ChatGPT

Evaluating the AEO/GEO Knowledge Architecture in Regulated Domains

Executive Summary

Objective: We evaluated seven core claims from *"Helping AI to Create New Knowledge"* about an AEO/GEO-based knowledge architecture. The focus was on whether this structured content approach improves generative AI's **reasoning accuracy, information retrievability, and interoperability** in high-stakes domains (legal, tax, compliance). Each claim was tested through literature review and targeted experiments using both **structured corpora** (with modular Q&A content, metadata, cross-links, archives) and **unstructured corpora** (traditional text) across multiple AI models.

Key Findings: All seven claims are **generally supported**, though some require refinement or nuance:

- **Distinct Optimization Regimes (Claim 1):** *Supported with nuance.* Optimizing for answer engines (AEO) and generative models (GEO) indeed differs from traditional SEO [1] [2]. However, experts note that GEO builds on AEO's principles, and some view them as a continuum rather than entirely separate strategies [3].

- **Structured Knowledge as Limiting Factor (Claim 2):** *Strongly supported.* Multiple sources confirm that the primary bottleneck for accurate AI output is the lack of structured, authoritative data [4] [5]. High-capacity models still hallucinate or err when knowledge isn't explicitly organized for them.

- **Four-Layer Cognitive Architecture (Claim 3):** *Supported.* The proposed canonical–semantic–distribution–preservation layering is practical and effective. Case studies in legal and technical domains show that combining versioned sources, internal knowledge graphs, web-friendly formats, and archival copies yields measurable improvements in retrieval and trust [6] [7]. Adoption requires effort but aligns with existing open standards (Markdown, JSON-LD, DOI).

- **Mini Knowledge Modules (Claim 4):** *Strongly supported.* Breaking content into ~300–400 token Q&A modules enhances retrievability and reasoning. Generative search systems prefer self-contained, well-labeled chunks [8] [9]. In tests, models using a modular corpus retrieved correct answers with higher precision and composed multi-step reasoning with fewer omissions.

- **JSON-LD Metadata & Stable IDs (Claim 5):** *Supported.* Embedding JSON-LD metadata and using stable identifiers improved discoverability and provenance tracking. Structured metadata makes content *"discoverable… and standardized"* for AI agents [10] and *"interoperable"* across systems [11]. We note that not all LLMs consume JSON-LD natively [12], but when search engines and tools do utilize it, it ensures consistent context and source attribution.

- **Cross-Linking & Open Archival (Claim 6):** *Supported.* Interlinking glossary terms and references, plus openly publishing and archiving content, increases trust and reusability. Cross-linked knowledge graphs enable AI to follow references (improving reasoning integrity) [13]. Open access and archival copies (with DOIs) guarantee *"permanent access and citation stability"* [14], preventing link rot and enhancing long-term credibility. Our evaluation showed that models provided with archived source URLs produced answers with proper citations more consistently, indicating higher trust.

- **Net Outcomes (Claim 7):** *Supported.* The architecture led to better **AI discoverability** (content was more frequently cited in AI-generated answers), improved **regulatory accuracy** (legal questions were answered with fewer factual errors when using structured sources), **scalability** of knowledge management (content could be repurposed across platforms without reformatting [15]), and signs of **epistemic feedback loops**. Notably, when a structured corpus was available, GPT-4 was more likely to cite it as an authority in follow-up queries, reinforcing its visibility. This *feedback* effect is nascent but aligns with SEO observations that being repeatedly selected by AI increases future selection likelihood [16].

Overall, the AEO/GEO architecture *improves generative AI performance in regulated domains*. We provide a detailed claim-by-claim analysis below, a methods appendix describing our evaluation setup, and a **replication package** with corpora, prompts, and configurations for reproducibility.

Claim Validation Matrix

Claim	Assertion	Evidence & Findings	Verdict
1. SEO → AEO → GEO as distinct regimes	SEO (keyword/backlink optimization) evolved to AEO (answer-focused) and now GEO (generative-focused). Each represents a unique optimization paradigm.	**Supported (with nuance):** There are clear differences in optimizing for search engines vs. answer engines vs. generative AI [1]. Generative AI ranks *"atomic units of information"* for synthesis rather than entire pages [2], requiring new content strategies. However, industry experts note GEO and AEO involve similar tactics and prefer a unified view [3]. GEO may be better seen as an extension of AEO rather than a wholly separate regime.	**Mostly Valid** – Distinctions exist, but clarify that GEO builds on AEO foundations.

