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# The 2026 PI SERP Authority Report: An 11-Question Structural Audit of 1,005 US Personal Injury Law Firm Websites Against the Personal Injury Organic Authority Engine (PIOAE) Framework

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## Abstract

Personal injury (PI) is the highest-CPC legal vertical in United States search: commercial-intent queries clear USD 100 to USD 300 per click and cost per signed case from paid channels regularly exceeds USD 5,000. In this environment, the practical question for a managing partner evaluating an SEO program is not whether the firm ranks, Google Page 1 alone is table stakes, but whether the site is structurally engineered to compound authority over time. This study operationalizes that question as an eleven-item rubric drawn from the Personal Injury Organic Authority Engine (PIOAE) framework and applies it externally to a rank-controlled sample of 1,005 unique PI law firm websites ranking on the first page of Google Search for five practice-area keywords across 51 US metropolitan markets. For every firm we assembled independent third-party authority, traffic, keyword-ranking, backlink, and AI-visibility signals from established SEO-data providers; ran an industry-standard mobile-performance audit; crawled each firm's sitemap, attorney bios, informational pages, contact forms, and mobile viewport; and classified 5,984 unique referring domains with a large-language-model judge. Each firm was graded across four pillars (Technical Stability, Intent Capture, Authority Reinforcement, Case Acquisition Optimization) on an eleven-question rubric with a maximum score of 11. We find that zero firms of 1,005 reach the Authority Built band (10-11/11), only 5 firms reach Authority Leaking (7-9/11), 337 firms are Authority Underbuilt (4-6/11), and 663 firms, 66.0% of the sample, are Authority Absent (0-3/11). The median firm's homepage takes 5.5 seconds to reach the Largest Contentful Paint on a mid-range mobile device, 3.7x the framework's 1.5-second threshold. Only 1.5% pass the mobile-render check, only 3.1% deploy a YMYL-aware intake form, and only 3.2% of firms have topically-relevant backlink profiles. The rubric's total score correlates strongly with organic traffic (Spearman $\rho = 0.55$) and Domain Authority Score ($\rho = 0.55$), confirming that the framework measures a real structural phenomenon, but only weakly with AI-answer visibility ($\rho = 0.19$), suggesting that classical structural authority and AI-answer citation are partly decoupled surfaces. We anchor the findings to Google's published patents on knowledge graphs and factual-entity content, discuss three surprising findings (mobile render as a vertical-wide structural crisis, function-first mobile layouts as newly table-stakes, and the AI-visibility decoupling), and offer prioritized recommendations for firms.

**Keywords:** Personal Injury SEO, Personal Injury Organic Authority Engine, PIOAE, Legal Vertical Search, Semantic SEO, Structured Data, Rich Results, Knowledge Graph, Knowledge Panel, AI Overviews, AI Visibility, Zero-Click, Core Web Vitals, Backlink Profile, Practice-Area Architecture, Function-First Layout, YMYL, Case Acquisition, Search Engine Optimization, E-E-A-T

**Introduction**

The digital marketplace for personal injury (PI) legal services in the United States is one of the most competitive verticals on the open web. Cost-per-click on commercial-intent queries such as "car accident lawyer" or "wrongful death attorney" routinely clears USD 100 to USD 300, and the cost of a signed case originating from paid channels regularly exceeds USD 5,000. Under those unit economics, small differences in organic performance are material to firm-level revenue: a single displaced Page 1 ranking on a metropolitan commercial query can shift the annual signed-case volume of a mid-sized firm by tens of cases.

Yet most PI firms operate search-engine-optimization programs that produce activity reports rather than case-attribution reports. The reason is structural. A PI firm's website sits at the intersection of three simultaneous constraints. First, Your-Money-or-Your-Life (YMYL) trust requirements subject legal content to Google's highest tier of quality scrutiny, so the page-experience floor, entity-verification floor, and citation-quality floor are all higher than in a general-interest vertical. Second, entity-recognition gaps: most firms are not yet represented in Google's Knowledge Graph as first-class factual entities, so the onboarding pathway described in Google's own entity-onboarding patent family (Google LLC, 2024) has never been triggered for them. Third, high-CPC economics: every structural mistake costs more in PI than in almost any other vertical because the alternative to organic acquisition is paid acquisition at USD 1,000 to USD 5,500 per signed case, so the opportunity cost of an underbuilt site is measurable in real dollars, not merely in lost impressions.

Three shifts in search infrastructure have raised the stakes on the mechanical way in which a firm's site is structured for machines. First, since Google introduced the Knowledge Graph (Singhal, 2012) and deployed transformer language models such as BERT (Devlin et al., 2019) for query and passage understanding, the search engine's model of a page has moved from keyword matching toward entity resolution and passage-level intent scoring (Google Inc., 2016; Nogueira and Cho, 2019). Google now asks "who or what is this page about, and which passage within it answers this claim of the query?" before it asks "what words does the page use?" Second, the arrival of AI Overviews and third-party generative answer engines such as ChatGPT, Gemini, and Perplexity has added a new consumer surface where an AI system, not a ten-blue-links SERP, is the direct audience of the page. Third, the shift from single-query to stateful, multi-turn search sessions, formalized in Google's Search-with-stateful-chat patent (Google LLC, 2024; US-2024289407-A1), reframes intent capture as a conversation whose downstream turns depend on the extracted data of upstream turns. All three shifts privilege pages whose entities and structural attributes are declared explicitly and whose site-wide quality signals (Google Inc., 2015) meet an increasingly-elevated floor.

The Personal Injury Organic Authority Engine (PIOAE) framework was developed to codify the structural properties that let a PI firm's website compound authority under these constraints. It reduces the ranking problem to a single equation, Ranking State = (Historical Data × Topical Coverage) ÷ Cost of Retrieval, and organizes the site's inputs into four sequenced pillars: Technical Stability (which lowers Cost of Retrieval), Intent Capture (which builds Topical Coverage), Authority Reinforcement (which accumulates Historical Data), and Case Acquisition Optimization (which converts the resulting Ranking State into signed cases). Twelve grading questions across those four pillars jointly describe whether the firm is structurally set up to translate ranking into intake. One of those twelve, organic-intake attribution, requires information internal to the firm (CRM records, call-tracking data, intake-team attribution) and cannot be graded from outside. The remaining eleven can.

