AI Intermediaries and Consumer Choice:

An Empirical Investigation of Brand Selection by Large Language Models

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1. Introduction

For over two centuries, microeconomics has developed sophisticated frameworks for modeling and predicting human decision-making. From the rational consumer maximizing utility under budget constraints to behavioral economics accounting for cognitive biases, our theoretical apparatus assumes one constant: humans make purchasing decisions. This foundational assumption is about to become obsolete.

Commercial large language models (LLMs) such as ChatGPT, Gemini, and Perplexity now serve over one billion weekly active users, with adoption growing exponentially. These AI systems are no longer mere information retrieval tools; they have evolved into recommendation engines that actively shape consumer behavior. Users increasingly ask AI assistants which products to purchase given their specific context, preferences, and constraints. The next evolutionary step is already emerging: agentic AI systems capable of executing purchases autonomously on behalf of users.

Consider the near-future consumer economy. AI assistants will order groceries when refrigerators run low, purchase clothing when detecting attractive discounts aligned with user preferences, select gifts for upcoming birthdays, and book restaurants for special occasions. Each of these decisions will be executed seamlessly, optimized for user preferences, and accomplished without direct human deliberation at the moment of choice. Yet a fundamental question remains unanswered: when an AI must select among competing brands of milk, choose between similar hoodies, or recommend one restaurant among many romantic options within budget, what determines its choice?

Remarkably, not even the creators of these AI systems can fully answer this question. Modern LLMs contain trillions of parameters, and knowing these parameter values provides essentially no insight into the decision-making process. The traditional tools of consumer economics, including revealed preference theory, discrete choice models, and demand estimation, were designed to understand human agents with interpretable preferences and bounded complexity. They offer little guidance when the decision-maker is an opaque neural network.

This opacity creates a profound challenge for economic analysis. In a world where AI intermediaries conduct an increasing share of commercial transactions, standard microeconomic frameworks and marketing practices may simply not apply. We cannot derive the AI's utility function from first principles, nor can we assume that traditional quality signals, brand positioning, or price competition will influence AI choices in predictable ways. A posteriori empirical investigation becomes not merely useful but essential.

This research proposal outlines an empirical study to investigate the determinants of brand selection by LLMs when responding to consumer queries. By systematically analyzing which factors correlate with brand mentions across different AI platforms, consumer personas, and product categories, we aim to provide the first comprehensive economic analysis of AI-mediated consumer choice. The findings will inform both economic theory regarding intermediated markets and practical strategies for firms navigating the emerging landscape of AI-driven commerce.

2. Research Questions and Contribution

2.1 Core Research Questions

This study addresses three interconnected research questions designed to unpack the economic mechanisms underlying AI brand selection:

RQ1: What is the relationship between traditional market signals (price, quality indicators, market share) and the probability of a brand being recommended by LLMs in response to consumer queries?

RQ2: How do information environment characteristics (third-party reviews, authoritative citations, online sentiment, content relevance) influence LLM brand selection, and do these effects vary across consumer segments?

RQ3: To what extent do technical factors (structured data availability, crawlability, AI-specific indexing) explain variation in brand mentions, controlling for brand quality and market position?

2.2 Contribution to Literature

This research makes three primary contributions to the economic literature. First, we provide the first systematic empirical analysis of AI systems as economic agents in consumer markets. While a growing literature examines AI decision-making in controlled experimental settings, no study has investigated how commercial LLMs allocate attention and recommendations across competing brands in realistic consumer scenarios. This fills a critical gap as AI-mediated commerce becomes economically significant.

Second, we extend the economics of information and intermediation to AI platforms. Classic work by Stigler (1961) on information and search costs, Akerlof (1970) on quality uncertainty, and subsequent literature on market intermediaries assumes human information processing. Our study examines whether and how these frameworks apply when the intermediary is an AI system with fundamentally different information processing capabilities and constraints.

Third, we contribute to the nascent literature on machine learning in economics by demonstrating how ML methods can be applied to study AI systems themselves. Rather than using ML as a tool for prediction or causal inference in traditional economic settings, we use empirical methods to reverse-engineer the implicit preferences of AI systems, treating the AI as the object of economic analysis.

3. Theoretical Framework

We conceptualize LLM brand selection through the lens of information economics and intermediation theory. When a consumer queries an LLM for product recommendations, the AI acts as an information intermediary, aggregating signals from its training data and accessible information sources to produce a recommendation. The LLM's "choice" can be modeled as emerging from an implicit objective function that weights various input signals.

