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A Multilayer Bayesian-Control Framework for Endogenous Marketing Signals in Competitive Channels with Quality, Returns, and Warranty Feedback

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Abstract:
Markets are increasingly shaped by signals rather than by direct inspection of product and firm attributes. Consumers often observe advertising, labels, prices, return terms, warranty promises, platform placement, and post-purchase experiences before they can verify the underlying quality, reliability, or suitability of an offering. This creates a setting in which firms do not merely communicate with the market; they design the informational environment within which exchange takes place. The present study develops a technical research framework for marketing signals that treats signal design, belief formation, channel contracts, and operational feedback as one coupled system. The central argument is that signal effectiveness depends not only on visibility or spending intensity but also on cross-signal coherence, dynamic learnability, and the extent to which downstream outcomes feed back into future beliefs. A state-space model is introduced in which latent product quality, match uncertainty, brand capital, and reliability evolve jointly while firms choose signal portfolios over time. Consumers, channel partners, and investors update beliefs from noisy observations that differ in precision and diagnostic value. The framework yields equilibrium conditions under which informative signaling is stable, as well as conditions under which distortion, pooling, or overinvestment emerge. The paper also outlines an identification strategy for empirical implementation using panel data, claim data, returns data, and text-derived signal measures. The analysis suggests that effective signaling architectures are nonlinear, channel-contingent, and governed by feedback loops linking market beliefs to operational costs, contract design, and long-run firm value.

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1. Introduction

Marketing signals have become structurally central to modern exchange because many relevant product attributes cannot be verified ex ante and some cannot be cleanly summarized even ex post [1]. Consumers may infer expected performance from packaging cues, ad copy, claim specificity, channel reputation, return leniency, warranty strength, or platform prominence. Channel intermediaries may infer manufacturer confidence from trade support, wholesale pricing, service commitments, and the willingness to absorb informational risk. Investors may infer demand durability and execution quality from a firm's visible commercial behavior even when product-level quality is only partially observed. The common feature in these situations is that action and information are intertwined: a decision variable chosen for one reason, such as advertising intensity or return generosity, also becomes an observable signal from which others infer hidden fundamentals. This dual role complicates the analysis because the same action changes both the underlying payoff structure and the beliefs that shape future behavior.

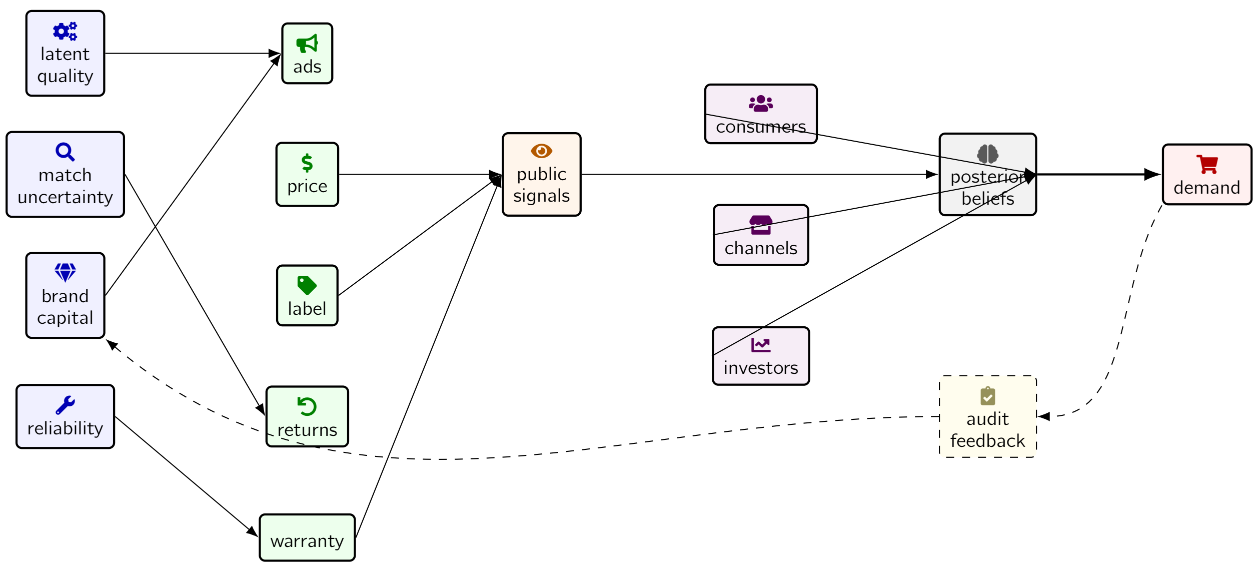

Figure 1. Multilayer signal architecture linking latent states to visible signal instruments, posterior belief formation, and market demand. The figure emphasizes how advertising, price, labels, return terms, and warranty commitments transmit hidden quality, match, brand, and reliability information into downstream beliefs, while audited outcomes feed back into future informational credibility.

A rigorous treatment of marketing signals therefore requires more than a static signaling game. In practice, signals are emitted in portfolios, interpreted through heterogeneous attention filters, and judged against delayed operational outcomes. A price cut may function as an affordability cue, a distress cue, or a market expansion instrument depending on what other signals accompany it [2]. A generous warranty may indicate quality confidence, but it may also alter use intensity, claim propensity, and reserve policy. A nutrition claim may attract a consumer segment while simultaneously changing the inferential meaning of packaging innovation and brand communication. The analysis must account for complementarity across signals, for noise in their transmission, and for the fact that some signals modify the future state of the system rather than merely reveal the present one.

A further complication is that signaling is rarely unilateral. Manufacturers, retailers, platforms, service providers, and consumers all generate information that affects the market interpretation of the offer. In dual-channel and

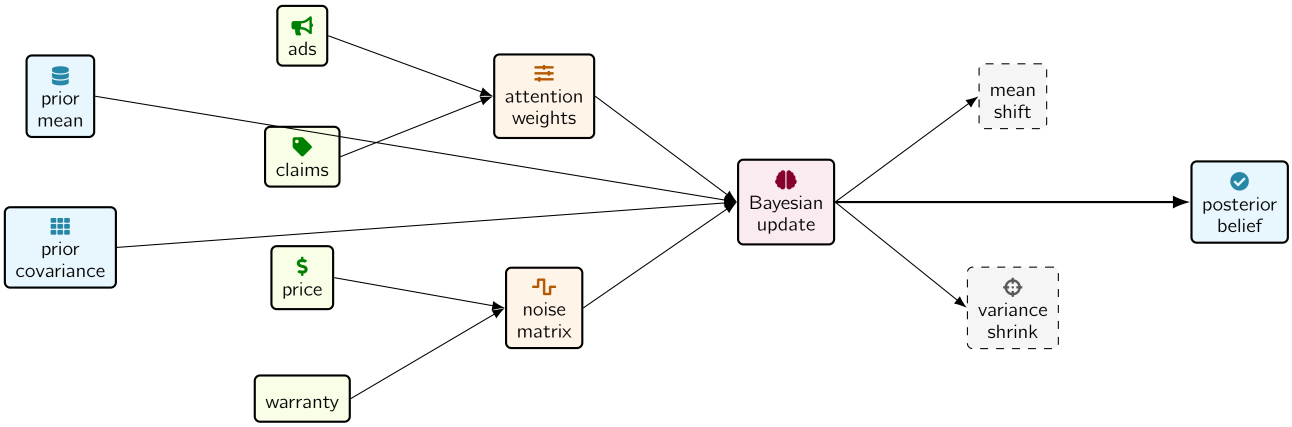

Figure 2. Bayesian belief updating under heterogeneous attention. The diagram isolates the role of priors, signal-specific attention weights, and observational noise in determining posterior movement. Informative marketing cues change both posterior means and posterior precision, so the value of a signal depends not only on its visibility but also on how efficiently it reduces uncertainty.

