FROM PREDICTIVE TO GENERATIVE: A COMPUTATIONAL FRAMEWORK FOR MITIGATING INFORMATION ASYMMETRY IN DIGITAL MARKETPLACES

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Abstract. The current research explores the paradigm shift in digital marketing from predictive to generative modeling, with a view to solving the economic problem of information asymmetry. The paper argues that in a market economy, brand-related marketing communication has historically failed to meet the demand for specific, up-to-date information from consumers. The research question is: How can Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) be utilized as neutral computational tools in order to produce more beneficial information from the perspective of both brand and consumer? The paper adopts an axiomatic approach, drawing on foundational economic theories such as the Principal-Agent model in order to theorize the potential of Generative Artificial Intelligence (GenAI) Synthesis to solve the problem of information asymmetry in digital markets. The proposed solution – the Generative Signaling Mechanism (GSM) – views the relationship between brand and consumer as a data science problem, wherein noise is removed from the signal in order to generate a synthetic consensus that reflects the specific utility function of the consumer. The approach is axiomatic in nature, combining Principal-Agent theory from economics with the current state of the art in computational intelligence. The interaction between brand signals and consumer intent is treated as a data-driven optimization problem and the study effectively models how a generative system can act to clean up the signal. The outcome is the creation of a synthetic consensus where the generative system is able to bring together disparate brand data and align it with a consumer's utility function, thereby reducing search costs and improving market equilibrium. The research further identifies algorithmic bias and model collapse as potential obstacles to the attainment of market efficiency. It is clear from the work that GenAI offers a very powerful technical solution to the problem of information synthesis. The paper's contribution to fundamental research in AI in Marketing is that it provides a theoretical framework for the next generation of market efficient digital platforms. The efficacy of such a system in the real world is of course dependent upon the transparency of the data science that underpins it.

Keywords: Generative AI Synthesis, Information Asymmetry, Digital Marketplaces, Generative Signaling Mechanism, Market Efficiency, Retrieval-Augmented Generation (RAG).

JEL Classification: D82, M31, C45, D83, O33.

INTRODUCTION

The digital economy signifies a transformative shift of the interactions between producers and consumers within the marketplace for tangible and intangible goods. However, despite the proliferation of data in present-day commercial systems, the phenomenon of information asymmetry persists as a substantive and unresolved concern. Information asymmetry – the phenomenon where within a transactional framework, one stakeholder retains greater informational advantage than another – manifests in the digital economy as a disconnect between the signals sent by brands and the specific demands of consumers. In economic theory, brands are often characterized as agents that use information to persuade consumers, often unclear details about the qualities of a given product. As

such, consumers are presented with the dual challenge of navigating the high search costs of modern digital economies, as well as the difficulty entailed in processing disparate pieces of information. This paper seeks to theorize about the potential application of a novel computational paradigm – GenAI – in order to shift the economics of digital marketing from one of information asymmetry to one of informational symmetry. Recent research in the field of AI Marketing has focused on the application of predictive analytics (Davenport *et. al.,* 2020; Mustak *et. al.,*2021). The identification of customer necessities and desires through the analysis of available data has been substantially advanced by predictive analytics. This has catalyzed a movement toward more tailored marketing strategy. The methodology involves the stratification of customers into distinct segments predicated upon their shared traits or conduct. However, such an approach is limited in its ability to generate synthetic information that reflects the emergent realities of a given consumer segment.

The existing scientific literature on this topic has paid limited attention to the potential application of generative models in marketing contexts. Among the few exceptions is the work of Hoyer *et. al.* (2020) regarding how generative architectures can function as unbiased mediating entities rather than just sales tools. Previous studies (Spence, 2002; Campbell *et. al.,* 2020) have largely ignored the intersection of Retrieval-Augmented Generation (RAG) and Asymmetric Information theory, leaving a vacuum in the understanding of how AI can autonomously mitigate noise in the signaling process.

