directly characterizes the level of uncertainty after integration. Since posterior uncertainty is always smaller than the uncertainty of any single information source (i.e., $\sigma^2_{posterior} < \min(\sigma^2_{brand}, \sigma^2_{design})$), this means that the complementary information provided by the brand and design increases confidence in the value judgment after integration, making the posterior distribution more concentrated. If both types of information are highly precise (both variances are small), the posterior variance is further reduced, indicating that the individual has higher subjective certainty in the value judgment. Conversely, if the brand prior or design cues are vague (large variances), the posterior variance increases accordingly, reflecting that significant uncertainty remains in the integrated judgment.

This structural relationship not only clarifies the conditions under which value judgments rely more on brand priors or design evidence but also reveals how the integration of multi-source information shapes an individual' s subjective certainty. When the brand prior has high precision, the integrated posterior estimate leans toward the brand direction and is accompanied by lower uncertainty; conversely, clear and reliable design cues pull the posterior toward the current evidence. Consequently, "brand loyalty" is no longer understood merely as an emotional preference or habitual choice; rather, it can be formulated at a computational level as a structural advantage in prior precision—that is, brand information dominates the contribution weight of value inference in a Bayesian sense. This analysis characterizes the fundamental mechanism by which brand and design information influence value integration through the structure of uncertainty within a normative Bayesian framework.

Building upon the principles of information integration revealed by the normative Bayesian framework, this study further adopts the normal distribution assumption at the parametric modeling level—specifically, assuming that the brand prior and the value estimate induced by design cues follow normal distributions. It should be emphasized that this assumption is not intended to assert that brand evaluations in real-world decision-making scenarios are strictly normal in a statistical sense. On the contrary, in actual consumer decision-making, brand attitudes may exhibit significant skewness due to long-term usage experience, emotional attachment, or identity identification; for instance, highly concentrated and stable value evaluations may form in contexts of extreme brand loyalty. Simultaneously, they may exhibit a multi-modal structure due to differences between various sub-series or product lines within a brand, where consumers form coexisting or even conflicting value representations for the same brand (Chaudhuri & Holbrook, 2001; Thomson, MacInnis, & Park, 2005; Aaker & Keller, 1990). In cases of conflict, brand value judgment is no longer just a matter of weighted integration of multiple information sources; it may also trigger the monitoring and evaluation of inconsistencies between different value representations. When there is a significant deviation between the means of the brand prior and the design cues, an individual may still experience subjective feelings of conflict, such as hesitation, confusion, or decision-making delay, even if normative Bayesian updating statistically increases posterior certainty. In such scenarios, the value judgment process may no longer follow a single Bayesian integration strategy but instead trigger an assessment of the applicability of the current generative model. When the deviation between the prior and evidence exceeds an acceptable range, the decision system may delay selection by introducing conflict signals or increasing decision thresholds, thereby gaining time for further information sampling, situational reappraisal, or strategic adjustment. In this sense, strong prior-evidence conflict does not imply that Bayesian inference itself has failed, but rather likely reflects the value system' s monitoring process regarding the reliability of the current generative model.

Despite the potential for skewness, multi-modality, or conflict in real-world decision-making, introducing the normal distribution still offers clear modeling advantages for the continuous subjective assessment task of brand-design value judgment. First, a large body of research in perception and decision-making indicates that subjective value assessments and their inherent noise can often be effectively approximated as unimodal continuous distributions at the individual level, allowing uncertainty to be intuitively characterized in the form of variance (Knill & Pouget, 2004; Körding & Wolpert, 2006). Second, under the Gaussian assumption, Bayesian updating of the prior and likelihood yields a closed-form analytical solution, allowing the roles of different information sources in integration to be explicitly expressed as a precision-weighted relationship. In this sense, the linear integration form characterized by Equation (7) is not an empirical simplification but a normative result for achieving an optimal posterior estimate given certain uncertainty conditions; this form has also been widely used to characterize the relationship between value judgment and uncertainty (Lebreton et al., 2015).

It should be emphasized that the Bayesian integration framework proposed in this paper does not theoretically depend on the normal distribution assumption itself. When brand evaluations exhibit multi-modal characteristics, coexisting value representations corresponding to different brand sub-series or value prototypes can be characterized by introducing Gaussian Mixture Models. In scenarios with significant skewness, such as extreme brand loyalty, non-conjugate Bayesian methods can be employed to model asymmetric or heavy-tailed distribution forms (Gelman et al., 2013). In these extended cases, value integration is no longer expressed as simple linear weighting but is achieved through the weighted updating of different component distributions. Thus, the Gaussian-Gaussian conjugate model used in this paper can be viewed as a first-order normative approximation of the brand-design value integration process. Its core purpose is to reveal the key psychological variables and their interrelationships that influence value judgment, providing a unified theoretical starting point for subsequent model extensions and empirical tests targeting complex distribution forms (Griffiths et al., 2008).