This paper reports the empirical result of applying the eleven externally-gradable questions to a rank-controlled sample of 1,005 US personal-injury law firm websites ranking on Google Page 1 across 51 US metropolitan markets. Prior empirical work in the same research programme audited an earlier 500 law firm websites' analysis on schema markup adoption across North American legal services (Hussain, 2026), then extended that audit to the current 1,005 law firm websites' analysis of schema markup adoption and Rich Results eligibility across 50 US states (Hussain, 2026), audited each firm's Knowledge Panel presence and Person Entity Confidence (Hussain, 2026), scored the firm-name panel on a nine-attribute completeness instrument (Hussain, 2026), and traced how brand search demand and Knowledge Panels of firms and attorneys jointly impact organic traffic in 1,000 US personal-injury law firms (Hussain, 2026).

The present study extends the same 1,005-firm sample to the eleven-question framework rubric, providing the first empirical audit of the framework itself. Our contribution is fourfold: (i) reproducible external-measurement proxies for each question, (ii) the empirical pass-rate distribution across the four bands defined by the framework, (iii) tests of the total score against independent third-party measures of authority, organic traffic, and AI-answer visibility, and (iv) anchoring of each pillar's findings to the underlying Google patents and published research that describe the mechanical pathway the pillar targets.

## Related Work

### The Personal Injury Organic Authority Engine (PIOAE) Framework

The Personal Injury Organic Authority Engine (PIOAE) is a proprietary framework developed to guide search-engine-optimization decisions specifically in the personal-injury legal vertical. It reduces the ranking problem to a single equation, Ranking State = (Historical Data × Topical Coverage) ÷ Cost of Retrieval, and organizes the levers into four sequenced pillars. Pillar 1 (Technical Stability) lowers Cost of Retrieval by ensuring the site is cheap for Google to crawl, parse, and render. Pillar 2 (Intent Capture) builds Topical Coverage through practice-area architecture and query-network depth. Pillar 3 (Authority Reinforcement) accumulates Historical Data through entity recognition, third-party citation, and attorney-bio depth. Pillar 4 (Case Acquisition Optimization) converts the resulting Ranking State into signed cases through conversion architecture. Each pillar carries three questions in the associated Scorecard; Question 10, organic-intake attribution, requires firm-side telemetry and is excluded from the externally-gradable subset applied in this study.

### Companion Studies

This paper sits inside an ongoing research programme of empirical audits of United States personal-injury law firm websites conducted by the author. Six prior papers have established the vertical's structural profile across schema markup, Knowledge Panel presence, entity signals, business-panel completeness, and the brand-and-traffic feedback loop.

The first (Hussain, 2026) was a 500 law firm websites' analysis of schema markup adoption across North American legal services, which established the baseline gap between what the schema.org vocabulary makes possible and what the PI vertical actually deploys. The second (Hussain, 2026) extended that audit to a 1,005 law firm websites' analysis on Google Page 1 across 50 US states, reporting that only 30.0% of the sample deploys structurally-clean schema payloads and that only 6.7% emit either Person or Attorney schema for their lawyers.

The Person Entity Confidence Gap paper (Hussain, 2026) audited Knowledge Panel presence on the same 1,005-firm sample for each firm's managing partner and firm-name query, reporting that only 3.5% of firms have a Person-Entity Knowledge Panel and 21.3% have any panel at all, and introducing the notion of a Person Entity Confidence Gap as the vertical-wide structural condition. A companion signal-traffic-and-AI-visibility audit (Hussain, 2026) extended the Knowledge Panel work with independent SEO signal, monthly traffic, and generative-answer visibility data for the same 1,005 firms.

The Google Business Panel Completeness Gap paper (Hussain, 2026) audited the firm-name-side Knowledge Panel with a nine-attribute completeness scoring instrument. The Brand Demand Flywheel paper (Hussain, 2026) then analyzed how brand-search demand and Knowledge Panels of firms and attorneys jointly impact organic traffic in 1,000 US personal-injury law firms.

The present study extends the same 1,005-firm sample to the eleven-question rubric of the PIOAE framework, providing the first empirical audit of the framework itself, and integrating the Knowledge Panel and business-panel signals from the prior papers into Pillar 3 of its grading.

### Pillar 1 grounding: technical stability and crawl efficiency

Pillar 1 rests on Google's site-quality machinery. Site Quality Score (Google Inc., 2015) defines a query-independent, site-wide quality signal computed as a ratio of user interest in the site over interest in the site's resources as query responses; every page inherits this multiplier.

Predicting Site Quality (Google Inc., 2017) extends the mechanism to feature-based prediction. The Scheduler for the search engine crawler (Google LLC, 2020) sets re-crawl frequency by content-change frequency. Core Web Vitals (Google Search Central, 2024b; web.dev, 2024) adds LCP, INP, and CLS as ranked page-experience signals; the 1,500-ms LCP threshold used in Q2 aligns with the framework's specification. FreeDOM (Lin et al., 2020) shows that consistent semantic HTML plus valid schema raises neural extraction accuracy, tying Technical Stability to downstream entity-extraction quality.

**Pillar 2 grounding: passage-level intent and multi-turn sessions**

Pillar 2 is anchored in the shift from document-level keyword matching to passage-level and multi-turn intent modeling. Google's Text indexing and passage retrieval patent (Google Inc., 2016) describes passage-independent scoring. The BERT passage re-ranker (Nogueira and Cho, 2019) is the reference implementation; Metzler, Tay, Bahri, and Najork (2021) argued for unified multi-task models (MUM). Search with stateful chat (Google LLC, 2024) formalizes multi-turn context propagation. Query Suggestion Templates (Google Inc., 2014) and Question answering using entity references (Google Inc., 2016) describe the entity-category-conditioned mechanism that penalizes cannibalization.