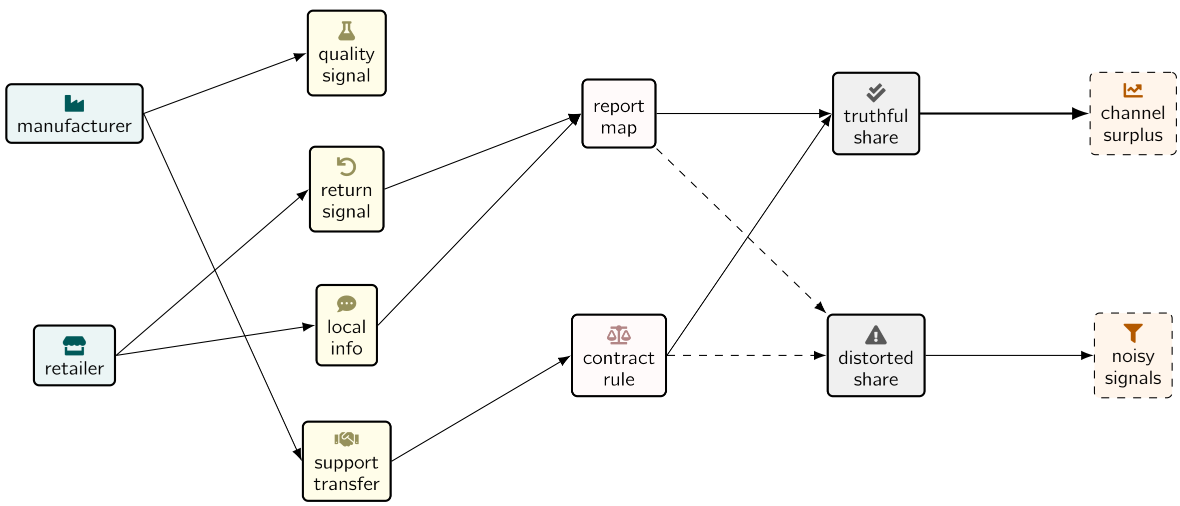

Figure 3. Contractual signaling in a distributed information channel. The manufacturer and retailer observe different information streams, and contractual rules determine whether local return and fit information is shared truthfully or strategically distorted. Efficient channel design converts fragmented observations into a coordinated signal architecture, while weak incentive alignment amplifies noise and misallocates signal effort.

platform-mediated environments, one party often controls local market observations while another controls broad brand communication or contractual infrastructure. Yan, Cao and Pei (2016) showed in a dual-channel setting that cooperative advertising can improve channel performance under demand uncertainty while simultaneously inducing incentives to distort shared forecasts, which suggests that signal design and information governance cannot be separated analytically [3]. That insight is broader than advertising alone. Whenever one actor finances or amplifies a signal generated by another actor, the market value of that signal depends on the credibility of the transmission mechanism and on how private information is filtered before dissemination [4].

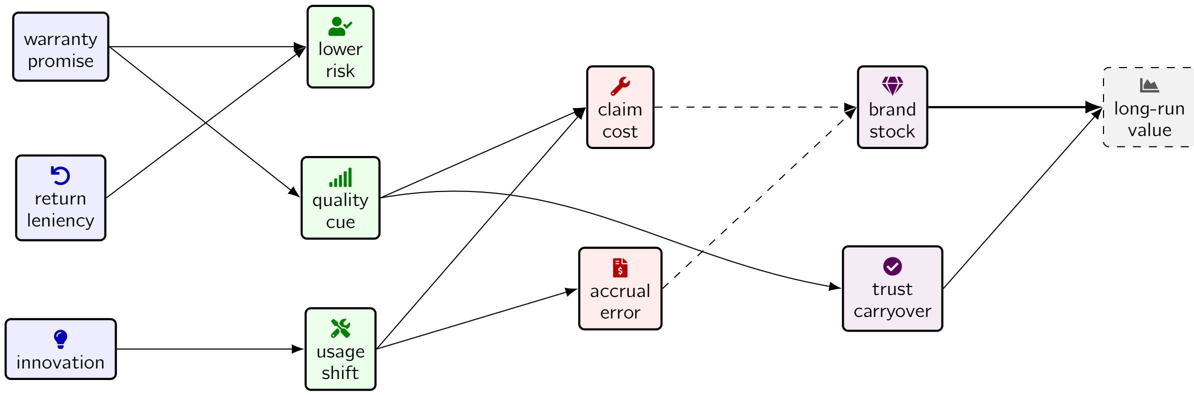

Figure 4. Reliability signaling with cost-side feedback. Warranty and return policies influence perceived downside protection and can act as confidence signals, but they also affect claim incidence, reserve behavior, and service costs. Persistent operational outcomes then reshape brand capital and trust carryover, creating a two-sided loop in which commercial promises are continuously audited by realized execution quality.

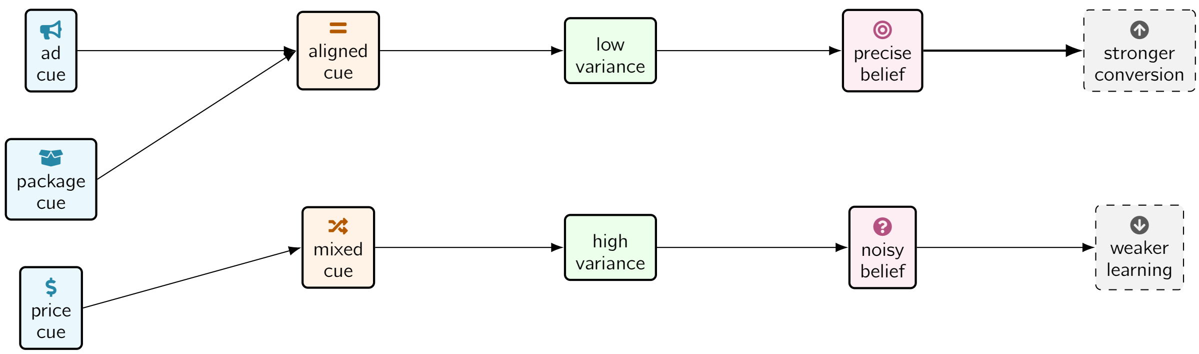

Figure 5. Signal coherence and learnability. A coherent portfolio aligns advertising, package, and price cues so that the market receives mutually reinforcing evidence and posterior variance contracts efficiently. Incoherent bundles generate interpretive conflict, producing noisier beliefs and weaker cumulative learning even when total signal expenditure remains high.