Formalizing brand-design integration as a Bayesian optimal inference process holds clear theoretical value. This framework does not assume that consumers necessarily achieve optimality in actual decision-making; rather, it provides a testable normative benchmark to clarify the ideal weighting of priors and evidence under different uncertainty conditions. Based on this benchmark, researchers can systematically characterize the deviation patterns of actual behavior compared to optimal integration, thereby analyzing the patterns of change in information dependence across different individuals and contexts. Furthermore, by unifying the brand prior and design evidence within a probabilistic updating mechanism, this framework identifies the key computational variables involved in the value estimation process and provides a clear conceptual anchor for subsequent explorations of their representation in the brain.

3 价值决策的神经基础研究

Neural Mechanisms of Value Integration

A substantial body of research in decision neuroscience demonstrates that value judgment is not the responsibility of a single brain region, but is instead achieved through the coordination of multiple neural networks [FIGURE:1]. By applying the Bayesian integration framework proposed previously, existing neuroimaging evidence can be functionally mapped onto three key components: "prior beliefs," "instantaneous evidence," and "value integration." This mapping provides an insightful roadmap for understanding the underlying neural foundations of brand-design integration.

[FIGURE:1] Schematic diagram of key brain regions involved in processing brand and design-related value information.

1. Neural Representation of Prior Beliefs (Brand Value)

In the context of consumer choice, brand information often serves as a "prior" that shapes expectations before a product is even fully evaluated. Research indicates that the ventromedial prefrontal cortex (vmPFC) and the striatum play critical roles in encoding the subjective value associated with brand equity. When consumers encounter familiar or preferred brands, these regions exhibit increased activation, reflecting the retrieval of stored affective associations and prestige. Furthermore, the hippocampus is often recruited to process the declarative memories and episodic associations linked to a brand' s history, providing the contextual "prior" that influences subsequent perception.

2. Processing of Instantaneous Evidence (Design Features)

The "instantaneous evidence" in this framework corresponds to the visual and aesthetic properties of the product' s design. This processing primarily involves the sensory and evaluative circuits of the brain. The occipitotemporal cortex and the fusiform gyrus are responsible for the initial structural encoding of product form and aesthetics. Subsequently, the insula and the lateral orbitofrontal cortex (lOFC) are often engaged to evaluate the sensory appeal and the "reward value" of the design' s visual features. These regions provide the immediate, bottom-up data that must be weighed against the brand' s top-down influence.

3. Value Integration and Decision Output

The final stage of the Bayesian framework—value integration—requires the synthesis of prior brand expectations and current design evidence into a unified "posterior" value signal. The vmPFC is widely regarded as the primary hub for this integration, as it receives inputs from both the affective centers (striatum, amygdala) and the sensory evaluative centers. Studies using functional connectivity analysis have shown that the strength of the interaction between the vmPFC and the posterior cingulate cortex (PCC) predicts the consistency of consumer choices

3.1 内侧前额叶–纹状体回路在品牌先验信念中的核心作用

Previous research has demonstrated that brand preferences formed through long-term experience can alter the baseline value coding of the reward system. The classic "Coke Challenge" study showed that the mere presentation of a brand name as a prior cue can enhance responses in the ventral striatum, particularly the nucleus accumbens (NAcc), and increase subjective value ratings [**?**, **?**]. Subsequent studies have also found that individuals with high brand loyalty exhibit stronger functional connectivity between the medial prefrontal cortex (mPFC) and the NAcc when viewing preferred brands; the strength of this connectivity can predict their willingness to pay a premium [**?**, **?**]. These findings suggest that long-term brand-related experiences are systematically associated at a functional level with reward-related activity patterns in the prefrontal-striatal pathway, thereby causing the value assessment process to exhibit a relatively stable bias at its initial stage.

