



OPTIMIZING BRAND VISIBILITY IN GENERATIVE AI SEARCH

GROUP 8

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Online search behaviour is changing, people used to search on Google, but now over a billion users ask AI tools for advice. If our brand is not mentioned in those answers, we would lose a lot of potential traffic.

CAC from organic and paid search on google is increasing. We need to focus on Generative Engine Optimization and improve our citation rate in AI answers to win high-intent traffic

WHY THIS MATTERS

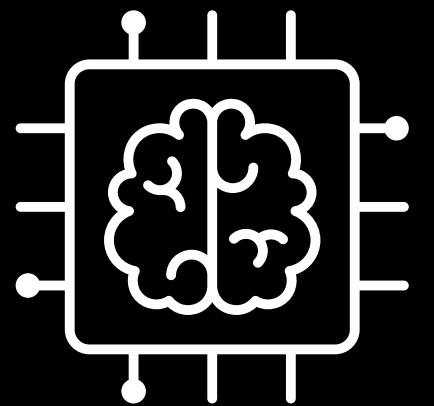
Increase LLM citation share on priority queries and buyer personas

Translate those AI mentions into higher conversion and lower CAC

Create a repeatable playbook across Content, PR/Authority, and Technical SEO

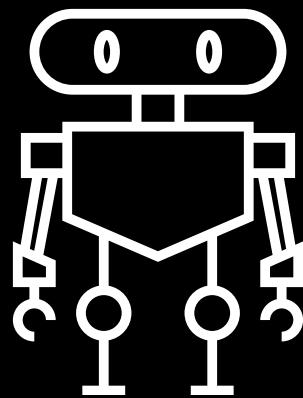
WHAT WINNING LOOKS LIKE

CORE KPIs



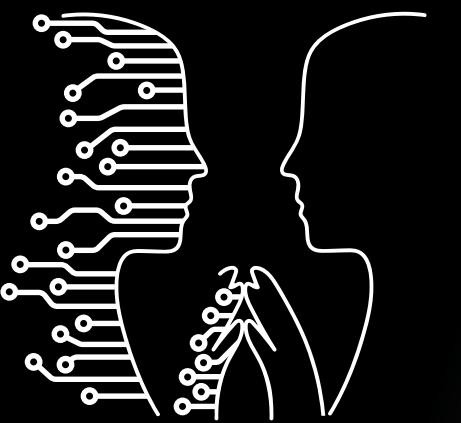
LLM Citation Rate

mentions per 100
prompts, weighted
by prominence



AI Share of Voice

our mentions ÷ all
brand mentions



CAC (AI)

GEO spend
(content/PR/tech) ÷
AI-referred
conversions

RESEARCH QUESTIONS

RQ1

Impact of **targeted content** (social, community, blog) on LLM mention probability for specific buyer personas.

RQ2

Lift from **technical optimizations** (llms.txt, structured Q&A/FAQ, Bing/google indexing) on citations.

RQ3

Effect of **external factors** (reviews, sentiment, authoritative listicles /Wikipedia) on being referenced.

HYPOTHESES

Because Generative Engine Optimization is a nascent, rapidly evolving field, the existing literature is fragmented and thin. We therefore advance the following hypotheses and will build on prior studies with original, context-specific research to address our needs.

H1

Content Depth/Relevance: In-depth persona-aligned guides/FAQs/comparisons increase inclusion.

H2

Technical AI-Readiness: Crawlability + structured data + llms.txt + indexation raise LLM citations

H3

Authority & Sentiment: Third-party lists, ratings, and forum/blog coverage boost recommendations. Lower expected correlation with legacy SEO tactics (e.g., keyword density, generic backlinks).

METHODOLOGY

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.

Dependent Variable: Brand Mention Incidence is a binary indicator. Let i index a (query $q \times$ persona $p \times$ LLM l) response.

Platforms: ChatGPT, Gemini, Perplexity. **Sample plan:** 100 queries \times 6 personas \times 3 LLMs = 1,800 responses (low temperature; 3 runs/model).

METHODOLOGY

Model: Logistic Regression

Controls: query popularity (Trends proxy); FE for persona, LLM, Topic.

Reporting: log(1+x) for skewed counts; z-score continuous vars; report AMEs (pp change per 1-SD).