Let Y denote the binary outcome of whether brand j is mentioned in response to query i. We hypothesize that P(Y=1) depends on three categories of factors:

Market Signals (M): Traditional economic indicators including price positioning, market share, and objective quality metrics. Economic theory would predict these matter if LLMs have learned to approximate human preferences.

Information Environment (I): The quantity and quality of information available about the brand, including presence in authoritative sources, review volume and sentiment, social media discourse, and semantic content relevance to query topics. Information economics suggests these signals help resolve quality uncertainty.

Technical Accessibility (T): The ease with which AI systems can access and process brand information, including structured data markup, AI-crawler permissions, and indexing status. These factors may create "frictions" analogous to search costs in traditional markets.

Our empirical strategy aims to estimate the relative importance of each category and identify which specific signals within each category drive brand selection. A key theoretical question is whether LLMs approximate rational consumer choice (weighting quality and price appropriately) or exhibit systematic biases toward easily accessible or frequently mentioned brands regardless of quality.

4. Empirical Strategy

4.1 Data Collection

The study combines synthetic LLM response data with real-world brand characteristics. For the LLM responses, we will construct a dataset by querying three major LLMs (ChatGPT, Gemini, Perplexity) with 100 consumer queries across six distinct buyer personas (price-sensitive, quality-focused, feature-oriented, sustainability-conscious, convenience-prioritizing, and brand-loyal).

Example queries include: "What is the best running shoe for marathons under $150?", "Which laptop offers the best value for college students?", and "What smartphone should I buy for photography?" Personas are implemented through prompt engineering, prepending context such as "I am a budget-conscious consumer who prioritizes value over brand names..."

For each query-persona-LLM combination, we collect three responses at low temperature settings to address stochastic variation. This yields 5,400 individual responses ($100 \times 6 \times 3 \times 3$). Our unit of analysis is the aggregated combination (1,800 observations), where we compute mention frequencies across responses. For each observation, we record: (1) mention frequency, (2) binary mention indicator, (3) position and prominence, (4) sources cited, and (5) sentiment.

Brand characteristic data will be collected from multiple sources. Market signals come from industry reports and public financial data. Information environment metrics are constructed using SEMrush for backlink analysis and authority scores, aggregated review data from major platforms, and social media monitoring tools for sentiment analysis. Technical factors are measured through direct auditing of brand websites for structured data, robots.txt configurations, and indexing status.

4.2 Econometric Specification

Let i index a unique (query q, persona p, LLM l) combination, and let j index brands. Our primary dependent variable is Mention_ij, a binary indicator equal to 1 if brand j is mentioned in at least one of the three responses for combination i. We estimate the following logistic regression:

$$P(Mention\_ij = 1 \mid X) = \Lambda(\alpha + \beta' M\_j + \gamma' I\_j + \delta' T\_j + \theta' Z\_i + \mu\_p + \nu\_l + \tau\_c(q))$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function, M_j is a vector of market signals for brand j (log price, market share percentile, quality rating), I_j captures information environment characteristics (log review count, average rating, authority score, log social mentions, semantic content coverage score), T_j includes technical factors (binary indicators for structured data types, crawlability score), and Z_i contains query-level controls (search volume as popularity proxy, query specificity). We include fixed effects for persona (μ_p), LLM platform (ν_l), and product category (τ_c(q)), where c(q) maps each query to its product category.

Continuous variables are transformed using log(1+x) for counts and z-score standardization to facilitate comparison of effect sizes. We report average marginal effects (AMEs) as percentage-point changes in mention probability per one-standard-deviation increase in each regressor.

4.3 Machine Learning Methods

Beyond the primary logistic specification, we employ machine learning methods for three purposes. First, we use random forests and gradient boosting (XGBoost) to assess variable importance and detect potential nonlinearities and interactions that the linear-in-parameters logit may miss. Feature importance rankings from these models will complement our coefficient estimates and may reveal threshold effects or interaction patterns.

Second, we use LASSO and elastic net regularization to address potential multicollinearity among our regressors (many information signals are correlated) and to perform variable selection. The regularized estimates will help identify which signals provide independent predictive power versus those that are redundant.

Third, we employ text embeddings (using sentence transformers) to construct our semantic content coverage measure, which enters the I_j vector. For each query, we compute the cosine similarity between the query embedding and embeddings of each brand's online content, measuring how well a brand's information environment matches the consumer need.

The ML methods complement rather than replace the parametric logit specification. The logit provides interpretable coefficients and allows formal hypothesis testing, while the ML approaches offer flexibility for discovery and robustness checks.

