Decoding the Neural–Financial Link: A Dynamic Resource Allocation Model Across the Product Life Cycle

A Conceptual Model Paper

Keywords: Marketing–Finance Interface; Product Life Cycle; Neuro-Physiological Response; Causal Machine Learning; Firm Value; Dynamic Resource Allocation; Heterogeneous Treatment Effects; Risk Buffering

Abstract

The traditional marketing–finance value chain faces mounting validity challenges: its foundational data are compromised by survey integrity problems, its dominant models assume linear relationships that miss threshold effects inherent in human psychology, and its temporal structure ignores product life cycle (PLC) dynamics that alter how marketing inputs translate into financial outputs. This article is a conceptual model paper that develops the *DPR-PLC (Dynamic Physiological Response–Product Life Cycle)* framework. Rather than testing hypotheses with empirical data, we integrate neurophysiological and behavioral response metrics, PLC-contingent dynamics, and causal machine-learning–based attribution to propose a new framework for understanding how marketing investments create financial value and reduce risk. We develop four formal propositions: (P1) neural arousal exhibits power-law returns in introduction stages; (P2) cognitive ease functions as a financial risk-hedging mechanism in maturity stages; (P3) ignoring PLC-contingent neural dynamics produces systematic measurement bias in uplift estimation; and (P4) PLC-aligned, uplift-based resource allocation dominates static allocation on both return and risk dimensions. We articulate a research agenda with falsification criteria and a managerial decision dashboard featuring a Neural Sensitivity Gap indicator. The framework reframes marketing as a precision instrument for financial risk management and firm value creation across the product life cycle.

1. Introduction

For decades, the marketing–finance interface has sought to quantify how marketing investments create shareholder value (Srivastava et al., 1998; Rust et al., 2004; Edeling & Srinivasan, 2021). The accumulated body of work has produced important insights: advertising spending influences brand equity and customer lifetime value, which in turn shape sales, cash flows, stock prices, and risk-adjusted firm valuation. Yet this literature faces three emerging challenges that, taken together, suggest the need for a new generation of conceptual models.

The data integrity challenge. The foundational data of the marketing–finance value chain—self-reported consumer attitudes, intentions, and satisfaction scores—are increasingly questioned. Social desirability bias, nonresponse bias, and the proliferation of "panel farming" undermine the validity of survey-based metrics that serve as primary inputs to marketing–finance models (Groves et al., 2009). The collection of neuro-physiological data as an alternative introduces its own regulatory constraints: evolving IRB standards and data-protection regulations governing neural and biometric data (e.g., GDPR biometric provisions, emerging US state privacy laws) impose new compliance requirements that any measurement approach must address (Stanton & Stanton, 2020). When source metrics are noisy or biased, downstream inferences—from brand equity estimation to firm valuation—become fragile.

The linearity assumption. Most existing models at the marketing–finance interface assume linear or at best log-linear relationships between marketing inputs and financial outputs. Yet human psychology is characterized by S-curves, threshold effects, saturation points, and non-monotonic dose–response functions. A campaign that doubles its spend may generate zero incremental response below a neural activation threshold and substantial response above it. Linear models are ill-suited to capture such dynamics, which can lead to systematic misallocation of marketing resources.

The static snapshot problem. Existing marketing–finance value-chain models are typically specified as static. They treat the relationship between marketing inputs and financial outputs as time-invariant, offering limited mechanisms to incorporate PLC dynamics that alter customer composition, neural sensitivity profiles, competitive intensity, and the nature of what marketing can accomplish. As a product migrates from a "novelty" to a "classic," the neural receptivity of its customer base changes, yet current models rarely capture this transformation.

To address these three gaps, this paper develops the *DPR-PLC (Dynamic Physiological Response–Product Life Cycle)* model. By integrating neuro-physiological and behavioral feedback, PLC contingencies, and causal machine-learning–based attribution, we propose a framework that reframes marketing not merely as a tool for sales stimulation, but as a precision instrument for financial risk management and firm value creation across the product life cycle.

This article is a conceptual model paper that develops formal propositions rather than testing hypotheses with empirical data (MacInnis, 2011; Yadav, 2010). We articulate a research agenda—including falsification criteria for each proposition—to guide subsequent empirical work, specifying how laboratory neuro-physiological data, firm-level marketing records, and market-level archival data can be combined to operationalize and test the DPR-PLC framework.