At the same time, recent research suggests that the neural implementation of brand priors may not be limited to reward pathways but may also involve more abstract knowledge structures supported by the mPFC. According to the theory of "cognitive maps," a critical function of the mPFC-hippocampal system is to represent abstract relationships within experience in a structured manner, enabling individuals to generalize, transfer, and make inferences across different contexts [**?**, **?**, **?**]. A substantial body of research has also shown that this system can encode relational structures within abstract task spaces and social conceptual spaces [**?**, **?**, **?**, **?**]. Applying this perspective to a branding context, a "brand" is not merely a single-point value impression; rather, it is more likely organized in a relational manner as a knowledge background that can be transferred across products and scenarios. This includes relatively stable associations between the brand and its category positioning, typical attributes, usage scenarios, and social significance, which collectively provide a structured prior reference for subsequent value judgments.

Within this framework, μ_{pr} can be understood as the central tendency of a consumer' s overall value inclination toward a brand, while σ_{pr} characterizes the degree of uncertainty of this inclination at either the intra-individual or group level. Together, they summarize the overall bias and the relative influence of the brand prior in value judgments. Regarding the neural signatures of "uncertainty," population coding research suggests that the more stable a belief is, the more consistent the associated neural activity tends to be during repeated presentations; conversely, the more unstable a belief, the greater the fluctuations across trials [?, ?, ?]. In the context of brand value judgments, when the same brand is presented repeatedly, a more stable brand belief may manifest as more consistent value-related activity patterns, whereas an unstable brand belief may be accompanied by greater trial-to-trial variability.

In summary, existing research indicates, on one hand, that brand cues can form systematic associations with reward-related responses through the prefrontal-striatal pathway. On the other hand, it suggests that the mPFC-hippocampal system may support the structured organization of brand experience, allowing it to provide a transferable prior reference for value judgments across different contexts. From a functional perspective, these neural processing characteristics are conceptually consistent with the description of the role of prior information in value inference within a Bayesian framework.

3.2 眶额皮层及相关脑区对设计线索的价值加工作用

Unlike the long-term experience embodied by brand priors, product design cues represent an immediately perceptible source of information that typically influences subjective value assessment at an earlier stage. Numerous neuroimaging studies on aesthetic processing and product perception have demonstrated that design features with high aesthetic value or high perceived fluency can activate the orbitofrontal cortex (OFC), the anterior cingulate cortex (ACC), and the parieto-occipital regions associated with visual fluency processing [?, ?, ?, ?]. The activation intensity in these regions is not only closely correlated with subjective aesthetic ratings but also serves as a predictor for product preference and purchase intention, reflecting the immediate impact of design cues on value formation.

Furthermore, the role of design cues in value judgment is not limited to perceptual-level aesthetic processing; it also involves the conceptual and semantic integration of design attributes. The posterior middle temporal gyrus (pMTG) is situated at a key node of the semantic network and participates in processes such as the identification of object attributes, functional significance, and conceptual combination. When a product' s appearance and functional features are more interpretable and align more closely with existing conceptual structures, the semantic system dominated by this region provides stable meaningful support for value assessment, thereby indirectly enhancing subjective preference and judgment certainty [?, ?, ?, ?, ?]. Taken together, these neural responses are primarily driven by currently available design features, underscoring the critical role of immediate evidence in the process of value evaluation.

3.3 腹内侧前额叶的价值整合机制与背外侧前额叶的权重调控

The ventromedial prefrontal cortex (vmPFC) is widely regarded as a critical region for integrating diverse value cues, and its neural activity is typically closely associated with final subjective value judgments [?, ?]. Whether value information originates from preferences formed through long-term experience (such as brand impressions), perceptual attributes in the current context (such as product design features), or involves multiple evaluative dimensions (such as quality, price, and risk), these inputs tend to converge in the vmPFC to form a relatively unified value-related representation [?, ?, ?]. Building on this foundation, an increasing number of studies have found that neural activity in the vmPFC not only varies with the magnitude of value judgments but is also systematically linked to an individual' s subjective confidence or judgment certainty during the decision-making process. For instance, the activation intensity or multivariate activity patterns of the vmPFC can change according to the individual' s level of certainty regarding the choice outcome and can predict subjective confidence ratings across various decision tasks [?, ?, ?].

Relevant domestic reviews have also pointed out that the mPFC/vmPFC plays an important role in both value judgment and decision confidence processing, suggesting that its function may transcend the encoding of a single value magnitude [?, ?].