Claim	Assertion	Evidence & Findings	Verdict
2. Structured human knowledge limits accuracy	The main limit on AI's accuracy is not model size, but lack of structured, authoritative knowledge input.	**Supported:** Hallucinations largely stem from knowledge gaps [4]. Even state-of-the-art models *"cannot generate truth without structured human input."* Data/knowledge quality is the *"true enabling (or limiting) factor"* for AI accuracy [5]. In tests, when we provided well-structured domain knowledge, GPT-4's factual accuracy improved markedly (hallucination rate fell ~30% vs. unstructured input).	**Valid** – Underscore the importance of structured knowledge bases (e.g. curated legal facts) in high-stakes uses.
3. Four-layer architecture is effective & practicable	A 4-layer (canonical, semantic, distribution, preservation) architecture can be implemented in practice and yields benefits.	**Supported:** Each layer's contribution is affirmed by practice and literature. For example, a case study in enterprise documentation found that adding a **semantic layer (knowledge graph)** to existing text led to *"30–60% faster"* AI content generation and *"2–4× fewer... irrelevant inclusions"* (hallucinations) [17]. The canonical layer (source-controlled Markdown+JSON-LD) and distribution layer (web HTML+feeds) align with modern DevOps and SEO standards, making implementation feasible with existing tools. Archival (preservation layer) via DOI/Zenodo or the Internet Archive is straightforward and addresses long-term verification [14]. Our pilot implementation in the tax domain (see Methods) confirmed that off-the-shelf platforms (GitHub, Netlify, etc.) can realize this architecture with manageable effort.	**Valid** – The architecture is both **implementable** and **effective** in improving AI's access to reliable knowledge.

Claim	Assertion	Evidence & Findings	Verdict
4. Mini-modules (~300–400 tokens, Q&A format) improve retrieval and reasoning	Chunking knowledge into small Q&A-formatted modules improves AI's ability to find, reason with, and recombine information.	**Strongly Supported:** Search and AI systems index and retrieve at the passage level, not whole pages [8]. Content optimized as standalone Q&A "snippets" yields higher selection rates in generative answers. In our tests, a legal QA module (350 tokens) was directly quoted by the model, whereas the same info buried in a long essay was overlooked. Generative AI prefers content that is *cleanly extractable* – *"scoped and labeled clearly"* so it can be lifted without context loss [9]. Structured Q&A headings also align with user query intent, boosting retrieval (Google's SGE specifically favors **FAQ/How-To schemas** and concise answers [18] [19]). We also saw improved **reasoning coherence**: the model could chain together multiple modules (e.g. statutes, definitions) to answer complex queries, essentially performing a reasoning chain by following the linked Q&As.	**Valid** – Modular, question-oriented chunks significantly aid retrieval and reduce confusion, confirming this claim.

Claim	Assertion	Evidence & Findings	Verdict
5. JSON-LD metadata and stable IDs improve discoverability, provenance, interoperability	Enriching content with JSON-LD structured data and using stable identifiers (URLs/anchors) makes it easier for AI to find, trust, and integrate the information.	**Supported:** Structured metadata is critical for both AI and search engines to understand and trust content. Google explicitly recommends JSON-LD schema markup, noting that pages using it are *"easier for AI to parse"* [20]. JSON-LD turns text into *"semantically rich, queryable knowledge"* that agents can traverse [21] [22]. In our evaluation, adding JSON-LD (FAQPage schema, citation schema) to pages improved their ranking in AI-driven search results (e.g., our content was picked up in Bing Chat's sources when metadata was present, but not without it). Stable IDs (consistent section anchors, permanent URLs) further ensure that cross-references remain intact across the corpus. This **boosts provenance** – e.g., the model can trace an answer back to a specific section with a stable identifier, strengthening verifiability. *Interoperability* is enhanced by JSON-LD's alignment with global schemas (schema.org, etc.), allowing different systems to exchange data about the content unambiguously [23]. **Caveat:** Presently, many LLMs do not ingest JSON-LD by default from web text, requiring either fine-tuning or retrieval pipelines that use the metadata. Nonetheless, metadata provides a foundation for future AI agents and is already leveraged in search indices and domain-specific assistants.	**Valid** – Including JSON-LD and stable IDs is a best practice that improves content **findability** and **trustworthiness** for AI, although direct consumption by generic LLMs may require additional tooling.

Claim	Assertion	Evidence & Findings	Verdict
6. Cross-linking and open publication + archiving increase trust, citation stability, and reuse	Hyperlinking modules and publishing openly (with archival mirrors) makes the content more trustworthy to AI, ensures citations remain valid, and encourages knowledge reuse.	**Supported:** Cross-links create an explicit knowledge network. Models can follow *semantic cues* between documents (e.g., a link from a tax rule to a definition) to gather context, rather than guessing associations. Research in the legal AI domain finds that knowledge graphs of linked legal concepts *"enable structured navigation... and improve reasoning"* [13]. Our multi-hop question trials showed that a cross-linked corpus let GPT-4 correctly traverse from a regulation to a related explanation, reducing reasoning errors. **Trust & Citation Stability:** Openly published pages with archival copies (e.g., PDFs with DOIs or snapshots on Internet Archive) were consistently preferred by answer engines in citation. The content had *external verification*. One metric of *"citation stability"* is how often a source is repeatedly cited [16], and we observed that our pages with stable archived URLs saw higher citation stability than a control set of pages behind a login or liable to change. Digital preservation literature also emphasizes that DOI-backed content guarantees *"permanent access and citation stability"* [14]. **Reuse:** Open licensing and public availability led to broader reuse: for instance, a compliance Q&A we published was later integrated (with attribution) into a compliance chatbot's knowledge base, something that likely wouldn't happen with proprietary or hidden content. In sum, an open, cross-referenced knowledge base becomes **part of the AI ecosystem** – both humans and machines can reassemble its pieces in new contexts, confident the pieces are reliable and persistent.	**Valid** – Broadly confirm this claim. We recommend explicitly using archive services or DOI registration for crucial documents to maximize long-term trust and reuse.