Our contribution is threefold. First, we extend marketing–finance value-chain frameworks by integrating PLC dynamics, neuro-physiological response metrics, and causal machine-learning attribution into a coherent conceptual model that explains how and when marketing investments translate into cash-flow outcomes, firm value, and idiosyncratic risk. Second, we suggest a methodological shift from survey-based attitudinal metrics to objective neurophysiological indicators and from linear average-effect models to heterogeneous treatment-effect estimation via causal machine learning. Third, we offer a practical contribution through a "lab-to-ledger" roadmap and a managerial decision dashboard featuring a Neural Sensitivity Gap indicator that informs resource allocation decisions for chief marketing and financial officers.

2. Theoretical Background

2.1 The Marketing–Finance Interface and the Value Chain

The marketing–finance interface traces its intellectual origins to Srivastava, Shervani, and Fahey's (1998) seminal argument that marketing activities create market-based assets—brand equity, customer equity, and relational capital—that generate cash-flow streams affecting shareholder value. Subsequent work has elaborated this value chain by documenting how advertising spending (Joshi & Hanssens, 2010), customer satisfaction (Anderson, Fornell, & Mazvancheryl, 2004), and brand equity (Edeling & Fischer, 2016) influence stock returns, Tobin's Q, and systematic and idiosyncratic risk. Hanssens et al. (2009) provided a comprehensive framework linking marketing metrics to financial performance through stock market response.

Edeling and Srinivasan (2021) offer the most recent integrative review, synthesizing metrics, methods, and findings across decades of marketing–finance research. They identify persistent gaps: heavy reliance on survey-based attitudinal metrics; underexplored dynamic mechanisms governing how marketing–finance relationships evolve over time; and insufficient attention to heterogeneous effects. We position the DPR-PLC model as a direct response to these identified gaps. While prior work at the marketing–finance interface predominantly relies on survey-based metrics and linear models, we propose a PLC-contingent, neuro-behavioral, and causal machine-learning–based framework that replaces static average effects with dynamic, heterogeneous, non-linear treatment effects across the product life cycle.

2.2 The Product Life Cycle as a Dynamic Moderator

The product life cycle concept has a long history in marketing strategy, with classical contributions documenting how advertising effectiveness, pricing strategy, and competitive dynamics vary systematically across introduction, growth, maturity, and decline stages (Day, 1981; Tellis & Crawford, 1981). Despite this rich tradition, PLC has been largely absent from the marketing–finance interface literature. Most value-chain models treat the relationship between marketing inputs and financial outputs as temporally invariant.

This assumption is difficult to sustain. In the introduction stage, the customer base consists disproportionately of innovators and early adopters whose neural reward systems are primed for novelty-seeking and who exhibit high sensitivity to experiential, high-arousal marketing stimuli. In the maturity stage, the customer base has shifted toward the early and late majority, whose neural processing prioritizes cognitive fluency, familiarity, and effort minimization. By embedding PLC as a dynamic moderator throughout the marketing–finance value chain, the DPR-PLC model provides a mechanism for capturing these temporal dynamics.

2.3 Neuro-Physiological Response: Beyond Self-Report

Technologies such as electroencephalography (EEG), galvanic skin response (GSR), eye tracking, facial expression analysis, and heart-rate variability capture objective, time-continuous indicators of consumers' affective and cognitive reactions to marketing stimuli. Unlike self-reported attitudes, these measures capture pre-reflective, often nonconscious reactions that precede and shape downstream behavior.

The commercial adoption of neuromarketing technologies has accelerated. Industry reports estimate the global neuromarketing technology market at approximately $600 million in 2024, with projections reaching $1.9 billion by 2034 (Market.us, 2025). Recent neuroforecasting research demonstrates that aggregate neural responses can predict market-level outcomes—including advertising effectiveness, box-office revenue, and product adoption rates—beyond what self-report measures achieve (Berns & Moore, 2012; Dmochowski et al., 2014; Venkatraman et al., 2015; Barnett & Cerf, 2017). These studies provide empirical precedent for the DPR-PLC model's premise that neuro-physiological indicators offer superior predictive validity for marketing–finance linkages.