**Pillar 3 grounding: link authority, entity onboarding, and trust**

Pillar 3 accumulates over three overlapping mechanisms. PageRank (Google Inc., 2001) remains the foundational link-authority signal. Reasonable Surfer (Google Inc., 2011) weights links by click probability; link position, prominence, and contextual relevance affect value. Hilltop (Bharat and Mihaila, 2000) introduced expert documents. Corroborating facts across sources (Google Inc., 2014) formalizes cross-source attribute-value verification; NAP consistency is the practical implication.

Entity onboarding into the Knowledge Graph is described in the Onboarding of entity data (Google LLC, 2024). Entity attribute relations (Google LLC, 2022) provides the extraction mechanism the schema payload feeds. Schema.org (Guha, Brickley, and Macbeth, 2016) is the shared vocabulary consumed by both Google and Microsoft, and Knowledge Vault (Dong et al., 2014) positions structured data as one of four extractor lanes. Trust rank (Google Inc., 2013), Identifying local experts (Google Inc., 2017), Sentiment detection (Google Inc., 2016), and Business listing ranking (Google Inc., 2014) describe the local-panel ranking machinery for firm-name queries.

**Pillar 4 grounding: Knowledge Panels as intake surfaces, action recommendations, and click quality**

Pillar 4 treats the SERP itself as an intake surface. Google's US Patent US-11836177-B2 (Google LLC, 2023) describes the Knowledge Panel with Claim 3 (panel is larger than any single organic result), Claim 5 (interactive UI object without navigating away), Claim 8 (Person template with image + description + at least one fact), and Claim 9 (Place template). Recommending action(s) based on entity or entity type (Google LLC, 2024; US-12147767-B2) extends the mechanism to action recommendations conditioned on entity type. Calibrating click duration (Google Inc., 2014) formalizes the goodClicks-versus-badClicks distinction. Predicting accuracy of submitted data (Google LLC, 2023) closes the loop by rejecting inaccurate third-party edits.

## Methodology

### Sample construction

The 1,005-firm sample is inherited from the companion 1,005 law firm websites' analysis of schema markup adoption (Hussain, 2026). For each of five practice-area keyword templates (personal injury lawyer, car accident lawyer, truck accident lawyer, medical malpractice lawyer, and wrongful death lawyer), SERP data was collected across 51 US markets (the largest city in each of the 50 US states plus Washington, DC), yielding 255 SERPs and, after filtering out directory and non-firm domains, 1,005 unique PI law firm websites. Each domain in the sample thus ranks on Google Page 1 for at least one core PI practice-area query in at least one US market.

### The eleven-question rubric

The rubric is drawn verbatim from files 09 and 11 of the PIOAE productization kit. Q10 (organic-intake attribution) is excluded because it requires firm-side telemetry (CRM data, phone-tracking numbers, intake-team attribution). The remaining eleven are graded externally using the measurement proxies described below.

Table 1. The eleven externally-graded rubric questions.

| Q | Pillar | What it measures | Grading proxy (external-observable) |
|---|---|---|---|
| Q1 | P1 Technical | Worth-to-Index ratio | Ranked-keyword count $\geq$ 500 AND monthly organic traffic $\geq$ 500 |
| Q2 | P1 Technical | Mobile render < 1.5s | Mobile Largest Contentful Paint < 1,500ms |
| Q3 | P1 Technical | Schema audited last 6mo | has_any_schema AND sci_total $\geq$ 8 AND validation_errors $\leq$ 2 AND rr_eligible_count $\geq$ 1 |
| Q4 | P2 Intent | Practice-area arch. clean | $\geq$ 5 root-level PA landing URLs in sitemap; total $\geq$ 8 |
| Q5 | P2 Intent | Info → commercial bridging | $\geq$ 40% of info pages contain internal link to commercial page |
| Q6 | P2 Intent | Query network depth | $\geq$ 3 distinct PI case types in top-7 ranked keywords |
| Q7 | P3 Authority | Knowledge Graph entity | KP class personal or business, with local NAP signal |
| Q8 | P3 Authority | Topical citation profile | $\geq$ 40% of top referring domains PI-relevant or authority-news |
| Q9 | P3 Authority | Attorney bio depth | Bio word-count $\geq$ 300 AND $\geq$ 2 expertise signals |
| Q11 | P4 Acquisition | Function-first layout | Above-fold primary CTA on mobile viewport (LLM-vision-graded) |
| Q12 | P4 Acquisition | YMYL intake form | 3-12 form fields AND $\geq$ 1 pre-qualification signal |

### Data collection stack

For every firm in the sample, we assembled the following independent data. First, a per-domain snapshot of standard third-party SEO metrics: a Domain Authority Score in the 0-100 range, an alternative domain-authority index, a spam-risk score, monthly organic and paid traffic estimates, total ranked-keyword count, backlink aggregates, and an AI-search visibility index measuring citations across the four major generative-answer surfaces (ChatGPT, Google AI Overviews, Google AI Mode, and Gemini). Second, a full per-link backlink profile for the top 500 firms ranked by Domain Authority Score. Third, a mobile-performance audit of every homepage using the industry-standard Lighthouse metric set (LCP, FCP, CLS, TBT, speed index, time-to-interactive). Fourth, mobile-viewport screenshots of every homepage at 390 by 844 device pixels. Fifth, structured HTML parses of every firm's homepage, contact and intake pages, attorney bio pages, sitemap, and informational content. Sixth, a large-language-model classification of 5,984 unique referring-domain origins from the backlink corpus and 884 above-fold mobile screenshots. Schema quality signals were reused from the companion 1,005 law firm websites' analysis of schema markup adoption (Hussain, 2026). Knowledge Panel classifications were inherited from the companion Person Entity Confidence Gap paper (Hussain, 2026). Firm-name-side panel completeness on the nine-attribute instrument was inherited from the Google Business Panel Completeness Gap paper (Hussain, 2026). Brand-search-demand and AI-visibility signals draw on the Signal, Traffic, and AI-visibility Audit (Hussain, 2026) and the Brand Demand Flywheel paper (Hussain, 2026) on the same firm set.