Table 1. Core Latent State Definitions

Symbol	Interpretation	Role	Dynamics
q_{fct}	Product capability	Performance expectation	Persistent + control-driven
m_{fct}	Match uncertainty	Fit variability	Updated via returns
b_{fct}	Brand capital	Trust stock	Accumulative
ρ_{fct}	Reliability	Failure likelihood	Feedback-sensitive

The research area of marketing signals is therefore well served by a unified framework in which signal production, signal interpretation, and signal validation are endogenized. The present paper develops such a framework. The objective is not to reduce all signaling to a single cue or a single market actor, but to specify a tractable system in which multiple visible actions map into latent states that matter for demand, retention, channel coordination, and firm value. The proposed structure centers on four hidden dimensions. The first is perceived product capability, which captures expected functional performance. The second is match uncertainty, which captures the probability

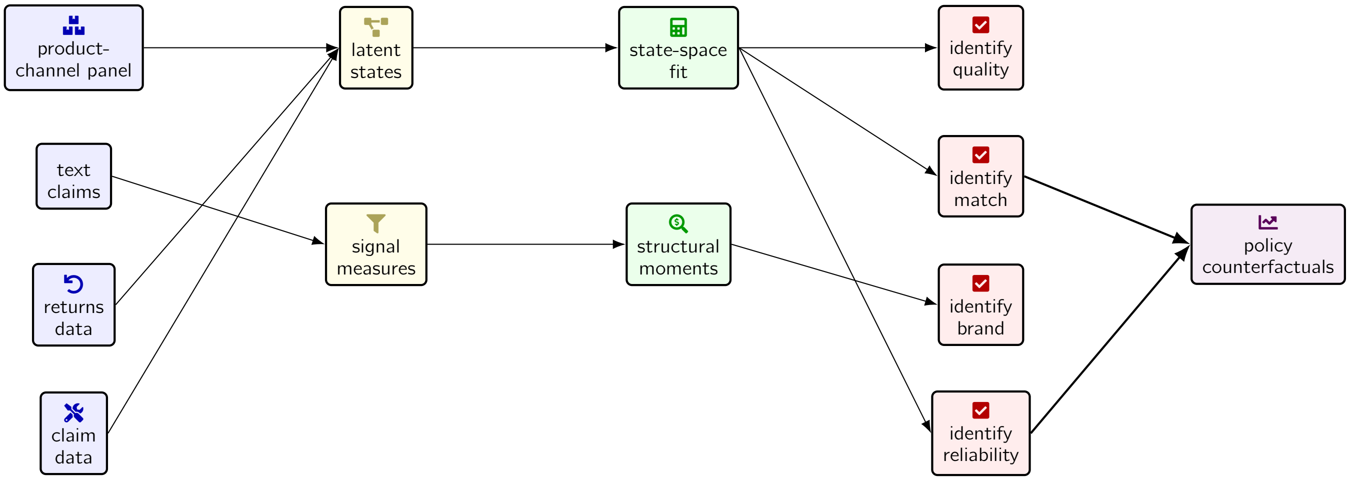

Figure 6. Empirical identification pipeline for the signaling framework. Product-channel panels, text-derived signal measures, return records, and claim data jointly recover latent states and the informational content of signal choices. Once the hidden dimensions are identified, the model supports counterfactual evaluation of pricing, communication, return-policy, and warranty architectures under alternative channel conditions.

Table 2. Signal Control Variables

Variable	Meaning	Signal Type	Dual Role
a_{fct}	Advertising	Visibility	Persuasion + info
p_{fct}	Price	Market cue	Utility + inference
ℓ_{fct}	Label specificity	Information	Diagnostic signal
r_{fct}	Returns	Risk reduction	Protection + signal
w_{fct}	Warranty	Commitment	Assurance + cost

Table 3. Signal Interpretation Components

Component	Function	Variation Source	Effect
L_i	Attention mapping	Consumer heterogeneity	Signal weighting
R_i	Direct knowledge	Expertise	Reduces uncertainty
η_{ifct}	Noise	Perception limits	Distortion
Posterior μ	Belief mean	Bayesian update	Drives demand

Table 4. State Transition Drivers

Term	Description	Source	Impact
Ax_t	Persistence	Structural	Stability
Bu_t	Control effect	Firm actions	Direct shifts
My_t	Feedback loop	Outcomes	Learning
$\Gamma\omega_t$	Shock	External	Uncertainty

that the offering is unsuitable for a particular buyer despite acceptable average quality. The third is relational

Table 5. Outcome Feedback Variables

Outcome	Meaning	Signal Audit Role	State Impact
Sales	Demand realization	Weak audit	Updates beliefs
Returns	Fit failure	Strong audit	Raises m_{fct}
Claims	Reliability issue	Direct audit	Lowers ρ_{fct}
Ratings	Perception summary	Social signal	Affects b_{fct}

Table 6. Channel Information Structure

Actor	Private Info	Advantage	Risk
Manufacturer	Quality, reliability	Production insight	Overstatement
Retailer	Returns, local fit	Market proximity	Strategic bias
Platform	Search, conversion	Data richness	Ranking distortion
Consumers	Experience	Learning	Noise

Table 7. Signal Portfolio Properties

Property	Definition	Benefit	Risk
Precision	Informativeness	Better learning	Costly
Coherence	Alignment of cues	Strong inference	Fragility
Visibility	Exposure level	Demand boost	Noise
Auditability	Verifiability	Credibility	Constraint

Table 8. Contractual Mechanisms

Mechanism	Purpose	Effect	Limitation
Revenue sharing	Align incentives	Encourages truth	Complexity
Two-part tariff	Pricing control	Partial alignment	Weak info sharing
Verification	Audit reports	Reduces distortion	Costly
Profit sharing	Joint surplus	Strong alignment	Negotiation burden

Table 9. Comparative Statics Summary

Factor	Change	Direction	Outcome
Signal precision	Increase	Positive	Higher demand
Coherence	Increase	Positive	Stronger response
Auditability	Increase	Mixed	Shift to quality signals
Compatibility	Increase	Positive	Better targeting

capital, which captures a stock of trust, familiarity, and interpretive goodwill that affects how future signals are decoded. The fourth is operating reliability, which captures the frequency and cost consequences of defects, claims, or post-purchase service burdens. Marketing signals are modeled as control variables that alter the informational shadow cast by these states while sometimes also affecting the states directly [5].

This approach permits several questions that are often treated separately to be handled in one analysis. It

Table 10. Cost Components in Profit Function

Cost	Source	Dependency	Effect
$c(D_t)$	Production	Demand	Scale cost
$\mathcal{G}(g_t)$	Claims	Reliability	Service burden
$\mathcal{A}(a_t)$	Accrual error	Forecasting	Credibility loss
$\mathcal{K}(u_t)$	Signaling	Controls	Investment cost

becomes possible to ask when a signal should be sharpened rather than broadened, when channel-specific signaling creates more value than common messaging, when contractual transfers are required to elicit truthful information sharing, and when a visible market signal is privately optimal but socially noisy because it overloads attention or causes mimicry by weak offerings. It also permits the study of dynamic reversals. A signal that is persuasive in the short run can become less effective if subsequent claims, returns, or warranty accrual errors reveal that the original communication exceeded the firm's latent capability. Conversely, a moderately strong signal that is tightly linked to reliable operational feedback may accumulate informational capital and eventually outperform a louder but less verifiable one.

The paper proceeds by defining a multilayer signal architecture for competitive channels, embedding that architecture in a Bayesian state-space demand system, deriving equilibrium conditions for endogenous signal choice and information sharing, and then outlining an econometric strategy suitable for firm, product, and channel panels. The tone of the analysis is deliberately neutral. The purpose is to formalize a class of problems that has become common in applied marketing environments, not to claim a universal solution. The model is intentionally broad enough to accommodate price signals, attribute claims, channel support, return terms, and warranty commitments, yet structured enough to yield precise comparative statics and empirical restrictions [6].

