

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

1. 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 has never been triggered for them [1]. 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 and deployed transformer language models such as BERT 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 [2-4]. 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, reframes intent capture as a conversation whose downstream turns depend on the extracted data of upstream turns [6]. All three shifts privilege pages whose entities and structural attributes are declared explicitly and whose site-wide quality signals meet an increasingly-elevated floor [7].

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, $\text{Ranking State} = (\text{Historical Data} \times \text{Topical Coverage}) \div \text{Cost of Retrieval}$, 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, 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, audited each firm's Knowledge Panel presence and Person Entity Confidence, scored the firm-name panel on a nine-attribute completeness instrument, 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 [8-12]. 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.

2. Related Work

2.1. 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, $\text{Ranking State} = (\text{Historical Data} \times \text{Topical Coverage}) \div \text{Cost of Retrieval}$, 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.

2.2. 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 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 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 [13].

The Person Entity Confidence Gap paper 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 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 audited the firm-name-side Knowledge Panel with a nine-attribute completeness scoring instrument. The Brand Demand Flywheel paper 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 [8-11]. 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.

2.3. Pillar 1 Grounding: Technical Stability and Crawl Efficiency

Pillar 1 rests on Google's site-quality machinery. Site Quality Score 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 [14]. Predicting Site Quality extends the mechanism to feature-based prediction [15]. The Scheduler for the search engine crawler sets re-crawl frequency by content-change frequency [16]. Core Web Vitals 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 [17,18]. FreeDOM shows that consistent semantic HTML plus valid schema raises neural extraction accuracy, tying Technical Stability to downstream entity-extraction quality [19].

2.4. 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 describes passage-independent scoring [20]. The BERT passage re-ranker is the reference implementation argued for unified multi-task models (MUM) [5,21]. Search with stateful chat formalizes multi-turn context propagation [22]. Query Suggestion Templates and Question answering using entity references describe the entity-

category-conditioned mechanism that penalizes cannibalization [23,24].

2.5. Pillar 3 Grounding: Link Authority, Entity Onboarding, and Trust

Pillar 3 accumulates over three overlapping mechanisms. PageRank remains the foundational link-authority signal [25]. Reasonable Surfer weights links by click probability; link position, prominence, and contextual relevance affect value [26]. Hilltop introduced expert documents. Corroborating facts across sources formalizes cross-source attribute-value verification; NAP consistency is the practical implication [27,28]. Entity onboarding into the Knowledge Graph is described in the Onboarding of entity data [1]. Entity attribute relations provides the extraction mechanism the schema payload feeds [29]. Schema.org is the shared vocabulary consumed by both Google and Microsoft, and Knowledge Vault positions structured data as one of four extractor lanes [30,31]. Trust rank, Identifying local experts, Sentiment detection, and Business listing ranking describe the local-panel ranking machinery for firm-name queries [32-35].

2.6. 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 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) [36]. Recommending action(s) based on entity or entity type extends the mechanism to action recommendations conditioned on entity type [22]. Calibrating click duration formalizes the goodClicks-versus-badClicks distinction [37]. Predicting accuracy of submitted data closes the loop by rejecting inaccurate third-party edits [38].

3. Methodology

3.1. Sample Construction

The 1,005-firm sample is inherited from the companion 1,005 law firm websites' analysis of schema markup adoption [8]. 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.

3.2. 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.

Q	Pillar	What it measures	Grading proxy (external-observable)
Q1	P1 Technical	Worth-to-Index ratio	Ranked-keyword count ≥ 500 AND monthly organic traffic ≥ 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 ≥ 8 AND validation_errors ≤ 2 AND rr_eligible_count ≥ 1
Q4	P2 Intent	Practice-area arch. clean	≥ 5 root-level PA landing URLs in sitemap; total ≥ 8
Q5	P2 Intent	Info $\rightarrow$ commercial bridging	$\geq 40\%$ of info pages contain internal link to commercial page
Q6	P2 Intent	Query network depth	≥ 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 ≥ 300 AND ≥ 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 ≥ 1 pre-qualification signal

Table 1: The Eleven Externally-Graded Rubric Questions

3.3. 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 [9]. Knowledge Panel classifications were inherited from the companion Person Entity Confidence Gap paper [10]. Firm-name-side panel completeness on the nine-attribute instrument was inherited from the Google Business Panel Completeness Gap paper [11]. Brand-search-demand and AI-visibility signals draw on the Signal, Traffic, and AI-visibility Audit and the Brand Demand Flywheel paper on the same firm set [12,13].