In the field of computational neuroscience, different theoretical explanations persist regarding the hierarchy of information represented by the vmPFC during value inference. On one hand, a classic view posits that the vmPFC primarily encodes the expected value or dominant value signal after integrating multi-source value cues; its activity patterns are highly correlated with subjective preferences and choice tendencies, leading it to be viewed as the core output node of value computation [?, ?, ?]. On the other hand, as research has gradually introduced paradigms involving confidence judgments, risky decision-making, and uncertainty regulation, results suggest that the experience of certainty accompanying the value judgment process is not entirely independent of the value representation itself.

Some studies have found that neural activity in the vmPFC correlates with both value magnitude and confidence intensity in certain tasks, suggesting its involvement in a more comprehensive value assessment process rather than merely reflecting a single expected value signal [?, ?, ?, ?]. However, whether such confidence-related neural signals can be directly equated to posterior uncertainty in a Bayesian sense remains to be clarified by further research.

Furthermore, regarding the neural substrates of "uncertainty" or "confidence" information in value judgments, current research tends to interpret these as distributed, process-oriented neural features rather than information independently encoded by the average activation levels of a single brain region. Related studies propose that uncertainty-related information may manifest as variability in neural population activity across temporal or spatial dimensions—for example, changes in response consistency across trials, the enhancement or weakening of representational stability, or systematic adjustments in network coupling patterns across brain regions [?, ?, ?]. This perspective provides important insights into the potential neural representations of uncertainty. However, in high-level value-based decision tasks, particularly within the value integration system centered on the vmPFC, the correspondence between neural activity variability and Bayesian posterior uncertainty still requires more direct empirical evidence. Existing neuroimaging studies more commonly interpret the vmPFC as a vital output node for integrated value signals, while uncertainty-related processes may manifest in a more distributed manner through the coordination and state regulation of the prefrontal-value network. Future research could combine neural measurement methods with higher temporal resolution and computational modeling to characterize both value output and uncertainty changes within the same framework, thereby more clearly testing the relationship between the two.

In contexts where conflict, competition, or trade-offs exist between multi-source value information, the value integration process is not a simple passive summation but often relies on the dynamic regulation of the frontal control system. A substantial body of research indicates that functional connectivity between brain regions undergoes systematic adjustments during decision-making according to changes in task goals and attentional focus, reflecting the capacity for flexible control in value assessment [?, ?, ?, ?]. In this process, the dorsolateral prefrontal cortex (DLPFC) is thought to play a key role in regulating the relative influence of different value cues. Research has found that when individuals need to consciously down-weight certain attributes (such as price or immediate rewards) while strengthening others (such as healthiness or long-term benefits), the activity of the DLPFC and its functional connectivity with the vmPFC are significantly enhanced, accompanied by systematic shifts in final choice bias [?, ?].

The synergy between the DLPFC and vmPFC can be described as a goal-directed "weight gating" process. Specifically, control signals selectively enhance the processing of cues consistent with current goals and relatively inhibit goal-irrelevant cues, thereby altering the relative contribution of different information to the integrated value representation in the vmPFC. At the computational level, this process can be mapped to weight adjustments in Bayesian integration: the allocation of attention and selective reinforcement change the relative reliability of cues during the integration stage, which in turn affects their weights in the comprehensive value assessment. Thus, weight changes can be achieved through the selective modulation of information input by the control system, aligning with the DLPFC' s function in top-down selection and control [?, ?]. Existing neuroimaging studies provide more evidence regarding functional correlations related to "weight regulation," while direct testing of computational parameters such as prior precision and evidence precision, as well as their updating processes, still needs to be deepened. Based on this, this paper proposes a hierarchical perspective that distinguishes between value cue representation, weight-gating regulation, and value integration outcomes, providing an integrative explanatory framework for understanding value-based decision-making under multi-source information conditions.

In summary, existing research outlines a multi-level neural processing framework ranging from prior beliefs and immediate perceptions to integrated value judg-

Figure 2

Figure 1: Figure 2

ments. Long-term experience related to brands primarily shapes the baseline state of value assessment through the medial prefrontal-striatal pathway, while product design cues provide immediate value input regarding current external features via the orbitofrontal cortex and related perceptual-semantic networks. Building on this, the ventromedial prefrontal cortex integrates value information from different sources to form a relatively unified value representation, while the dorsolateral prefrontal cortex implements goal-directed regulation of the relative weights of different information sources in value computation through functional coupling with the vmPFC

. Although existing research has not yet directly tested the specific computational operations of reliability weighting within a Bayesian framework at the neural level, the processing patterns revealed by these studies show clear consistency with Bayesian information integration principles in terms of functional structure. Furthermore, this multi-source value integration network not only provides a neural basis for understanding individual-level value judgments but also offers a potential entry point for neural prediction research in consumer neuroscience—moving "from brain responses to behavior and market performance." Studies have shown that the aggregate neural responses of value-related brain regions, such as the vmPFC and striatum, can, under certain conditions, surpass individual self-report metrics in predicting real choice behavior and even market-level outcomes [**?**, **?**, **?**]. From this perspective, viewing the integration characteristics of brand priors and design evidence within the prefrontal-value network as stable neural representational inputs helps in understanding how individual value computations converge at the population level and ultimately manifest as systematic patterns of market behavior.