4.4 Identification and Causality

We emphasize that our primary specification is explicitly associational. Coefficients indicate correlations with mention probability conditional on controls and fixed effects, not causal effects. Endogeneity concerns are substantial: brands with higher quality may invest more in their information environment, and both quality and information investment may respond to AI visibility. Reverse causality is less concerning in our cross-sectional design (current AI mentions cannot cause past investment decisions), but omitted variables remain problematic.

We outline paths toward causal identification that could be pursued in future work. For technical factors, we could exploit variation from exogenous platform policy changes (e.g., when a major AI platform updates crawler permissions) or phased rollouts of technical implementations. For information signals, instrumental variable approaches using PR event timing or third-party editorial decisions could provide identification. We implement a two-stage residual inclusion (2SRI) framework as a robustness check, using plausible instruments where available, though we acknowledge limitations in instrument validity and treat these results as suggestive rather than definitive.

5. Robustness Checks and Extensions

We plan several robustness exercises. First, we examine sensitivity to functional form by comparing logit, probit, and linear probability model estimates. Second, we address within-response correlation using clustered standard errors at the query level. Third, we test for heterogeneous effects by interacting key regressors with persona and platform indicators, examining whether price-sensitive consumers receive different brand recommendations than quality-focused ones.

As extensions, we conduct two additional analyses. We examine mention position and prominence (not just binary mention) using ordered logit models, testing whether the factors predicting any mention differ from those predicting prominent recommendation. We also analyze the text of brand mentions to classify sentiment and recommendation strength, examining whether certain brand characteristics correlate with more enthusiastic endorsements.

6. Weaknesses and Unanswered Questions

This study has several important limitations. First, the cross-sectional design limits causal inference. While we can identify which factors correlate with brand mentions, we cannot definitively establish that changing these factors would change LLM behavior. The instrumental variable approaches we propose require strong assumptions that may not hold.

Second, LLM behavior is not static. Models are updated frequently, and the determinants of brand selection may shift over time. Our findings represent a snapshot of current behavior and may have limited temporal validity. Longitudinal analysis tracking changes across model versions would strengthen external validity but is beyond our current scope.

Third, we observe LLM outputs but not the internal mechanisms generating them. Our analysis necessarily treats the LLM as a black box, identifying input-output relationships without understanding the underlying computation. This limits our ability to predict how LLMs will respond to novel interventions.

Fourth, generalizability across product categories may be limited. Brand selection dynamics likely differ between high-involvement purchases (electronics, vehicles) and low-involvement ones (groceries, basic apparel). Our persona-based design partially addresses this, but category-specific mechanisms may require dedicated analysis.

Several important questions remain unanswered. We do not address welfare implications: are AI recommendations improving consumer outcomes or systematically biased in harmful ways? We do not examine competitive dynamics: how might firms strategically respond to AI recommendation systems, and what equilibrium emerges? We do not consider regulatory implications: should AI recommendation systems face disclosure requirements or antidiscrimination standards? These questions represent important directions for future research as AI-mediated commerce matures.

7. Conclusion and Policy Relevance

This research proposal outlines an empirical investigation into the determinants of brand selection by large language models. By analyzing how market signals, information environment characteristics, and technical factors correlate with brand mentions across AI platforms and consumer segments, we aim to provide foundational evidence on how AI intermediaries make choices that increasingly substitute for human consumer decisions.

The findings have direct policy relevance. If AI systems systematically favor brands with superior information environments regardless of actual quality, market efficiency may suffer and information investment may crowd out quality investment. If technical factors create barriers to AI visibility for smaller firms, antitrust concerns may arise. If recommendations vary systematically across consumer personas in ways that harm vulnerable groups, fairness and discrimination issues become salient. Our empirical analysis provides the evidentiary foundation for informed policy discussion on these emerging issues.

More broadly, this study represents an early attempt to apply economic analysis to AI systems as market participants rather than merely as tools for analyzing human markets. As AI agents become increasingly capable and autonomous, understanding their behavior through an economic lens will become essential for both positive analysis of market outcomes and normative evaluation of welfare implications.

References

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, 84(3), 488-500.

Bailyn, E. (2025). Generative Engine Optimization (GEO): Explanation and Algorithm Breakdown. FirstPageSage. https://firstpagesage.com/seo-blog/generative-engine-optimization-geo-explanation/

Cohen, Z., & Amble, S. (2025). How Generative Engine Optimization (GEO) Rewrites the Rules of Search. Andreessen Horowitz. https://a16z.com/geo-over-seo/

Handley, R., Skopec, C., & Lahey, C. (2025). AI Mentions: How to Get LLMs to Mention Your Brand. *Semrush Blog*. https://www.semrush.com/blog/ai-mentions/

Stigler, G. J. (1961). The Economics of Information. *Journal of Political Economy*, 69(3), 213-225.