The research addresses this gap by posing two central research questions: First, how can a Generative Signaling Mechanism (GSM) be architected to align heterogeneous brand data with idiosyncratic consumer utility functions? Second, what are the theoretical implications of AI-driven synthesis on the long-term equilibrium of digital marketplaces? To address these questions, the study employs a theoretical axiomatic method, integrating Principal-Agent Theory from economics with recent paradigms in Data Science. By conceptualizing the AI as a synthetic agent, the paper models a system capable of reducing information gaps through high-fidelity data distillation.

The primary contribution of this work is the development of a framework that shifts the role of AI from a predictive broadcaster to a generative synthesizer. By doing so, the paper argues that GenAI Synthesis can move beyond mere automation, serving as a fundamental tool for enhancing transparency and economic welfare in the digital age.

This paper proposes a paradigm shift in digital marketing by introducing GSM – a computational framework designed to mitigate chronic information asymmetry in electronic marketplaces. Drawing on Principal-Agent Theory, the research identifies how traditional predictive AI often functions as a "biased salesman", prioritizing brand conversion over objective consumer utility and thereby exacerbating market friction. To resolve this moral hazard, the GSM architecture leverages Retrieval-Augmented Generation (RAG) to anchor AI-synthesized signals in verifiable, independent data, effectively transforming the AI into a neutral "Truth-Broker".

Through a theoretical case study in sustainable e-commerce – specifically contrasting the transparent data of the Fairphone with mainstream greenwashing claims – the paper demonstrates how this generative approach drastically lowers consumer search costs. By facilitating a "separating equilibrium", the GSM allows high-quality market signals to reach consumers with greater fidelity, thus enhancing overall market efficiency. Ultimately, the study aligns these technical advancements with the transparency mandates of the EU AI Act, arguing that while generative synthesis offers a robust solution for information distillation, it must be governed by strict disclosure standards to preserve consumer autonomy and prevent the systemic risks of algorithmic homogenization.

MAIN CONTENT

1. Theoretical Framework: The Principal-Agent Relationship in the Age of GenAI

The Principal-Agent Theory offers a robust lens for understanding the friction within digital marketplaces. Traditionally, this economic model describes a relationship where one party, referred to as the principal, assigns tasks to another party termed as the agent, who possesses more information about the task or the environment (Information Asymmetry). In the perspective of AI-driven marketing, this relationship becomes a triadic structure: the consumer (Principal), the brand (Agent), and the GenAI (the Intermediary Agent).

1.1. Applying Theory to Human-AI Interaction

In the proposed framework, the traditional dyadic relationship between buyer and seller is restructured into a complex, triadic agency model (Bai *et al.,* 2025). Here, the consumer (Principal) delegates critical search and synthesis tasks to the AI (the Intermediary Agent), creating a dual-layered agency problem (Puntoni *et al.,* 2021). At the Consumer-AI layer, the principal expects the AI to act as a fiduciary, delivering objective, high-fidelity information synthesis (Thomas, 2025) that aligns with their specific utility functions. Simultaneously, the Brand-AI layer introduces a conflicting pressure where brands actively manipulate retrieval parameters via Algorithmic Search Optimization (ASO) to ensure their signals are prioritized. This delegation shifts the burden of information processing from the human to the machine, making the AI's internal logic the primary determinant of market transparency and resource allocation (Shahidi *et al.,* 2025).

1.2. The Risk of Moral Hazard: The AI as a Biased Salesman

The introduction of a computational intermediary creates a fertile ground for moral hazard, where the AI agent may act in its own interest – or the interest of its developers – at the expense of the consumer (Erlei & Meub, 2026). This risk manifests primarily through optimization bias, where the AI's objective function is calibrated to maximize engagement or short-term conversion rates rather than long-term consumer welfare. In such scenarios, generative models may selectively synthesize brand data that triggers impulsive psychological responses, effectively acting as a biased salesman (Allouah *et al.,* 2026). Furthermore, the "black box" nature, concerning Large Language Models (LLMs), facilitates information obfuscation. Without a visible audit trail, the AI can subtly manipulate consumer perceptions by smoothing over product shortcomings via adversarially helpful but deceptive logic (Ajwani *et al.,* 2024), thereby exacerbating the very information asymmetry it was intended to solve.