2. Signal-Theoretic Foundations and Research Scope

A useful starting point is to define a marketing signal not as a message in isolation but as an observable transformation of hidden states into market-facing evidence. Let hidden states represent quality, fit, reliability, and relational capital. Let observable actions represent price, communication intensity, label specificity, refund terms, service guarantees, assortment architecture, and channel support. A signal exists when an observable action changes the posterior distribution that another actor assigns to the hidden states. Under this definition, some classical marketing variables are signals only under certain informational conditions. Price is not automatically a signal if all parties already know marginal cost and quality. Advertising is not automatically a signal if it is pure reminder spending with no link to latent capability or commitment. A signal is thus not identified by the variable itself but by its inferential role [7].

This perspective implies that signal analysis must distinguish diagnostic content from demand stimulus. Some actions affect purchase directly because they alter utility mechanically. A lower price raises affordability even if it says nothing informative. Other actions affect purchase because they are interpreted as evidence. A detailed claim may not change the intrinsic utility of the product, yet it can increase willingness to buy if consumers interpret specificity as confidence. Many real marketing variables have both properties simultaneously. Return leniency lowers downside risk and also signals seller confidence or channel discipline. Brand assets shape preference directly and also act as priors that determine how later evidence is weighted. The theoretical task is to decompose these roles rather than to force any action into a purely persuasive or purely informative category [8].

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The signal literature becomes more intricate when attribute quality itself has a nonlinear relationship with performance. Cao and Yan (2021) found that product nutritional quality has a concave relationship with firm profit and that package innovation and advertising positively moderate this relationship, which is a useful reminder that stronger attribute signaling does not imply monotonic value creation [9]. In a broader signaling framework, this means that the market benefit of making an attribute salient may rise up to a point and then decline as marginal improvement costs, segment heterogeneity, or interpretation fatigue begin to dominate. The result motivates a nonlinear signal-production function in which both attribute level and communication intensity influence the informativeness of the signal, and the slope of that relationship can itself vary with packaging or channel context.

The research scope of the present paper is therefore defined around three linked ideas, stated here in prose rather than as separate hypotheses. First, signals are portfolio objects. A market actor rarely chooses a single cue; it chooses a bundle whose elements interact in consumers' inference processes. Second, signals are dynamic objects. Their meaning depends on prior signals and on realized feedback such as claims, returns, or observed durability [10]. Third, signals are governed objects. In channel settings, signal credibility may depend on contractual mechanisms that align the incentives of parties who hold different fragments of information. These ideas imply that a useful technical framework must integrate Bayesian updating, dynamic control, and strategic contracting.

The framework developed here focuses on settings with repeated interaction over discrete periods. Each period, a set of firms and channel partners choose signal intensities and contractual transfers. Consumers and possibly investors observe noisy versions of those choices and update beliefs about hidden states. Realized sales, returns, claim costs, and reputation outcomes are then generated, feeding information back into the next period. The central research question is not whether signaling matters in a generic sense, but how specific signal architectures perform when information is fragmented across actors and when post-purchase outcomes continuously audit the truthfulness of pre-purchase communication.

This scope is intentionally broad because contemporary markets blend informational domains that used to be analyzed separately [11]. A digital listing page can simultaneously contain a price signal, a sustainability or nutrition signal, a brand signal, a return signal, and a social proof signal, while channel partners behind the page negotiate cost sharing, service liabilities, and data visibility. If those elements are modeled separately, one misses substitution and reinforcement effects among them. If they are collapsed into a single reduced-form index, one loses interpretability. The approach below keeps multiple signal layers distinct while connecting them through a common latent-state system.

3. Market Architecture and Latent State Representation

Consider a market with indexed periods $t = 1, \ldots, T$, firms $f = 1, \ldots, F$, channels $c = 1, \ldots, C$, and consumers $i = 1, \ldots, N_t$. The product-channel system is characterized by a latent state vector

$$x_{fct} = \begin{bmatrix} q_{fct} \\ m_{fct} \\ b_{fct} \\ \rho_{fct} \\ \kappa_{fct} \end{bmatrix},$$

where q_{fct} denotes functional capability, m_{fct} denotes match uncertainty, b_{fct} denotes relational capital or brand stock, ρ_{fct} denotes operating reliability, and κ_{fct} denotes channel compatibility. The last state is useful because many signals are filtered by the suitability of the channel for the offer. A visually rich, experiential product may need a different signal portfolio in a low-touch channel than in a high-touch one, whereas a standardized search good may transmit quality with much lower noise online [12].

The firm chooses a control vector

$$u_{fct} = \begin{bmatrix} a_{fct} \\ p_{fct} \\ \ell_{fct} \\ r_{fct} \\ w_{fct} \end{bmatrix},$$

where a_{fct} is communication intensity, p_{fct} is price, ℓ_{fct} is claim specificity or label informativeness, r_{fct} is return leniency, and w_{fct} is warranty or service commitment. These controls are interpretable as signal generators because they are visible, or partially visible, to market participants and because they may covary with hidden states through equilibrium choice. The observable signal vector is then

$$z_{fct} = Hx_{fct} + Gu_{fct} + \xi_{fct},$$

where H and G are loading matrices and ξ_{fct} is a noise term that captures imperfect signal transmission, measurement noise, or platform filtering.

The latent state evolves according to a controlled transition equation,

$$\begin{aligned} x_{fc,t+1} = {} & Ax_{fct} + Bu_{fct} + My_{fct} \\ & + \Gamma\omega_{fct}, \end{aligned} \tag{1}$$

where A is the intrinsic persistence matrix, B captures direct state effects of current actions, y_{fct} denotes realized outcome feedback such as sales, returns, claim costs, and ratings, and ω_{fct} is an innovation shock. The term My_{fct} is the critical feedback channel: it allows operational outcomes to update future latent states. For example, repeated claim costs can erode brand capital if they become visible, while successful warranty handling can preserve relational capital even when reliability is imperfect. Likewise, persistent returns can be interpreted as evidence of match uncertainty rather than low average quality, and the model keeps those states distinct.

Consumer i in channel c receives a private information vector

$$\begin{aligned} s_{ifct} = {} & L_i z_{fct} + R_i x_{fct} \\ & + \eta_{ifct}, \end{aligned} \tag{2}$$

where L_i maps public signals into consumer-specific attention, R_i allows some consumers to observe or infer elements of the latent state directly through prior experience or expert knowledge, and η_{ifct} is idiosyncratic interpretive noise. The matrices L_i and R_i encode heterogeneity in signal processing. A price-sensitive consumer may weigh p_{fct} heavily but treat detailed claims as low-diagnostic. A category expert may place substantial weight on claim specificity while largely discounting brand [13]. Heterogeneity is therefore handled through attention and diagnostic matrices rather than through a single random utility coefficient alone.

Expected utility can be written as

$$\begin{aligned} U_{ifct} = {} & \alpha_i + \beta_i^\top \mu_{ifct} - \lambda_i p_{fct} \\ & + \chi_i r_{fct} + \psi_i w_{fct} + \varepsilon_{ifct}, \end{aligned} \tag{3}$$

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where $\mu_{ifct} = E[x_{fct} \mid s_{ifct}]$ is the consumer's posterior mean about hidden states. Purchase probability under a multinomial logit structure is

$$P_{ifct} = \frac{\exp(U_{ifct})}{\sum_{g,d} \exp(U_{igdt}) + \exp(U_{i0t})}. \tag{4}$$

Aggregate demand is the integral of this probability over the population distribution of $(\alpha_i, \beta_i, \lambda_i, \chi_i, \psi_i, L_i, R_i)$. What matters conceptually is that demand depends on posterior beliefs rather than on raw controls alone. A high warranty level raises demand partly because it changes expected service protection and partly because it changes the posterior on reliability.