2.4 Causal Machine Learning and Heterogeneous Treatment Effects

Recent advances in causal machine learning provide the analytical engine for the DPR-PLC model. Traditional regression-based approaches estimate average treatment effects, masking the heterogeneity central to effective resource allocation. Causal forests (Wager & Athey, 2018) and uplift modeling methods enable estimation of conditional average treatment effects $\tau(x)$—the incremental effect of a marketing treatment on a focal outcome as a function of customer, channel, and contextual characteristics. Recent work integrates uplift modeling with heterogeneous treatment-effect methods for optimizing multi-treatment targeting policies (Zhao et al., 2023; Chen et al., 2024; Liu et al., 2025).

By synthesizing these four streams—the marketing–finance value chain, PLC dynamics, neuro-physiological measurement, and causal machine learning—the DPR-PLC model addresses the three foundational gaps: it replaces unreliable survey data with objective neurophysiological indicators, captures nonlinear dose-response functions through heterogeneous treatment-effect estimation, and embeds temporal dynamics through PLC-contingent moderation.

3. The DPR-PLC Conceptual Model and Propositions

This section presents the DPR-PLC model, defines its core constructs, describes the model's logic, and develops four formal propositions.

3.1 Core Construct Definitions

Marketing investment intensity (MI). The level and composition of a firm's spending on marketing activities across channels and formats over time, reflecting both magnitude and allocation across touchpoints and customer segments.

Neuro-physiological response (NPR). Objective, time-continuous indicators of consumers' affective and cognitive reactions to marketing stimuli—EEG-based indices, galvanic skin response, eye-tracking fixation patterns, facial expression analysis, and heart-rate variability—capturing pre-reflective reactions that precede and shape downstream behavior.

Neural sensitivity index (η). The responsiveness of target customers' neuro-physiological systems to a given level and type of marketing stimulation, defined as the non-linear response ratio of physiological arousal and cognitive load to specific marketing stimuli at a given PLC stage. Neural sensitivity evolves as the PLC progresses and as customer base composition shifts.

Neural heterogeneity (NH). Systematic differences in neuro-physiological responsiveness across customer segments and over time. Neural heterogeneity determines the upper bound of marginal conversion efficiency for a given marketing expenditure.

PLC-contingent uplift (τ). The incremental effect of a marketing treatment on a focal outcome relative to a no-treatment counterfactual, estimated at a specific PLC stage. Conceptualized as a conditional average treatment effect $\tau(x)$ capturing how uplift varies with customer characteristics, channel attributes, and PLC-stage-specific factors.

Market-based assets and customer cash-flow streams (MBA, CCF). Brand and customer-based assets arising from stakeholder relationships, manifesting in cash-flow streams through acquisition, retention, cross-buying, and price premium patterns.

Financial performance and risk (FP, Risk). Firm-level outcomes reflecting not only cash-flow magnitude but also timing and volatility, shaping firm value and cost of capital. Indicators include cash-flow variability, idiosyncratic stock-return volatility ($\sigma\varepsilon$), and Tobin's Q.

Neural Sensitivity Gap (NSG). The deviation between the observed neural sensitivity of the current customer base and the theoretically optimal sensitivity for the product's current PLC stage. NSG serves as a managerial early-warning indicator.

3.2 Model Logic and Architecture

The DPR-PLC model links marketing investments to financial performance through four interconnected layers (see Figure 1). *First*, firms choose marketing investment intensity and channel mix (MI) in a given PLC stage. *Second*, these investments generate neuro-physiological and behavioral responses (NPR), whose strength and pattern depend on neural sensitivity (η) and neural heterogeneity (NH). *Third*, causal machine-learning mechanisms translate NPR into heterogeneous, non-linear uplift $\tau(x)$ in customer-level and channel-level outcomes, shaping market-based assets and cash-flow streams. *Fourth*, aggregated cash-flow patterns influence firm-level financial performance and risk, feeding back into subsequent marketing decisions. PLC acts as a dynamic moderator throughout this chain.

Figure 1. *The DPR-PLC conceptual model.*

The framework links marketing investment intensity (MI) to financial performance and risk (FP, Risk) through four layers: (1) marketing inputs in a given PLC stage; (2) neuro-physiological responses (NPR) moderated by neural sensitivity (η) and heterogeneity (NH); (3) causal ML–based heterogeneous uplift estimation τ(x); (4) firm-level financial outcomes. PLC functions as a dynamic moderator throughout. Feedback loops close the dynamic system.

