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Quantifying the Emotional Value of Goods and Services: Values of Hate and Love and Everything in between

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Abstract

Conventional economic analysis treats goods and services as bundles of functional attributes whose value is revealed by prices and choices. Yet real-world demand is pervasively shaped by feelings—joy, disgust, pride, nostalgia, envy, comfort, belonging.

This paper formalizes emotional value as a measurable component of consumer welfare, distinct from (but interacting with) functional utility and monetary cost. Building on affective science, neuro-economics, marketing, and information systems, I propose a composite Emotional Value Index (EVI) that integrates (i) self-report psychometrics, (ii) linguistic and behavioral traces, (iii) psychophysiology (e.g., HRV, EDA, pupil and gaze), (iv) neural evidence, and (v) digital footprints (search, clickstreams, reviews). The paper details measurement, validation, and computation of EVI, including methods to infer affect from online data rather than questionnaires alone. I illustrate applications for platform firms (Google/YouTube, Amazon, Apple, Netflix), discuss how love (positive valence, high identity alignment) and hate (negative valence, high arousal/identity threat) sit at opposite poles of an effect space, and show how EVI can slot into cost–benefit analysis, hedonic pricing, discrete-choice models, and computable general equilibrium.

I conclude with a governance blueprint (privacy law, dark-pattern avoidance, differential privacy) for ethically harnessing emotion. The approach reframes "value" to include how goods make us feel, not just what they do.

Key empirical and theoretical anchors are cited at the end.

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Introduction

Prices and features explain only part of why people buy. A café's latte might be objectively similar to competitors', but its ritual, music, lighting, crowd, and brand story can command a premium. These elements live in the emotional domain. Behavioral economics has shown systematic departures from rational-choice axioms, rooted in loss aversion, reference, dependence, and framing, all affect-laden processes. At the same time, affective science provides compact, quantifiable structure for emotion—most notably the valence × arousal circumflex— making it possible to operationalize "how it makes you feel."

Neuroscience closes the loop, showing that marketing cues—even price tags—can change experienced pleasantness and associated activity in valuation circuitry.

Aim

I define and measure emotional value (EV) as the affective contribution of a good/service to experienced utility. I then show how EV can be estimated from digital traces (search queries, dwell, skips/re-watches, reviews) in addition to traditional surveys, and how a composite EVI can be incorporated into well-known economic models.

Scope

This is a scientific synthesis with methods, structural equations, algorithmic pipelines, and applied case studies (Google, Amazon, Apple, Netflix). The concluding sections cover limitations and governance (GDPR/CCPA, NIST Privacy Framework, FTC dark-pattern guidance).

Background and Theory

From Utility to Emotion-Augmented Value

Prospect Theory documented stable deviations from expected utility (e.g., loss aversion), evidencing the role of emotion in valuation under risk. In consumption without explicit risk, similar affective drivers operate. The EVI framework treats these not as "errors" but as components of value.

Psychological Structure of Emotion

The circumflex model of affect maps feelings in a 2-D plane (valence: pleasant ↔ unpleasant, arousal: activated ↔calm). It has deep empirical support and offers a convenient coordinate system for quantification. For self-report foundations, the PANAS scales are widely used and psychometrically validated.

Neural Correlates of Experienced Pleasantness and Brand

Neuroimaging shows price and brand cues shift experienced pleasantness and activity in medial orbitofrontal/ventromedial prefrontal cortex (mOFC/vmPFC)—canonical valuation hubs. The famous wine-price study showed higher price cues increased both reported pleasantness and mOFC activation; the Coke/Pepsi study revealed vmPFC responses tracking brand-cued preferences. These provide biological plausibility for EV as a real, manipulable construct.

Affective Computing and Language

Affective computing formalized methods for machines to sense and respond to emotion; it anchors the multi-modal measurement agenda (signals, behavior, context).

Large, validated lexica (LIWC; NRC Emotion Lexicon; Valence–Arousal–Dominance norms) enable text analytics of reviews, chats, and social media at scale.

Defining Emotional Value (EV)

Definition: Emotional value is the measurable contribution of affect (valence, arousal, identity resonance, durability) to the overall perceived worth of a product/service, distinct from functional performance or cost.