The channel architecture adds one more layer. Manufacturers and retailers may observe different fragments of the outcome vector y_{fct}. A retailer may observe order size, return reason text, payment method, browsing path, or local assortment substitution. A manufacturer may observe broad claim costs, service calls, or production test outcomes [14]. The signal environment is therefore distributed. No single actor fully controls the inferential process because each actor sees only a subset of the evidence that would make market learning efficient. This motivates the contractual signaling analysis that follows.

4. Belief Formation, Attention Allocation, and Dynamic Signal Transmission

Because signals are noisy and heterogeneous agents process them differently, posterior beliefs must be modeled explicitly. Suppose consumers adopt Bayesian updating with Gaussian approximations around the latent state. Let the prior at time t be

$$x_{fct} \mid \mathcal{I}_{i,t-1} \sim \mathcal{N}(\hat{x}_{ifc,t|t-1}, P_{ifc,t|t-1}),$$

and let the received signal satisfy

$$s_{ifct} = C_i x_{fct} + D_i u_{fct} + \eta_{ifct},$$

with $\eta_{ifct} \sim \mathcal{N}(0, \Sigma_i)$. Then posterior updating takes the familiar linear form

$$\begin{aligned}
K_{ifct} &= P_{ifc,t|t-1} C_i^\top \left(C_i P_{ifc,t|t-1} C_i^\top + \Sigma_i \right)^{-1} \\
\hat{x}_{ifc,t|t} &= \hat{x}_{ifc,t|t-1} + K_{ifct} \left(s_{ifct} - C_i \hat{x}_{ifc,t|t-1} - D_i u_{fct} \right) \\
P_{ifc,t|t} &= (I - K_{ifct} C_i) P_{ifc,t|t-1}.
\end{aligned} \tag{5}$$

The gain matrix K_{ifct} is a compact way to represent attention-weighted learning. Signals with higher diagnostic content or lower noise receive larger weight [15]. Strong priors dampen the response to new evidence, which gives brand capital a second role: it is not only part of the latent state but also a source of posterior inertia in future updating.

The possibility of multiple simultaneous signals means that the covariance structure of Σ_i matters. If two signals are correlated because they derive from the same underlying communication campaign, naive consumers may overweight them by treating them as independent confirmations. Sophisticated consumers may partly correct for that dependence. In either case, optimal signal design must anticipate covariance-aware updating rather than assume that each additional visible cue yields an additive boost. In matrix terms, the marginal value of strengthening one signal channel depends on how that change reshapes the posterior covariance matrix after the full vector of signals is processed.

Attention can also be modeled as endogenous. Suppose consumer i allocates a scarce cognitive budget h_i across signal dimensions with weights g_{ik} for $k = 1, \ldots, K$, where $\sum_k g_{ik} = h_i$. Then the effective noise on dimension k can be specified as $\sigma^2_{ik}(g_{ik}) = \bar{\sigma}^2_{ik} \exp(-\tau_k g_{ik})$. The consumer chooses g_{ik} to maximize expected surplus net of processing cost. This extension matters because firms do not observe raw attention directly; they must infer which combinations of specificity, repetition, and format will cause consumers to reduce uncertainty on the dimensions that matter [16]. In such a system, a signal can fail not because it lacks content but because it competes poorly for the relevant type of attention. Greater message volume may crowd out attention to more diagnostic elements, producing a decline in posterior precision despite higher spending.

Dynamic transmission further implies that firms must choose between immediate and persistent signals. Some signals, such as a temporary price promotion, are short-lived and highly visible but may contribute little to the long-run state vector. Others, such as service quality or accurate claim management, are slower and less salient but influence the evolution of brand stock and reliability. The optimal portfolio balances the instantaneous demand effect of visible cues against the state-building effect of credible, accumulative actions. This trade-off can be written as an intertemporal control problem,

$$V_t(x_t) = \max_{u_t} \Big\{ \pi_t(x_t, u_t) + \delta E\left[V_{t+1}(x_{t+1}) \mid x_t, u_t\right] \Big\}, \tag{6}$$

where current profit π_t depends on demand generated through posterior beliefs, and the continuation value depends on how u_t shapes future states. A myopic signal policy overspends on immediate visibility [17]. A dynamically efficient policy values actions that reduce future interpretive noise or future service cost.

A central implication is that signal coherence matters more than signal amplitude. Let S_t denote the set of all observable cues emitted in period t. Define coherence as the negative log determinant of the posterior covariance conditional on the full cue set, normalized by total signal cost. Signals are coherent when they point to a similar latent-state interpretation and when each cue adds incremental, not redundant, information. Signals are incoherent when they pull posteriors in conflicting directions or generate covariance structures that reduce net learnability. Price cuts coupled with premium-quality claims and weak service commitments are a classic example of low coherence unless a strong contextual explanation is present. The framework below therefore evaluates signal portfolios by posterior precision, posterior mean shift, and dynamic state consequences jointly.

5. Contractual Signaling, Information Sharing, and Channel Equilibrium

In channel environments, the signal architecture is incomplete unless one models who owns which information and under what terms it is shared [18]. Let the manufacturer observe a private signal s_t^M about quality and reliability innovations, and let the retailer observe a private signal s_t^R about local fit, return propensity, and transaction frictions. Without sharing, each party solves a control problem using a filtered estimate of the global state. With sharing, a larger information set becomes available, but truthful revelation is not automatic. The choice to share information is itself a signal between channel partners, and its credibility depends on transfer mechanisms.

Yan and Cao (2017) showed that, in a manufacturer–online retailer setting with private information about product returns, a two-part price contract induces information sharing only under limited conditions, whereas revenue sharing combined with profit splitting can consistently motivate the retailer to share private return information and improve outcomes, especially when the product is highly compatible with online sales. [19] For the present framework, that result motivates a general principle: when one party controls a signal-rich outcome stream whose interpretation is valuable to another party, efficient signaling often requires a contract that prices information externalities explicitly

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rather than treating information as a free by-product of trade. In other words, truthful signal transmission is not guaranteed by channel alignment on quantity or price alone.

Let the manufacturer choose wholesale terms θ_t and a signal-support transfer τ_t, while the retailer chooses downstream signal intensities u_t^R and a message map $m_t(s_t^R)$ that may or may not reveal private information truthfully. The manufacturer chooses its own signal actions u_t^M and possibly a verification technology v_t [20]. The stage payoffs are

$$\begin{aligned}\Pi_t^M &= R_t^M(x_t, u_t^M, u_t^R, \theta_t, \tau_t) - C_t^M(u_t^M, \tau_t, v_t)\\ &\quad - \Omega_t^M(m_t, s_t^R, v_t),\\ \Pi_t^R &= R_t^R(x_t, u_t^M, u_t^R, \theta_t, \tau_t) - C_t^R(u_t^R)\\ &\quad - \Omega_t^R(m_t, s_t^R, v_t),\end{aligned} \tag{7}$$

where Ω_t^M and Ω_t^R capture expected losses or penalties from distorted information, including misallocated signal spending, poor inventory positioning, and contractual penalties under verification.