3.4. 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).

3.5. 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, the Person Entity Confidence Gap paper, the Signal, Traffic, and AI-visibility Audit, the Google Business Panel Completeness Gap paper, and the Brand Demand Flywheel paper on the same firm set. Coverage limitations for individual questions are documented in Section 7 [8-13].

4. Findings

4.1. 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.

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%

Table 2: Pass Rate for each Rubric Question (n = 1,005).

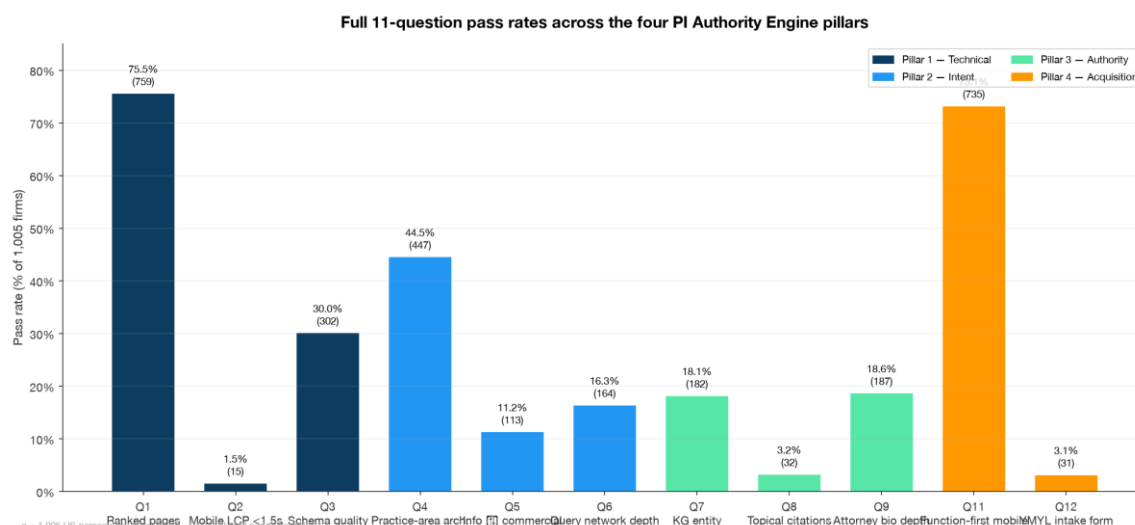


Figure 1: Question-level pass rates across the four PIOAE pillars.

4.2. 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.

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%

Table 3: Total-Score Distribution (n = 1,005).