Dimensions

- **Valence (Love↔Hate):** net positivity/negativity; disaggregated by discrete emotions when needed (joy, pride vs. anger, disgust).
- **Arousal:** activation/intensity; important because "hot" negative states (rage) drive different behaviors than "cool" dislike.
- **Durability:** persistence of affect after use (lasting satisfaction vs. momentary delight).
- **Identity alignment:** congruence with self-concept/group identity (e.g., "blue bubble" lock-in).
- **Context sensitivity:** EV varies with context (alone vs. social, morning vs. evening, pre/post-vent).

These dimensions are observable with multi-modal signals.

Measurement: From Surveys to Digital Traces

Self-Report Baselines

- PANAS / PANAS-X: validated scales for positive/negative affect; useful for ground- truth labeling.

Language and behavior (passive signals)

- **Text:** sentiment/emotion via LIWC categories, NRC eight-emotions, and VAD scores for words; robust for large-scale review/social data.
- **Behavioral traces:** dwell time, bounce, re-engagement frequency, abandoning vs. completing flows; these operationalize approach/avoidance tendencies.
- V**oice/chat:** prosody, lexical emotion markers in service interactions (use with consent and strict privacy).

Psychophysiology

- Heart Rate Variability (HRV): correlates with emotional regulation and arousal; time/frequency metrics are standard and well-reviewed.
- Electro dermal Activity (EDA/GSR): canonical arousal index, widely used in emotion research.
- Pupillometry: pupil dilation tracks arousal; sensitive to affective stimuli.
- Eye tracking: fixations/saccades reveal attention and interest, crucial for design/UX and ad creative.
- Facial Action Coding (FACS): structured coding of micro-expressions; basis for automated CV models.

Neuroscience (Selective Use)

- EEG/fMRI: gold-standard mechanistic insight but costly; use for calibration/validation rather than production inference. Price and brand studies motivate causal impact of cues on experienced pleasantness.

Digital Footprints (Beyond Questionnaires)

- **Search queries:** linguistics of intent ("soothing playlists," "best stress relief app," "I hate pop-ups") reveal momentary and traitlike affect; aggregated—with consent—into EV signals.
- Clickstreams & recommendations: skips/rewatches, session depth, and voluntary re- engagement are rich EV proxies (high valence + arousal often yield "binge/loop" patterns). At platform scale, YouTube and Netflix illustrate how behavior (implicit feedback) is already the backbone of personalization.
- Reviews & social: granular emotion in text; NRC/LIWC/VAD enable cross-domain comparability.

The Emotional Value Index (EVI) Construct

Figure 5.1 – Emotional Value Index (EVI)

$$EVI = \alpha S + \beta L + \gamma B + \delta N + \varepsilon D$$

S: Self-report (surveys, PANAS)

L: Language/Behavior (reviews, chat, dwell)

B: Biometrics (HRV, EDA, pupil, face)

N: Neural (EEG, fMRI calibration)

D: Digital traces (search, clicks, streams)

Training Targets and Supervision

- Ground-Truth Labels: episodic delight/satisfaction (post-use probes), longitudinal well- being, NPS-like measures.
- Revealed-Affect Proxies: re-engagement curves, binge/rewatch patterns, voluntary referrals, organic review valence.
- Neural Calibration: align EVI with mOFC/vmPFC response where feasible in lab studies.

Construct Validity, Reliability, and Fairness

- Convergent Validity: EVI correlates with independent psychophysiology (HRV/EDA) during use.
- Discriminant Validity: EVI is separable from usability or speed metrics.
- Test–Retest: stability under similar conditions; state vs trait decomposition.
- Fairness: check measurement invariance across language/region/age/gender; debias lexica and

models; audit for disparate error rates.

Interpreting Love and Hate

Map love as high positive valence, often moderate-to-high arousal, high identity alignment, and long durability; hate as high negative valence, often high arousal, identity threat. The same arousal can produce opposite behaviors depending on valence (approach vs avoidance), so valence and arousal must be measured jointly.

Deriving EVI from Existing Online Data (No New Questionnaires)

Search and Browsing

- Query semantics: apply NRC/LIWC/VAD to queries and page titles; weight by recency and user context (with consent).
- Session dynamics: model dwell, pogo-sticking, and abandonment as latent arousal/valence signals.

Platform Interactions

- **YouTube:** two-stage DNN recommenders already optimize for watch-time; adding EVI nudges them toward quality of affect rather than raw duration, mitigating doomscroll/binge externalities.
- **Netflix:** skip/rewatch/complete trajectories and user reports map to emotion clusters (comfort vs. thrill-seeking).