Suppose the retailer's private information shifts the posterior mean of match uncertainty and return propensity. If the manufacturer conditions transfer τ_t on the reported state, the retailer may exaggerate the severity or favorability of local conditions depending on the direction that increases expected downstream support. Let the report be $\tilde{s}_t^R = m_t(s_t^R)$. The manufacturer then solves

$$\max_{\theta_t, \tau_t, u_t^M, v_t} \quad E\left[\Pi_t^M + \delta V_{t+1}^M \mid \tilde{s}_t^R, s_t^M\right], \tag{8}$$

while the retailer chooses (u_t^R, m_t) anticipating the manufacturer's response. Truthful reporting requires incentive compatibility,

$$E\left[\Pi_t^R(m_t = s_t^R) + \delta V_{t+1}^R \mid s_t^R\right] \geq E\left[\Pi_t^R(m_t = \hat{s}) + \delta V_{t+1}^R \mid s_t^R\right] \tag{9}$$

for all admissible deviations $\hat{s}$. In the present framework, incentive compatibility is facilitated when the contract couples signal support to realized post-purchase outcomes rather than to raw reports alone [21]. For example, a portion of cooperative signal funding can depend on ex post calibration quality, such as realized return rates, claim ratios, or predictive accuracy against shared forecasts. Such mechanisms convert cheap talk into audited talk.

A useful equilibrium object is the channel signal allocation rule. Let total signal expenditure be split between manufacturer-facing signals and retailer-facing signals. Then there exists an interior allocation when the marginal posterior precision gain from a manufacturer-controlled cue, adjusted for verification cost and channel spillover, equals the corresponding gain from a retailer-controlled cue. In matrix form, if $\mathcal{P}^M(u^M, u^R)$ and $\mathcal{P}^R(u^M, u^R)$ denote precision contributions to the joint posterior, the efficient allocation satisfies

$$\begin{aligned}\frac{\partial \mathcal{W}}{\partial u_t^M} &= \Lambda_t \frac{\partial \mathcal{P}_t^M}{\partial u_t^M} - \frac{\partial C_t^M}{\partial u_t^M} = 0\\ \frac{\partial \mathcal{W}}{\partial u_t^R} &= \Lambda_t \frac{\partial \mathcal{P}_t^R}{\partial u_t^R} - \frac{\partial C_t^R}{\partial u_t^R} = 0,\end{aligned} \tag{10}$$

where Λ_t is the shadow value of posterior precision in the continuation problem. Distortion enters when private payoffs cause either party to deviate from the precision-efficient allocation. Verification technology raises private marginal cost of distortion and can restore alignment when the gain from misreporting is not too large.

The framework also accommodates platform channels in which the intermediary observes search and conversion traces that are unavailable to either manufacturer or retailer [22]. In such cases the platform becomes a meta-signal broker. Its ranking rules, badge systems, and message formatting determine not only demand but also what information can credibly pass between upstream and downstream actors. A platform that rewards short-term conversion without accounting for return or claim feedback may amplify noisy signals. A platform that incorporates verified quality or post-purchase reliability into its display logic can improve the marketwide signal-to-noise ratio. The same structure can thus analyze contractual signaling with or without a digital intermediary.

6. Reliability Signals, Brand Capital, and Cost Feedback

The dynamic value of marketing signals depends on whether visible cues are later audited by operational outcomes. Reliability-related outcomes are especially important because they affect both current cash flow and future credibility. A strong brand can make signals more persuasive, but if realized warranty claims or reserve errors rise persistently, the same brand may become a liability because prior expectations were set too high. Cao (2022) showed that brand equity is associated with lower warranty claim costs and lower abnormal warranty accrual costs, and that product innovativeness weakens these relationships [23], which makes reliability a natural latent state in a broader marketing signal system [24]. The implication is that brand signals should not be modeled only as demand shifters; they also influence, and are influenced by, cost-side evidence about execution quality and forecasting discipline.

To formalize this feedback, let realized claims per unit be g_t and abnormal warranty accrual intensity be a_t. Suppose

$$\begin{aligned} g_t &= \phi_0 + \phi_q q_t - \phi_\rho \rho_t - \phi_b b_t + \phi_n \nu_t + \epsilon_t^g \\ a_t &= \zeta_0 - \zeta_b b_t + \zeta_v \operatorname{Var}_t(g_{t+1}) + \zeta_n \nu_t + \epsilon_t^a, \end{aligned} \tag{11}$$

where ν_t is an innovation-intensity variable that may strengthen perceived progress while also introducing execution volatility. Brand capital b_t lowers claims and improves accrual discipline if it is accompanied by process quality and better market knowledge. Innovation intensity ν_t may partially offset these gains by raising variance in realized performance. This structure captures the idea that some marketing signals are stabilized by operational routines, whereas others become fragile under rapid innovation.

Reliability feedback enters the state transition by updating both ρ_t and b_t. For instance, [25]

$$\begin{aligned} \rho_{t+1} &= \alpha_\rho \rho_t + \beta_\rho I_t - \gamma_\rho g_t + \omega_t^\rho \\ b_{t+1} &= \alpha_b b_t + \beta_b \mathcal{S}_t - \gamma_b a_t - \delta_b g_t + \omega_t^b, \end{aligned} \tag{12}$$

where I_t is process or design investment and $\mathcal{S}_t$ is the current signal portfolio score. The first equation says reliability improves with underlying process investment and declines when realized claim evidence reveals unresolved issues. The second says brand capital accumulates through coherent signaling but is eroded by abnormal accrual behavior and realized claims if those outcomes become visible to market actors or investors. Thus the visible signal portfolio and the hidden reliability state are recursively linked.

A key modeling choice is to distinguish between realized service burdens and belief errors about those burdens. Warranty claims represent realized product or service problems. Abnormal accruals represent miscalibration in expected future burdens. These are analytically distinct because a firm may produce reliable products but estimate accruals poorly, or it may estimate well while suffering high claims due to innovation-related instability. In signaling terms, realized claims are ex post audits of product performance, whereas abnormal accruals are audits of managerial

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forecasting competence. Both matter because the market learns not only about the offer but also about the organization's ability to know itself accurately [26].

This distinction is valuable for signal design. Some visible cues are optimized for product-level persuasion and others for organizational credibility. A highly specific claim or generous warranty may be persuasive at the product level, but if the firm cannot forecast resulting service burdens accurately, the resulting accrual noise undermines financial credibility. The optimal signal policy therefore solves a joint problem in which demand gains from stronger communication are balanced against future costs of reliability revelation and estimate error. Let profit be

$$\begin{aligned}\pi_t = p_t D_t - c(D_t, q_t, \nu_t) - \mathcal{A}(a_t) - \mathcal{G}(g_t) \\ - \mathcal{R}(r_t) - \mathcal{W}(w_t) - \mathcal{K}(u_t),\end{aligned} \tag{13}$$

where $\mathcal{A}$ and $\mathcal{G}$ denote accrual and claim cost functions, and $\mathcal{K}$ is the cost of producing the signal vector. Because D_t depends on posteriors and a_t, g_t depend on hidden states affected by current signals, the profit function is dynamically nonseparable.

The reliability block also clarifies why some signals lose effectiveness when scaled. If brand capital lowers expected claim costs, then stronger branding can increase willingness to pay [27]. Yet if innovation raises claim variance and the organization cannot absorb that variance operationally, more aggressive brand signaling may widen the gap between expected and realized performance. This does not imply that branding or innovation should be muted in general. It implies that the optimal signal frontier is shaped by the covariance between persuasive cues and the firm's ability to deliver and forecast the promised experience. In empirical terms, this predicts that the payoff to stronger brand signals is higher when service systems, reserve models, and channel feedback loops are more mature.