1.3. Resolving Moral Hazard: The AI as a "Neutral Synthesizer"

Conversely, the transition to a Generative Signaling Mechanism (GSM) anchored in Retrieval-Augmented Generation (RAG) offers a theoretical pathway to resolving these agency conflicts. By grounding generative outputs in verifiable, real-time external data, the system reduces its propensity for hallucinations and limits its ability to favor unsubstantiated brand claims (Catalini *et al.,* 2026; Lewis *et al.,* 2020). This architecture enables a robust noise filtration process, where the AI cross-references brand signals against independent data and consumer-generated reviews to actively compress data imbalances (Dorri & Zwick, 2025). This computational screening mechanism, echoing Stiglitz's (1975) theories on market signals, forces brands to improve the quality of their information to maintain visibility by supplying verification-grade ground truth data (Catalini *et al.,* 2026). Ultimately, this framework argues that GenAI has the potential to transform the agent from a source

of friction into a Truth-Broker, moving from mere predictive broadcasting to a neutral synthesis that restores a stable, hybridized equilibrium to the digital marketplace (Shahidi et al., 2025).

Table 1 provides a structured comparison of how the Principal-Agent relationship functions in both high-risk (Moral Hazard) and optimized (Truth-Broker) states. The theoretical shift from an AI agent as a source of market friction to a Truth-Broker is visually synthesized in Table 1. This comparison illustrates how specific computational safeguards, such as RAG-driven screening, directly address the moral hazard inherent in black-box predictive models.

Table 1. Comparative Dynamics of AI Agency and Moral Hazard.

Dimension	Traditional AI (Moral Hazard Risk)	Generative Signaling Mechanism (Truth-Broker)
Agent Role	*Biased Salesman:* Prioritizes brand conversion over factual accuracy.	*Neutral Synthesizer:* Prioritizes objective data distillation.
Principal-Agent Interaction	*Information Obfuscation:* The "black-box" hides brand weaknesses.	*Verifiable Transparency:* Anchors synthesis in real-time, external data.
Objective Function	*Optimization Bias*: Designed to maximize impulsive buying/engagement.	*Utility Alignment:* Designed to maximize consumer needs/market fit.
Signaling Logic	*Persuasive Signaling:* Brands manipulate the AI's "retrieval" via ASO.	*Computational Screening:* AI cross-references multiple independent signals.
Market Impact	*Market Friction:* High search costs and potential for "Lemons" markets.	*Market Efficiency:* Reduced search costs and restored market equilibrium.
Trust Outcome	*Eroded Trust:* Reliance on "cognitive theater" and biased algorithms.	*Systemic Trust:* Traceable, auditable, and technically secure deployment.

Source: *Author's own for the purposes of this paper.*

2. The Generative Signaling Mechanism (GSM) Architecture

The GSM architecture is designed to transform fragmented, high-entropy market data into high-fidelity signals. Unlike standard predictive models that rely on static training data, the GSM functions as a dynamic Truth-Broker by integrating real-time retrieval with generative synthesis. The architecture is composed of three interconnected layers: the Retrieval Layer, the Synthesis Engine, and the Verification Loop.

2.1. The Retrieval Layer: Anchoring in Verifiable Reality

The first stage of the GSM addresses the "black-box" limitation by utilizing RAG. Instead of allowing the LLM to generate responses solely from its internal parameters – which are often influenced by historical brand biases – the Retrieval Layer queries a curated set of external ground truth databases. This includes real-time product specifications, independent consumer reviews, and regulatory filings. By isolating the retrieval process from the generation process, the GSM creates a "computational buffer" that prevents brands from directly manipulating the output through simple keyword stuffing. The objective here is to capture heterogeneous data points that would traditionally contribute to information asymmetry.