Figure 2: Schematic diagram of the neural processing and Bayesian integration framework for brand priors and design evidence.

4 小结与展望

Brand value decision-making is essentially a complex cognitive process that integrates long-term brand experience with immediate design cues. Using Bayesian inference as a normative analytical perspective, this review proposes a conceptual framework of "Brand Prior—Design Evidence—Value Integration" to characterize the functional roles and integrative relationships of different information sources in value judgment. Brand priors provide initial expectations formed based on past experiences, while product design features serve as immediate evidence to update these expectations; the final value judgment reflects the weighted integration of both. Under this framework, this paper systematically reviews neuroimaging evidence related to brand value judgment. Long-term brand-related experiences primarily rely on abstract cognitive structures supported by the medial prefrontal cortex (mPFC) and the mPFC–nucleus accumbens (NAcc) reward pathway. Immediate cues, such as product design, are processed through networks including the orbitofrontal cortex (OFC), anterior cingulate cortex (ACC), parieto-occipital regions, and the posterior middle temporal gyrus (pMTG) involved in semantic processing. The ventromedial prefrontal cortex (vmPFC), under the modulation of the dorsolateral prefrontal cortex (dlPFC), integrates value-related information from these diverse sources. Overall, these neural processing mechanisms correspond well at a functional level with the fundamental Bayesian concepts of "prior, evidence, and integration," providing neuroscientific support for understanding brand value judgment as a multi-source information integration process. From a practical standpoint, although this paper does not discuss specific marketing strategies, the framework offers a unified computational perspective for understanding how brand equity and product design interact across different market contexts. It emphasizes that long-term brand experience and immediate design cues are not simply additive; rather, they carry different weights during value integration based on information uncertainty and situational diagnosticity. This perspective helps explain various common marketing phenomena. For instance, in contexts involving mature brands or high brand loyalty, consumers often possess stable brand priors; thus, even if product design changes, its marginal impact on the final value judgment may be limited. Conversely, for new brand entries where brand awareness is unstable, or in brand extension scenarios, design cues acting as immediate evidence may play a more critical role in value integration. Consequently, within this unified value computation framework, brand equity and product design should not be viewed as independent factors, but rather as influences whose relative impact shifts systematically according to brand uncertainty and the decision-making context.

While the aforementioned discussion suggests that a Bayesian integration framework facilitates a unified computational understanding of how brand experience and design cues influence value judgment, several key issues remain to be addressed. First, although this review constructs a conceptual framework for brand value decision-making centered on Bayesian inference and proposes preliminary correspondences between brand priors, design evidence, and integration mechanisms, these mappings currently remain at the theoretical and conceptual level, lacking rigorous quantitative verification. Future research should explicitly model the mean and uncertainty of brand priors, the relative weights of design cues, and the characteristics of the resulting posterior distributions within experimental paradigms. Systematically testing whether these parameters can stably predict individual brand preferences, choice behavior, and their variability is essential to directly evaluate the explanatory and predictive potential of this framework. It should be noted that the Bayesian framework proposed here is primarily intended to characterize the computational roles of different information sources and their potential neural correlates, without introducing specific hypotheses regarding decision dynamics. Therefore, extending this framework into a generative model capable of producing behavioral metrics—such as reaction times, willingness-to-pay premiums, or choice probabilities—would typically require integration with additional mechanisms like evidence accumulation, decision boundaries, or noise structures. In such cases, the research focus would shift from information weighting to the dynamic modeling of the decision process, representing an important developmental stage for subsequent studies. Furthermore, this paper adopts the simplifying assumption that brand priors and design evidence approximately follow normal distributions. While this helps clarify the fundamental relationships in value integration, consumer brand evaluations in real-world scenarios may exhibit more complex statistical features, such as skewness or multimodality. Future research could incorporate more flexible distribution forms or non-linear integration mechanisms to more fully characterize the impact of complex brand cognitive structures on value judgment.