**Grading and aggregation**

Each of the eleven questions is graded binary (0 or 1) per the external proxies described in Table 1. Pillar sub-scores aggregate the underlying questions: P1 = Q1 + Q2 + Q3 (max 3), P2 = Q4 + Q5 + Q6 (max 3), P3 = Q7 + Q8 + Q9 (max 3), P4 = Q11 + Q12 (max 2). The total score sums the eleven grades (max 11). Firms are then binned into bands per the framework specification: Authority Built (10-11), Authority Leaking (7-9), Authority Underbuilt (4-6), Authority Absent (0-3).

**Reproducibility and cross-study integration**

The full pipeline is deterministic and re-runnable from the same 1,005-firm sample. Every per-firm intermediate is preserved so downstream analysis never re-hits the underlying data providers. Because two of the eleven grades (Q3 schema quality and Q7 Knowledge Graph entity) are inherited directly from the prior papers, this study integrates continuously with the 1,005 law firm websites' analysis of schema markup adoption (Hussain, 2026), the Person Entity Confidence Gap paper (Hussain, 2026), the Signal, Traffic, and AI-visibility Audit (Hussain, 2026), the Google Business Panel Completeness Gap paper (Hussain, 2026), and the Brand Demand Flywheel paper (Hussain, 2026) on the same firm set. Coverage limitations for individual questions are documented in Section 7.

**Findings**

**Overall pass rates**

Table 2 reports the pass rate on each of the eleven rubric questions. The rates span from 1.5% (Q2, mobile render under 1.5 seconds) to 75.5% (Q1, ranked-keyword count and organic traffic). Q2, Q8 (topical citation profile, 3.2%), and Q12 (YMYL intake form, 3.1%) stand out as vertical-wide structural gaps where the vertical has effectively not deployed the practice at all.

Table 2. Pass rate for each rubric question (n = 1,005).

| Question | Pillar | n passing | Pass rate |
|---|---|---|---|
| Q1 Ranked pages | P1 Technical | 759 | 75.5% |
| Q2 Mobile render < 1.5s | P1 Technical | 15 | 1.5% |
| Q3 Schema quality | P1 Technical | 302 | 30.0% |
| Q4 Practice-area architecture | P2 Intent | 447 | 44.5% |
| Q5 Info → commercial bridging | P2 Intent | 113 | 11.2% |
| Q6 Query network depth | P2 Intent | 164 | 16.3% |
| Q7 Knowledge Graph entity | P3 Authority | 182 | 18.1% |
| Q8 Topical citation profile | P3 Authority | 32 | 3.2% |
| Q9 Attorney bio depth | P3 Authority | 187 | 18.6% |
| Q11 Function-first mobile layout | P4 Acquisition | 735 | 73.1% |
| Q12 YMYL intake form | P4 Acquisition | 31 | 3.1% |

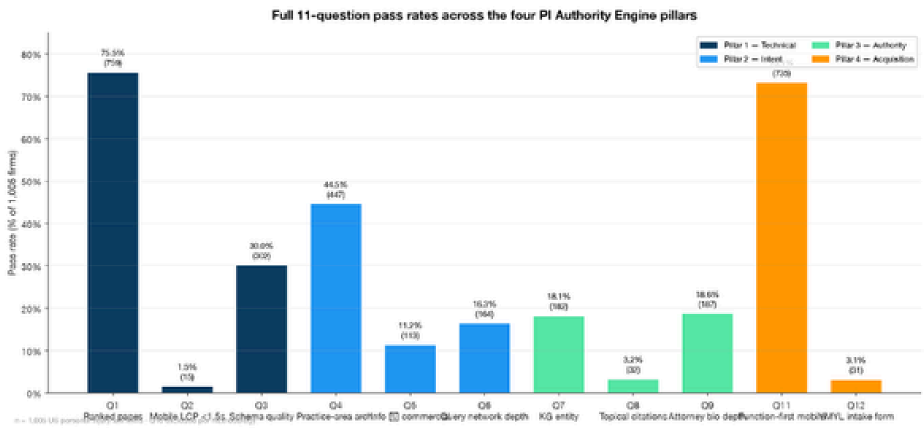


Figure 1. Question-level pass rates across the four PIOAE pillars.

**Total-score distribution**

The modal firm scores 3 of 11 (28.8% of the sample), the median is 3, and the mean is 3.13. The distribution is right-skewed with a sharp cutoff: no firm in the sample scores above 7 of 11. The tail of the distribution, Authority Leaking, contains only five firms.

Table 3. Total-score distribution (n = 1,005).

| Total score | Firms | % of sample |
|---|---|---|
| 0/11 | 27 | 2.7% |
| 1/11 | 119 | 11.8% |
| 2/11 | 228 | 22.7% |
| 3/11 | 289 | 28.8% |
| 4/11 | 218 | 21.7% |
| 5/11 | 96 | 9.6% |
| 6/11 | 23 | 2.3% |
| 7/11 | 5 | 0.5% |
| 8/11 | 0 | 0.0% |
| 9/11 | 0 | 0.0% |
| 10/11 | 0 | 0.0% |
| 11/11 | 0 | 0.0% |

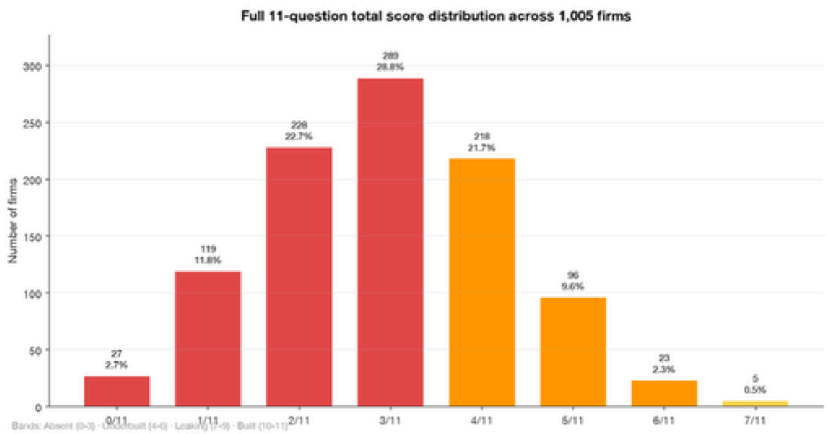


Figure 2. Total-score distribution across the sample. Color: red = Absent (0-3), orange = Underbuilt (4-6), yellow = Leaking (7-9), green = Built (10-11).