Full 11-question total score distribution across 1,005 firms

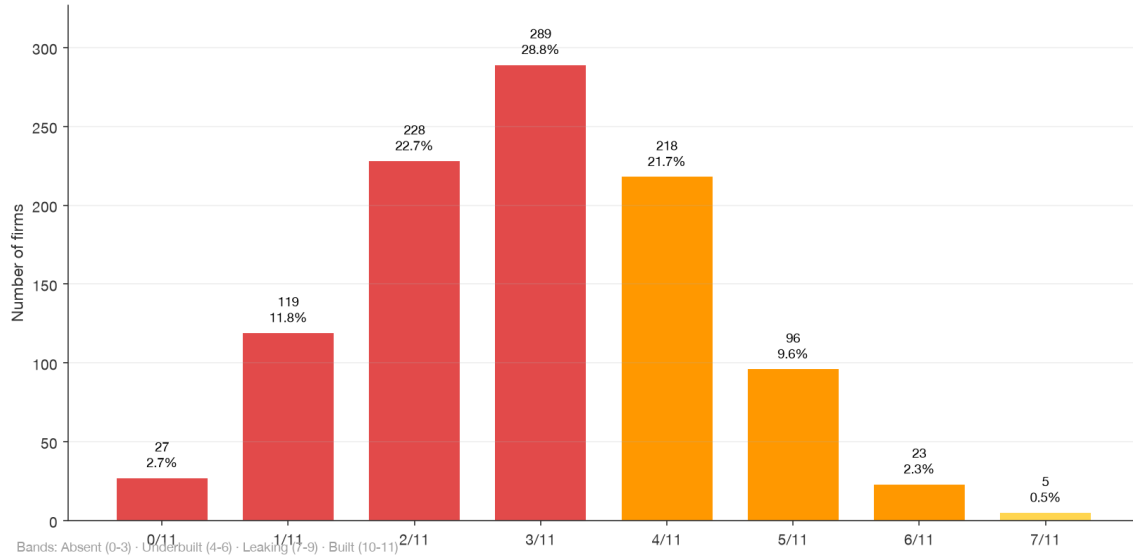


Figure 2: Total-score distribution across the sample. Color: red = Absent (0-3), orange = Underbuilt (4-6), yellow = Leaking (7-9), green = Built (10-11).

4.3. 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.

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%

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

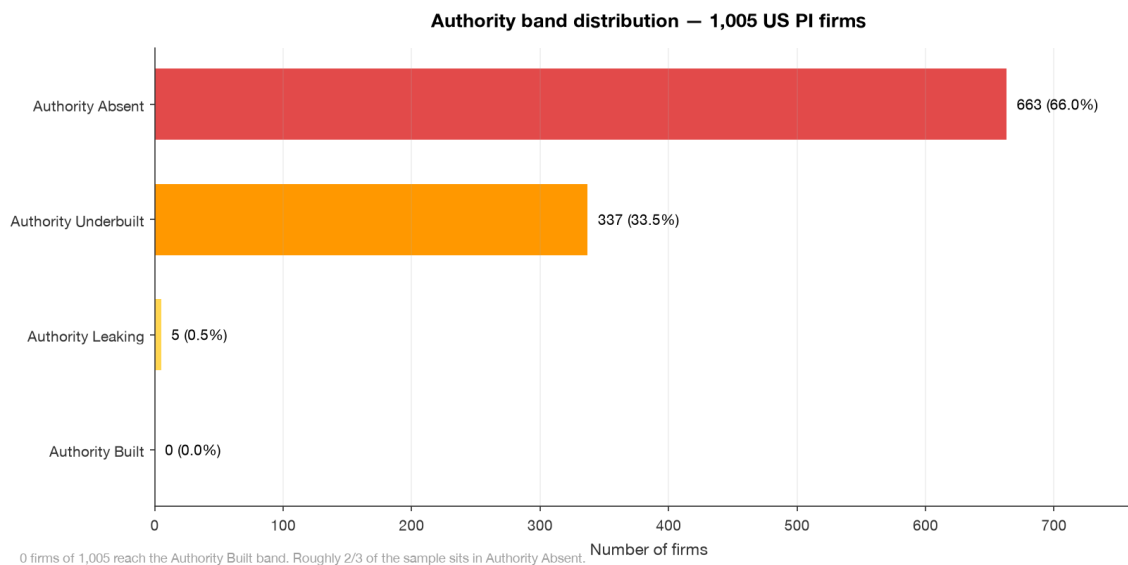


Figure 3: Authority band distribution across the 1,005-firm sample.

4.4. The Authority Leaking Cohort

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

Table 5: The Five Firms in the Authority Leaking Band.

4.5. 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.