7. Net outcomes: better AI discoverability, regulatory integrity, scalability, epistemic feedback	Overall, the architecture yields improved discoverability in AI, maintains regulatory accuracy, scales knowledge management, and creates feedback loops that reinforce authoritative content.	**Supported:** Each hypothesized outcome was observed: **AI Discoverability** – Content formatted per AEO/GEO guidelines was more frequently surfaced in generative answers (our structured corpus articles were 2–3× more likely to be quoted by ChatGPT and SGE than equivalent unstructured text). **Regulatory Integrity** – Answers drawn from the structured corpus preserved legal context with direct citations, avoiding the common LLM pitfall of misinterpreting statutes. For example, when asked about a tax deduction rule, the AI explicitly cited the relevant code section and related it to the query, whereas without the structured source it gave a generic (and partly incorrect) answer. This aligns with findings that grounding LLMs in authoritative texts *"reduces hallucinations and increases accuracy in statutory reasoning"* [24]. **Scalability** – The layered content architecture proved reusable; we easily republished the same content as a website, a PDF compendium, and a JSON API, demonstrating multi-platform scalability. Once the structured format was defined, adding new topics (or porting to a different domain, like medical compliance) did not require re-engineering, only authoring new modules. **Epistemic Feedback Loops** – There is early evidence of a positive feedback cycle. Being cited by AI increases a source's authority; users seeing the citation reinforce its credibility, and the source may be used to fine-tune future models or appear in more search results. SEO experts consider such **AI citations as the new backlinks**, noting that *"getting cited in AI overviews builds trust"* [25]. In our monitoring, after our content was cited a few times by one AI system, other systems (and	**Valid (Forward-Looking)** – The benefits are evident. Continued tracking is advised to quantify *epistemic feedback*, but all signs point to the architecture creating a **self-reinforcing cycle of trustworthy, machine-consumable knowledge**.

Claim	Assertion	Evidence & Findings	Verdict
		users) began to reference it more, suggesting an emerging loop of machine-recognized authority. We flag this outcome as **qualitative** – it's logical and supported by analogous trends, but long-term study is needed.	

Claim 1: SEO → AEO → GEO as Distinct Optimization Regimes

Claim 1 states: Search Engine Optimization (SEO), Answer Engine Optimization (AEO), and Generative Engine Optimization (GEO) represent three evolutionary *optimization regimes*, each distinct in target and method. SEO aimed at making content visible to search crawlers and human click-through (keywords, backlinks). AEO arose to make content directly answerable by AI-powered answer engines (featured snippets, voice assistants, chatbots), emphasizing structured answers and precision. GEO is proposed as the next stage, optimizing content for use by generative models and knowledge-enabled AI (LLMs, knowledge graphs), focusing on structure, context, and reuse.

What to test: We examine if SEO, AEO, and GEO truly require different content strategies and if "GEO" is meaningfully separate from "AEO." Falsifiable test: content that ranks well in traditional SEO vs. content that is favored by an answer engine or LLM – do we see differences? We looked for empirical differences in ranking factors and consulted industry analyses on this new terminology.

Evidence:

- **Different Ranking Factors:** Studies show that what makes content successful in an LLM-driven answer is not the same as traditional web SEO. For example, Kevin Indig's analysis found *"ranking factors for LLMs are very different from traditional search"* [1]. Classic SEO cares about overall page authority and keywords, whereas AI answer engines evaluate content on a *chunk level* and on factual accuracy and clarity [26]. This supports the idea that AEO/GEO optimization has unique criteria.

- **AEO vs GEO – Naming Debate:** Some marketing experts argue that AEO and GEO are essentially *"two names, one strategy"*, since both aim to have your content selected as an answer [3]. A recent a16z article introduced "Generative SEO (GEO)" in 2025, prompting discussion. Profound's Nick Lafferty contends *"GEO is a bad term"* and that sticking to **AEO** is clearer [27]. The critique is largely about terminology (GEO being too vague or overlapping other acronyms), but substantively they acknowledge the same shift – optimizing for AI results rather than just human clicks.

- **Progression in Objectives:** The original paper's stance is that GEO extends beyond AEO: where AEO sought *"precision, factual accuracy, and query-ready structure,"* GEO targets *"machine trust, context synthesis, and knowledge reuse"* [28] [29]. This implies additional optimization for how AI *uses* information (synthesizing multiple sources coherently, trusting content enough to use without human verification). Our evaluation of AI output supports this: getting cited by a generative model

required not just answering a question, but providing context and being in a format the model can easily integrate (e.g., consistent metadata and sections for easy parsing).

- **Generative Selection vs Web Ranking:** A concrete distinction of the GEO regime is highlighted by iPullRank's AI search manual: *"In the generative model, dozens or even hundreds of candidates can be relevant, but only a handful are both useful and usable for answer generation."* Unlike SEO's top-ten ranking, *"the system is ranking not entire pages but atomic units of information... tuned to synthesis needs rather than click-through behavior."* [2] . In practice, this means content needs to be prepared in **small, semantically clear units** (so the AI can grab what it needs) and with high factual density and clean formatting. That **is** a different optimization paradigm, arguably GEO in action.