Second, at the neural level, although this review proposes potential brain region correspondences for brand priors, design evidence, and value integration based on existing literature, these associations currently remain at the level of "functional analogy" and correlational evidence, which is insufficient for definitive causal inference. Future research needs to employ more directional and interventional neural methods to test these inferences. For example, Dynamic Causal Modeling (DCM) could be used to analyze the direction of information flow between different brain regions to test whether priors truly modulate downstream value encoding in a top-down manner. Additionally, non-invasive brain stimulation techniques (such as TMS or tACS) could be applied to exert causal control over key brain regions to verify whether the reliability of different information sources is measurably represented at the network level, and whether value or confidence encoding in the vmPFC adjusts systematically with changes in uncertainty. Through these causal and dynamic research methods, future work can more clearly elucidate the specific computational roles played by core regions such as the mPFC, OFC, pMTG, vmPFC, and dlPFC in value inference, and verify whether they truly follow Bayesian principles of information weighting.

Third, brand value judgment in real-world contexts is not an isolated, one-time inference but a dynamic learning process embedded in the continuous updating of consumer experience. Consumers' beliefs about a brand are constantly adjusted through usage experience, social evaluation, marketing stimuli, or quality feedback, making brand value more akin to a dynamic posterior that evolves over time. To characterize this process, future research could integrate reinforcement learning models into the Bayesian framework proposed here, using prediction errors from each experience as update signals and employing the learning rate to describe the extent to which new evidence modifies existing brand beliefs. Furthermore, from a Bayesian perspective, the learning rate can be understood as the weighted update intensity of prediction errors; its magnitude is not a fixed constant but can adaptively adjust based on uncertainty and environmental stability. When the reliability of new evidence is low or the environment is relatively stable, the update magnitude tends to decrease to avoid being driven by random fluctuations. Conversely, when environmental changes are observed, negative feedback persists, or the deviation between prior predictions and actual outcomes increases systematically, the update magnitude may be adjusted upward, accompanied by a re-evaluation of existing strategies or belief structures. Combining the Bayesian characterization of uncertainty and change with the value-updating mechanisms of reinforcement learning will help systematically explain the formation, maintenance, and change of brand preferences over time, providing a computational foundation for building more ecologically valid brand decision models.

In summary, a framework centered on Bayesian inference provides a unified and mechanistic perspective for understanding brand value decision-making, enabling a systematic connection between brand priors, design evidence, and value integration across behavioral, computational, and neural levels. In the future, the further integration of quantitative models, causal neural methods, and dynamic learning mechanisms will help more deeply reveal how brand value is formed, updated, and adjusted in the brain, thereby deepening our understanding of the core psychological process of brand value decision-making.

Chen, J., Yuan, W. P., Feng, T. Y., & Li, H. (2010). Cognitive mechanisms and neural basis of decision confidence. *Advances in Psychological Science*, 18(04), 630–638.

Aaker, D. A., & Keller, K. L. (1990). Consumer evaluations of brand extensions. Journal of Marketing, 54(1), 27 − 41. https://doi.org/10.2307/1252171 Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. NeuroImage, 76, 412 − 427. https://doi.org/10.1016/j.neuroimage.2013.02.06 Behrens, T. E., Muller, T. H., Whittington, J. C. R., Mark, S., Baram, A. B., Stachenfeld, K.

L., & Kurth-Nelson, Z. (2018). What is a cognitive map? Organizing knowledge for flexible behavior. Neuron, 100(2), 490 − 509. https://doi.org/10.1016/j.neuron.2018.10.002 Berns, G. S., & Moore, S. E. (2012). A neural predictor of cultural popularity. Journal of Consumer Psychology, 22(1), 154 − 160. https://doi.org/10.1016/j.jcps.2011.05.001 Binder, J. R., Desai, R. H., Graves, W. W., & Conant, L. L. (2009). Where is the semantic system? A critical review and meta-analysis of 120 functional neuroimaging studies. Cerebral cortex, 19(12), 2767 − 2796. https://doi.org/10.1093/cercor/bhp055 Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. Journal of Marketing, 65(2), 81 − 93. https://doi.org/10.1509/jmkg.65.2.81.18255 Churchland, M. M., & Shenoy, K. V. (2007). Temporal complexity and heterogeneity of single-neuron activity in premotor and motor cortex. Journal of neurophysiology, 97(6), 4235 − 4257. https://doi.org/10.1152/jn.00095.2007 De Martino, B., Bobadilla-Suarez, S., Nouguchi, T., Sharot, T., & Love, B. C. (2017).

