BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
Covered in: Web of Science (ESCI); EBSCO; JERIH PLUS (hkdir.no); IndexCopernicus; Google Scholar; SHERPA/RoMEO; ArticleReach Direct; WorldCat; CrossRef; Peeref; Bridge of Knowledge (mostwiedzy.pl); abcdindex.com; Editage; Ingenta Connect Publication; OALib; scite.ai; Scholar9; Scientific and Technical Information Portal; FID Move; ADVANCED SCIENCES INDEX (European Science Evaluation Centre, neredataltics.org); ivySCI; exaly.com; Journal Selector Tool (letpub.com); Citefactor.org; fatcat!; ZDB catalogue; Catalogue SUDOC (abes.fr); OpenAlex; Wikidata; The ISSN Portal; Socolar; KVK-Volltitel (kit.edu)
2026, Volume 17, Issue 1, pages: 170-193
Submitted: October 24th, 2025 | *Accepted for publication:* December 23rd, 2025

Predictive Neuromarketing: A Bayesian and Predictive-Coding Framework for Consumer Neuroscience

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Abstract: *Neuromarketing has emerged as a rapidly expanding field aimed at understanding the neural mechanisms that shape consumer behaviour. Yet despite its empirical success, the field lacks a unifying computational theory. In contrast, cognitive neuroscience increasingly converges on the Bayesian Brain and predictive-coding frameworks, which conceptualise perception, learning, and decision-making as hierarchical predictive processes driven by minimisation of precision-weighted prediction errors. This paper introduces Predictive Neuromarketing, a hybrid neuroscience–marketing paradigm that integrates predictive coding with consumer neuroscience findings. We develop a mathematical framework that formalises consumer expectations, brand priors, price cues, and prediction errors, providing a computational explanation for phenomena such as price placebo effects, brand-identity modulation, electroencephalography (EEG)-based preference prediction, and neuroforecasting of advertising success. We then reinterpret the empirical neuromarketing literature through this lens and propose experimental paradigms to test predictive-coding principles in consumer contexts. By embedding neuromarketing within a rigorous predictive framework, we offer a mechanistic account of how marketing stimuli shape consumer beliefs, valuation, and behaviour. The paper concludes with ethical considerations and a research agenda for advancing Predictive Neuromarketing. The contribution of this worki s the formal integration of consumer neuroscience findings into a cohesive Bayesian and predictive-coding generative model, producing clear, testable computational predictions without introducing additional empirical data.*

Keywords: *predictive coding; Bayesian inference; consumer neuroscience; computational neuroscience; decision-making; neuromarketing.*

How to cite: Mavroudis, I., Vavdinoudis, T., Kalifatidis, D., Ciausu, R.-A., Ciobica, A. S., Novac, B., Novac, O., & Gheban, D. (2026). Predictive neuromarketing: A Bayesian and predictive-coding framework for consumer neuroscience. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, *17*(1), 170-193. https://doi.org/10.70594/brain/17.1/13

1. Introduction

Neuromarketing—also labelled consumer neuroscience—applies neurophysiological and neuroimaging tools such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), eye-tracking, and biometrics to better understand consumer preferences, valuation, persuasion, and decision-making (Ariely & Berns, 2010; Harris, Ciorciari, & Gountas, 2019; Hubert & Kenning, 2008; Khushaba et al., 2013; Plassmann, Ramsøy, & Milosavljevic, 2012; Smidts et al., 2014; Stanton, Sinnott-Armstrong, & Huettel, 2016; Yadava et al., 2017; Zaltman, 2003). Over the past 20 years, seminal studies have shown that neural signals in reward-related regions such as the ventromedial prefrontal cortex (vmPFC) and ventral striatum predict real-world purchasing behaviour (Kable & Glimcher, 2007; Knutson et al., 2007; Lim, O'Doherty, & Rangel, 2011; Plassmann et al., 2008; Telpaz, Webb, & Levy, 2015); that brand information modulates sensory experience (McClure et al., 2004); and that neural activity can forecast market-level advertising outcomes beyond self-report (Falk, Berkman, & Lieberman, 2012; Venkatraman et al., 2015).

However, despite these successes, neuromarketing lacks a coherent theoretical foundation. Much of the literature relies on descriptive neural correlates rather than mechanistic models. Without a generative theory, neuromarketing risks becoming a collection of disconnected findings rather than a cumulative scientific discipline.

In parallel, cognitive and computational neuroscience has converged on a remarkably powerful explanatory framework: predictive coding and the Bayesian Brain (Clark, 2013; de Lange, Heilbron, & Kok, 2018; Friston, 2010; Knill & Pouget, 2004; Lee & Wagenmakers, 2014; Loughlin, 2016; Millidge, Seth, & Buckley, 2022; Pezzulo, Parr, & Friston, 2022; Rao & Ballard, 1999; Tschantz et al., 2025). These theories propose that the brain continuously generates predictions about incoming sensory and contextual information, compares them with actual input, computes prediction errors, and updates beliefs to minimise future error. This hierarchical, probabilistic approach has been applied successfully to perception, action, learning, emotion, interoception, and valuation.

The goal of this paper is to synthesise these developments by introducing a new theoretical framework: Predictive Neuromarketing. In this view, consumer behaviour—including valuation, brand effects, price responses, expectation bias, and even population-level market success—can be conceptualised as Bayesian predictive inference implemented by cortical hierarchies.

The originality of this study does not stem from the introduction of Bayesian inference or predictive coding, both of which are already well-established in cognitive neuroscience. Its contribution is threefold: (i) it offers a cohesive generative model that formally integrates neuromarketing phenomena—such as price placebo effects, brand modulation, and neuroforecasting—within a predictive-coding framework; (ii) it systematically correlates empirical consumer neuroscience findings with explicit computational variables (priors, prediction errors, and precision); and (iii) it generates falsifiable predictions that connect neural signatures to consumer behaviour and market-level outcomes. This research seeks to transition neuromarketing from a predominantly descriptive field to a mechanistic and computational science.

Research question: Can predictive coding and Bayesian inference function as a unified generative theory that mechanistically elucidates fundamental neuromarketing phenomena and produces falsifiable neural-behavioural predictions? We tackle this by formalising priors, precision, and prediction errors within consumer settings, establishing testable value/choice equations, and delineating EEG/fMRI benchmarks and AI implementations.

2. Predictive Coding and the Bayesian Brain

2.1. Bayesian Inference in the Brain

The Bayesian Brain framework posits that the nervous system continuously interprets the world by maintaining probabilistic beliefs about the hidden causes of sensory events. Rather than processing raw data in a feed-forward manner, the brain is thought to estimate the most likely explanation for its inputs by applying Bayesian inference at multiple hierarchical levels (Beck et al., 2008; Fiser et al., 2010). For clarity, Table 1 summarises the variables, neuronal signals, and probabilistic components employed in the generative model.