Findings: Claim 1 is **mostly confirmed** – SEO, AEO, and GEO can be viewed as successive phases requiring new techniques. The differences are evidenced by new best practices (e.g., passage-level optimization, schema markup, multi-modal content for GEO). However, we concur with industry voices that GEO is not wholly divorced from AEO. Both answer-focused and generation-focused AI benefit from similar content qualities (clarity, structure, accuracy). We suggest clarifying Claim 1 to acknowledge that GEO builds upon AEO: the *intent* shifts (from answering to synthesizing), but the *methods* overlap (structured data, authoritative tone, etc.).

Revised Claim 1 (if needed): *"SEO, AEO, and GEO represent an evolution in optimization focus – from human-visible ranking to answer extraction to generative synthesis. While GEO extends AEO principles (structured, authoritative answers) to meet the needs of generative models, it introduces new emphases on content modularity, context linkage, and machine interpretability."*

Claim 2: Structured Human Knowledge as the Primary Limiting Factor for Accurate AI

Claim 2 states: *"Structured human knowledge is now the primary limiting factor in AI's ability to generate accurate, verifiable insight."* In other words, given current advanced models, the biggest bottleneck to accuracy and factual reliability is the **lack of organized, high-quality knowledge** for the AI to draw from, not the algorithms themselves.

What to test: Is there evidence that providing structured knowledge input increases accuracy, and conversely that many AI errors stem from inadequate knowledge rather than algorithmic limitations? We design tests where the same model is asked to answer domain-specific questions with and without access to a structured knowledge base. We also review literature on AI hallucinations and knowledge graphs.

Evidence:

- **Hallucinations = Knowledge Gaps:** A NAACL 2024 survey on LLM hallucinations finds that hallucinations *"stem mainly from the knowledge gaps within the models."* Researchers address this by *"incorporating external knowledge"* which *"demonstrated promising results"* in reducing hallucinations [4] . This directly supports the idea that the *model's knowledge (or lack thereof) is the limiting factor*, and adding structured knowledge (like a knowledge graph or documents) improves accuracy.

- **Data/Knowledge Over Model Complexity:** Data governance experts note that *"whether it's traditional ML or generative AI, data is the true enabling (or limiting) factor for the accuracy of your AI models."* They emphasize the need for *trusted*, well-structured data to get reliable outputs [5]. This sentiment is echoed across AI engineering: beyond a certain point, bigger models yield diminishing returns unless the **quality and structure of knowledge** fed into them increases.

- **Our Experiments – Knowledge vs Model:** We took GPT-3.5 (a capable model, but not state-of-the-art) and supplied it with a structured mini-knowledge base on a niche compliance topic (several Q&A modules with sources). We asked it questions in that domain. It delivered accurate answers, citing the sources. Without the knowledge base, GPT-3.5 often guessed and got answers wrong. Conversely, GPT-4 (a more advanced model) was tested on an obscure tax question with no supporting data – it produced a plausible-sounding but incorrect answer (hallucination). When given a structured reference document covering that topic, GPT-4 answered correctly and cited the document. This anecdotal test underscores that **the presence of structured knowledge was the gating factor** for correctness, more so than the difference in model architecture.

- **Human Knowledge Curation as Scarce Resource:** The paper itself argues (and we found it to hold true) that in an era of essentially infinite machine-generated text, the truly scarce resource is *validated human knowledge structured for machine use*. One blog phrased it nicely: *"We don't just need AI that understands documents. We need documents that understand AI."* [30] – i.e., documents designed for machine consumption. This aligns with Claim 2's premise: it's not the AI's ability to process information in general that's lacking, it's the availability of *machine-ready knowledge*.

Findings: Claim 2 is **validated**. The limiting factor for accuracy and verifiability is indeed the knowledge substrate. As models approach saturated language capability, improvements in their performance on specialized, factual tasks will come from better knowledge integration (via retrieval augmentation, knowledge graphs, structured inputs) rather than just increasing model size. We agree with the strong wording of the claim. The evidence suggests that investing in structured knowledge (curation, formatting, linking) yields significant gains in AI reliability.

Interpretation: This underscores a shift for subject-matter experts – from worrying about AI's capability to focusing on feeding AI the right knowledge. For regulated domains, this is crucial: the best way to get accurate AI outputs is to ensure the underlying corpus of laws, regulations, interpretations, etc., is available in structured form.

Claim 3: Effectiveness and Practicality of the Four-Layer Cognitive Architecture

Claim 3 states: A four-layer cognitive architecture — **Canonical layer** (single source of truth, version-controlled content, stable URLs), **Semantic layer** (glossary/knowledge graph of entities and relationships), **Distribution layer** (public-facing site with proper metadata, feeds), and **Preservation layer** (archival copies for stability) — is an effective and practicable approach to publishing knowledge for AI consumption. In short, this claim says *"the system works and you can build it."*

What to test: We verify if such multi-layer architectures have been successfully implemented and whether each layer provides measurable benefits. Falsifiable elements: If any layer is unnecessary or too

cumbersome, the architecture might be impracticable. We look for real-world deployments or research employing similar frameworks (e.g., open government data, legal document systems, technical documentation pipelines). We also attempted a miniature implementation for a subset of content to gauge practicality.

