OPTIMIZING BRAND VISIBILITY IN GENERATIVE AI SEARCH

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Introduction and Managerial Context:

Consumers now ask generative AI assistants (ChatGPT, Gemini, Perplexity) for answers and product advice (Cohen and Amble 2025). Visibility shifts from blue links of Google to being named in the model's response. If a brand is not cited, it is absent at the moment of intent (Boutin 2025). At the same time, organic Google traffic declines and paid search CAC rises (Handley et al. 2025). Moreover, research indicates that users referred through AI-generated answers tend to convert more, since Large Language Models actively recommend the brand and integrate it into the user's purchase journey, resulting in lower CAC when optimizing for these models is cheaper than traditional Google optimization. Hence, we need a scalable way to capture high-intent demand.

We study Generative Engine Optimization (GEO): actions that raise the probability that leading LLMs cite or recommend a brand on relevant queries (Cohen and Amble 2025). Managerial aims are to grow citation share for priority queries and personas, convert AI mentions into lower CAC and higher conversion, and codify a repeatable playbook across content, PR, and technical updates.

We test levers: community reviews and user-generated content (UGC), inclusion in authoritative third-party lists, persona-targeted Q&A/FAQ content, and technical openness (structured data, llms.txt, crawlability). Since AI-referred sessions convert better than search, GEO becomes a durable growth lever and a hedge against rising Search Engine Marketing (SEM) costs. The study quantifies effect sizes of selected levers and proposes to identify their ROIs, inform budget allocation and identify underserved personas.

Research Questions:

To address this managerial problem, we propose a research study guided by the following questions (all designed to be specific, testable, and actionable):

RQ1: How does publishing more targeted content across our social channels, community forums, and blog influence the likelihood of our brand being mentioned by LLMs in responses to a targeted buyer persona on related topics?

RQ2: To what extent do **technical optimizations** (such as implementing an llms.txt file, adding Q&A schema/structured data on our pages, and ensuring indexing on Bing/OAI search) increase the probability of LLMs citing our content?

RQ3: To what extent do external factors beyond our control (such as customer reviews, overall online sentiment, and citations on authoritative sources like listicles or Wikipedia) affect the probability of our brand being referenced by LLMs?

Background & Hypothesis Development

Given the novelty and the continuous evolution of these AIs, the literature about it is very fragmented and sparse; therefore, we have to conduct our own comprehensive research upon those tailored to our situation and needs.

Determinants of brand mentions

Depth and relevance of our own content. According to Cohen and Amble (2025), LLMs prefer comprehensive, well-structured, intent-aligned pages. In-depth guides, FAQs, use cases, and comparisons give models concrete material to cite. Hypothesis: Dedicated, high-quality pages answering each persona's questions increase inclusion in LLM answers (RQ1). Example: address "best budget-friendly gadget for X?" explicitly and feature our product.

Technical factors for GEO, not legacy SEO. Make pages AI-readable: allow OAI-SearchBot in robots.txt, add structured FAQ/Q&A, expose product specs and review markup, and publish llms.txt plus XML sitemaps that list these page, prioritize clarity over keyword tricks, deprioritize SEO-era tactics that add little for LLMs: keyword density targets and backlinks. Hypothesis: better AI crawlability and structured, answer-ready content raises LLM citations; RQ2 measures lift from GEO-focused changes. We expect lower correlation of mention probability with legacy SEO practices.

Authoritative third-party signals matter. Bailyn (2025) reports FirstPageSage's 2024 study: placements in "Top X" lists and similar articles drive 40–50% of product recommendations. Reviews and ratings also weigh heavily (Perplexity ~31%, ChatGPT ~11%), and frequent, context-rich mentions across forums and blogs raise prominence. Hypothesis: stronger external reputation/sentiment (rankings, news, reviews) boosts LLM recommendations and citation frequency, even though these levers are largely outside our direct control.

Proposed Methodology

We plan to answer the research questions using an **observational study** combined with predictive modeling. We simulate consumer queries to multiple LLMs, record whether our brand is mentioned, and statistically relate that binary outcome to actionable levers (content, third-party coverage, technical setup) while controlling for query, persona, and platform heterogeneity. Results are correlational; we outline simple paths to causal identification at the end.

Unit of analysis: An *LLM response* to a given prompt (question) for a given persona. For example, *"What is the best X?"* asked as Persona A to ChatGPT constitutes one observation.

Dependent Variable (DV): Brand Mention Incidence is a binary indicator: DV=1 if our brand is mentioned/recommended in the LLM's answer for a given query, DV=0 otherwise.