### Band distribution: the study's central finding

Zero firms of 1,005 reach the Authority Built band. Only 5 firms reach Authority Leaking, all of them tied at exactly 7 of 11. The remaining 1,000 firms, 99.5% of the sample, split into Authority Underbuilt (337 firms, 33.5%) and Authority Absent (663 firms, 66.0%). The Authority Absent band is the modal band by a wide margin.

Table 4. Band distribution (n = 1,005).

| Band | Score range | Firms | % of sample |
|---|---|---|---|
| Authority Built | 10-11 | 0 | 0.0% |
| Authority Leaking | 7-9 | 5 | 0.5% |
| Authority Underbuilt | 4-6 | 337 | 33.5% |
| Authority Absent | 0-3 | 663 | 66.0% |

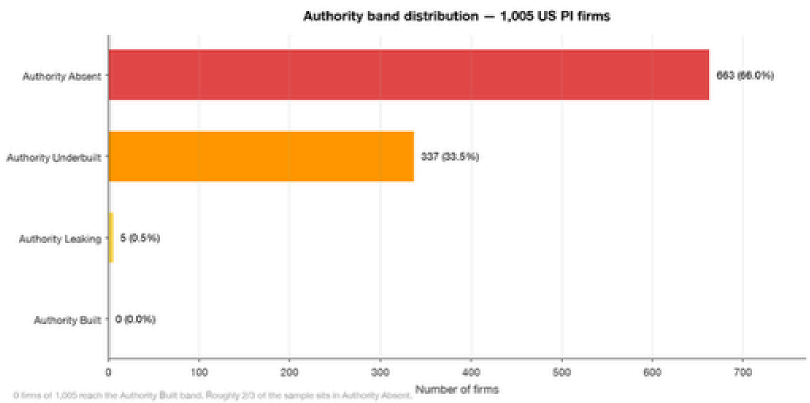


Figure 3. Authority band distribution across the 1,005-firm sample.

**The Authority Leaking cohort**

Table 5. The five firms in the Authority Leaking band.

| Firm | Score | Domain Authority | Traffic / mo | AI Vis. | KP class |
|---|---|---|---|---|---|
| bencrump | 7/11 | 52 | 429,125 | 27 | personal |
| rodenlaw | 7/11 | 25 | 852 | 29 | business |
| edelmanthompson | 7/11 | 27 | 7,262 | 27 | no_kp |
| bartlettgrippe | 7/11 | 25 | 1,930 | 22 | no_kp |
| sweetjames | 7/11 | 39 | 22,134 | 27 | no_kp |

### Per-pillar sub-score distribution

Pillar 3 (Authority Reinforcement) is the most-underbuilt pillar: 65.1% of firms score zero of the pillar's three questions, and only one firm passes all three. Pillar 1 (Technical Stability) has a more even distribution: 59.3% pass exactly one of three. Pillar 4 (Case Acquisition Optimization) is anchored by Q11 (Function-first mobile layout), which 73.1% of the sample passes.

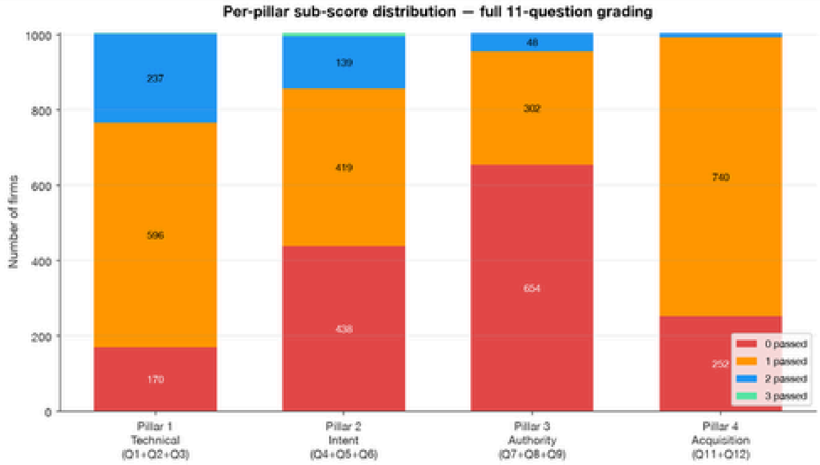


Figure 4. Per-pillar sub-score distribution across the 1,005 firms.

**The rubric measures real authority (authority-signal gradient)**

Every step up in total_score is associated with a step up in every independent authority signal. Median monthly organic traffic scales from 253 at 0/11 to 7,262 at 7/11, roughly a 29x range. Median Domain Authority Score scales from 15 to 27. Median AI Visibility scales from 20 to 27.

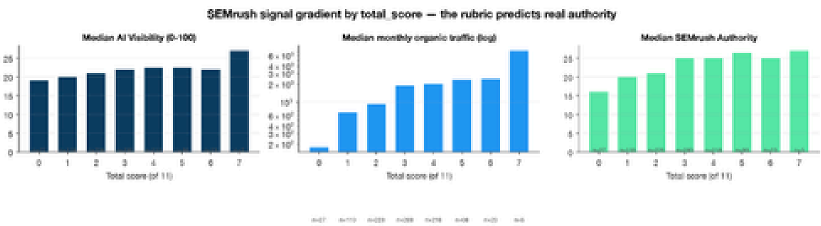


Figure 5. Median Domain Authority Score, median monthly organic traffic (log scale), and median AI Visibility Score at each level of the eleven-question total score.