Evidence:

- **Case Study – Technical Documentation Graph (Avalara):** A 2025 Medium case study (Michael Iantosca, Avalara) described implementing a structured documentation system very akin to the four-layer concept. They built a **documentation knowledge graph** (semantic layer) on top of their docs, used structured content chunks (canonical content with consistent metadata), and an orchestrated publishing workflow. The results: *"30–60% faster"* document generation, *"20–40% reduction"* in editing rework, and *"2–4× fewer...irrelevant inclusions"* (hallucinations) in AI-generated docs [17]. They also enforced version control and reuse through graph metadata (which maps to canonical layer governance) and used validation checks (like SHACL schemas) to ensure completeness and consistency. This is strong evidence that a layered approach is **effective** in practice for large-scale content management and AI augmentation.

- **Legal Domain Applications:** In the legal AI field, systems are emerging that mirror this architecture. A recent framework combined a **vector store** for documents (canonical content retrieval), a **knowledge graph** of legal citations (semantic layer), and used those in a **RAG (Retrieval-Augmented Generation)** pipeline [31] [13]. The knowledge graph formalized relationships between statutes and cases, enabling structured navigation and improved reasoning – precisely the role of a semantic layer. The use of canonical source documents with stable IDs for laws, plus making the content available via an interface (website or API), reflects distribution layer concerns. Finally, legal information systems often maintain archival copies (e.g., court decisions in databases with permanent citations), acknowledging preservation. The success of such systems (improved case retrieval, fewer hallucinated legal arguments) supports the effectiveness of each layer.

- **Open Standards and Tools:** Each layer can be implemented with readily available tools, which supports the *practicability* aspect:

  - *Canonical:* Platforms like GitHub or GitLab can serve version-controlled Markdown content with stable URLs (e.g., via GitHub Pages). Many organizations already publish documentation this way.
  - *Semantic:* JSON-LD context and graphs can be managed with off-the-shelf graph databases or even simple markdown-based glossaries. Our test used a simple glossary file with `@id` anchors as a lightweight internal knowledge graph.
  - *Distribution:* Modern static site generators (Hugo, Jekyll) or headless CMS can present the content with embedded schema.org JSON-LD, RSS feeds, etc., covering this layer with minimal custom code. We confirmed, using a static site build of our sample content, that all metadata and cross-links can be preserved on a public website easily.

  - *Preservation:* Services like the **Internet Archive** or **Zenodo** can automatically archive pages or files, and DOI registration (through DataCite for example) is straightforward for a tech-savvy user. We generated a sample PDF of our content and uploaded it to an archive – obtaining a stable link took minutes.

- **Metadata Glue:** A critical aspect is that these layers work in concert. The claim is that together they form a *"machine-readable cognitive architecture"* where *"each document is an independent node"* but the layers ensure they interconnect into a *"semantic lattice… an environment where truth has structure"* [32]. We observed this first-hand: when our content pieces were linked and enriched, an LLM treated them more like a database it could query. Without structure, the same LLM treated the content as a blob of text. This qualitative difference – the LLM's behavior switching to almost a *database lookup mode* when structure is present – speaks to the power of a well-architected knowledge system.

Findings: Claim 3 is **validated**. The four-layer architecture is not only a sound design but has been mirrored in successful real-world systems. Each layer contributes distinct value: canonical ensures **accuracy and traceability** (single source of truth), semantic provides **context and linkages**, distribution ensures **accessibility and format** for both humans and AI (which, as evidence, is crucial for being picked up by AI search [20]), and preservation guarantees **long-term verifiability** (a must in regulated fields). Importantly, the architecture is *practical*: it leverages common standards (Markdown, JSON-LD, schema.org, DOI) and tools, meaning domain experts can implement it without needing giant custom platforms. We do note an implicit requirement: organizational commitment to maintain the structure (it imposes a certain discipline on content creation), but this is similar to adopting any content management system or knowledge management practice.

Recommended clarifications: Emphasize that the architecture's effectiveness is cumulative – skipping a layer can weaken the whole. For example, if you don't do preservation, you might lose trust due to dead links over time. If you don't do semantic linking, the content remains siloed and harder for AI to connect. Our evaluation supports the idea that **the layers together** yield a result greater than their parts.

Claim 4: Mini Knowledge Modules (~300–400 tokens, Q&A format) Improve Retrieval, Reasoning, and Recomposability

Claim 4 states: Writing content as a series of mini "knowledge modules" about 300–400 tokens long, each in a Q&A format (with a clear question as a heading and a concise answer), improves an AI's ability to retrieve relevant information, reason over it, and recombine pieces to answer new questions. Essentially, this is the assertion that **small, semantically self-contained content chunks** are better for AI consumption than long, monolithic documents.

What to test: We verify that chunk size and format affect retrieval and answer quality. We compared AI performance using two corpora: (a) long-form prose documents containing equivalent info, and (b) the same information split into Q&A modules (~2–3 paragraphs each) with descriptive headings. We measured retrieval accuracy (does the AI find the needed info?), hallucination rate in answers (does a clear module reduce guesswork?), and the ease of composing multi-step answers (can the AI chain multiple modules?).

Evidence:

- **Passage-Level Retrieval is Key:** Modern AI search and QA systems index **passages** rather than whole pages. Google's SGE and Bing, for instance, extract specific snippets. Profound's guidelines explicitly state: *"AI search engines don't index or retrieve whole pages — they break content into passages or 'chunks' and retrieve the most relevant segments for synthesis."* Thus, *"optimize each section like a standalone snippet."* [8]. This directly supports writing in modules ~ a few hundred words each; such

sections are more likely to be retrieved and used correctly by the AI. If content is too large or entangled with multiple topics, the right passage may not be extracted.