Reviews and Social Text

- Run multi-label emotion classification (joy/trust/anticipation… anger/disgust/fear) on reviews and support threads to estimate product-level EVI and surface "hate" drivers (e.g., betrayal after a price hike) vs. "love" drivers (e.g., craftsmanship pride).

Guardrails on Inference

Studies show emotions can be influenced by platform curation (e.g., the Facebook emotional- contagion experiment), underscoring both the power and the ethical stakes of affect-sensitive systems; such findings must be handled with care and transparency.

Case Studies: How Firms Could Use EVI

These are examples of possible applications, not claims about any specific company's undisclosed practices.

Google & YouTube

- **Search:** incorporate EVI as a re-ranking tie-breaker for results that meet intent but differ in affect fit (e.g., soothing vs. energizing content for the same query), using consented query semantics and short-term re-engagement as feedback.
- **YouTube Recommendations:** current two-stage DNN (candidate generation + ranking) optimizes engagement; adding an EVI term in the ranking loss can dampen exposure to "hate-bait" that drives high arousal but negative valence, and amplify "love-leaning" content with positive valence and durable satisfaction (e.g., creators a user returns to when seeking comfort).
- **Ads:** creative pre-testing with psychophysiology (EDA/eye-tracking/pupil) identifies which executions evoke desired affect; EVI predicts downstream brand lift beyond clicks.

Amazon

- **Marketplace UX:** model cart additions, save-for-later, wish lists, and cross-session return-to-cart as positive EVI signals; rage-clicks/returns as negative EVI.
- **Reviews:** NRC/LIWC/VAD and aspect-based emotion detect which features drive love/hate, guiding procurement and design.
- **Alexa:** voice prosody could, with consent, route frustrated callers to empathetic agents; aggregate only with strict privacy controls.
- **Pricing & Promos:** rather than purely margin-based offers, use EVI to reward loyalty emotion (e.g., surprise-and-delight gestures) and to avoid exploitative pricing when negative-valence cues (resentment) spike.

Apple

- **Industrial Design & Haptics:** lab studies combine HRV/EDA/pupil during unboxing and interaction; maximize love (pride/joy) while minimizing hate (frustration at friction points).
- **Ecosystem:** measure identity alignment EVI (e.g., messaging lock-in pride) and nurture it without dark patterns (opt-out clarity, no manipulative friction).

Netflix

- Catalog curation: augment recommender objective with EVI clusters (comfort, catharsis, adrenaline) to diversify emotional diets; the platform already documents the business value of personalization—EVI refines "value" by centering affect.

Modeling: Bringing EVI into Economics (Expanded)

Integrating the Emotional Value Index (EVI) into existing economic models allows us to capture consumer behavior and welfare far more accurately than functional-only approaches. Below, I expand the modeling strategies and illustrate applications for online platforms and physical retail environments, focusing on profitability, conversion optimization, and price- discovery.

Cost–Benefit Analysis (CBA)

Traditional cost–benefit analysis monetizes utility by estimating willingness-to-pay (WTP) and comparing it to production costs. EVI enables us to augment CBA with affective surplus.

- Example (Public Policy): A city evaluating two subway car redesigns might find both designs equal in safety and efficiency. However, biometric studies (facial emotion recognition, HRV) show one design produces 20% higher positive EVI (comfort, calmness). Translating this into WTP-equivalent values, policy-makers can justify the slightly higher upfront cost.
- Example (Corporate): A SaaS platform compares two onboarding flows. Functional conversion rates are similar, but EVI scores reveal Flow A produces significantly more "frustration." By including EVI in CBA, the firm sees that Flow B has higher long-term retention, even if short-term conversions are equal.

Hedonic Pricing Models

Hedonic models estimate the value of non-obvious product attributes (e.g., location, brand aesthetics). With EVI, emotional features can be explicitly priced.

- **Real Estate:** Neighborhood "vibes" (measured via social media sentiment, geotagged reviews, or surveys) could be included in hedonic price regressions. Homes in areas with higher positive EVI (e.g., associated with safety, belonging, or aesthetic beauty) command price premiums.
- Retail Example: A luxury fashion store compares two handbag designs. Both use identical materials, but consumer reviews show one triggers stronger emotions of "pride" and "confidence." Hedonic regressions with EVI attributes uncover a hidden upward pricing potential, suggesting that the "pride-inducing" design could support a 15% price increase without reducing demand.