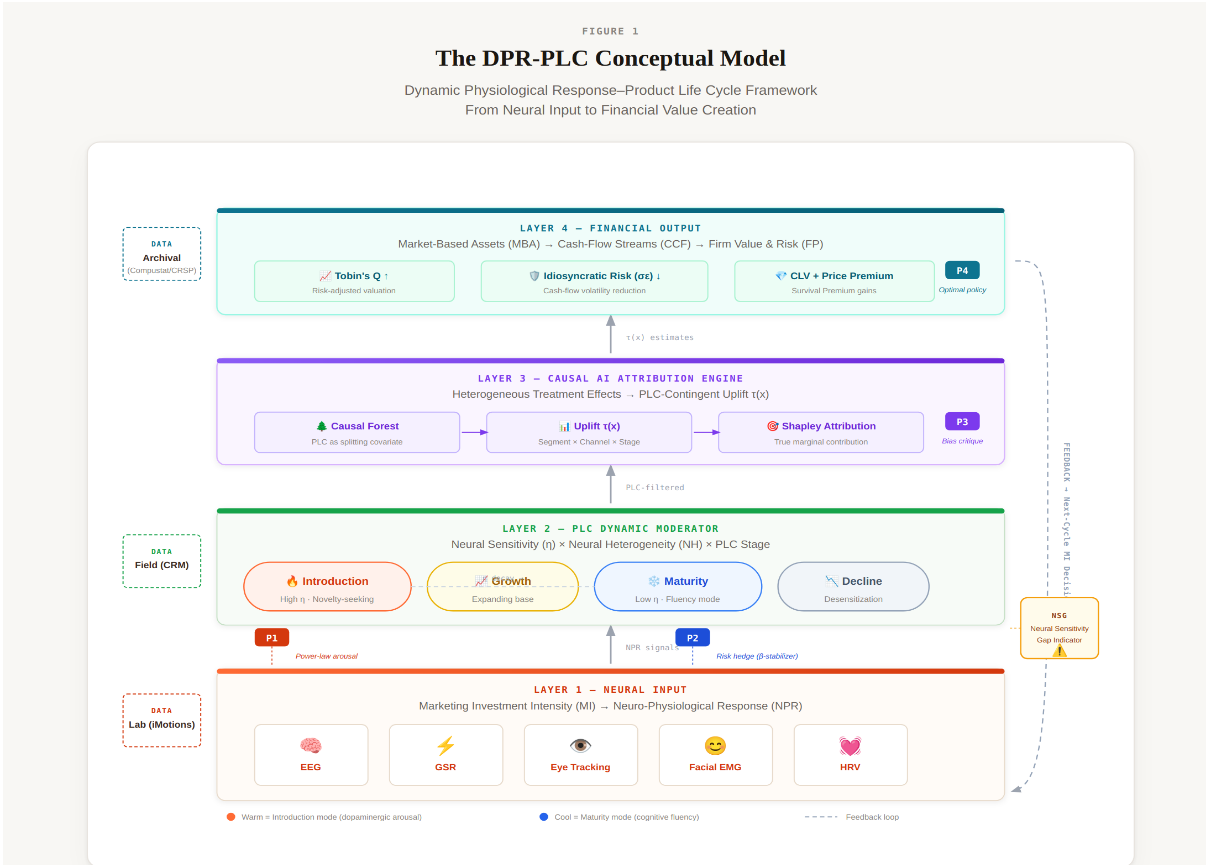

Figure 1. The DPR-PLC conceptual model links marketing investment intensity (MI) to financial performance through four layers: (1) neuro-physiological responses captured via laboratory sensors; (2) PLC-stage moderation of neural sensitivity (η) and heterogeneity (NH); (3) causal ML–based heterogeneous uplift estimation τ(x) with PLC as structural splitting covariate; (4) firm-level financial outcomes including Tobin's Q, idiosyncratic risk reduction, and cash-flow stability. Proposition tags (P1–P4) indicate where each theoretical contribution enters the framework. The feedback loop connects financial outcomes to next-cycle marketing decisions. The Neural Sensitivity Gap (NSG) indicator monitors deviation between observed and optimal neural sensitivity.