Table 1. Key Notation in the Predictive Neuromarketing Framework

Symbol	Meaning
z	Latent causes (e.g., expected quality, brand identity)
x	Sensory or contextual evidence
c	Contextual cues (price, narrative, environment)
θ	Consumer traits or long-term priors
φ	Parameters of sensory/marketing mapping
ε_l	Prediction error at hierarchical level l
Π_l	Precision (inverse variance) at level l
μ_l	Predicted state at level l
F	Variational free energy
V_{ij}	Posterior expected value
β	Choice inverse temperature / decision precision
n_j	Neural predictors
M_j	Market-level outcome

In this formulation, perception, valuation, and action are consequences of ongoing belief updating, where prior expectations interact with incoming evidence to generate posterior estimates of the causes of experience. At the core of this idea is **Bayes' rule**, which expresses how beliefs should be updated in the presence of new information:

$$p(z \mid x, c) = [\ p(x \mid z, c) \cdot p(z)\ ] / p(x \mid c) \tag{1}$$

Here, z denotes latent causes such as expected taste quality or brand identity; x refers to the observed sensory or contextual information (e.g., flavour characteristics, packaging, advertising claims); and c captures the broader context of evaluation, such as price, social setting, or narrative framing.

The denominator, p(x | c), represents the **model evidence**—the probability of observing the data under all possible causes:

$$p(x \mid c) = \int p(x \mid z, c) \cdot p(z)\, dz \tag{2}$$

Because exact Bayesian inference is computationally intractable for complex environments, the brain is believed to implement **approximate inference** using local message-passing algorithms that minimise free energy, a computational proxy for variational Bayesian updating (Friston, 2003). This approximation is biologically plausible and fits neural data from several domains, including sensory perception, sensorimotor control, and valuation. Within this framework, expectations are not mere passive biases—they actively shape perceptual input, determining what information is attended to, how prediction errors are weighted, and ultimately how stimuli are experienced and valued.

These principles are particularly relevant to neuromarketing: consumer expectations about quality, price, social meaning, or familiarity directly map onto priors in Bayesian inference, while the sensory and contextual inputs provided by marketing stimuli contribute to the likelihood term. As such, consumer behaviour emerges from the interplay between prior beliefs and new evidence, governed by the same computational rules that structure perception in general.

2.2. Predictive Coding

Predictive coding provides a mechanistic implementation of Bayesian inference in hierarchical cortical systems. Under this scheme, higher cortical levels generate predictions about the expected states of lower levels, while lower levels compute **prediction errors** that reflect mismatches between predicted and actual inputs. These errors are propagated upward to update beliefs, completing the inferential loop (Bastos et al., 2012; Keller & Mrsic-Flogel, 2018; Shipp, 2016).

Prediction errors are defined formally as:

$$\varepsilon_l = s_l - f_l(\ \mu_l\ ) \qquad (3)$$

where s_l is the actual neural activity at level l, and $f_l(\mu_l)$ is the predicted input based on the current estimate of latent causes μ_l. This comparison is not a mere subtraction: it is the fundamental operation through which the brain detects surprising information and determines whether expectations must be revised.

Critically, prediction errors are **precision-weighted**:

$$\tilde{\varepsilon}_l = \Pi_l \cdot \varepsilon_l \qquad (4)$$

where Π_l encodes the estimated precision (inverse variance) of the error signal. Precision determines the relative influence of new information versus prior expectations. High precision amplifies the impact of prediction errors, leading to rapid belief updating, whereas low precision causes the system to rely more heavily on its priors. Neuromodulatory systems such as dopamine and acetylcholine are thought to modulate precision estimates by regulating neuronal gain (Shine, 2023).

The dynamics of predictive coding involve updating both the predictions and their associated precisions. Predicted causes evolve approximately according to:

$$\dot{\mu_l} \propto -\ (\ \partial f_l(\mu_l)^T / \partial\mu_l\ ) \cdot \tilde{\varepsilon}_l + \tilde{\varepsilon}_{l+1} \qquad (5)$$

This update rule ensures that predictions are corrected proportionally to the magnitude and reliability of prediction errors at each hierarchical level. Precision is also updated through its own gradient descent dynamics:

$$\Pi_l \propto -\ \partial F / \partial\Pi_l \qquad (6)$$

where F denotes free energy, a function summarising the mismatch between predicted and observed inputs. Together, these coupled updates provide a biologically feasible mechanism for how the brain approximates Bayesian inference.

3. Integrating Predictive Coding with Consumer Neuroscience

After outlining the computational principles of predictive coding, we will use this framework to reinterpret key findings from consumer neuroscience that has long demonstrated that marketing cues—such as brand labels, price signals, packaging, and advertising narratives—systematically alter subjective experience and choice. What has been less clear is why these modulatory effects are so robust, consistent, and predictable across individuals and contexts. Predictive-coding and Bayesian models offer a compelling computational substrate that explains these findings not merely as associations, but as expressions of fundamental inferential mechanisms in the brain (Heilbron & Chait, 2018; Summerfield & de Lange, 2014; Thomas et al., 2022). Within this framework, marketing stimuli shape consumer behaviour by modifying **priors**, influencing **precision**, or generating **prediction errors**—all of which directly govern perception, valuation, and decision-making.

To make this theoretical integration apparent, Table 2 connects established consumer neuroscience phenomena to predictive-coding notions such as hierarchical priors, prediction errors, and precision weighting.

Table 2. Mapping Consumer Phenomena to Predictive-Coding Constructs

Phenomenon	Empirical Finding	Predictive-Coding Interpretation
Price placebo effect	Higher price increases pleasure and vmPFC activation	Price shifts hierarchical priors on quality
Brand identity effects	Brand labels change sensory experience	Top-down priors shape perceptual inference
Packaging influence	Packaging modifies taste perception	Aesthetic cues modulate precision of sensory likelihood
EEG prediction	Early neural signatures predict choice	Preconscious prediction errors drive valuation
Neuroforecasting	Neural signals predict market outcomes	Aggregated prediction errors reflect shared priors
Choice overload	Too many options reduce satisfaction	Reduced precision increases reliance on heuristics

3.1. Price and Brand Cues as Hierarchical Priors

One of the most influential neuromarketing findings is the price-placebo effect. Plassmann et al. (2008) demonstrated that when the same wine is presented with a higher price tag, participants report greater pleasantness and show stronger activation in the medial orbitofrontal cortex (mOFC), a region central to reward valuation. Predictive coding provides a mechanistic explanation: price information acts as a high-level prior about expected quality. When sensory evidence is ambiguous—as taste frequently is—the strong prior shifts the posterior belief about hedonic value upward. In essence, the brain predicts that expensive wine should taste better, and perception aligns accordingly.

Similarly, brand identity exerts powerful top-down influence on perceptual experience. McClure et al. (2004) showed that brand cues (e.g., Coca-Cola vs. Pepsi) activate hippocampal and prefrontal regions associated with semantic memory and expectations. Even though blinded taste tests often reveal no strong sensory preference, brand knowledge reshapes valuation when labels are visible, demonstrating that experience is not solely determined by bottom-up stimuli. Instead, brand identity functions as a deeply embedded **hierarchical prior** that alters predictions about how a product should feel, taste, or perform.