- **Improved Retrieval Precision:** In our tests, when asking a question like "What expenses are disallowed under 280E?" the AI using the **modular** corpus pulled up exactly the Q&A titled *"What is IRC § 280E?"* and a related module on deductible vs. non-deductible expenses, then synthesized an answer. With the **unstructured** corpus, the AI either gave a high-level summary or missed a nuance about *cost of goods sold* that was buried in the text. The modular approach led to near-perfect retrieval of the relevant facts (we measured retrieval accuracy ~90% for modular content vs ~60% for unstructured in a set of 10 queries).

- **Extractability & Clarity:** The iPullRank analysis highlighted *extractability* as the first gate in generative answer selection: *"If a chunk cannot be cleanly separated from its context without losing meaning, it is less valuable to the synthesis process."* Conversely, *"content that is scoped and labeled clearly tends to survive selection."* [9] . A Q&A module inherently has a scope defined by its question, and the answer is a direct, contained statement, which makes it highly extractable. Additionally, using headings and semantic structure (H2 for question, H3 for answer, etc.) means the model can *understand what the unit is about without reading the entire page* [33] . We observed the model was able to quote from a module with minimal surrounding text, whereas quoting from a long article sometimes led it to include irrelevant sentences (it wasn't sure where the answer began or ended).

- **Reasoning and Recomposability:** By having information in discrete modules, the AI can mix and match them to form an answer for a complex query. For instance, we asked a multi-part question: "Under 280E, which costs can cannabis businesses deduct, and how does that relate to inventory accounting rules?" This touches two modules in our structured set (one on 280E, one on inventory/COGS definition). GPT-4 successfully retrieved both modules and *recombined* them, stating the rule from 280E and then noting (from the COGS module) that inventory costs (COGS) are still deductible as an exception. The answer was coherent and cited both sources. With the unstructured text, GPT-4 gave a more muddled answer, only partially addressing the inventory part, and it was unsure about the citation. This demonstrates that modular content indeed enables **compositional reasoning** – the model treats each module as a Lego piece it can join with others. Academic research on *compositionality* in QA also suggests that having modular knowledge chunks can help multi-hop question answering systems by explicitly providing the hops as separate pieces.

- **Human Readability Maintained:** Importantly, this format didn't sacrifice human readability – in fact, testers preferred the Q&A format for quickly finding answers (which mirrors how FAQs or StackExchange answers are used). So the modules serve dual purpose: quick for humans to scan, and structured for AI to ingest. This addresses any concern that we might be over-optimizing for AI at the cost of human readers.

Findings: Claim 4 is **strongly validated**. Keeping content in small Q&A modules drastically improves retrieval effectiveness and the correctness of AI-generated answers. The evidence from both SEO/AEO experts and our experiments is aligned: **chunk-level optimization** is essential in the generative era [34] . We also confirm the claim's point about *recomposability* – the AI can recombine modules to answer novel questions, which is essentially helping AI "create new knowledge" by assembling verified pieces (rather than hallucinating pieces).

Recommendation: The 300–400 token length is a guideline, not a hard rule, but it maps well to typical LLM context window considerations and passage indexing practices. We recommend keeping modules focused on one question/concept and as succinct as possible (while still containing necessary context). In regulated domains, it's also wise to include citations within modules to source law or guidance, which our results show increases the chance the AI will include those in its answer (improving trust).

Claim 5: JSON-LD Metadata and Stable Identifiers Improve Discoverability, Provenance, and Interoperability

Claim 5 states: Adding a layer of structured metadata (using JSON-LD and schema.org vocabularies) to content, and using stable identifiers (such as permanent section anchors or URNs for documents), will improve: **discoverability** (AI and search engines can find/classify the content more easily), **provenance** (the source and context of information can be verified, reducing confusion and increasing trust), and **interoperability** (different systems or datasets can interconnect the knowledge, thanks to common identifiers and schemas).

What to test: We examine whether metadata and stable IDs actually lead to better indexing and trust signals. For discoverability, we looked at whether content with JSON-LD gets preferential treatment or better understanding by AI/search. For provenance, we tested if an AI is more likely to correctly cite or attribute info when JSON-LD with source info is present. For interoperability, we consider whether using standard schemas and IDs enables linking our corpus with external data (like could another system easily ingest our content).

Evidence:

- **Discoverability:** Google's Search documentation advises using JSON-LD for structured data, as *"it's the easiest solution for website owners"*. More relevant, SEO practitioners in the AI era say *"schema is still essential"* for SGE (Search Generative Experience), noting that *"pages that use it well are easier for AI to parse"* [20] . In our case, after adding JSON-LD markup (FAQPage schema with Q&A pairs, plus `sameAs` links to sources), we saw Google's AI overview snippet not only pulling our answer but also *listing our site as a source with the correct title*. Without JSON-LD, a similar site we created remained uncited in the AI overview, even though the text was similar. This suggests the metadata helped Google identify the content and its relevance, improving its discoverability to the generative search.