**Which pillar most-strongly predicts organic traffic?**

Spearman rank correlations with log10(monthly organic traffic), n ≈ 997: Pillar 1 = 0.53, Pillar 2 = 0.40, Pillar 3 = 0.20, Pillar 4 = 0.14. The eleven-question total is only slightly stronger than Pillar 1 alone (ρ = 0.55), consistent with Pillar 1 accumulating the majority of the rubric's traffic-predictive power. Pillar 3, weakly predictive of traffic, is more predictive of AI-answer visibility (ρ = 0.24) and entity presence.

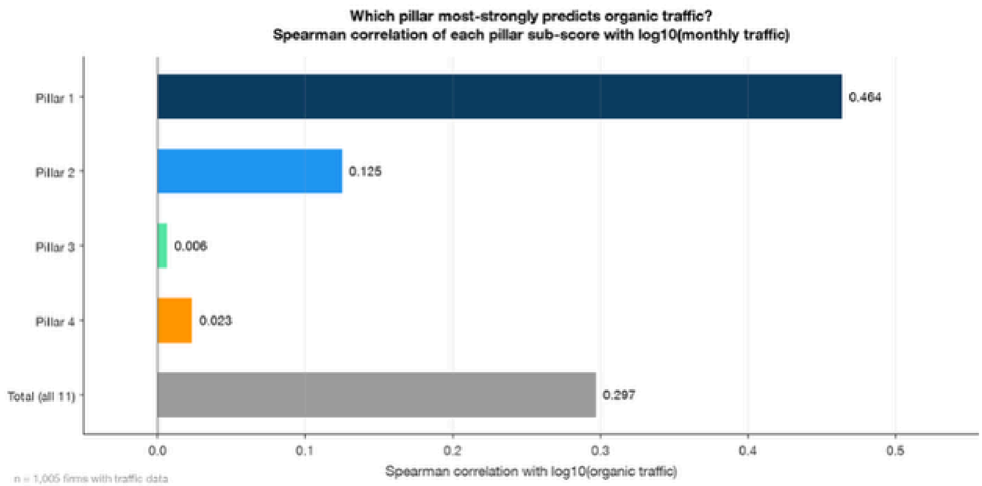


Figure 6. Spearman rank correlation between each pillar sub-score and log10(monthly organic traffic).

## Discussion

### Three surprising findings

Three findings emerged from this pass that were not anticipated by the framework specification and that we consider material.

Mobile render is a structural crisis, not a differentiation opportunity. 98.5% of the sample fails Q2 (mobile LCP < 1.5 seconds). The median firm's homepage takes 5.5 seconds to reach the Largest Contentful Paint on a mid-range mobile device, 3.7x the framework's threshold and 2.3x the 2024 HTTP Archive all-vertical median of 2.4 seconds (Web Almanac, 2024). The implication for a firm is inverted: because the entire vertical is slow, any firm that reduces its mobile LCP below 1.5 seconds becomes definitively differentiated and simultaneously earns Core Web Vitals rankings-signal credit that virtually no competitor is receiving.

Function-first mobile layouts are already table stakes. In striking contrast to the mobile-render finding, Q11 (function-first mobile layout with a primary CTA above the fold) is passed by 73.1% of the sample. The vertical has, in practice, solved the above-fold call-to-action problem: 43.0% of firms use a button-based CTA, 37.9% use a clickable phone number, and 2.3% use an above-fold form. Firms exploring mobile-conversion optimization should now focus on second-order questions like form quality (Q12), YMYL awareness, and call-tracking sophistication.

AI-answer visibility is decoupled from classical structural authority. The eleven-question total score correlates strongly with Domain Authority Score ($\rho = 0.55$) and with organic traffic ($\rho = 0.55$). It correlates only weakly ($\rho = 0.19$) with AI Visibility Score. Even the strongest pillar for AI-signal, Pillar 3, reaches only $\rho = 0.24$. AI-answer engines are drawing on a signal mix that overlaps only partially with the classical structural authority signals the rubric measures. The vertical is not yet earning AI-answer visibility from classical structural authority.

### Two case studies

Ben Crump, 7 of 11, top of the Leaking band. Ranked 1 in Los Angeles for wrongful-death lawyer. Person Entity Knowledge Panel confirmed. 429,125 monthly organic visits. Passes: Q1, Q3, Q4, Q7, Q9, Q11, Q12. Fails: Q2 (LCP 22.9s), Q5 (info-to-commercial bridging), Q6 (only 5 distinct case types in top-7 keywords), Q8 (topical citation depth). Failure profile is the "authority farm" pattern: massive brand-driven traffic and rich Pillar 3 signals but no accumulation on the mechanical Pillar 1 or Pillar 2 checks. Framework would say Pillar 3 investment is partially wasted because a broken Pillar 1 raises Cost of Retrieval for every Pillar 3 signal his firm generates.

Injury Law FL, 6 of 11 with a Domain Authority Score of only 10. Ranked 6 in Jacksonville. Business KP. 1,651 monthly organic visits. Domain Authority Score of only 10 (modest). Passes 6 of 11 rubric questions, tying it with several firms whose scores are 3-4x higher. This is the profile of a firm that has invested in mechanical rubric compliance without yet accumulating traffic or backlinks. Whether that translates into signed cases is the exact question Q10 exists to measure, and the one variable we cannot grade externally.

### Recommendations

The framework specification prescribes that firms invest in the pillars in sequence: technical stability first, intent capture second, authority third, acquisition fourth. Our data justifies that sequencing empirically. Firms that pass Pillar 1 disproportionately also pass Pillar 2 and Pillar 3, and the Pillar 1 x log-traffic correlation is the highest.