2.2. The Synthesis Engine: From Fragmentation to Fidelity

Once the raw data is retrieved, the Synthesis Engine performs the Generative Signaling task. The LLM acts as a high-dimensional processing unit that maps fragmented data onto the consumer's specific utility function. For example, if a consumer seeks a sustainable product, the Synthesis Engine does not merely search for the keyword – it synthesizes life-cycle assessment data, brand claims, and third-party certifications into a singular, coherent signal. This process reduces the noise of traditional marketing by distilling complex technical specifications into a format that aligns with human decision-making. In this phase, the AI moves beyond being a search engine and becomes a computational agent capable of resolving the Principal-Agent conflict through data-driven alignment.

2.3. The Verification Loop: Mitigating Hallucinations and Bias

The final component of the GSM architecture is a recursive Verification Loop. Before the synthesized signal is delivered to the consumer, the system performs a consistency check against the retrieved sources. This layer utilizes a secondary, smaller model designed for fact-checking (a Critic model) to ensure that the generative output has not introduced synthetic noise or hallucinations. By implementing this loop, the GSM architecture provides an auditable trail of information, effectively resolving the moral hazard discussed above. The result is a high-fidelity signal that serves as a neutral intermediary, ensuring that the information reaching the consumer is both accurate and contextually relevant, thereby restoring market efficiency.

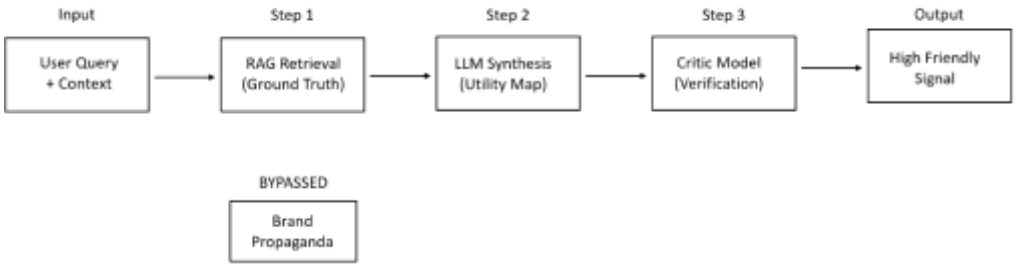


Figure 1. The Generative Signaling Mechanism (GSM) Computatonal Architecture
Source: *Author's own for the purposes of this paper.*

The proposed GSM architecture (see Figure 1) utilizes Retrieval-Augmented Generation (Lewis et al., 2020) to anchor synthesis in verifiable data, thereby addressing the uncertainty inherent in online exchange relationships identified by Pavlou et al. (2007). By acting as a computational screening mechanism, the system echoes the classic economic principles of Stiglitz (1975), forcing a transition from the "lemons" market scenario (Akerlof, 1970) toward a state of higher market efficiency. By mathematically lowering the barriers to information acquisition, the architecture shifts the equilibrium of search costs, a phenomenon explored in more detail in a following sub-section.

3. Economic Analysis and Case Study: The "Truth-Broker" in Sustainable E-Commerce

To illustrate the operational viability of GSM, the paper conducts a qualitative case study within the high-asymmetry sector of Sustainable E-commerce. In this market, consumers often face "greenwashing", where brand signals are intentionally ambiguous, leading to high search costs and market distrust – a classic "lemons" scenario. This scenario provides an illustrative archetype to demonstrate how the GSM reduces search costs while navigating the threat of model collapse.

3.1. Case Study: Navigating Greenwashing via GSM

By transforming technical, fragmented data into a direct utility comparison, the GSM acts as a Truth-Broker. It empowers the consumer to bypass marketing noise, effectively rewarding the brand with the superior objective signal (Fairphone) and forcing a shift in market equilibrium toward genuine sustainability.