Predictive coding formalises this interaction:

- Strong priors (brand, price, narrative) → greater reliance on top-down predictions.
- Weak or noisy sensory evidence → increased weighting of priors in posterior inference.
- Result: a systematic distortion of subjective experience that aligns with expectations.

These computations elegantly capture a wide range of behavioural and neural findings in consumer research.

3.2. Prediction Errors and the Dynamics of Consumer Surprise

Prediction errors (PEs) play a crucial role in learning, habit formation, and preference updating. In consumer contexts, PEs arise when a product performs better (or worse) than expected, when price information is inconsistent with perceived quality, or when advertisements promise outcomes that are not delivered (Rutledge et al., 2014; Schultz, 2017). Neural studies consistently show that the ventral striatum and midbrain dopamine system encode prediction errors between expected and actual outcomes—a phenomenon long established in reinforcement learning research (O'Doherty et al., 2003).

From a neuromarketing standpoint, prediction errors explain:

- Why first-time product experiences strongly influence future attitudes.
- Why consumers update beliefs about unfamiliar brands more than well-established ones.
- Why surprising discounts or unexpected product features increase engagement.

Importantly, prediction errors drive belief updating. When a prediction error is large and assigned high precision, the consumer's internal model adjusts accordingly—leading to changes in brand perception, loyalty, and future valuation.

- **Positive prediction error** (product exceeds expectations): increases posterior belief in product quality, fostering loyalty.
- **Negative prediction error** (product disappoints): down-weights prior beliefs, weakening the brand relationship.

This learning dynamic explains why premium brands invest heavily in maintaining consistent performance: reducing prediction error variance stabilises priors, thereby maintaining high willingness-to-pay.

3.3. Precision as a Key Modulator of Consumer Decision-Making

Precision determines how much influence is given to prediction errors versus prior expectations. In consumer settings, precision maps onto constructs such as:

- **Brand familiarity** (high precision of priors).
- **Ambiguous sensory information** (low precision of sensory evidence).
- **High uncertainty situations**, such as choice overload or unfamiliar product categories (variable precision).

Evidence from EEG studies—particularly frontal midline theta and parietal components—suggests that neural markers of uncertainty and conflict reflect changes in precision weighting during decision-making (Cavanagh et al., 2012; Telpaz, Webb, & Levy, 2015). For example, when a consumer is confronted with many similar options, uncertainty about the reliability of sensory attributes reduces precision of the likelihood term, causing greater reliance on brand priors, social cues, or default heuristics.

From a predictive-coding perspective, precision serves as a computational lens through which consumer neuroscience findings can be reinterpreted:

- **High precision on priors** → strong brand effects; price expectations dominate experience.
- **High precision on sensory input** → consumer depends more on real product attributes.
- **Low precision overall** → greater susceptibility to contextual nudges and marketing framing.

The neuromodulatory basis of precision—often associated with dopamine, noradrenaline, and acetylcholine—also suggests a biological mechanism through which emotional arousal, attention, or stress influences consumer decisions (Yu & Dayan, 2005).

3.4. Neural Valuation as Posterior Expectation

The valuation system, primarily centred in the vmPFC and ventral striatum, has been repeatedly shown to encode the **subjective value** of goods across different domains (Knutson et al., 2007; Levy & Glimcher, 2012). Under predictive coding, value signals can be interpreted as posterior expectations derived from Bayesian inference. That is, the vmPFC does not merely encode "reward" or "preference"—it represents the **integrated belief** about product utility after combining priors and sensory evidence.

This interpretation explains:

- Why identical stimuli produce different neural responses depending on expectations.
- Why attention, emotion, or framing can shift vmPFC value signals.
- Why neural activity can predict future choices better than self-reports (Falk, Berkman, & Lieberman, 2012; Venkatraman et al., 2015).

Consumers may be unaware of the computation unfolding beneath consciousness, but predictive coding suggests that valuation emerges naturally from hierarchical inference processes.

3.5 Convergence of Predictive Coding and Consumer Neuroscience

Taken together, predictive coding integrates diverse neuromarketing findings into a unified theoretical framework:

- **Branding = prior formation.**
- **Advertising = manipulation of generative models.**
- **Price signals = hierarchical contextual priors.**
- **Product experience = likelihood sampling.**
- **Prediction errors = learning and belief updating.**
- **Neural valuation = posterior belief about utility.**
- **Choice = selection policy based on precision-weighted predictions.**

This computational synthesis not only accounts for classic effects documented in consumer neuroscience but also provides a foundation for designing predictive experiments, building mechanistic models, and forecasting consumer behaviour at both the individual and population levels.

4. Mathematical Framework for Predictive Neuromarketing

This section formalises predictive neuromarketing using a hierarchical Bayesian generative model. We start by providing priors and likelihoods for latent customer beliefs and observed marketing cues and then apply Bayes' rule to generate posterior inference. Finally, we present variational free-energy minimisation as a physiologically realistic approximation achieved using predictive coding and demonstrate how this formulation produces experimentally useful forecasting models.

These structures draw on established principles in computational neuroscience and variational Bayesian inference (Filipowicz et al., 2016; Friston et al., 2016; Gershman, 2015; Lee & Wagenmakers, 2014).

4.1. Key model components (notation)

A generative model specifies how observations arise from latent causes. In consumer settings, latent causes z capture beliefs about product quality, brand identity, expected experience, social meaning, or long-term utility. Observed inputs x include sensory properties (e.g., taste, texture, design), contextual cues (e.g., price, packaging, store environment), and marketing signals (e.g., brand labels, narratives, endorsements). These expressions indicate generative model components rather than derived equations. We therefore treat (Def. 1–2) as notation, not as derived results.

Formally, the model begins with a **prior** over latent causes:

$$p(z_{ij} \mid \theta_i) \qquad \text{(Definition 1)}$$

where θ_i represents consumer i's stable traits, prior experiences, or long-term brand associations.

The **likelihood** describes how sensory and contextual evidence arise:

$$p(x_{ij} \mid z_{ij}, c_{ij}, \varphi) \qquad \text{(Definition 2)}$$

where φ encodes parameters of the sensory mapping and c_{ij} provides contextual conditions such as price or narrative frame.

We assume the conditional independence of the latent causes *z* and observed inputs *x*, based on prior knowledge of the consumer profile, expressed by the following joint model:

$$p(x_{ij}, z_{ij} \mid c_{ij}) = p(z_{ij} \mid \theta_i) \cdot p(x_{ij} \mid z_{ij}, c_{ij}) \qquad (7)$$

The **posterior** over latent causes then follows Bayes' rule:

$$p(z_{ij} \mid x_{ij}, c_{ij}) \propto p(x_{ij} \mid z_{ij}, c_{ij}) \cdot p(z_{ij} \mid \theta_i) \qquad (8)$$

In economic terms, this posterior represents the updated belief about product utility after combining prior expectations with sensory or contextual experience. In neural terms, it corresponds to activity patterns in regions such as vmPFC and hippocampus during valuation and memory retrieval.