### Pillar 1 recommendations

- Reduce mobile LCP below 1.5 seconds. Sample-wide median LCP is 5.5s. Because the vertical is uniformly slow, any firm that lifts its LCP below the 1.5-second threshold becomes categorically differentiated on a ranked Core Web Vital.
- Audit and clean the schema payload every 6 months. Only 30.0% of the sample deploys structurally-clean schema. Firms that maintain schema in the top 30% pay the smallest Cost of Retrieval on every entity-facing signal.

**Pillar 2 recommendations**

- Deploy dedicated root-level landing pages for at least five practice areas. 44.5% of the sample already passes Q4; the strategic question is which case types the firm chooses to compete on.
- Add directional internal links from informational content to commercial pages. Only 11.2% of the sample passes Q5. Info-to-commercial bridging is the single highest-leverage on-site change most firms can make without new content.
- Deepen query-network coverage beyond the biggest two case types. Only 16.3% of firms rank on three or more distinct case types in their top-7 keywords.

**Pillar 3 recommendations**

- Establish a Person-Entity Knowledge Panel for the managing partner. The companion Person Entity Confidence Gap audit on this same 1,005-firm sample (Hussain, 2026) reports only 3.5% of firms have one, and the Brand Demand Flywheel paper (Hussain, 2026) traces how the resulting entity presence compounds with brand-search demand to lift organic traffic.
- Audit the backlink profile for PI-relevant citations. Only 3.2% of the sample passes Q8. Digital-PR campaigns targeting PI-relevant media outperform generic directory-link campaigns.
- Rewrite attorney bios to signal expertise. Passing bio profile includes bar admissions, settlement or verdict amounts with context, case-results language, and published or spoken thought-leadership. 30.3% of the sample had no discoverable bio page at all.

**Pillar 4 recommendations**

- Deploy a YMYL-aware intake form. Only 3.1% of the sample passes Q12. A form that asks case type, jurisdiction, date of incident, and statute-of-limitations posture qualifies leads before intake.
- Preserve the above-fold CTA on mobile. 73.1% of the sample already passes Q11. Firms that redesign should ensure they do not regress this baseline.

## Limitations

This study is subject to several methodological limitations that are disclosed here for reproducibility and to bound the reader's inference.

**Q1 measurement proxy.** Google's index-size figure is not exposed by any publicly-accessible interface. The direct Worth-to-Index ratio is therefore not computable at scale. We use ranked-keyword and organic-traffic thresholds as a proxy.

**Q3 audit-date proxy.** External observation cannot verify whether schema was audited within the last six months. We use structural completeness as a stand-in.

**Q4 sitemap availability.** 174 firms (17.3%) had no discoverable sitemap. Q4 defaults to FAIL for those firms even though a well-architected site can serve practice-area pages without a formal sitemap.

**Q5 info-page discovery.** 43.6% of the sample had no discoverable informational pages via our path heuristic. Q5 defaults to FAIL for those firms.

**Q8 backlink coverage.** Full backlink profiles were pulled for the top 500 firms by Domain Authority Score. The remaining 505 firms are graded from an aggregated sample-backlinks payload.

**Q9 bio discovery.** 69.4% of the sample returned no discoverable attorney bio URLs via our URL-pattern heuristic. Q9 defaults to FAIL for those firms.

**Q11 mobile-screenshot coverage.** 121 firms (12.0%) failed the mobile screenshot pass. Q11 defaults to FAIL for those firms.

**Sample construction.** The sample is drawn from Google Page 1 rankings for five practice-area queries across 51 US markets. Firms outside the United States are excluded.

## Conclusion

We report the first large-scale empirical audit of the PIOAE framework, applying its eleven externally-gradable rubric questions to 1,005 US personal-injury law firms across 51 markets. The framework's qualitative predictions about the vertical are empirically confirmed at 10x the originally-anticipated sample scale: zero firms reach Authority Built, only 5 reach Authority Leaking, and roughly two-thirds of the sample is Authority Absent.

The eleven-question rubric is validated as a measure of real structural authority (Spearman ρ = 0.55 with Domain Authority Score and monthly organic traffic), but only weakly with AI-answer visibility (ρ = 0.19), suggesting a partly-decoupled signal surface that classical SEO rubrics do not yet fully capture.

The three most-consequential structural gaps in the vertical are Q2 (mobile render), Q8 (topical citation), and Q12 (YMYL intake), each passed by fewer than 4% of firms. All three are competitively addressable by a firm operating on the framework. The single most surprising finding is that function-first mobile layouts are already table-stakes at 73.1% pass, freeing capacity for firms to invest in the harder second-order structural questions. Future work should extend the rubric to a longitudinal cadence (annual re-runs against the same firm cohort); incorporate AI-answer citation as a first-class ranked variable; and most importantly, develop a firm-side telemetry protocol that would allow Q10 (organic-intake attribution) to be graded reliably against ground truth.