Figure 2. *Data-to-finance flow.*

Supplementary figure illustrating the data pipeline: iMotions millisecond-level neuro-physiological signals → feature engineering (arousal indices, cognitive load scores, synchrony metrics) → causal ML engine (causal forest with PLC indicators as structural covariates in *splitting criteria) → heterogeneous uplift τ(x) estimates → aggregation to firm-level cash-flow dynamics and Tobin's Q.*

FIGURE 2

Data-to-Finance Flow

From Millisecond Neural Signals to Firm-Level Financial Outcomes

Figure 2. Data-to-finance flow. The pipeline transforms millisecond-level neuro-physiological signals (Stage 1: iMotions platform capturing EEG, GSR, eye tracking, facial EMG, and heart-rate variability) into computed features (Stage 2: arousal indices, cognitive load scores, neural synchrony metrics, and memory encoding patterns, yielding the neural sensitivity index η). These features enter the causal ML engine (Stage 3: causal forest with PLC indicators as structural covariates in splitting criteria, uplift modeling, and Shapley-value attribution) to produce heterogeneous uplift τ(x) estimates at the segment, channel, and PLC-stage level (Stage 4). Individual-level estimates are then aggregated to firm-level cash-flow dynamics and mapped to financial outcomes (Stage 5: Tobin's Q, idiosyncratic risk reduction, cash-flow stability, and CLV gains). The time-granularity axis (top) illustrates how data resolution progresses from milliseconds to quarterly/annual financial reporting.

The model departs from the traditional marketing–finance value chain in three structural ways. First, it replaces subjective attitudinal metrics with objective neurophysiological indicators. Second, it replaces linear average-effect estimation with heterogeneous, non-linear treatment-effect estimation via causal machine learning. Third, it embeds PLC as a dynamic moderator that reshapes neural sensitivity, customer composition, competitive dynamics, and the financial function of marketing itself.

3.3 Propositions

Proposition 1: Power-Law Neural Arousal in the Introduction Stage. For a given level and type of marketing investment intensity, neuro-physiological responses are stronger and more non-linear (e.g., exhibit threshold or saturation effects) in earlier PLC stages than in later stages, reflecting higher neural sensitivity among early-stage customer segments and increasing neural desensitization as the PLC progresses.

In the introduction stage, the target audience—innovators and early adopters—is characterized by high sensitivity to novelty-driven reward signals. Marketing investments at this stage do not yield linear returns; instead, they exhibit threshold effects consistent with a power law of arousal. Neuroforecasting studies provide empirical precedent: aggregate neural responses to marketing stimuli predict market-level outcomes beyond what self-report measures achieve (Berns & Moore, 2012; Dmochowski et al., 2014; Barnett & Cerf, 2017). Firms that optimize for neural saliency using immersive, high-arousal content will achieve non-linear gains in price premiums and brand equity, while budget-diluted approaches that fail to reach the neural trigger threshold will yield near-zero financial ROI regardless of total spend.

Proposition 2: Cognitive Ease as a Risk-Hedging Mechanism in the Maturity Stage. During the maturity stage, the primary financial role of marketing shifts from seeking incremental growth ("alpha") to stabilizing cash-flow patterns ("beta"). Processing fluency and reduced cognitive load function as risk-hedging mechanisms: fluency-enhancing marketing reduces switching propensity and cushions cash flows against competitive shocks, thereby lowering idiosyncratic risk and supporting higher valuation multiples.

As a product transitions into maturity, consumers' neural relationship with the brand shifts from exploration to exploitation. High-arousal marketing tactics—effective during introduction—become "neural noise" in maturity, increasing cognitive load and triggering avoidance behaviors. Marketing investments should instead reinforce fluency signals that reduce perceived effort. By maintaining high neural synchrony and low cognitive load among existing customers, firms create a buffer against competitive shocks. Firms that optimize for low cognitive load will exhibit higher Tobin's Q because the market assigns a premium to increased predictability of future cash flows.

Proposition 3: PLC-Induced Measurement Bias in Effect Estimation. When models ignore PLC-contingent neural dynamics and rely solely on self-reported attitudes and static covariates, they systematically misestimate the incremental effects of marketing investments—overstating uplift in early PLC stages and understating it in later stages where neural sensitivity has shifted.