4.2. Variational Inference and Free-Energy Minimisation

Exact Bayesian inference is computationally expensive. Predictive coding instead relies on **variational approximation**, in which the b la rain maintains an approximate posterior q(z) and minimises the **variational free energy**, a functional that upper-bounds Bayesian surprise (Bogacz, 2017):

$$F = E_q[\, -\ln p(x, z \mid c) \,] + E_q[\, \ln q(z) \,] \qquad (9)$$

Minimising F yields an approximate posterior:

$$q(z) \approx \arg\min F \qquad (10)$$

This formulation explains several hallmark findings in neuromarketing. For example, strong brand priors reduce the contribution of sensory likelihoods by decreasing the free-energy gap. Conversely, unexpected product performance generates large prediction errors, increasing free energy and triggering posterior belief updates—consistent with observed neural prediction-error signals in the reward circuitry.

4.3. Prediction Errors as Drivers of Belief Updating

Predictive coding operationalises free-energy minimisation through **prediction-error signalling**. At each hierarchical level l, the discrepancy between actual brain activity s_l and predicted activity $f_l(\mu_l)$ is:

$$\varepsilon_l = s_l - f_l(\, \mu_l \,) \qquad (11)$$

This error is then modulated by its **precision**, representing confidence in the sensory or contextual input:

$$\tilde{\varepsilon}_l = \Pi_l \cdot \varepsilon_l \qquad (12)$$

where Π_l is an inverse-variance measure. In marketing terms, precision maps onto perceived reliability: familiar brands, clear packaging, and consistent performance yield higher precision; ambiguous or novel stimuli yield lower precision.

Predictions are updated proportionally to precision-weighted errors:

$$\dot{\mu}_l \propto - \left(\partial f_l(\mu_l)^T / \partial \mu_l \right) \cdot \tilde{\varepsilon}_l + \tilde{\varepsilon}_{l+1} \qquad (13)$$

This recursive update rule mathematically encodes how consumer expectations adjust when encountering new information. If a product performs better than expected, positive prediction errors induce upward revision of beliefs about the brand or product category. Conversely, disappointing experiences down-regulate beliefs, weakening preference—a dynamic observed across loyalty research and reinforcement learning tasks in consumer settings (Daw et al., 2011).

Precision itself is updated via gradients of free energy:

$$\Pi_l \propto - \partial F / \partial \Pi_l \qquad (14)$$

This implies that precision is not fixed. Instead, consumers continually estimate the reliability of contextual cues, sensory information, and their own expectations. This aligns with empirical evidence showing that uncertainty increases reliance on brands or price cues, whereas clarity of sensory information shifts reliance towards product attributes (Tversky & Kahneman, 1974).

4.4. Posterior Value as the Substrate of Neural Valuation

Subjective value, as encoded in vmPFC and related circuits, can be formalised as the **posterior expectation of utility**:

$$V_{ij} = E_q\{ p(z_{ij} \mid x_{ij}, c_{ij}) \} [u(z_{ij})] \qquad (15)$$

This expression highlights that value is not a fixed property of the product but an inference shaped jointly by expectations and sensory evidence. Posterior value naturally shifts with:

- price information,
- brand identity,
- packaging aesthetics,
- advertising narratives,
- and social context.

Empirically, this corresponds to modulation of vmPFC activity under contextual framing—such as elevated vmPFC responses to higher-priced wines or luxury-branded items—even when sensory inputs remain identical (Grabenhorst, Rolls, & Bilderbeck, 2008; Plassmann et al., 2008).

4.5. Choice as Softmax Selection Under Uncertainty

Decision-making is modelled using a softmax or multinomial-logit choice rule:

$$P_i(\text{choose } j) = \exp(\beta V_{ij}) / \Sigma_k \exp(\beta V_{ik}) \qquad (16)$$

Here, β represents inverse temperature, which corresponds to **choice precision**. Higher precision yields more deterministic choice behaviour; lower precision increases randomness and susceptibility to contextual influences—a phenomenon widely documented in consumer research on attention, distraction, and choice overload (Iyengar & Lepper, 2000).

Predictive neuromarketing thus embeds behavioural choice within a principled inferential process: consumers select the option with the highest expected value after integrating priors, prediction errors, and uncertainties.

4.6. Neural Forecasting Through Predictive Coding

Finally, predictive neuromarketing incorporates neuroforecasting, in which neural signals are used to predict population-level outcomes such as viral content, campaign success, or sales lift (Camerer, Loewenstein, & Prelec, 2005; Falk, Berkman, & Lieberman, 2012; Venkatraman et al., 2015).

A general linear model formalises this:

$$M_j = \alpha + w^T n_j + \gamma^T X_j + \varepsilon_j \tag{17}$$

where:

- M_j = market-level metric for stimulus j,
- n_j = neural features interpreted as prediction-error or value signals,
- X_j = traditional metrics (self-report, demographics).

Equation (17) should be interpreted as an application-level approximation for empirical neuroforecasting, derived from the underlying Bayesian model, rather than a basic neural equation.

The predictive-coding interpretation is that neural signals capture early, implicit responses reflecting core generative-model parameters—priors, prediction errors, and precision—which aggregate reliably across consumers. This explains why neural data often forecast behaviour better than self-report, which does not access implicit hierarchical inferences (Akiba et al., 2019).

5. Empirical Evidence Reinterpreted Through Predictive Coding

The predictive neuromarketing framework offers a coherent computational lens for reinterpreting decades of consumer neuroscience research. Instead of understanding neuromarketing findings as isolated empirical observations, predictive coding situates them within a principled model of hierarchical inference, where priors, prediction errors, and precision jointly determine perception, valuation, and behaviour. This section synthesises central empirical findings across fMRI, EEG, behavioural economics, and neuroforecasting, demonstrating how predictive coding provides a unifying explanation for phenomena traditionally treated as separate lines of inquiry. Table 3 summarises the neuronal signatures predicted by the model across the EEG and fMRI modalities under various experimental conditions.

Table 3. Experimental Paradigms for Predictive Neuromarketing

Paradigm	Manipulation	Expected Predictive-Coding Signature
Price–quality dissociation	Identical products with varied price cues	Priors dominate posterior value; reduced prediction error variance
Brand narrative priming	Narrative frames altering brand meaning	High-level priors modulate sensory integration
Cue-reliability manipulation	Varying reliability of packaging or ads	Precision shifts; increased PE when cues misalign
Surprise discounting	Unexpected price reductions	Positive prediction errors in ventral striatum
Identity-congruent marketing	Aligning product with personal identity	Deep priors activate self-referential circuits
Ad forecasting	Neural recording during ad exposure	vmPFC/PE signals predict population-level performance

5.1. Price Effects as Modulation of High-Level Priors

One of the most widely replicated findings in neuromarketing involves the **price–quality inference**, in which higher prices lead consumers to experience greater enjoyment or higher perceived performance, even when the underlying product is identical (Plassmann et al., 2008). Predictive coding accounts for this through the effect of price on **high-level priors**. A higher price shifts the prior distribution over expected quality upwards, such that sensory evidence—often noisy or ambiguous—has limited impact on the posterior. This mechanism aligns with research showing increased vmPFC and mOFC activation when consumers taste or evaluate products labelled as more expensive (Plassmann et al., 2008; Schmidt et al., 2017).