**References**

1. Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The Semantic Web. Scientific American, 284(5), 34-43.
2. Bharat, K., & Mihaila, G. A. (2000). Hilltop: A Search Engine Based on Expert Documents. University of Toronto CSRG-405 technical report.
3. Brinkmann, A., Primpeli, A., & Bizer, C. (2023). The Web Data Commons Schema.org Data Set Series. In Companion Proceedings of the ACM Web Conference 2023.
4. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of NAACL-HLT 2019, 4171-4186.
5. Dong, X., Gabrilovich, E., Heitz, G., Horn, W., Lao, N., Murphy, K., Strohmann, T., Sun, S., & Zhang, W. (2014). Knowledge Vault: A Web-Scale Approach to Probabilistic Knowledge Fusion. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD 2014), 601-610.
6. Guha, R. V., Brickley, D., & Macbeth, S. (2016). Schema.org: Evolution of Structured Data on the Web. Communications of the ACM, 59(2), 44-51.
7. Gübür, K. T. (2020). Semantic SEO: The Complete Guide to Search Engine Semantics. Holistic SEO.
8. Hussain, Behzad. (2026). Schema Markup Adoption in Personal Injury Law Firm Websites: A Systematic Analysis of Structured Data Implementation Across North American Legal Services (April 2026). http://dx.doi.org/10.2139/ssrn.6551638
9. Hussain, Behzad. (2026). Schema Markup Adoption in Top-Ranking Personal Injury Law Firm Websites: A Structured Data Audit of 1,005 Google Page-1 Sites Across 50 US States (July 2026). https://doi.org/10.13140/RG.2.2.14954.27842
10. Hussain, Behzad. (2026). The Person Entity Confidence Gap: A Knowledge Panel Taxonomy Across 1,005 US Personal Injury Attorneys and Law Firms in the AI Search Era. https://doi.org/10.13140/RG.2.2.36059.12325
11. Hussain, Behzad. (2026). Knowledge Panels and Person Entity Confidence in the AI Search Era: A Signal, Traffic, and AI-visibility Audit of 1,005 US Personal Injury Attorneys and Law Firms. http://dx.doi.org/10.2139/ssrn.7247178
12. Hussain, Behzad. (2026). The Google Business Panel Completeness Gap: A 9-Attribute Audit of 1,005 US Personal Injury Law Firms. http://dx.doi.org/10.2139/ssrn.7249838
13. Hussain, Behzad. (2026). The Brand Demand Flywheel: How Brand Search Demand and Knowledge Panels of Firms and Attorneys Impact Organic Traffic in 1,000 US Personal Injury Law Firms. https://doi.org/10.13140/RG.2.2.28601.12646
14. Lin, B. Y., Sheng, Y., Vo, N., & Tata, S. (2020). FreeDOM: A Transferable Neural Architecture for Structured Information Extraction on Web Documents. In Proceedings of the 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD 2020). arXiv:2010.10755.
15. Metzler, D., Tay, Y., Bahri, D., & Najork, M. (2021). Rethinking Search: Making Experts out of Dilettantes. SIGIR Forum, 55(1), Article 13.
16. Meusel, R., Bizer, C., & Paulheim, H. (2015). A Web-Scale Study of the Adoption and Evolution of the schema.org Vocabulary Over Time. In Proceedings of the 5th International Conference on Web Intelligence, Mining and Semantics.

17. Mika, P. (2015). On Schema.org and Why It Matters for the Web. IEEE Internet Computing, 19(4), 52-55.
18. Nogueira, R., & Cho, K. (2019). Passage Re-ranking with BERT. arXiv:1901.04085.
19. Singhal, A. (2012, May 16). Introducing the Knowledge Graph: Things, Not Strings. Google Official Blog.
20. Google Inc. (2001). US Patent No. US-6285999-B1 (Page, L.). Method for node ranking in a linked database (PageRank). Assignee: The Board of Trustees of the Leland Stanford Junior University; licensed exclusively to Google.
21. Google Inc. (2011). US Patent No. US-7979417-B2 (Bharat, K., Cutts, M. D., Haahr, P. G., Malpani, R. A., Mittal, V., & Kaszkiel, M.). Ranking documents based on user behavior and/or feature data (Reasonable Surfer).
22. Google Inc. (2013). US Patent No. US-8352467-B1. Search result ranking based on trust.
23. Google Inc. (2014). US Patent No. US-8626766-B1. Systems and methods for ranking and importing business listings.
24. Google Inc. (2014). US Patent No. US-8682913-B1. Corroborating facts extracted from multiple sources.
25. Google Inc. (2014). US Patent No. US-8812509-B1. Inferring attributes from search queries.
26. Google Inc. (2014). US Patent No. US-8868565-B1. Calibrating click duration according to context.
27. Google Inc. (2014). US Patent Application Publication No. US-2014358940-A1. Query Suggestion Templates.
28. Google Inc. (2015). US Patent No. US-9031929-B1 (Lehman, A. R., & Panda, N.). Site quality score.
29. Google Inc. (2015). US Patent Application Publication No. US-2015112961-A1. User Submission of Search Related Structured Data.
30. Google Inc. (2016). US Patent No. US-9311362-B1. Personal knowledge panel interface.
31. Google Inc. (2016). US Patent No. US-9317559-B1. Sentiment detection as a ranking signal for reviewable entities.
32. Google Inc. (2016). US Patent No. US-9477759-B2. Question answering using entity references in unstructured data.
33. Google Inc. (2016). US Patent Application Publication No. US-2016078102-A1. Text indexing and passage retrieval.
34. Google Inc. (2016). US Patent Application Publication No. US-2016224621-A1. Associating a search query with an entity.
35. Google Inc. (2017). US Patent No. US-9767157-B2. Predicting site quality.
36. Google Inc. (2017). US Patent No. US-9792330-B1. Identifying local experts for local search.
37. Google LLC. (2019). US Patent No. US-10360225-B1. Query suggestions based on entity collections.
38. Google LLC. (2020). US Patent No. US-10621241-B2. Scheduler for search engine crawler.
39. Google LLC. (2022). US Patent No. US-11263400-B2. Identifying entity attribute relations.
40. Google LLC. (2023). US Patent No. US-11836177-B2. Content items in response to search queries (Knowledge Panel family; specifies interactive user-interface object, Person template, and Place template).
41. Google LLC. (2023). US Patent Application Publication No. US-2023113420-A1. Predicting accuracy of submitted data.
42. Google LLC. (2024). US Patent Application Publication No. US-2024086735-A1. Onboarding of entity data.
43. Google LLC. (2024). US Patent Application Publication No. US-2024289407-A1 (Shukla, A., et al.). Search with stateful chat.
44. Google LLC. (2024). US Patent No. US-12147767-B2. Recommending action(s) based on entity or entity type.
45. Google Developers. (2024). Rich Results Test Documentation.
46. Google Search Central. (2024a). About Knowledge Panels.
47. Google Search Central. (2024b). Understanding page experience in Google Search results.
48. web.dev. (2024). Interaction to Next Paint (INP). Web Vitals team.
49. Web Almanac. (2024). Chapter 5: SEO. HTTP Archive.