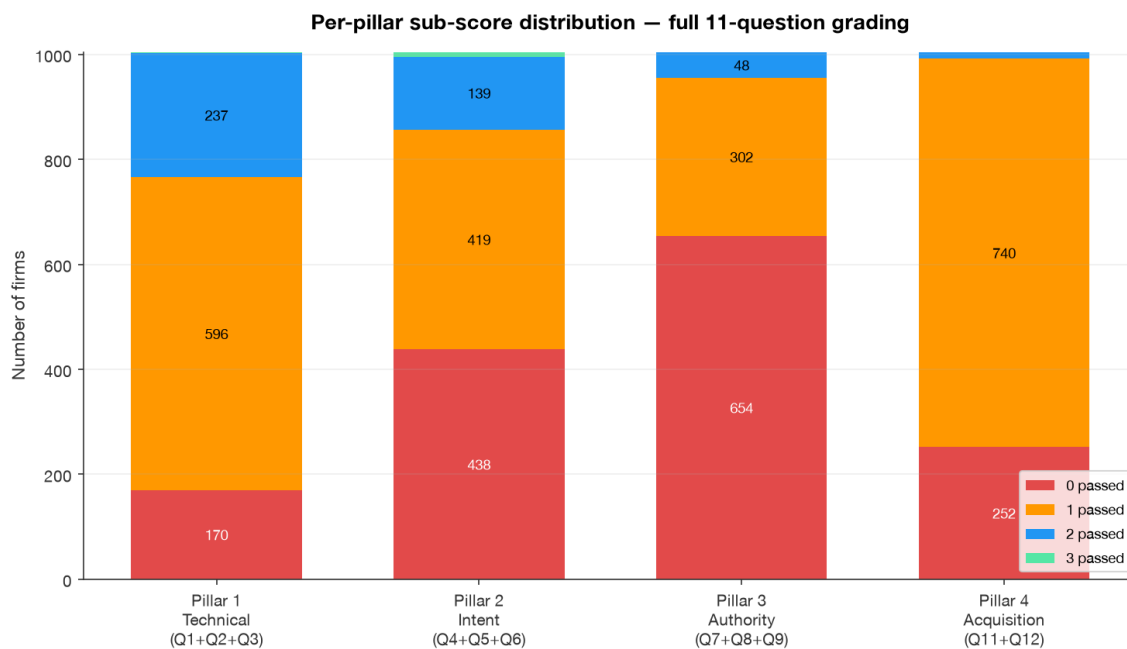


Figure 4: Per-Pillar Sub-Score Distribution across the 1,005 Firms.

4.6. 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.

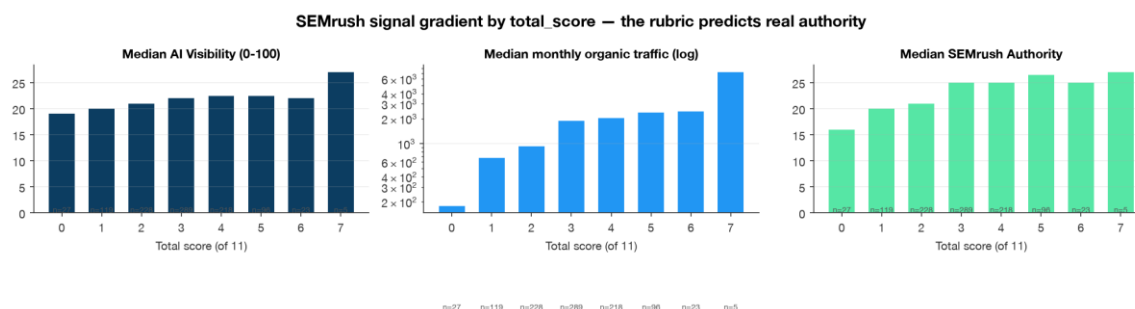


Figure 5: Median Domain Authority Score, median monthly organic traffic (log scale), and median AI Visibility Score at each level of the eleven-question total score.

4.7. Which Pillar Most-Strongly Predicts Organic Traffic?

Spearman rank correlations with $\log_{10}(\text{monthly organic traffic})$, $n \approx 997$: 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 ($\rho = 0.55$), 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 ($\rho = 0.24$) and entity presence.