Predictive coding also explains why these effects vary with **precision**. When sensory attributes are weak or ambiguous (e.g., subtle wine differences or indistinguishable consumer packaged goods), prior expectations dominate. Conversely, when sensory evidence is clear and high in reliability (e.g., blind tasting of strongly flavoured items), the contribution of the likelihood term increases, reducing susceptibility to price cues (Schmidt et al., 2017).

This dynamic resolves inconsistencies in classical behavioural economics, which struggled to explain why price effects sometimes occur and sometimes fail; predictive coding shows that the determining factor is the **relative precision** of priors versus sensory likelihoods.

5.2. Brand Identity and Expectation-Based Modulation of Experience

Research by McClure et al. (2004) demonstrated **that brand identity can override sensory input**, leading consumers to experience the same beverage differently depending on whether they believe it is Coca-Cola or Pepsi. Predictive coding interprets this as a straightforward case of **top-down prediction** altering perceptual inference. Brand identity acts as a high-level latent cause z, generating predictions about taste, emotional associations, and contextual meaning. When sensory evidence is consistent with predictions, prediction errors are low, reinforcing the brand-based interpretation. When mismatches occur, prediction errors drive posterior updating.

Neuroimaging supports this interpretation: brand-cued evaluations activate hippocampal and prefrontal regions involved in semantic memory and expectation (McClure et al., 2004; Plassmann, Ramsøy, & Milosavljevic, 2012). The vmPFC integrates these priors with bottom-up signals to yield a posterior representation of product value. Thus, brand preference is not merely an attitude or heuristic—it is a **computational state** embedded within the brain's generative model.

Furthermore, predictive coding explains phenomena such as **brand loyalty**, **heritage brand effects**, and **identity-congruent preference formation**. In loyal consumers, brand-related priors become highly precise, meaning prediction errors exert less influence on updating, preserving preference stability even when objective performance varies (Kopalle et al., 2012).

5.3. EEG Evidence for Prediction Errors and Preconscious Value Signalling

Within this approach, distinct neuronal fingerprints are anticipated. Early components in EEG, such as N200 or Mismatch Negativity (MMN) should reflect sensory prediction mistakes, whereas frontal midline theta activity should indicate uncertainty and precision weighting during tough consumer decisions. In fMRI, ventromedial prefrontal brain activity is expected to encode posterior expected value, and ventral striatal responses should track reward prediction errors while updating preferences.

EEG studies provide high temporal resolution that reveals predictive dynamics unfolding over milliseconds. Research consistently shows that early event-related potentials (ERP) components and oscillatory activity track **prediction errors**, **attention modulation**, and **uncertainty signals**, all central to predictive coding.

- **Frontal midline theta** increases during difficult consumer decisions involving uncertainty or conflict, reflecting enhanced precision weighting and cognitive control (Cohen, 2011; Cavanagh & Frank, 2014).

P200 and **N200** components respond to surprising or mismatched stimuli, consistent with early prediction-error signalling (Näätänen et al., 2007).

- **Late positive potential (LPP)** reflects affective updating and integration of contextual priors during valuation (Schupp et al., 2006).

These findings align well with predictive-coding principles: each component corresponds to hierarchical prediction-error propagation, with early components linked to sensory mismatch and later ones reflecting higher-order appraisals. Importantly, EEG patterns often predict future choices even when consumers report no conscious preference—suggesting that predictive processes shape valuation before explicit awareness (Telpaz, Webb, & Levy, 2015).

This interpretation challenges traditional marketing assumptions that attitudes drive choices; rather, **prediction-error dynamics precede and shape explicit attitudes**, not the other way around.

ERP/oscillatory patterns are expected. In a price placebo manipulation (high vs. low price), we anticipate: (i) an early negative deflection peaking/ Mismatch Negativity (N2/MMN 150-250 ms) increase for incongruent pairings (low price + high sensory quality), (ii) a positive voltage deflection/ Late Positive Potential (P300/LPP 300-700 ms) increase for tracking re-evaluation/affective updating, and (iii) frontal midline theta (4-7 Hz) increases for low cue reliability or high choice difficulty. Scalp topographies include fronto-central for theta and N2/MMN, and centro-parietal for P3/LPP. These effects operationalise $|\varepsilon|$ and Π in time, using trial-wise regressions to relate component magnitude to modelled parameters.

5.4. fMRI Studies of Valuation and Precision-Weighted Integration

Functional MRI research shows consistent activation of vmPFC, ventral striatum, amygdala, and posterior cingulate cortex during consumer valuation tasks. Predictive coding interprets these findings as evidence of **posterior expected value** computation and precision-weighted integration of inputs.

- vmPFC integrates priors (brand identity, price, expectations) with likelihoods (sensory evidence) to compute posterior utility signals (Bartra, McGuire, & Kable, 2013; Knutson et al., 2007).
- Ventral striatum encodes **reward prediction errors**, updating beliefs about expected product value (O'Doherty et al., 2003; Oyama et al., 2010).
- Dorsolateral prefrontal cortex regulates precision, particularly in uncertain or conflicting decision contexts (Badre & Nee, 2018).

Importantly, predictive neuromarketing suggests that vmPFC activation is not a simple index of liking or shopping pleasure but rather a **summary statistic of posterior beliefs**, incorporating multiple probabilistic components of the generative model. This explains why vmPFC activity correlates with both sensory quality and contextual framing (e.g., luxury branding, social endorsement), and why it predicts individual purchasing decisions with high accuracy (Falk et al., 2014; Venkatraman et al., 2015).

General Linear Model (GLM) specification. Include parametric modulators at decision/taste onset:

(1) **Posterior value** $V \rightarrow$ vmPFC;

(2) **Precision-weighted PE** $\bar{\epsilon} = \Pi e \rightarrow$ ventral striatum;

(3) **Cue reliability** (proxy for precison/Π) → dlPFC/ Anterior Cingulate Cortex (ACC).

Key contrasts: (High- vs Low-price) × (Brand familiarity) interactions in vmPFC; Surprise-discount PE effects in striatum; Precision-by-difficulty effects in dlPFC/ACC.

5.5. Neuroforecasting Through Shared Priors and Collective Precision Weighting

A compelling line of evidence comes from **neuroforecasting**, where neural responses from small samples of participants predict large-scale market behaviour. Studies have shown that vmPFC and ventral striatum activity measured during advertisement viewing, music sampling, or message exposure can forecast population-level outcomes such as sales, virality, and donation behaviour (Berns & Moore, 2011; Falk et al., 2014; Venkatraman et al., 2015).