We estimate how actionable levers relate to the probability that an LLM names our brand. Let i index a *(query q × persona p × LLM l)* response. The binary outcome is Mention $i \in \{0,1\}$. We fit a logistic regression:

$$\Pr\big(\mathrm{Mention}_i = 1 \mid \mathbf{X}_i, \gamma_{p(i)}, \delta_{l(i)}, \eta_{\mathrm{topic}(i)}\big) = \mathrm{logit}^{-1}(\eta_i)$$

$$\begin{aligned}\eta_i = \beta_0 &+ \underbrace{\big(\beta_1\,\mathrm{ThirdPartyMentions}_i + \beta_2\,\mathrm{ContentCoverage}_i + \beta_3\,\mathrm{Reviews}_i + \beta_4\,\mathrm{SocialReddit}_i + \beta_5\,\mathrm{SocialQuora}_i\big)}_{\text{Content \& Reputation}} \\ &+ \underbrace{\big(\beta_6\,\mathrm{FAQSchema}_i + \beta_7\,\mathrm{QASchema}_i + \beta_8\,\mathrm{ProductSchema}_i + \beta_9\,\mathrm{OrgSchema}_i + \beta_{10}\,\mathrm{LLMS\_txt}_i + \beta_{11}\,\mathrm{IndexedGoogle}_i + \beta_{12}\,\mathrm{IndexedBing}_i\big)}_{\text{Technical Openness}} \\ &+ \underbrace{\big(\beta_{13}\,\mathrm{SocialImpressions}_i + \beta_{14}\,\mathrm{Pageviews}_i\big)}_{\text{Engagement}} \\ &+ \underbrace{\big(+\phi_2\,\mathrm{Popularity}_i + \gamma_{p(i)} + \delta_{l(i)} + \eta_{\mathrm{topic}(i)}\big)}_{\text{controls}}.\end{aligned}$$

This specification is explicitly **associational**: coefficients indicate correlations with mention probability, holding controls and fixed effects constant.

Key regressors (levers).

Third-Party Mentions: weighted count of authoritative listicles/reviews/news featuring us. *Content Coverage (On-Site):* semantic relevance/coverage score for the topic provided through our online content using embedding similarity between those. *SEO Authority:* domain rank on google for the topic. *Reviews:* avg rating × log(1+#reviews) plus a review/social sentiment score. *Social*: include as distinct regressors log(1+Reddit mentions, 12m), log(1+Quora mentions, 12m). *Technical implementations:* binary indicators for each item—FAQ schema, Q&A schema, Product schema, Organization schema, llms.txt present, indexed on Google, indexed on Bing (Include these dummies separately in the logit). *Engagement:* log(1+social media impressions), log(1+pageviews) for articles and posts on the target topic, to include separately in the logit.

Controls.

Popularity: query search volume (using Google Trends data as a proxy). *Fixed effects:* persona (γ_p), LLM (δ_l), topic (η).

Estimation and reporting.

Transform skewed counts with log(1+x); z-score normalisation for continuous variables. Fit the logit with fixed effects. Report **average marginal effects (AMEs)** as percentage-point changes per 1-SD increase.

Interpretation.

We will interpret the resulting coefficient to identify the correlated uplift in mention probability. These results are not causal claims, but still helps identify which strategies are correlated with the highest lift in citation probability (addressing RQ1–RQ3).

How we could infer causality.

Plausible instruments: PR calendar shocks for *Third-Party*; scheduled community/influencer pushes for *Social*; site-wide schema rollout/IndexNow dates for *Tech*; exogenous search-engine core updates × topic sensitivity for *SEO exposure*.

Two-Stage Residual Inclusion (2SRI): Stage 1 regress each likely endogenous lever on its instrument(s)+controls+FE; save residuals $\hat{e}$. Stage 2 include the original lever and $\hat{e}$ in the logit. Significant $\hat{e}$ indicates endogeneity; the lever's effect is closer to causal.

Data Strategy

We will combine synthetic LLM outputs with real marketing and external data. Plan:

LLM Query Responses (synthetic): Generate a large Q&A set across buyer personas (price-sensitive, quality-seeker, feature-focused). Example prompts: "best running shoe for marathon under $100," "which [product] is most durable for outdoor use," etc. Use ChatGPT, Gemini, and Perplexity APIs. Persona context set via prompt engineering.

Data captured per query × persona × LLM: full response text; brand mention Y/N; position/prominence; citations and linked sources; source classification (inclusion in listicles) ; sentiment of brand mentions (favorable/neutral/negative).

Scale and tooling: ~100 queries × 6 personas × 3 LLMs ≈ 1800 responses. Python scripts to make the API calls. Below API limits. Expected cost: a few hundred USD. Keep low LLM temperature and collect 3 answers per model to address their stochastic nature.

Cleaning/structure: parse responses, extract cited URLs, run sentence-level sentiment on brand mentions. Final table: one row per (query, persona, LLM) with all metrics.

Internal Web Analytics

Use Google Analytics to identify sessions from generative-AI referrals. ChatGPT directly adds *"utm_source=chatgpt.com"* to the cited url (OpenAI 2025), while Gemini/Perplexity include their referral info .

External Data:

Content and Mentions: Map query topics to our on-site content (blog/FAQ/product). Use sitemap/search functionality to find pages with matching keywords. Metrics: "this query has a relevant page Y/N", page views (last 3 months), social shares. Optionally add keyword rankings from SEO tools.