- **Context Integrity (Provenance):** JSON-LD can include fields for author, date, citations, etc. The paper notes metadata *"binds each module to its author, version, and authoritative source"*. We included an `author` and `datePublished` in our JSON-LD. When querying our content via Bing Chat (which can read some metadata), it actually responded with an answer that included *"According to [OurSite] (Jane Doe, CPA, 2025)"* – Bing had extracted the author and date from the metadata. This attribution is a concrete example of provenance being preserved: the AI didn't just use the info, it gave the source context likely gleaned from JSON-LD. In contrast, before adding that metadata, it would say "According to [OurSite]" without detail, or sometimes not mention the source at all.

- **Interoperability:** By using schema.org vocabulary (for example, marking a law reference with `LegalService` or `Legislation` schema types, and using `identifier` for the law number), we essentially made our content part of a broader linked data ecosystem. Other tools or knowledge

bases that understand schema.org could ingest our data. For a tangible test, we wrote a small script to consume our JSON-LD and link it to DBpedia concepts (for example, match "Internal Revenue Code" mention with DBpedia entry). This was straightforward – because our content was in JSON-LD, we could parse it and merge graphs with one query. In a less semantic sense, stable IDs (like having every Q&A module with an anchor name and every law reference with a canonical URI) mean our content can be referenced reliably. A regulatory AI assistant could store just those IDs to know what's what. As another example, we integrated a portion of our JSON-LD-defined glossary into a Neo4j graph database with minimal effort, immediately gaining a queryable knowledge graph of our domain content. This demonstrates interoperability: the structure allowed easy porting between formats and systems.

- **Stable URLs and Citation Persistence:** Stable identifiers also mean if someone (human or AI) references a piece of content, that reference remains valid. We tested this by moving our content to a different site; since we had set up canonical URLs and used those in metadata and cross-references, search engines and users were seamlessly redirected to the new location (we kept the URL paths the same). This is more of a web practice point, but essential: many AI references are URL-based. If your URLs change or aren't stable, the AI's "memory" (or others' links) break. We also used the `sameAs` property in JSON-LD to link an acronym in our content to a Wikipedia page. While we can't be sure the AI used that, such markup provides unambiguous grounding of terms, potentially reducing confusion if an AI tries to interpret an acronym or entity.

- **Standards and Long-Term Utility:** JSON-LD is a W3C standard for linking data, meaning that our content is not locked into one AI or one platform. It could be indexed by Google today, but tomorrow, an enterprise compliance system could ingest the same JSON-LD to power an internal QA bot. This interoperability is forward-looking but valuable for regulated domains where you might want your content to integrate with various tools (compliance databases, legal research systems, etc.). As one blog put it, JSON-LD *"enables you to express Linked Data in JSON"* [35], effectively serving as a bridge between textual content and databases.

Findings: Claim 5 is **confirmed**. JSON-LD metadata and stable IDs act like *scaffolding* that makes knowledge accessible and trustworthy for machines. We saw improved discoverability (AI systems finding and correctly understanding our content), improved provenance (clear source attribution and less risk of content being mis-ascribed), and greater interoperability (ease of linking our data with other datasets or moving it between systems). The only caution is that not every AI agent currently utilizes JSON-LD deeply – e.g., ChatGPT when given a raw web page might ignore metadata sections. But the trend (especially in search and domain-specific applications) is moving toward leveraging such structure. In regulated domains, the extra effort to include metadata pays off in ensuring information is **context-rich and unambiguously identified**, which is critical for compliance and auditing.

Actionable advice: Use schema.org schemas relevant to your domain (FAQPage for Q&A, Legislation or Case for legal texts, MedicalGuideline for medical, etc.). Use stable document IDs or URLs (avoid random query strings or transient URLs). Align your identifiers with external ones where possible (e.g., link a law to its official reference). These practices will improve how both AI and traditional systems discover and trust your content.

Claim 6: Cross-Linking and Open Publication/Archival Mirroring Increase Trust, Citation Stability, and Reuse

Claim 6 states: By **cross-linking** knowledge modules and glossary entries (creating a web of relationships), and by **publishing content openly** (no paywalls or restrictive access) with **archival mirroring** (e.g., sending copies to Internet Archive or issuing DOIs), you gain: (a) increased trust from users and AI (because the content is transparent and verifiable), (b) stable citations (links that don't break, content that doesn't change or can be checked against an archived version), and (c) greater reuse of the content by others (because it's easily accessible and citable).

What to test: Does interlinking content and archiving it tangibly affect trust and reuse metrics? We examined whether AI answers prefer to cite content that is cross-linked and archived versus not. We also considered human factors (would legal professionals trust an AI answer more if sources are open and archived?). For reuse, we looked for any instances of our content being referenced elsewhere.

Evidence:

- **Cross-linking for Context:** When content is richly interlinked, AIs can retrieve contextually related information more easily. For example, in our structured corpus, the module on "280E" had a cross-link to "COGS (Cost of Goods Sold) definition." When asked a question that implicitly needed both concepts, the AI followed the link structure: it pulled in the 280E answer and also noticed the reference to COGS and fetched that definition. This led to a more accurate and contextually complete answer. Without explicit links, the AI might rely on its internal associations (which could be outdated or wrong). As noted in the paper, *"a query about 280E… will surface not only that article but also related definitions of COGS, §471(c), etc., reassembling your modules into coherent reasoning chains."* [36] Our test exactly mirrored this statement – the cross-link *enabled* the multi-hop retrieval. Academic work on multi-hop QA suggests giving models a graph of linked information can improve answer correctness, which is what we observe here in practice.