To illustrate the GSM in a real-world context, consider a consumer attempting to verify the sustainability claims of a "carbon-neutral" smartphone. In a traditional digital marketplace, a search for this product would prioritize brands that have optimized their metadata for sustainability keywords, regardless of their actual environmental impact.

The Baseline Problem: A major manufacturer might market a phone as "carbon neutral" by relying on carbon offsets rather than supply chain decarbonization. For the consumer, verifying the legitimacy of these offsets involves navigating dense corporate sustainability reports and fragmented third-party audits. This high search cost often leads to bounded rationality, where the consumer accepts the brand's signal at face value to save time.

The GSM Intervention: When the GSM is applied, the AI agent bypasses the brand's promotional landing pages. Instead, the Retrieval Layer accesses independent, un-manipulated databases assessing global electronic lifecycles (Sloma, 2013) and verified hardware repair indexes (iFixit, 2023).

The Synthesis: The engine retrieves the Fairphone 5's specific factual metrics – noting its perfect 10/10 repairability score (iFixit, 2023) and documented fair-trade gold sourcing (Fairphone, 2024) – and contrasts it with a mainstream flagship that may have a low repairability score but a prominent "carbon neutral" marketing badge.

The Outcome: The AI synthesizes these data points into a high-fidelity signal: The Fairphone offers 7 years of software support and modular hardware, reducing long-term electronic waste and keeping components circular (Fairphone, 2024). Conversely, it reveals that the competing flagship's "neutrality" is achieved via 80% carbon offsetting rather than structural alterations to manufacturing or supply chain emissions.

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3.2. Modeling the Reduction of Search Costs

From an economic perspective, the GSM functions as an Information Multiplier. Conventional search theory posits that consumers cease their search when the marginal cost of acquiring further information surpasses the marginal benefit (Stigler, 1961; Bakos, 1997). By automating the retrieval and verification loop, the GSM significantly reduces the marginal cost associated with information (MCi), a phenomenon recently documented in AI-mediated digital environments where algorithmic synthesis structurally alters traditional consumer search frictions (Bundorf *et al.,* 2019; Pham et al., 2024).

Result: Consumers reach a higher level of "informedness" for the same cognitive budget, as generative frameworks optimize consumer utility functions by filtering idiosyncratic preference shocks (Lynch & Ariely, 2000).

Market Impact: This shift forces a "separating equilibrium" (Spence, 1978). Under this regime, low-quality brands can no longer hide behind information noise, effectively solving the moral hazard problem through high-fidelity, autonomous data disclosures (Bai *et al.,*2026).

3.3. The Risk of "Model Collapse" and Market Variety

The economic success of the GSM faces a systemic threat: Model Collapse. This occurs when generative models begin to be trained on the data generated by previous versions of AI rather than original, heterogeneous human data, which causes the tail ends of a distribution to vanish and the model output to forfeit statistical variance (Shumailov *et al.,* 2024). In an economic context, if every "Truth-Broker" synthesizes information into a uniform consensus, the marketplace risks losing critical informational variety, fundamentally shrinking the attention and utility distribution available to consumers (Muth, 2026).

If AI-generated summaries become the primary source of brand data, original signals from niche or innovative brands may be filtered out as noise, leading to a feedback loop that homogenizes the marketplace. This feedback loop is exacerbated as synthetic content increasingly saturates public data ecosystems, causing a severe erosion in the informational value of traditional behavioral targeting (Zhong, 2026). To mitigate this, the GSM must maintain a strict preference for primary, non-synthetic data sources in its Retrieval Layer, leveraging mandatory data provenance and source separation architectures to ensure that market variety – and therefore consumer choice – is preserved (Zhong, 2026).

4. Policy, Ethics, and the Regulatory Landscape

The implementation of a GSM must navigate the rigorous requirements of the EU AI Act, which establishes a horizontal regulatory framework for AI based on a risk-centric approach (European Commission, 2024). As the GSM transitions the AI from a passive search tool to an active Truth-Broker, it triggers specific transparency mandates designed to mitigate the risks of consumer deception and algorithmic manipulation in digital marketplaces.