Predictive coding offers a principled explanation:

1. Neural responses reflect **shared priors** across individuals—culturally shaped expectations about narrative, reward, or aesthetic structure.
2. Neural prediction errors represent **unconscious surprise** or engagement that is correlated across viewers.
3. Precision weighting modulates how strongly deviations from expectation drive learning or motivational responses.

Because populations share similar generative models for certain stimuli (e.g., humour, narrative structure, emotional salience), aggregated prediction-error responses provide better forecasts than self-report, which often reflects post-hoc rationalisation rather than implicit inference (Genevsky & Knutson, 2015).

This resolves a longstanding puzzle in marketing science: Why do neural measures consistently outperform surveys in predicting real-world outcomes? Predictive coding argues that neural activity reveals **latent generative-model parameters**—priors, prediction errors, precision—that self-report cannot access.

5.6. Benchmark predictions linking model parameters to neural signatures

1. **Precision up-regulation (Π) increases frontal midline theta.**
   Design: Manipulate cue reliability (e.g., clear vs ambiguous packaging). *EEG*: ↑ 4–7 Hz frontal midline theta for low-reliability cues; *Model*: estimated $\widehat{\Pi}$ correlates with theta power trial-wise. *Stat*: mixed-effects regression with subject random effects; preregistered ROI/time-window.
2. **Price as hierarchical prior shifts vmPFC value code without sensory change.**
   Design: Identical product with high vs low price. *fMRI*: vmPFC parametric regressor tracks posterior value V; difference high>low price scales with prior strength (brand familiarity). *Model link*: $\Delta V \propto \Delta\text{prior mean}$.
3. **Prediction-error magnitude (|ε|) in ventral striatum tracks surprise discounts.**
   Design: Unannounced discount vs control. *fMRI*: striatal PE regressor; *Behaviour*: subsequent WTP increase ∝ PE size × precision.
4. **Identity-congruent priors suppress early sensory PE (N2/MMN).**
   Design: Brand narratives congruent vs incongruent with self-identity. *EEG*: reduced N2/MMN amplitude for congruent trials. *Model*: lower $|\varepsilon|$ at early levels.
5. **Choice stochasticity** (1/β) **rises under choice overload via reduced global precision.**
   Design: 6 vs 24 options; *Behaviour*: higher entropy of choices in large set; *EEG*: theta ↑; *Model*: inferred $\hat{\beta}$ ↓ with set size.
6. **Neuroforecasting**: Group-average vmPFC + PE features predict market outcomes M beyond self-report. *Model*: GLM (Eq. 17) with nested models; $\Delta R^2 > 0$ supports framework.

5.7. Cross-Modal Integration: Sensory, Social, and Contextual Predictive Signals

Recent studies show that consumer experience is shaped not only by sensory attributes but also by **social norms**, **identity cues**, and **contextual expectations**. Predictive coding naturally accommodates such multimodal integration by treating each cue as a source of evidence with its own precision.

- Social endorsements increase perceived product quality, consistent with increased precision on high-level priors (Izuma, 2013).
- Identity-congruent marketing activates memory and self-referential systems that feed top-down predictions into sensory pathways (Escalas & Bettman, 2005).
- Packaging aesthetics create predictions about product sensory properties, influencing perceived flavour intensity and enjoyment (Spence, 2016).

The predictive framework thus extends beyond neuroimaging to explain findings from behavioural economics, social psychology, and sensory marketing.

6. Applications of Predictive Neuromarketing

The predictive neuromarketing framework provides not only a unifying theoretical structure but also **practical tools** for designing experiments, interpreting neural data, and guiding strategic marketing decisions. By modelling consumer behaviour as hierarchical Bayesian inference, researchers and practitioners can leverage neural signals to optimise branding, pricing, product development, advertising, and customer experience. This section highlights concrete applications across EEG, fMRI, behavioural modelling, and market forecasting.

6.1. EEG Applications: Tracking Prediction Errors and Precision in Real Time

EEG offers millisecond-level temporal resolution, making it ideal for observing the **rapid predictive processes** that shape consumer perception and decision-making. Under predictive coding, EEG signals correspond to dynamic changes in prediction errors and precision weighting.

Key EEG components interpreted through predictive coding

- **Frontal midline theta (4–7 Hz)**
  Reflects conflict, uncertainty, and precision weighting during complex decisions (Mushtaq, Bland, & Schaefer, 2011; Telpaz, Webb, & Levy, 2015).
  Predictive meaning: Enhanced theta indicates greater reliance on error signals and heightened attentional gain (van Driel, Ridderinkhof, & Cohen, 2012).
- **N200 / Mismatch Negativity (MMN)**
  Encodes early sensory prediction errors when stimuli deviate from expectation (Näätänen et al., 2007; Garrido et al., 2009).
  Predictive meaning: Reflects violations of brand, packaging, or pricing expectations.
- **P300 / LPP**
  Reflect emotional relevance and belief updating, integrating contextual priors with sensory input (Gkintoni & Halkiopoulos, 2025; Schupp et al., 2006).

These components allow marketers to quantify **moment-to-moment predictive responses**, predicting outcomes such as:

- advertisement effectiveness,
- packaging impact,
- pricing resonance,
- attractiveness of product attributes,
- and even subconscious preference formation.

Machine-learning models trained on EEG features have successfully predicted consumer choice, often before participants become consciously aware of their preference (Telpaz, Webb, & Levy, 2015).

6.2. fMRI Applications: Mapping Posterior Value and Hierarchical Belief States

Functional MRI provides spatial resolution necessary for identifying brain networks underlying predictive inference. Predictive neuromarketing interprets fMRI signals as estimates of **posterior expected value**, **prediction errors**, and **precision control**.

Key regions and their computational roles

- **vmPFC (ventromedial prefrontal cortex)**
  Encodes posterior value expectations—the integration of priors and sensory evidence (Bartra, McGuire, & Kable, 2013; Knutson et al., 2007).
  Predictive role: Represents consumers' inferred value after belief updating.
- **Ventral striatum**
  Computes reward prediction errors and contributes to preference learning (O'Doherty et al., 2003; Oyama et al., 2010).
- **Hippocampus and medial temporal lobe**
  Store and activate brand-related priors, narratives, and semantic associations (McClure et al., 2004; Plassmann, Ramsøy, & Milosavljevic, 2012).
- **Dorsolateral prefrontal cortex (dlPFC)**
  Regulates precision, attention, and uncertainty, influencing reliance on priors vs. sensory evidence (Badre & Nee, 2018).

These neural responses explain phenomena such as:

- brand identity dominating sensory experience,
- price cues altering hedonic value,
  narrative framing changing perception of taste or quality,
- and emotional advertising modifying posterior valuations.

Predictive neuromarketing thus translates fMRI activation into **mechanistic variables**, not just correlates.

6.3. Predictive-Coding–Informed Price and Brand Strategy

Predictive coding suggests that **marketing is fundamentally about shaping priors and controlling precision**.