Social information is integrated into value and confidence judgments according to its reliability. Journal of Neuroscience, 37(25), 6066 − 6074. https://doi.org/10.1523/JNEUROSCI.3880-16.2017 De Martino, B., Fleming, S. M., Garrett, N., & Dolan, R. J. (2013). Confidence in value-based choice. Nature Neuroscience, 16(1), 105 − 110. https://doi.org/10.1038/nn.3279 Erdem, T., & Swait, J. (1998). Brand equity as a signaling phenomenon. Journal of Consumer Psychology, 7(2), 131 − 157.

Erdem, T., & Swait, J. (2001). Brand equity as a signaling. Journal of consumer Psychology, 7(2), 131 − 157.

Ernst, M. O., & Banks, M. S. (2002). Humans integrate visual and haptic information in a statistically optimal fashion. Nature, 415(6870), 429 − 433. https://doi.org/10.1038/415429a Fetsch, C. R., DeAngelis, G. C., & Angelaki, D. E. (2013). Bridging the gap between theories of sensory cue integration and the physiology of multisensory neurons.

Nature Reviews Neuroscience, 14(6), 429 − 442. https://doi.org/10.1038/nrn3503 Friston, K. J., Harrison, L., & Penny, W. (2003). Dynamic causal modelling. NeuroImage, 19(4), 1273 − 1302. https://doi.org/10.1016/S1053-8119(03)00202-7 Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013).

Bayesian Data Analysis (3rd eds.). CRC Press. Genevsky, A., & Knutson, B. (2015). Neural affective mechanisms predict market-level microlending. Psychological Science, 26(9), 1419 − 1427. https://doi.org/10.1177/0956797615588467 Gherman, S., & Philiastides, M. G. (2015). Neural representations of confidence emerge from the process of decision formation during perceptual choices. Neuroimage, 106, 134 − 143. https://doi.org/10.1016/j.neuroimage.2014.11.036 Griffiths, T. L., Kemp, C., & Tenenbaum, J. B. (2008). Bayesian models of cognition. The Cambridge Handbook of Computational Psychology (pp.59 − 100). London:

Cambridge University Press. Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. Science, 324(5927), 646 − 648. https://doi.org/10.1126/science.1168450 Hiser, J., & Koenigs, M. (2018). The multifaceted role of the ventromedial prefrontal cortex in emotion, decision making, social cognition, and psychopathology. Biological psychiatry, 83(8), 638 − 647. https://doi.org/10.1016/j.biopsych.2017.10.030 Kawabata, H., & Zeki, S. (2004). Neural correlates of beauty. Journal of Neurophysiology, 91(4), 1699 − 1705. https://doi.org/10.1152/jn.00696.2003 Kirk, U., Skov, M., Hulme, O., Christensen, M. S., & Zeki, S. (2009). Modulation of aesthetic value by semantic context: An fMRI study. NeuroImage, 44(3), 1125 − 1132. https://doi.org/10.1016/j.neuroimage.2008.10.009 Knill, D. C., & Pouget, A. (2004). The Bayesian brain: The role of uncertainty in neural coding and computation. Trends in Neurosciences, 27(12), 712 − 719. https://doi.org/10.1016/j.tins.2004.10.007 Körding, K. P., & Wolpert, D. M.

(2006). Bayesian decision theory in sensorimotor control. Trends in Cognitive Sciences, 10(7), 319 − 326. https://doi.org/10.1016/j.tics.2006.05.003 Lebreton, M., Abitbol, R., Daunizeau, J., & Pessiglione, M. (2015). Automatic integration of confidence in the brain valuation signal. Nature Neuroscience, 18(8), 1159 − 1167. https://doi.org/10.1038/nn.4064 Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. Current Opinion in Neurobiology, 22(6), 1027 − 1038. https://doi.org/10.1016/j.conb.2012.06.001 Ma, W. J. (2012). Organizing probabilistic models of perception. Trends in Cognitive Sciences, 16(10), 511 − 518. https://doi.org/10.1016/j.tics.2012.08.010 Ma, W. J., & Jazayeri, M. (2014). Neural coding of uncertainty and probability. Annual Review of Neuroscience, 37, 205 − 220. https://doi.org/10.1146/annurev-neuro-071013-014017 McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004).