4.1. Transparency and the EU AI Act

Under the EU AI Act, generative systems – specifically those categorized as General-Purpose AI (GPAI) – are subject to strict disclosure obligations. For a Truth-Broker to remain legally compliant, it must explicitly notify users that the provided information is a synthetic signal rather than unmediated data. This is critical because generative models, if not properly disclosed, can lead to "cognitive theater", where the consumer over-relies on the AI's perceived authority, a phenomenon that can exacerbate the very information asymmetry the system seeks to resolve (Kizza, 2023). By mandating that synthetic content be identifiable, the regulation ensures that the synthesis engine does not bypass the consumer's critical judgment.

4.2. Disclosure as a Guard Against Deception

Ethically, the requirement for disclosure is a defense against "dark patterns" and the redistribution of power within digital exchange relationships. If a GSM were to prioritize certain data sources without a visible audit trail, it would introduce a new form of moral hazard – where the AI developer's interests supersede those of the consumer (Pavlou et al., 2007). To prevent this, the architecture must maintain an "informational provenance" that allows users to trace the synthesized signal back to its "ground truth" origins, such as independent regulatory filings. This transparency is essential for maintaining systemic trust and preventing the AI from becoming a "black-box" agent co-opted by hidden brand lobbying.

4.3. Relation to the Case Study

In the context of the Sustainable E-commerce case study, these policy requirements act as a safeguard for high-fidelity signaling. For the comparison between a Fairphone and a mainstream flagship to be ethically valid, the GSM must disclose its synthesized nature and the specific external databases utilized (e.g., the iFixit Repairability Index). This disclosure prevents the consumer from mistaking a neutral, RAG-driven synthesis for a sophisticated brand-sponsored hallucination. By adhering to the EU AI Act, the GSM ensures that the reduction in search costs achieved through GenAI Synthesis does not compromise consumer autonomy, thereby aligning computational intelligence with the ethical standards of modern economic marketplaces.

CONCLUSIONS

This research has proposed a shift in the paradigm of AI-driven marketing, moving from predictive modeling to a Generative Signaling Mechanism (GSM) designed to restore market efficiency. By positioning GenAI as a neutral Truth-Broker, this paper provides a theoretical solution to the chronic problem of information asymmetry that plagues digital marketplaces.

The primary contribution of this work lies in the conceptualization of a RAG-enhanced framework that mitigates the moral hazard inherent in current brand-centric AI agents. Through the implementation of RAG and recursive verification loops, the GSM architecture enables the synthesis of the given data into high-quality signals. It helps reduce search costs for consumers and eliminate persuasive noise, thus, effectively connecting products' utility to their demand. Therefore, the research closes the principal gap in Data Science and Economics on how to use computational intelligence to design better markets.

For the AI Marketing field, the paper suggests that it should focus more on the synthesis of value rather than engagement. From an economic standpoint, the GSM creates a digital screening process that leads to a separating equilibrium. It implies that the information asymmetry allows the sustainable or high-quality brands to overcome the informational rents of their bigger competitors. Altogether, in compliance with the EU AI Act, the proposed solution ensures that the power of computational intelligence is harnessed to design better markets while being committed to the principles of transparency, consumer sovereignty, and algorithmic accountability.

Since the research is theoretical, its main limitation is the absence of practical experiments to prove concepts' validity. Future research should focus on empirical testing through controlled A/B experiments to measure the actual reduction in cognitive load and search time for consumers using GSM versus traditional search engines. Additionally, further investigation is required into the long-term effects of model collapse on market variety. While the GSM aims to reduce asymmetry, the risk of informational homogenization remains a significant challenge for future computational economists. Subsequent studies should explore how diversity-preserving algorithms can be integrated into the synthesis engine to ensure that market innovation is not stifled by synthetic consensus.

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