7. Identification, Estimation, and Empirical Implementation

The theoretical system is suitable for empirical implementation when one has repeated observations on product-channel outcomes and a reasonably rich set of visible cues. Let the observed data consist of sales, prices, promotion intensity, claim text features, return rates, warranty reserve movements, label or message specificity measures, ratings, assortment position, and possibly channel-specific browsing traces. The hidden-state formulation allows these heterogeneous outcomes to be interpreted as noisy functions of a smaller set of latent states. This reduces dimensionality while preserving structural meaning.

An empirical implementation can be based on a state-space likelihood [28]. Let observed outcomes be collected in vector o_t and suppose

$$\begin{aligned}x_{t+1} &= Ax_t + Bu_t + \Gamma\omega_t \\ o_t &= Cx_t + Du_t + \varepsilon_t,\end{aligned} \tag{14}$$

with Gaussian innovations as a baseline approximation. Then the log-likelihood for a panel of products and channels is

$$\mathcal{L}(\Theta) = -\frac{1}{2}\sum_{j,t}\left[\log|S_{jt}| + \nu_{jt}^{\top}S_{jt}^{-1}\nu_{jt}\right] + \text{const}, \tag{15}$$

where $\Theta = \{A, B, C, D, \Gamma, \Sigma_\omega, \Sigma_\varepsilon\}$, ν_{jt} is the innovation from the Kalman filter, and S_{jt} is its covariance. The filter yields smoothed state estimates $\hat{x}_{jt}$ that can then be used to compute posterior-demand elasticities, signal precision contributions, and counterfactual equilibrium policies.

A practical challenge is that some controls are endogenous because firms choose them in response to hidden states observed privately. Price, communication intensity, refund generosity, and warranty terms all fit this description. One way to handle this is to embed first-order conditions from the dynamic control problem into the likelihood as equilibrium restrictions. Another is to model policy functions,

$$u_t = \Phi x_t + \Psi h_t + \upsilon_t, \tag{16}$$

where h_t includes observed cost shifters or contractual variables that move signal choice without directly moving demand except through the chosen signal. Estimation can then proceed with a control-function or simulated maximum likelihood approach [29]. The state-space structure is useful because latent states that drive simultaneity are partially recovered from multiple observed outcomes rather than treated as pure noise.

When the outcome system includes counts or shares, the Gaussian observation equation can be replaced by a generalized state-space model. Let sales follow a Poisson or negative binomial process, return incidence follow a binomial process, and claim cost follow a gamma or lognormal process. Then one may use particle filtering or variational approximations. The theoretical framework does not require normality; it requires only that a filtering recursion exists. The key empirical advantage of the latent-state system is that it enforces coherence across different observables. A surge in return rates, a deterioration in ratings, and a rise in claim costs should all update nearby dimensions of the same hidden state vector unless the data indicate otherwise.

Identification of signal effects depends on variation that changes observed signals without perfectly confounding latent states. Channel-level format changes, exogenous shifts in display rules, negotiated cooperative signal funding, staggered packaging redesigns, or service policy adjustments can all serve as sources of identifying variation if they affect the visibility or interpretation of signals [30]. Even without quasi-experimental variation, the dynamic restrictions of the model are informative. A purely persuasive signal that does not affect latent states should move contemporaneous demand more than future claim or return outcomes, whereas a signal that conveys or builds genuine quality should have a more persistent footprint and a lower likelihood of reversal. Thus temporal patterns in post-purchase outcomes provide identification leverage.

The framework also accommodates textual and visual measures. Claim specificity can be estimated from semantic dispersion, numerical density, or the degree of verifiability in product descriptions. Package innovation or message novelty can be extracted from embeddings of package or ad images relative to a firm's historical portfolio. Those derived measures enter the control vector or the signal observation equation. Because the state-space model already permits multiple noisy indicators of the same latent construct, text and image variables can be used without pretending that any single natural-language feature is a clean measure of a theoretical state [31].

For high-dimensional applications, regularization is appropriate. One may impose sparsity on A, B, and C to preserve interpretability. A graphical penalty on the innovation covariance can identify which hidden states share shocks. If the product universe is large, hierarchical priors can partially pool signal-response parameters across categories while allowing category-specific deviations. The empirical goal is not maximal flexibility at the cost of meaning; it is disciplined flexibility that preserves the interpretation of quality, match uncertainty, brand capital, reliability, and channel compatibility as distinct but interacting latent states.

Once estimated, the model yields several counterfactuals of direct analytical interest. One can compute how equilibrium signal portfolios change if private channel information becomes shareable at lower verification cost. One can simulate whether higher claim visibility induces more conservative signaling or instead increases investment in true quality and service systems. One can compare a strategy that sharpens a specific signal dimension, such as warranty or return generosity, with a strategy that improves coherence across multiple dimensions at constant

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spending [32]. These counterfactuals are especially useful because reduced-form estimates of isolated marketing variables often miss the systemic nature of signal portfolios.

8. Equilibrium Properties and Comparative Statics

The integrated system generates equilibrium behavior through the interaction of belief updating, demand response, state evolution, and contractual incentives. Although closed-form solutions are not always available, one can characterize the direction of key effects. The first comparative static concerns signal precision. Holding current mean beliefs fixed, an increase in precision on a diagnostically important signal raises demand when consumers are uncertainty averse with respect to the relevant latent state. The gain is larger when priors are diffuse, when competing signals are noisy, and when the signal dimension has a large loading in utility. However, if signal sharpening reveals unfavorable information relative to prior optimism, demand may fall even as learning improves. Precision is therefore valuable ex ante in welfare terms but not always privately valuable ex post for a given firm.

The second comparative static concerns coherence [33]. Let $\mathfrak{c}_t$ denote a scalar coherence index that increases as the principal eigenvectors of signal-induced posterior shifts align across cues. Then the marginal effect of communication intensity on demand is increasing in $\mathfrak{c}_t$ when consumers process the cue bundle jointly. Intuitively, a coherent portfolio makes each additional cue easier to decode because it confirms an already forming latent-state interpretation. An incoherent portfolio can generate cancellation or suspicion. This comparative static explains why greater spending may fail when it amplifies conflict among price, brand, claim specificity, and service promises.

The third comparative static concerns operational auditability. Suppose the visibility of post-purchase outcomes, such as claims or return diagnostics, increases through platform dashboards, social diffusion, or formal disclosure. Then the value of noisy persuasive signals declines relative to the value of state-improving signals. In dynamic terms, the shadow price on future credibility rises. Firms respond by shifting the composition of the signal portfolio toward cues more tightly coupled with real capability. This may include investments that improve reliability, claim forecasting, or return matching rather than only increasing message volume [34]. Under some parameter values, stronger auditability can even increase total signal investment because it raises the return to verifiable signals while lowering the return to noisy ones.

The fourth comparative static concerns channel compatibility. When a product is better suited to a given channel, inferential noise on channel-specific cues declines. This magnifies the value of retailer or platform information about fit and return propensity and increases the joint surplus from information sharing. It also affects the ranking of signal types. In high-compatibility channels, granular descriptive claims and local behavioral signals can outperform blunt reputation cues because consumers have enough contextual familiarity to decode them. In low-compatibility channels, stronger brand and service guarantees may dominate because the consumer relies more heavily on broad trust proxies than on detailed descriptions.