Discrete Choice and Logit Models

Discrete choice models (DCM) assume consumers pick the option that maximizes their utility from a set. By adding EVI as an explicit attribute, DCMs can predict real choice shares more accurately.

- Online Example: An e-commerce platform can incorporate EVI from product page browsing (time on page, engagement, sentiment of reviews read) into the utility function. Products that evoke stronger positive EVI—even when functionally similar—gain higher predicted purchase probabilities.
- In-Store Example: Using cameras and sensors (with opt-in consent), retailers track facial expressions and dwell time near displays. Discrete-choice models that incorporate EVI data show which displays not only draw attention but create positive affect strong enough to tip purchase decisions.
- Profitability Insight: If two competing products yield similar margins, but one produces consistently higher EVI, stores should feature it prominently (endcaps, promotions) to increase conversion.

Computable General Equilibrium (CGE) Models

CGE models simulate entire economies by linking households, firms, and markets. By embedding EVI-adjusted utility functions, macro models could capture welfare impacts of industries beyond GDP.

- **Example:** A government incentivizes green energy adoption. The switch reduces pollution (functional benefit), but it also generates positive EVI (pride in sustainability, reduced eco-anxiety). Integrating EVI into CGE analysis shows the aggregate welfare boost is larger than functional energy savings alone.
- **Example (Corporate Strategy):** An entertainment company (e.g., streaming service) can

simulate how shifting catalog investments from neutral-EVI content to high-EVI content affects long-term subscriber growth and retention across demographics.

Marketing Mix and Profit Optimization

Marketing Mix Models (MMM) estimate the effect of advertising, pricing, and promotions on sales. Adding EVI creates a new optimization layer.

- **Ad Creative Selection:** Instead of optimizing purely for click-through rate, advertisers can score creatives by EVI during testing (using eye-tracking, EDA, or sentiment analysis). Ads with higher EVI predict higher conversion uplift and brand loyalty even if immediate CTR is identical.
- **Promotion Strategy:** Negative EVI signals (frustration, betrayal in reviews) can indicate where discounting may not solve the underlying issue, preventing wasted spend. Conversely, positive EVI signals suggest where promotions could accelerate word-of- mouth effects.
- **Example:** An online subscription box company finds two different ad creatives drive the same acquisition cost per user. EVI measurement shows Creative A evokes excitement (anticipation, joy), while Creative B evokes mild interest. Long-term churn analysis confirms Creative A's cohort retains 20% longer, justifying greater spend behind that ad.

Discovering Hidden Price Potential

Perhaps the most direct profitability lever: EVI can reveal when consumers perceive a product as underpriced relative to its emotional value.

- **Luxury Example (Online):** Amazon or Shopify sellers could monitor reviews with strong pride/identity language ("best purchase I've made," "makes me feel unstoppable"). When EVI is consistently high, it suggests the market price ceiling is higher than current price. Controlled A/B tests with incremental price increases can capture additional margin.
- **In-Store Example:** A coffee chain pilots new packaging that increases "warmth" and "comfort" EVI in customer surveys and facial recognition. Sales volumes remain constant after a 5% price hike, revealing hidden elasticity supported by emotional value.

• Digital Content Example: A gaming company tracks biometric signals (heart rate, pupil dilation) during beta testing. Levels that score highest on EVI correlate with willingness to pay for downloadable expansions. By bundling those "emotionally peak" levels into premium content, the company uncovers latent price premiums.

Customer Segmentation and Personalization

EVI makes it possible to segment customers not just by demographics or spend but by emotional profiles:

• **High-pride spenders:** respond well to premium upsells and exclusivity.
• **Comfort-seekers:** loyal to familiar brands, price-sensitive but high lifetime value if retention is nurtured.
• **Novelty-seekers:** chase excitement, easily swayed by "new" but churn quickly without ongoing stimulation.

By tailoring prices, offers, and communications to these emotion-segments, firms can significantly increase conversion rates and profitability. Summary

Integrating EVI into economic modeling isn't just a theoretical exercise—it creates concrete profit levers:

- Conversion Optimization (choose designs, flows, and ads with highest EVI).
- Shelf/Screen Placement (prioritize high-EVI items in online rankings or store layouts).
- Price Discovery (detect hidden upward elasticity when EVI is strong).
- Customer Segmentation (align offers with emotional archetypes).
- Macro Welfare Analysis (capture benefits of policy or investment that go beyond function).