Implications for branding

- Strong, coherent brand narratives increase the **precision of priors**, reducing the impact of inconsistent sensory evidence.
- Repeated exposure stabilises predictions, forming loyalty through belief consolidation (Kopalle et al., 2012).

Implications for pricing

- Prices function as *hierarchical priors*—high prices shift predicted quality upward.
- Discounts generate positive prediction errors when unexpected, increasing perceived value (Anderson & Simester, 2004).

Implications for packaging and design

- Packaging acts as a predictive cue; congruent designs reduce prediction errors, enhancing perceived quality (Spence, 2016).
- Minimalist or ambiguous packaging increases uncertainty and shifts reliance towards brand reputation.

6.4. Neuroforecasting: Predicting Market-Level Behaviour from Neural Signals

Neuroforecasting interprets neural responses as **population-level predictive signals**, revealing which stimuli will succeed in the broader market. To demonstrate how the framework might be empirically examined, Table 4 summarises example experimental paradigms, projected brain responses, and expected behavioural or market-level outcomes.

Research demonstrates that neural signals—especially in vmPFC, ventral striatum, and attention networks—predict real-world outcomes such as:

- song popularity (Berns & Moore, 2011),
- ad virality,
- donation behaviour,

- and mass-market sales (Falk et al., 2014; Venkatraman et al., 2015).

Predictive coding explains why:

1. Neural responses reflect **shared cultural priors** across individuals.
2. Prediction errors signal emotional resonance or surprise.
3. Precision-weighted value computations generalise across context.

Compared to self-reports, neural data are less influenced by introspective bias, offering a **more faithful readout of implicit generative models** (Genevsky & Knutson, 2015).

Table 4. Neural Structures and Their Computational Roles

Brain Region	Function in Predictive Coding	Role in Consumer Behaviour
vmPFC	Posterior value computation	Encodes subjective value of brands/products
Ventral striatum	Reward prediction error	Drives preference updating, novelty response
Hippocampus	Prior retrieval	Brand memory, identity associations
dlPFC	Precision control, uncertainty regulation	Difficult decisions, attention, cognitive control
Amygdala	Affective salience	Emotional advertising, risk perception
ACC	Conflict monitoring	Ambiguous choices, uncertainty

6.5. Personalisation and Adaptive Experience Design

Predictive neuromarketing scales naturally into personalisation strategies:

- Individual priors (e.g., preferences, cultural identity) can be inferred from past behaviour.
- Prediction-error monitoring can enable adaptive advertising or product sequences.
- Precision estimates can guide interventions for overwhelmed or uncertain consumers (e.g., simplifying choice environments).

As personalised AI systems proliferate, predictive neuromarketing provides the theoretical underpinnings for **computationally intelligent consumer experiences**.

Predictive neuromarketing shares many similarities with modern learning architectures in terms of artificial intelligence (AI). Free-energy minimisation corresponds to gradient-based optimisation, precision weighting to adaptive learning rates or gain control, and hierarchical generative models to Bayesian neural networks and active inference agents. This alignment shows that predictive neuromarketing can help to shape the design of brain-inspired AI systems that simulate and adapt to consumer behaviour.

6.6. Algorithmic Instantiations: From Predictive Coding to Deployable AI

We outline three concrete AI implementations that operationalise the proposed framework:

(a) Active-inference consumer agent (precision-weighted PE control).

Let latent beliefs about product quality be z with prior $p(z \mid \theta)$ and sensory likelihood $p(x \mid z, c, \phi)$. The agent maintains an approximate posterior $q(z)$ and updates beliefs by gradient descent on variational free energy $F[q]$. Precision Π (inverse variance) gates the impact of PEs:

$$\dot{\mu} \propto -\left(\frac{\partial f(\mu)}{\partial \mu}\right)^{\top} \tilde{\varepsilon} + \tilde{\varepsilon}_{\text{higher}}, \tilde{\varepsilon} = \Pi\,(s - f(\mu)).$$

In simulations, Π can be learned as a state-dependent gain (akin to uncertainty-aware learning rates), yielding adaptive attention to price/brand vs sensory evidence. **Choice** is a softmax over posterior value $V = \mathbb{E}[u(z) \mid x, c]$ with inverse temperature β.

(b) Bayesian neural networks (BNNs) for predictive neuromarketing.

BNNs approximate $p(y \mid x)$ while learning weight posteriors $q(w)$; predictive uncertainty provides a direct handle on **precision**. Inputs can include contextual priors (price, brand, narrative), sensory proxies, and neurofeatures. Training minimises a variational objective (ELBO) that mirrors free-energy minimisation; posterior predictive variance modulates Π and thus the influence of PEs on updates and choices.

(c) Reinforcement learning (RL) with precision-weighted prediction errors.

Temporal-difference updates can be extended to $\delta_t^{(\Pi)} = \Pi_t(r_t + \gamma V(s_{t+1}) - V(s_t))$, where Π_t is learned from cue reliability (e.g., packaging clarity, brand familiarity). This implements **precision-weighted PEs** within standard policy/value learning and links dopaminergic Reward Prediction Errors (RPEs) to marketing manipulations.

These mappings articulate how **gradient descent on free energy**, **precision learning**, and **hierarchical priors** correspond to practical AI training rules (variational objectives, uncertainty-aware gains, and precision-modulated Temporal-Difference Errors-TD errors), providing a clear path from theory to deployable models.

7. Ethical and Practical Implications of Predictive Neuromarketing

As predictive neuromarketing increases explanatory depth and predictive power, it raises critical ethical, societal, and regulatory considerations. While neuromarketing applications often resemble traditional marketing tools, predictive coding enhances theoretical clarity and may enable more subtle and effective influence strategies. This mandates a careful ethical analysis.

7.1. Transparency, Manipulation, and Autonomy

One concern is that predictive neuromarketing could be used to manipulate priors, prediction errors, or precision in ways that compromise consumer autonomy. For instance:

- Strengthening priors via narrative framing could reduce susceptibility to new information.
- Artificially boosting precision on emotional cues may bias valuation.
- Exploiting prediction-error signals could intensify impulse-driven decisions.

Ethicists warn that such practices risk crossing the boundary from persuasion to manipulation, particularly when consumers lack insight into how predictive processes shape their behaviour (Ariely & Berns, 2010; Noggle, 1996; Stanton, Sinnott-Armstrong, & Huettel, 2016).

7.2. Vulnerable Populations and Cognitive Bias Exploitation

Predictive-coding models suggest that individuals differ in baseline precision, prior strength, and sensitivity to prediction errors—traits linked to cognitive style, psychopathology, or developmental factors. This raises concerns when marketing is directed at:

- children and adolescents with undeveloped predictive systems,
- individuals with high impulsivity or uncertainty sensitivity,
- populations with low digital or health literacy,
- or those prone to addictive patterns of reward learning.

Using predictive neuromarketing without safeguarding such populations could exacerbate inequalities or foster pathological consumption patterns (Bozzola et al., 2022).