Key regressors (actionable levers): Third-party mentions; on-site content coverage/relevance; SEO authority; reviews & sentiment; social/forum activity (Reddit/Quora); technical flags (FAQ/Q&A/Product/Org schema, llms.txt, Google/Bing indexed); engagement (impressions/pageviews).

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

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

METHODOLOGY

Estimation & Reporting: average marginal effects

Interpretation: strategy correlation with increases in citation probability

How could we prove causality?

Instruments: PR calendar shocks (third-party); scheduled community pushes (social); schema/IndexNow rollouts (tech); search-engine core updates × topic sensitivity (SEO exposure).

2SRI: Stage 1 instrumented levers → residuals; Stage 2 logit with lever + residuals.

DATA STRATEGY

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



LLM Query Responses (synthetic): Generate a large Q&A set across buyer personas. Simple python script with prompt engineering. Total cost less than €300

Internal Web Analytics: Track sessions from AI referrals – Compare conversion & CAC vs organic / paid

External Data: sitemap/content mapping, pageviews and social shares; Semrush/Ahrefs brand mentions & authority lists; ratings/reviews (avg × log count); social sentiment (Twitter/Reddit).

Technical SEO: presence/timing of “llms.txt”, IndexNow usage, page speed and mobile friendliness scores

MANAGERIAL RELEVANCE



Allocation

invest in the levers with highest AMEs for citation lift (content vs. tech vs. PR)

Competitive intel

mine AI-cited sources to see why competitors appear and counter accordingly.

Persona gaps

identify underserved segments and create targeted, answer-ready assets.

Channel ROI

if AI referrals outperform SEO/SEM, fund GEO as a durable growth lever.

TIMELINE

FEASIBLE? Yes

Data Collection Setup

Define personas/prompts;
run pilot; pull analytics
baseline

WEEK 1-2

Data Processing & Variable Construction

Engineer variables; merge
datasets; quick
exploratory analysis

WEEK 3

Full Data Collection

Run LLM queries; gather
external signals; parse
and archive

WEEK 4

Modeling & Analysis

Fit logit; compare
CVR/CAC; run robustness
checks

WEEK 5

Synthesis of Results & Presentation Prep

Produce GEO playbook;
finalize deck and report

WEEK 6



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THANK YOU

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APPENDIX

A. Research Questions

RQ1. Does publishing targeted, persona-aligned content on our site and social channels increase the chance that leading LLMs mention our brand in answers to related queries?

RQ2. Do technical optimizations (e.g., an llms.txt file, structured Q&A/FAQ markup, and confirmed indexing on Bing/OAI/Google) raise the probability that LLMs cite our content?

RQ3. To what extent do external signals outside our direct control (customer reviews, overall online sentiment, and inclusion in authoritative third-party lists or encyclopedic sources) affect LLM references to our brand?

APPENDIX

B. Unit of Observation and Variables specification

Unit of observation: one LLM answer to one query asked under one buyer persona (e.g., “best X under €Y” asked as a budget-conscious persona in ChatGPT).

Dependent variable (DV): Brand Mention Incidence, a binary indicator equal to 1 if our brand is named or recommended in the answer, 0 otherwise. When multiple answers are sampled per model, we take each answer as a separate observation and retain a “run” identifier.

Third-party mentions (authority coverage): weighted count/score of our inclusion in “Top X/best of” listicles, editorial reviews, and reputable news features for the focal topic.

On-site content coverage & relevance: semantic similarity between the query/topic and our dedicated page(s); presence of a purpose-built page answering the persona’s question; recent pageviews for that content.

SEO authority (topic-level): domain/topic authority metrics used as controls for baseline exposure.

Ratings & reviews: average rating multiplied by $\log(1 + \text{number of reviews})$ for the relevant product(s); sentiment score from review text when available.

Community & social footprint: $\log(1 + \text{Reddit mentions, last 12 months})$ and $\log(1 + \text{Quora mentions, last 12 months})$ for the topic; social impressions for our related posts.

Technical openness flags: separate binary indicators for FAQ schema, Q&A schema, Product schema, Organization schema, presence of llms.txt, and confirmed indexation on Google and Bing/IndexNow.

Engagement on owned content: $\log(1 + \text{recent pageviews})$ and $\log(1 + \text{social impressions})$ for the specific asset mapped to the query.

Query popularity: search interest via Google Trends for the topic as a proxy for baseline demand.

Fixed effects: persona, LLM, and topic.