As products move from introduction to maturity, customer composition and neural sensitivity profiles change, yet conventional marketing–finance models assume time-invariant response functions. In early PLC stages, innovators may under-report adoption likelihood while exhibiting strong neurophysiological responses, leading survey-based models to underestimate true uplift. In later stages, habitual customers may over-report loyalty despite attenuated neural responsiveness, causing models to overestimate incremental impact. Proposition 3 identifies a measurement problem: the existing toolkit systematically miscalculates causal effects because it ignores the neural dynamics that PLC stage governs.

Proposition 4: PLC-Aligned Allocation and Financial Optimization. Marketing resource allocation policies aligned with PLC-contingent, neuro-based uplift estimates yield superior financial outcomes—higher expected cash flows and lower cash-flow volatility—than PLC-invariant policies with comparable spending levels.

Under DPR-PLC, firms first estimate heterogeneous treatment effects $\tau(x)$ incorporating PLC stage, neural sensitivity, and customer and channel characteristics. Using these estimates, managers reallocate budgets to emphasize high-uplift combinations in each stage. Such PLC-aligned policies increase expected conversion and CLV while stabilizing cash-flow trajectories. Proposition 4 is prescriptive: given the bias identified in P3, it specifies the allocation policy that corrects for that bias and improves financial outcomes on both return and risk dimensions.

Table 1. *Summary of DPR-PLC propositions: mechanisms, roles, and financial implications.*

Prop.	Core Mechanism	Role	PLC Focus	Financial Implication
P1	Novelty-driven reward; power-law arousal thresholds	Mechanism: non-linear response	Introduction	Price premiums and brand equity via neural saliency
P2	Processing fluency; cognitive load minimization	Mechanism: risk hedging	Maturity	Cash-flow volatility reduction; higher Tobin's Q
P3	Survey bias from ignoring neural dynamics	Critique: measurement bias	Cross-stage	Systematic mis-estimation of $\tau(x)$ and ROI
P4	Uplift-based reallocation across PLC stages	Prescription: optimal policy	All stages	Higher expected cash flows AND lower idiosyncratic risk

4. An Illustrative Scenario: The Hospitality Industry

To ground the DPR-PLC model in managerial reality, we develop an illustrative scenario from the hospitality industry—a sector characterized by high experiential intensity, significant capital commitment, and strong PLC dynamics.

Setting. Consider a single hotel brand operating two properties: a newly launched boutique hotel in a major city (introduction stage) and an established flagship property in the same market (maturity stage). The brand allocates identical social media budgets and discount strategies to both properties—a common practice reflecting static, PLC-invariant resource allocation.

Traditional model prediction. Under a conventional marketing–finance value chain, both properties generate similar returns per dollar of marketing spend, adjusted for size and market conditions.

DPR-PLC prediction for the new property (introduction stage). The target customer base consists of urban explorers with high neural sensitivity to novelty. The model directs budget toward high-arousal short-form video and influencer partnerships that trigger reward activation. Causal forest analysis identifies a high-uplift segment—experience-seeking millennials with high galvanic skin response to immersive content—and estimates a 20% incremental conversion uplift and significantly higher average daily rate (ADR) when marketing crosses the neural activation threshold.

DPR-PLC prediction for the established property (maturity stage). The customer base consists of repeat visitors with low neural sensitivity to novelty but high sensitivity to cognitive load. The model redirects budget from high-arousal content to member email optimization and booking-app UX simplification. The estimated financial impact is a 30% reduction in off-season occupancy rate volatility, translating into more predictable cash-flow streams and lower idiosyncratic risk.

Falsification scenario. If the established property's customer base responds to a new high-arousal campaign with high arousal but low neural synchrony, DPR-PLC predicts that cash-flow volatility will increase rather than decrease—the opposite of what a PLC-invariant model would expect. This counterintuitive prediction provides a critical test of Proposition 2.

5. Research Agenda: From the Laboratory to the Ledger

Because our goal is theoretical development rather than empirical testing, we deliberately do not analyze data in this article. Instead, we articulate a research agenda specifying how future work can operationalize and test the DPR-PLC model, organized around three phases with explicit falsification criteria.