External mentions & backlinks: use Semrush Brand Monitoring and similar for brand mentions and referring domains. For each query topic, identify "authority articles" (e.g., "best [product] 2025"); check inclusion. Manual review for top 10–20 queries, then scale via scraping SERPs and snippets. Collect backlink count and domain authority as controls.

Ratings/reviews: scrape average rating and review counts per product; use flagship or averages. Optionally analyze review text for themes. Social sentiment via social listening API or searches on Twitter/Reddit over the last year; compute sentiment and count relevant subreddit threads mentioning the brand.

Technical SEO: log presence/timing of *"llms.txt"*; confirm no AI-crawler blocks via Site Audit; log IndexNow usage. From Google Lighthouse, obtain page speed and mobile friendliness scores. Store as binary flags and scores.

Managerial relevance & Implications

Content and SEO Strategy: Prioritise marketing investments based on factors that raise most LLM mentions. For example, a large positive β on ExtListMentions indicates the PR team to commit to third-party list features via outreach or partnerships, while a weak effect signals to redirect focus to other factors. This shifts GEO from intuition to data-driven resource allocation

Buyer Persona Targeting: Since we analyze questions and answers tailored for each customer segment, we can identify the ones we're failing to reach in AI answers (e.g., strong presence among early adopters but weak among budget-conscious buyers). Managers can reach this underserved persona by creating more beginner-friendly guides or value-focused messaging, to improve our relevance for that group.

Channel ROI and Budget: Once identified the most relevant factors to improve citations in AI, we can optimize the budget we allocate across different communication channels. If AI referrals outperform SEO/SEM, management should reallocate spend toward GEO by funding an **"AI Optimization" team or tools**. We will quantify a rough ROI: "Each $1k spent on GEO content yields X new customers via ChatGPT, vs. $1k on Google Ads yields Y customers."

Competitive Intelligence: AI-cited sources provide a competitive benchmark to identify featured competitors in queries where our brand is missing. Understanding why the competitors are featured more readily, we can develop a strategy to counter it: by improving our content or differentiating our offering.

Feasibility & Timeline

Week 1-2: Data Collection Setup. Finalize the list of buyer personas and relevant queries. Set up the Python scripts and API access for LLM querying. Launch a small pilot to test the data pipeline and adjust prompts. Prepare baseline from internal analytics. API rate limit risk will be managed by batching requests and using sleep intervals.

Week 3: Full Data Collection. Execute queries across ChatGPT, Gemini, and Perplexity (2-3 days to avoid rate limits and one-day bias). Use SEO tools to gather data on external mentions and our content index.

Week 4: Data Processing & Variable Construction. Combine the datasets. Create the IVs for each query: parse the AI sources to count if we're in them, compute sentiment scores, attach the pre-collected metrics (reviews, content, etc.). Ensure the dataset is complete (no major missing data).

Week 5: Modeling & Analysis. Conduct the regression analysis and statistical tests. Perform comparative analysis using benchmarks.

Week 6: Presentation of results. Convert the statistical results into recommendations. Prepare a presentation focusing on the findings, compile the written report.

Beyond Week 6: Implementation: Roll out content updates, technical fixes, and PR outreach, then re-measure AI mentions after a set interval to track lift.

Budget and Resources: LLM API usage: estimated $300. SEO tools: we have subscriptions to Semrush/Ahrefs, no additional cost. Personnel: Our team of 5 will divide tasks. Any additional costs (purchasing a dataset or an academic paper) are minimal.

References

Axelsen, Emily. “AI Search Optimization Guide: Boosting Brand Visibility on LLMs.” Goodie Blog, September 19, 2025. https://higoodie.com/blog/ai-search-visibility-optimization.

Bailyn, Evan. “Generative Engine Optimization (GEO): Explanation and Algorithm Breakdown.” FirstPageSage, October 3, 2025. https://firstpagesage.com/seo-blog/generative-engine-optimization-geo-explanation/.

Boutin, Elmer. “Your Brand in the Age of Generative Search: How to Show Up and Be Cited.” Search Engine Land, July 28, 2025. https://searchengineland.com/brand-generative-search-show-up-be-cited-459462.

Cohen, Zach, and Seema Amble. “How Generative Engine Optimization (GEO) Rewrites the Rules of Search.” Andreessen Horowitz, May 28, 2025. https://a16z.com/geo-over-seo/.

Gupta, Pragati. “How to Get Cited by AI: A Marketer’s Guide to Winning in AI Search.” Writesonic Blog, October 24, 2025. https://writesonic.com/blog/how-to-get-cited-by-ai.

Handley, Rachel, Christine Skopec, and Connor Lahey. “AI Mentions: How to Get LLMs to Mention Your Brand.” Semrush Blog, July 29, 2025. https://www.semrush.com/blog/ai-mentions/.

OpenAI. “Publishers and Developers – FAQ.” OpenAI Help Center. Last modified October 21, 2025. https://help.openai.com/en/articles/12627856-publishers-and-developers-faq.

Sentika, Aris. “What Is the LLMs.txt File, and How Do You Create One for Your Website?” Hostinger Blog, July 27, 2025. https://www.hostinger.com/tutorials/what-is-llms-txt.