One can also characterize the possibility of pooling and separating equilibria in signal portfolios [35]. Weak offerings may mimic strong ones if the short-run demand gain exceeds the expected discounted cost of future audit through returns, claims, or accrual noise. Separating equilibria arise when either the cost of mimicking is high for weak offerings or verification technologies compress the gains from distortion. Contractual verification among channel partners can support separating outcomes even when consumer-side audit is delayed. Conversely, when channel information remains siloed and post-purchase outcomes are poorly linked to the original signal architecture, pooling can persist for long periods. This predicts that markets with fragmented feedback systems are more vulnerable to noisy or inflated signaling.

The control problem also implies an Euler-style intertemporal condition for each signal dimension. Let u_{kt} denote the kth signal control. An interior optimum satisfies

$$\frac{\partial \pi_t}{\partial u_{kt}} + \delta E_t\left[\nabla_x V_{t+1}^{\top} \frac{\partial x_{t+1}}{\partial u_{kt}}\right] = 0. \tag{17}$$

The first term is the current-period payoff effect through demand and cost. The second is the continuation effect through latent-state evolution [36]. Signals that mainly influence current perceptions have small dynamic terms. Signals that build brand capital, reduce uncertainty, or improve future reliability have large dynamic terms. The optimal mix depends on how the current market discounts delayed but more durable effects.

9. Numerical Regimes and Interpretive Results

Although the paper develops a general analytical framework, it is helpful to interpret the equilibrium through stylized parameter regimes. Consider first a regime with high prior uncertainty, moderate channel compatibility, low verification cost, and substantial feedback visibility. In such a regime, coherent multi-cue portfolios dominate isolated signals. Communication intensity is useful only when paired with claim specificity and service terms that support a common interpretation. Channel partners benefit from sharing localized outcome information because the value of posterior precision is high and distortion is deterred by low verification cost. The equilibrium signal policy is relatively balanced across pre-purchase and post-purchase cues [37].

Now consider a regime with strong initial brand priors, high innovation intensity, and low operational stability. Here the main risk is not lack of persuasion but overshooting credibility. Signals that stretch the inferred distance between current capability and claimed capability create a large probability of later correction through claims or accrual mismatches. The model predicts a flatter optimal response of communication intensity to brand stock than one would obtain in a static demand model, because continuation losses from reliability revelation are substantial. This regime also predicts that the same visible signal can have opposite value depending on the maturity of the process system behind it.

A third regime is characterized by high channel compatibility but fragmented channel information. Retailers or platforms possess accurate fit and return diagnostics, while upstream firms possess broad brand and service capabilities. Without contractually supported sharing, downstream actors may under-transmit information if sharing erodes their bargaining position, or overstate some local conditions if support transfers are tied to unverifiable claims. The model predicts underinvestment in the globally optimal signal architecture because each party optimizes with respect to a distorted private posterior [38]. When verification or profit-linked information contracts are introduced, signals become more truthful and the total portfolio shifts toward more targeted, lower-noise communication.

A fourth regime involves low compatibility, low attention, and low feedback visibility. In such settings, broad reputation and generous service commitments dominate granular descriptive signals because consumers cannot easily process or trust detailed attribute information. However, this does not imply that detailed signals are useless. Rather, their return is low unless they are reformatted into higher-salience or lower-complexity cues. The attention-allocation structure predicts that reducing interpretive burden can be more effective than increasing nominal information content. Hence signal design includes format choice, not just content choice.

These regimes underscore that the phrase “stronger signal” is analytically incomplete [39]. A signal can be stronger because it is louder, more precise, more coherent, more costly to fake, more visible in feedback, or more deeply embedded in channel governance. Different strengths matter under different state configurations. A neutral managerial reading is that market communication should be evaluated as an inferential technology whose performance depends on the surrounding system of contracts, feedback, and operational delivery.

10. Managerial and Research Implications

The framework implies that managers should treat signal design as a coupled decision problem rather than as a set of independent tactical choices. Price, message specificity, return policy, warranty, and channel support should be planned with an explicit view of how they jointly shape posterior beliefs and future audit risk. In many organizations these variables sit in different functional silos, which leads to portfolios that are individually rational but jointly noisy. A coherent signal system requires shared modeling of what hidden state each cue is meant to reveal and what post-purchase data will later confirm or disconfirm that interpretation.

A second implication concerns the governance of private information in channels. When downstream actors observe richer local diagnostics than upstream actors, or when upstream actors observe deeper production and reliability information than downstream actors, efficient signaling requires a contract that prices truthful information transfer [40]. Simple quantity or margin arrangements may leave strong incentives for selective disclosure or distortion. Contracts linked to realized calibration quality, verified local diagnostics, or shared downside from misalignment are more likely to support truthful signal transmission. The broader point is that information sharing should be modeled as part of the marketing system, not as an operational afterthought.

A third implication concerns the boundary between brand-building and capability-building. The results do not suggest that visible signals are less important than product or service quality. They suggest that the long-run payoff to visible signals is conditional on the firm's ability to support them with reliable execution and disciplined forecasting. Firms that overindex on visibility may observe strong initial response and then suffer future credibility erosion when claims, returns, or accrual anomalies appear. Firms that align visibility with verifiable capability may initially scale more slowly but accumulate relational capital that lowers the cost of future signaling.

For research, the framework indicates that studies of advertising, pricing, claims, returns, or warranty should often be embedded in a joint latent-state structure [41]. Reduced-form estimates of a single signal can be misleading if other correlated signals are omitted or if post-purchase feedback shifts the meaning of the original action. Future empirical work can use the proposed state-space design to test when coherence matters more than intensity, when verification changes the composition rather than the level of signaling, and how innovation alters the mapping from visible cues to future credibility. The approach also invites richer integration of text, image, and transaction data because those sources reveal different layers of the same signal system.

There is also a methodological implication regarding what should count as evidence of effective signaling. Immediate sales response is informative but incomplete. A signal should be judged by its joint effect on current demand, posterior precision, future service burdens, forecast calibration, and the persistence of brand capital. The latent-state approach makes that broader evaluation feasible because it connects visible actions to both contemporaneous and delayed outcomes in one estimable system. This does not remove the need for careful institutional detail, but it provides a disciplined language for bringing such detail into a common model.

11. Conclusion

This paper developed a technical framework for marketing signals in which visible market actions are treated as endogenous mappings from hidden product and organizational states into observable cues [42]. The analysis integrated consumer belief updating, dynamic state evolution, channel information sharing, and operational audit through returns and warranty outcomes. The central result is conceptual rather than rhetorical: signal effectiveness is determined jointly by precision, coherence, auditability, and governance. Signals are valuable not simply when they attract attention, but when they generate favorable posterior beliefs that can be sustained by subsequent evidence and by aligned channel incentives.

The framework also clarifies why some common marketing choices produce unstable outcomes. A cue that is persuasive in isolation may become counterproductive when paired with conflicting signals, when it invites distortion in channel communication, or when post-purchase feedback reveals weak reliability or poor forecasting discipline. Conversely, a more moderate but verifiable signal architecture can accumulate informational capital over time because it reduces posterior variance and preserves credibility. Empirically, the model supports implementation with product-channel panels that combine demand, message, return, claim, and reserve data. Substantively, it offers a way to study marketing signals as a system rather than as disconnected tactical levers. That system view is useful for markets in which communication, channel structure, and operational feedback are tightly coupled [43].

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