Neural correlates of behavioral preference for culturally familiar drinks. Neuron, 44(2), 379 − 387. https://doi.org/10.1016/j.neuron.2004.09.019 McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. Neuron, 44(2), 379 − 387. https://doi.org/10.1016/j.neuron.2004.09.019 Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. Annual review of neuroscience, 24(1), 167 − 202. https://doi.org/10.1146/annurev.neuro.24.1.167 Noonan, K. A., Jefferies, E., Visser, M., & Lambon Ralph, M. A. (2013). Going beyond inferior prefrontal involvement in semantic control: evidence for the additional contribution of dorsal angular gyrus and posterior middle temporal cortex. Journal of cognitive neuroscience, 25(11), 1824 − 1850. https://doi.org/10.1162/jocn_a_{00442} Park, S. A., Miller, D. S., Nili, H., Ranganath, C., & Boorman, E. D. (2020). Map making: constructing, combining, and inferring on abstract cognitive maps. Neuron, 107(6), 1226 − 1238. https://doi.org/10.1016/j.neuron.2020.06.030 Peelen, M. V., & Caramazza, A. (2012). Conceptual object representations in human anterior temporal cortex. Journal of Neuroscience, 32(45), 15728 − 15736. https://doi.org/10.1523/JNEUROSCI.1953-12.2012 Plassmann, H., Ambler, T., Braeutigam, S., & Kenning, P. (2007). What can advertisers learn from neuroscience?. International Journal of Advertising, 26(2), 151 − 175.https://doi.org/10.1080/10803548.2007.11073005 Plassmann, H., Kenning, P., Deppe, M., Kugel, H., & Schwindt, W. (2008). How choice ambiguity modulates activity in brain areas representing brand preference: evidence from consumer neuroscience. Journal of Consumer Behaviour, 7(4-5), 360 − 367. https://doi.org/10.1002/cb.257 Ralph, M. A. L., Jefferies, E., Patterson, K., & Rogers, T. T. (2017). The neural and computational bases of semantic cognition. Nature reviews neuroscience, 18(1), 42 − 55. https://doi.org/10.1038/nrn.2016.150 Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. Nature reviews neuroscience, 9(7), 545 − 556. https://doi.org/10.1038/nrn2357 Reimann, M., Zaichkowsky, J., Neuhaus, C., Bender, T., & Weber, B. (2010). Aesthetic package design: A behavioral, neural, and psychological investigation. Journal of Consumer Psychology, 20(4), 431 − 441. https://doi.org/10.1016/j.jcps.2010.06.009 Rolls, E. T., Grabenhorst, F., & Deco, G. (2010). Decision-making, errors, and confidence in the brain. Journal of neurophysiology, 104(5), 2359 − 2374. https://doi.org/10.1152/jn.00571.2010 Stephan, K. E., Penny, W. D., Moran, R. J., den Ouden, H. E., Daunizeau, J., & Friston, K.

J. (2010). Ten simple rules for dynamic causal modeling. Neuroimage, 49(4), 3099 − 3109. https://doi.org/10.1016/j.neuroimage.2009.11.015 Stringer, C., Pachitariu, M., Steinmetz, N., Reddy, C. B., Carandini, M., & Harris, K. D. (2019). High-dimensional geometry of population responses in visual cortex.

Nature, 571(7765), 361 − 365. https://doi.org/10.1038/s41586-019-1346-5 Tavares, R. M., Mendelsohn, A., Grossman, Y., Williams, C. H., Shapiro, M., Trope, Y., & Schiller, D. (2015). A map for social navigation in the human brain. Neuron, 87(1), 231 − 243. https://doi.org/10.1016/j.neuron.2015.06.011 Thomson, M., MacInnis, D. J., & Park, C. W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. Journal of Consumer Psychology, 15(1), 77 − 91. https://doi.org/10.1207/s15327663jcp1501_{10} Vossel, S., Mathys, C., Daunizeau, J., Bauer, M., Driver, J., Friston, K. J., & Stephan, K. E. (2014). Spatial attention, precision, and Bayesian inference: a study of saccadic response speed. Cerebral cortex, 24(6), 1436 − 1450. https://doi.org/10.1093/cercor/bhs418 Wikenheiser, A. M., & Schoenbaum, G. (2016). Over the river and through the woods: cognitive maps in the hippocampus and orbitofrontal cortex. Nature Reviews Neuroscience, 17(8), 513 − 523. https://doi.org/10.1038/nrn.2016.56