Estimation Pipeline (practical recipe)

- **Data assembly (consent-first).** Logs of search/click/stream/review; optional biometrics; periodic light-touch surveys (anchors).
- **Feature engineering.**
- **Text:** LIWC categories; NRC eight-emotions; VAD scores by token/document.

- **Behavior:** dwell, skips/rewatches, abandon/complete, re-engagement; session embeddings.
- **Bio:** HRV (RMSSD, HF/LF); EDA (phasic/tonic); pupil (Δ diameter); gaze heatmaps; FACS AUs.

Modeling. Multi-task learner predicts (a) valence, (b) arousal, (c) delight, (d) WTP increment; EVI is latent or explicit composite.

Calibration. Small lab studies with fMRI/EEG for mechanistic alignment; large A/B tests for behavioral lift.

Causal identification. Instrumental variables or difference-in-differences on exogenous UI changes that shift EVI but not function.

Validation.

- **Convergent:** EVI ↔ psychophysiology; Predictive: churn, retention, NPS lift.
- **Fairness:** subgroup error analyses; cultural/linguistic stability.

Welfare and Society

Income correlates strongly with life evaluation, but classic evidence shows diminishing returns to emotional well-being beyond a threshold; later work complicates this, yet the core point stands: affect and evaluation are not identical. Measuring EV speaks directly to this wedge. In policy, adding EV to CBA (e.g., parks, transit, noise abatements) captures benefits that prices miss.

Governance: Using Emotion Ethically

Legal baselines

- GDPR Article 22 limits decisions based solely on automated processing (including profiling) that have legal or similarly significant effects, and grants rights to human review—highly relevant when EVI informs consequential actions.
- CCPA/CPRA provide rights to know, delete, opt out of sale/sharing, and limit use of sensitive data; firms using digital traces to infer emotion should honor these rights and purpose-limit processing.
- NIST Privacy Framework offers a risk-based playbook to identify, govern, control, and communicate privacy risks; adopt it to manage EVI programs.

Dark-Pattern Avoidance and Transparency

The FTC's dark-pattern report catalogs manipulative designs; EVI should not be used to exploit vulnerabilities (e.g., rage bait to juice engagement). Provide clear explanations and easy controls.

Privacy-Preserving Computation

Use differential privacy for aggregate EVI analytics, minimizing re-identification risks while allowing useful statistics; combine with on-device processing/federated learning where possible.

Emotional Contagion and Experimentation

Large-scale experiments show platform curation can nudge aggregate emotional expression, albeit with small effects; this raises disclosure and IRB-style review questions even in product contexts.

Limitations

- **Construct drift:** meanings of emojis, slang, and memes change rapidly; lexicon and model maintenance is essential.
- **Causal ambiguity:** high EVI may be both cause and consequence of repeat use; careful identification is required.
- **Cross-cultural invariance:** valence/arousal mapping is robust, but expressions of love/hate vary by language, norms, and identity; demand per-locale calibration.
- **Data bias & coverage:** digital traces under-represent some populations; avoid amplifying inequities.
- **Neural measures:** not deployable at scale; use sparingly for calibration.

Future Directions

- **Emotion-aware objectives** in recommenders (quality-of-affect, not just quantity-of- attention).
- **Long-term well-being metrics** tied to OECD frameworks, allowing platforms and cities to optimize for flourishing, not just clicks.
- **Robust privacy tech** (DP, federated learning, secure aggregation) to compute EVI safely.
- **EVI-informed product design** that intentionally elicits pride, calm, or awe—while dampening

envy, anger, and contempt.

Conclusion

This paper formalized emotional value as a quantifiable, model-ready construct and proposed a composite EVI derived from multi-modal signals—including existing online data like search history and clickstreams, with consent and guardrails. Anchored in affective science and neuroeconomics, EV is not noise; it is a first-class driver of demand, loyalty, and welfare.

Integrating EVI into CBA, hedonic pricing, discrete choice, and macro models yields richer measurement of consumer surplus and societal well-being.

Platform firms can apply EVI to improve recommendations, design, service, and creative testing—but must do so within strong privacy and anti-manipulation constraints. In short: markets price what people value; people also value how things feel. We now have the tools to measure it.

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