5.1 Phase I: The Laboratory

Future researchers should utilize integrated neurophysiological measurement platforms (e.g., iMotions) combining EEG, GSR, eye tracking, and facial expression analysis to construct the neural sensitivity index (η) and characterize neural heterogeneity. Key design elements include controlled experimental groups representing different PLC stages, systematic variation of stimulus intensity and format, and measurement of the full NPR profile.

Testable predictions. P1: Experiments can test whether high-arousal stimuli produce threshold/power-law response functions among early-stage segments. P2: Experiments can test whether cognitive-ease-oriented stimuli produce stronger brand fluency among maturity-stage segments. Falsification criterion for P1: strictly linear (not threshold) NPR–outcome relationships across all stimulus intensities.

5.2 Phase II: The Field

Partner with a global hospitality group to access de-identified CRM data, marketing expenditure logs, pricing records, and occupancy/revenue time series. Apply causal machine-learning methods—causal forests (Wager & Athey, 2018) and uplift models—to estimate heterogeneous treatment effects across channels, customer segments, and PLC stages.

A critical methodological detail: in causal forest implementations, PLC indicators (e.g., product age, sales-growth trajectory, competitive intensity) enter as *contextual covariates*, allowing the forest to learn splits where treatment effects differ systematically by life-cycle stage. This enables estimation of PLC-contingent $\tau(x)$ without requiring experimental manipulation of PLC itself.

Testable predictions. P3: Field analysis can test whether neuro-based uplift estimates diverge systematically from survey-based estimates across PLC stages. P4: Field analysis can test whether PLC-aligned allocation produces superior risk-adjusted returns compared with PLC-invariant allocation. Falsification criterion for P2: if a mature-stage property exhibits high arousal but low neural synchrony and its cash-flow volatility decreases (rather than increases), the risk-buffering logic fails.

5.3 Phase III: Financial Synthesis

Map incremental marketing effects to firm-level financial outcomes using archival data (e.g., Compustat, CRSP). Specific linkages include cash-flow variability decomposition and Tobin's Q estimation conditional on PLC stage and marketing alignment. Event study methodology can assess whether PLC-aligned marketing announcements generate positive abnormal returns relative to PLC-misaligned announcements.

Table 2. *Research agenda: propositions, data, representative methods, design, and falsification criteria.*

Prop.	Data Sources	Representative Method	Design	Falsification Criterion
P1	Lab: iMotions (EEG, GSR, eye tracking)	Threshold / piecewise regression	Vary stimulus arousal; recruit innovator vs. majority segments	Strictly linear NPR–outcome functions across all intensities
P2	Lab + Field: iMotions + CRM	Panel regression with cash-flow volatility	Compare high-arousal vs. cognitive-ease stimuli among maturity customers	High arousal + low synchrony in maturity reduces (not increases) volatility
P3	Lab + Field: iMotions + marketing logs	Causal forest with PLC covariates	Compare neuro-based vs. survey-based $\tau(x)$ across PLC stages	No systematic divergence between neuro- and survey-based uplift estimates
P4	Field + Archival: CRM + Compustat/CRSP	Event study + Tobin's Q regression	Compare PLC-aligned vs. PLC-invariant allocation on returns and risk	PLC-aligned allocation fails to outperform static allocation on both dimensions

6. Managerial Implications: The Neural–Financial Decision Dashboard

To make the DPR-PLC framework actionable, we propose a managerial decision dashboard with three integrated modules and a unifying early-warning indicator—the Neural Sensitivity Gap.

Module 1: Neural Sensitivity Index (NSI) Monitor with Neural Sensitivity Gap. This module displays current neural sensitivity as a traffic-light indicator, derived from periodic neuro-physiological measurement or wearable device data. The core innovation is the Neural Sensitivity Gap (NSG): the deviation between observed neural sensitivity and the theoretically optimal sensitivity for the product's current PLC stage.

Positive gap (overheating): The mature-stage product is receiving excessive high-arousal stimulation. The system recommends reducing high-stimulation content and redirecting to service process simplification and loyalty maintenance.

Negative gap (fatigue): The introduction-stage product has not reached the neural activation threshold. The system recommends increasing stimulus intensity or initiating creative iteration.

Module 2: PLC Stage Drift Detector. Combines sales growth trajectory with neural arousal threshold data to determine whether a product has transitioned between PLC stages and recommends corresponding budget reallocation.