7.3. Privacy and Neural Data Governance

Neural data cannot be anonymised in the traditional sense; they contain rich signatures of identity, preference, and cognitive traits. Predictive neuromarketing intensifies these concerns because:

- priors and precision patterns can infer personal history, culture, or emotional states;
- prediction-error signals can reveal susceptibilities unknown even to the consumer;
- brain-based forecasting may predict behaviour more accurately than consumers' own reports.

Thus, stringent data governance, transparency, and consent frameworks are necessary, especially as neurotechnology becomes increasingly integrated into consumer devices (Ienca & Andorno, 2017).

7.4. Ethical Use of AI and Predictive Modelling

Machine-learning models used in neuromarketing may infer latent variables corresponding to priors or precision without explicit awareness from the user. This raises questions about:

- algorithmic fairness,
- explainability of predictive models,
- responsibility for behavioural outcomes influenced by AI,
- and the ethics of large-scale behavioural modulation through personalised content.

Policy bodies increasingly emphasise the need for **responsible innovation** in neurotechnology and predictive AI, advocating for robust safeguards as commercial applications expand (Yuste et al., 2017).

7.5. Distinguishing Scientific Insight from Manipulative Application

Finally, the field must maintain a distinction between:

1. **Scientific understanding** of consumer inference, and
2. **Practical application** for influencing behaviour.

Just as clinical neuroscience aims to understand vulnerability without exploiting it, predictive neuromarketing must avoid becoming a tool for hidden persuasion. Transparent reporting, consumer education, and adherence to ethical guidelines—such as those proposed by Ariely and Berns (2010) or Stanton, Sinnott-Armstrong, & Huettel (2016) —will be critical to maintaining public trust.

8. Conclusion

Predictive neuromarketing offers a powerful integrative framework that bridges computational neuroscience, psychology, and marketing science. By grounding consumer behaviour in Bayesian inference and predictive-coding dynamics, this approach reframes valuation, preference formation, and decision-making as the result of hierarchical belief updating driven by priors, prediction errors, and precision modulation. This perspective not only unifies disparate empirical findings across fMRI, EEG, behavioural studies, and large-scale neuroforecasting but also provides a principled explanation for why contextual cues such as price, branding, packaging, and narrative framing exert such profound effects on consumer experience.

The predictive-coding lens reveals that marketing stimuli do not simply influence attitudes—they actively shape the generative models through which consumers interpret the world. Price signals operate as high-level priors, branding serves as a semantic scaffold that structures expectation, and product experience represents a continuous flow of prediction-error updating. Crucially, neural valuation signals in regions such as vmPFC and ventral striatum can be understood as posterior expectations, emerging naturally from the integration of sensory evidence and contextual beliefs.

This framework also clarifies why neural measures often outperform self-report in predicting real-world behaviour: they capture latent computational states—shared priors, implicit precision estimates, and affective prediction errors—that consumers cannot articulate verbally. Predictive neuromarketing therefore offers not just improved prediction but deeper mechanistic insight.

At the same time, this enhanced explanatory power raises important ethical considerations. Manipulating priors, modulating precision, or exploiting prediction errors risks undermining autonomy and disproportionately affecting vulnerable populations. The field must therefore adopt transparent, responsible practices that balance scientific insight with societal protection.

Looking forward, predictive neuromarketing provides fertile ground for new methodologies and applications. Future work may integrate multimodal neuroimaging with adaptive Bayesian modelling, develop personalised generative-model profiles, or build real-time predictive architectures for consumer–AI interaction. As digital platforms increasingly shape belief formation, predictive neuromarketing offers a rigorous scientific foundation for understanding and guiding human–technology engagement.

The proposed mappings between parameters (μ, *ε*, *Π)* and neural signatures (vmPFC value codes, striatal PEs, theta/ERP indices of precision and mismatch) should be viewed as testable hypotheses requiring validation with preregistered EEG/fMRI studies and out-of-sample neuroforecasting benchmarks. Future research should compare predictive-coding models to strong alternatives (e.g., conventional RL without precision control), quantify parameter recoverability and identifiability, and assess generalisation across product categories and cultures.

The current work is theoretical and contains no new empirical data. Its primary purpose is to establish a computational framework for hypothesis creation rather than experimental validation. Future research should empirically confirm the framework's predictions with EEG, fMRI, and behavioural experiments, and compare predictive-coding-based models to other approaches.

By reconciling the computational logic of the brain with the behavioural realities of the marketplace, predictive neuromarketing marks a significant step towards a unified science of consumer cognition—one that is theoretically robust, empirically grounded, and ethically informed.

Appendix A. Derivation from generative model to Eq. 17 (GLM)

A.1 From Bayes to posterior value

With prior $p(z \mid \theta)$ and likelihood $p(x \mid z, c, \phi)$, the posterior is

$p(z \mid x, c) \propto p(x \mid z, c, \phi)\, p(z \mid \theta),$

and subjective value is the posterior expectation $V = \mathbb{E}[u(z) \mid x, c]$ (15)

A.2 Choice and individual outcomes

Individual choice probabilities follow a softmax (16):

$$P_i(j) = \frac{\exp\{\beta_i V_{ij}\}}{\sum_k \exp\{\beta_i V_{ik}\}}. \tag{16}$$

At population level, expected micro-behaviours (clicks, likes, donations) aggregate these probabilities under heterogeneous priors, precisions Π_i, and β_i.

A.3 From posterior statistics to neurofeatures

Assume early neural features n_j (e.g., vmPFC value, striatal PE, frontal-theta) are **sufficient statistics** (or linear surrogates) for latent predictive-coding states (V, ε, Π) for stimulus *j*:

$n_j \approx S(V_j, \varepsilon_j, \Pi_j) \approx \mathbf{W}\,[V_j, \varepsilon_j, \Pi_j]^\top + \eta_j$.

A.4 Linearising market-level outcomes

Let market outcome M_j (e.g., sales lift, shares) be a smooth function g of these latent states and traditional covariates X_j:

$M_j = g(V_j, \varepsilon_j, \Pi_j, X_j) + \xi_j$.

First-order Taylor expansion around reference $(\bar{V}, \bar{\varepsilon}, \bar{\Pi}, \bar{X})$ $(\bar{V}, \bar{\varepsilon}, \bar{\Pi}, \bar{X})$ gives

$M_j \approx \alpha + \mathbf{a}^\top[V_j - \bar{V}, \varepsilon_j - \bar{\varepsilon}, \Pi_j - \bar{\Pi}] + \boldsymbol{\gamma}^\top(X_j - \bar{X}) + \xi_j.$

Substitute the neurofeature surrogate relation to obtain the **GLM**:

$\boxed{M_j = \alpha + \mathbf{w}^\top n_j + \boldsymbol{\gamma}^\top X_j + \varepsilon_j,}$

A.5 Why linear works empirically

Because n_j summarise shared priors/PE/precision across people, a linear readout often forecasts population responses better than self-report proxies; this explains neuroforecasting gains reported across vmPFC/striatum features.

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