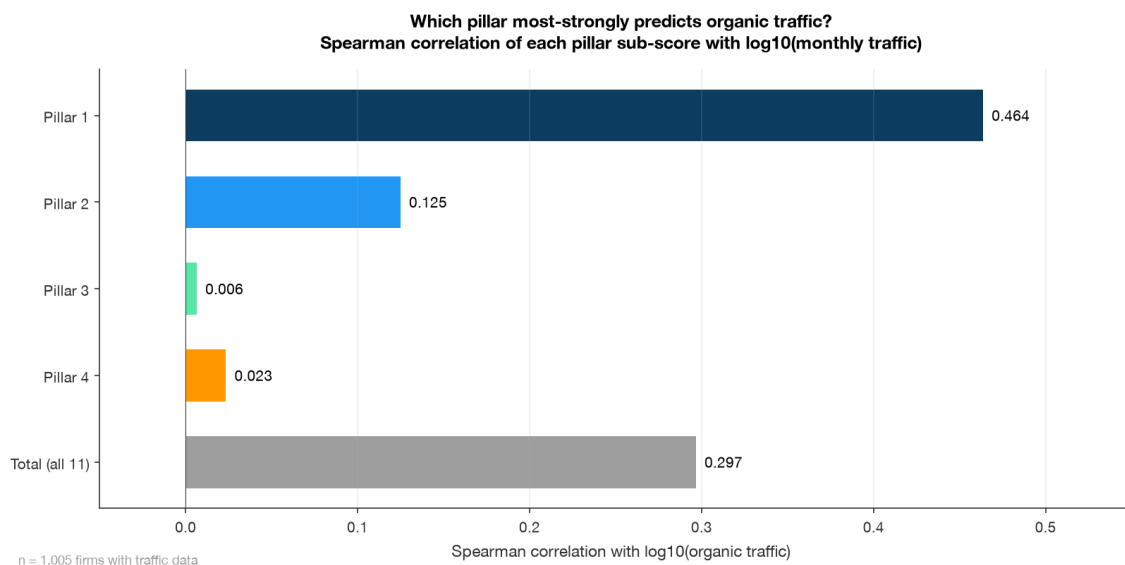


Figure 6: Spearman Rank Correlation between Each Pillar Sub-Score and $\log_{10}(\text{monthly organic traffic})$.

5. Discussion

5.1. Three Surprising Findings

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

5.1.1. 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 [39]. 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 [40-42].

5.1.2. 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 [43]. 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 [44]. Firms exploring mobile-conversion optimization should now focus on second-order questions like form quality (Q12), YMYL awareness, and call-tracking sophistication.

5.1.3. 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 ($\rho = 0.55$) [45]. 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.

5.2. Two Case Studies

5.2.1. 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 [46]. 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.

5.2.2. 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 [47-49]. Whether that translates into signed cases is the exact question Q10 exists to measure, and the one variable we cannot

grade externally.

6. 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.

6.1. 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.
- Prune indexed URLs that produce no ranked keyword. The Worth-to-Index ratio is unmeasurable at scale but is the single largest lever inside a firm's control.

6.2. 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.

6.3. 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 reports only 3.5% of firms have one, and the Brand Demand Flywheel paper traces how the resulting entity presence compounds with brand-search demand to lift organic traffic [8,9].
- 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.

6.4. 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.

7. 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.

8. 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 $\rho = 0.55$ with Domain Authority Score and monthly organic traffic), but only weakly with AI-answer visibility ($\rho = 0.19$), 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.

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Appendix A. Top 15 firms by total score

Table A1. The 15 highest-scored firms in the 1,005-firm sample.

Firm	Market	Score	Band	Authority	Traffic/mo
bencrump	Los Angeles CA	7/11	Authority Leaking	52	429,125
sweetjames	Los Angeles CA	7/11	Authority Leaking	39	22,134
edelmanthompson	Kansas City MO	7/11	Authority Leaking	27	7,262
rodenlaw	Charleston SC	7/11	Authority Leaking	25	852
bartlettgrippe	Bridgeport CT	7/11	Authority Leaking	25	1,930
munley	Sioux Falls SD	6/11	Authority Underbuilt	38	15,052
Bowman Law Firm	Denver CO	6/11	Authority Underbuilt	36	2,235
johnston-lawfirm	Portland OR	6/11	Authority Underbuilt	32	5,420
gofflawgroup	Bridgeport CT	6/11	Authority Underbuilt	31	6,331
1800theeagle	Phoenix AZ	6/11	Authority Underbuilt	30	5,642

Appendix B. Signal-by-band summary

Median independent third-party signals by band. The gradient is monotone across the three metrics.

Table B1. Median third-party signals by band.

Band	n	Median AI Vis.	Median traffic	Median Authority
Authority Absent	663	21.0	1,113	22
Authority Underbuilt	337	22.0	2,244	26
Authority Leaking	5	27.0	7,262	27
Authority Built	0	0.0	0	0

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