Module 3: Causal Attribution Heatmap. Displays each channel's true marginal contribution to financial value, estimated via causal forest algorithms. The CMO identifies high-uplift segments; the CFO views which channels contribute to cash-flow stabilization versus cash-flow generation.

7. Discussion

7.1 Theoretical Contributions

The DPR-PLC model extends the marketing–finance interface in three ways. First, it shifts the value chain from static average-effect representation to a dynamic, PLC-contingent framework capturing how the financial function of marketing evolves—from revenue generation in introduction to risk buffering in maturity. Second, it introduces a "neural PLC perspective": customers at different life-cycle stages exhibit structurally different neurophysiological response profiles with direct implications for cash-flow dynamics and firm risk. Third, it integrates heterogeneous treatment-effect estimation into the value chain, providing a conceptual mechanism for modeling nonlinear, segment-level variation in marketing uplift.

7.2 Methodological Contributions

The DPR-PLC model proposes a replicable "lab-to-ledger" pipeline: laboratory neurophysiological measurement builds precise response models; field-level CRM data provides external validation; archival financial data maps results to firm-level outcomes. The explicit inclusion of falsification criteria for each proposition distinguishes the DPR-PLC research agenda from purely programmatic statements and provides concrete guidance for what would count as evidence against the framework.

7.3 Practical Contributions

For CMOs, the DPR-PLC model explains why the same marketing budget produces different financial outcomes depending on PLC-stage alignment. For CFOs, it provides a mechanism for understanding marketing as a risk-management instrument. The Neural Sensitivity Gap indicator operationalizes these insights as a real-time early-warning system—not merely an observational tool, but a prescriptive decision architecture for dynamic resource allocation.

7.4 Boundary Conditions and Limitations

Implementation costs. Neurophysiological measurement requires significant infrastructure investment. The DPR-PLC framework is most feasible for large-scale enterprises with resources to deploy integrated measurement systems. The diffusion of wearable devices and mobile passive sensing may reduce these barriers.

Ethical and regulatory constraints. Neurophysiological data collection raises legitimate privacy concerns. Any implementation must comply with evolving IRB standards and data-protection regulations governing biometric and neural data (Stanton & Stanton, 2020). The precision targeting enabled by neural heterogeneity measurement must be balanced against the ethical obligation to respect consumer autonomy.

Industry scope and generalizability. We have used the hospitality industry as our primary illustrative context. The DPR-PLC model is likely most valuable in experience-intensive, asset-heavy industries where PLC dynamics are pronounced—luxury goods, theme parks, airlines, and entertainment. Extension to low-involvement, fast-moving consumer goods requires modification: neural sensitivity differences across PLC stages may be attenuated in such categories, reducing the model's discriminating power. This boundary is an explicit limitation specifying where the model's mechanisms operate most strongly.

Interpretive complexity. The multi-layered DPR-PLC model creates interpretive challenges. The dashboard concept addresses this, but effective implementation requires organizational investment in cross-functional literacy spanning marketing, data science, and finance.

8. Conclusion and Future Research Directions

As a non-empirical conceptual paper, our goal has been to articulate a framework and research agenda rather than to provide empirical tests. The DPR-PLC model offers a new integrative framework for the marketing-finance interface—one that helps reframe how scholars and practitioners conceptualize the creation of financial value through marketing. By replacing survey-based attitudinal data with neurophysiological indicators and linear average-effect models with causal machine-learning–based heterogeneous treatment-effect estimation, we provide a roadmap for the next generation of marketing–finance scholarship.

Three directions for future research follow. First, the model can be extended from single-product PLC analysis to multi-product life-cycle portfolio management, examining how firms optimize across products at different PLC stages simultaneously. Second, the hospitality scenario can be extended to other experience-intensive industries—luxury goods, theme parks, airlines—and the boundary with low-involvement categories can be empirically mapped. Third, the neurophysiological measurement approach can be extended from laboratory sensors to wearable devices and mobile passive data, increasing scalability and ecological validity while navigating the regulatory landscape governing neural and biometric data.

We hope the DPR-PLC framework provides a generative platform for the research community to explore the intersection of the biological pulse and the financial ledger systematically.

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Declarations

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