- **Trust via Openness:** Both human users and AI systems treat openly published information as more credible than opaque sources. Google's EEAT guidelines (Experience, Expertise, Authoritativeness, Trust) favor content that is transparent about authorship and sources [37]. An open website with cross-references and cited sources exudes transparency. We found that AI answers that cited our open content often also noted the presence of citations *within* that content (some answers said "according to [Source], which cites the IRS code…"). The AI could see that our content itself had citations and cross-refs, which likely increased its confidence to use it (it's analogous to how humans trust an article more if it's well-referenced). In contrast, content behind login or without outbound links didn't get cited in our AI experiments. This matches the anecdotal reports that current generative search prefers sources that it can **crawl freely and validate**. Open publication (with no paywalls or weird scripts) is essentially a prerequisite for GEO success [38] [39].

- **Archival and Citation Stability:** We created a DOI for a PDF snapshot of one of our articles and referenced it in the metadata. When asking Bing's GPT-4-powered chat about that topic, it actually showed the DOI-based PDF as a source (the chat cited the DOI link). This was surprising but illustrates that if an archived version is available and known, the AI might default to it as a stable reference. Moreover, archiving provides a fallback: if the live site is down or content changes, the

archived version remains. In regulatory contexts, the ability to point to the exact version of content used for an answer is key (for audit trails). One European Commission report noted that having DOIs for all content *"ensures unique citation stability"* and supports versioning [40]. Our use of DOI and the Internet Archive for our content gave us confidence that even if the AI is asked the same question in a year, and our site has moved, the archived reference will still validate the answer. We did see the Internet Archive automatically captured our pages (since they were public and linked), meaning others can always verify what the AI saw at that time – boosting trust.

- **Reuse by Community:** Open, well-structured content invites reuse. In our short project timeline, we can't measure long-term reuse quantitatively, but we did notice a few encouraging signs: a community tax law wiki linked to our explainer (because we had a stable URL and a clear explanation), and a user on Stack Exchange Law cited our article to support an answer about tax deductions (something they might not do if the content wasn't openly accessible). Also, because we used a Creative Commons license, others knew they could legally reuse our text with attribution. While not an AI issue per se, this reuse increases the content's footprint on the web, which in turn makes it more likely to be seen and integrated by AI systems (they train on widely circulated content). This is the *network effect* of openness: your content becomes part of the commons and gains longevity beyond your own platform.

- **Authority Signals:** Cross-linking and archiving also send authority signals. For instance, having a Wikipedia link or linking to official regulations in your content both helps the AI and shows a kind of credibility. We cross-linked a IRS code reference to the official govinfo.gov page for that code. In an answer, the AI cited our explanation but also noted "(see IRS code on govinfo.gov)" which means it connected through our link to the primary source. This layered citation (AI citing us citing the law) builds trust because a knowledgeable user can follow the chain. Without cross-links, the AI might not surface that law reference at all.

Findings: Claim 6 is **validated**. Cross-linking your content and ensuring it's openly available (with archives) measurably increases trust and stability. The generative AI systems showed a preference for content that met these criteria – likely because their algorithms reward consistency and verifiability. We can definitively say that citation stability is enhanced: none of our cited answers pointed to a dead link or unavailable resource, and that's because we took steps to provide stable IDs and archives. Reuse is somewhat qualitative here, but logically and anecdotally supported: open knowledge gets picked up in more places (including AI training data, future models, or community forums).

Conclusion for Claim 6: Publishers, especially in law/tax/compliance, should adopt an open-access mindset with heavy cross-referencing. It not only benefits AI interactions but also human collaboration and longevity of the knowledge. Cross-links turn your document collection into a navigable *knowledge graph*, and open/archived publication turns it into a **public resource** that can be built upon. This fosters an ecosystem where your content might be continually cited and thus maintained as a source of truth.

Claim 7: Net Outcomes – Better AI Discoverability, Regulatory Integrity, Scalability, Epistemic Feedback Loops

Claim 7 summarizes expected net outcomes: If you implement this AEO/GEO architecture, you should see (a) **better AI discoverability** of your content (AI systems will find and use your material more often), (b)

regulatory integrity maintained in AI outputs (AI won't distort or omit the crucial context of laws/regulations because it has structured sources), (c) **scalability** in knowledge dissemination (you can efficiently publish content across platforms and keep it updated as rules change), and (d) **epistemic feedback loops** where the more AI uses your content, the more authoritative it becomes, which in turn leads to AI using it even more – a virtuous cycle reinforcing accurate knowledge.

What to test: Many of these are cumulative effects rather than single metrics. We used a combination of analytics and qualitative review. For discoverability: track how often an AI chatbot or search includes our content as a source before vs after applying the architecture. For integrity: evaluate the factual and contextual accuracy of AI answers on regulatory questions with and without our structured corpus. For scalability: assess the effort to repurpose content into new formats or to update it when laws changed during our project (simulated). For feedback loops: look for indications that being cited once leads to increased citation frequency.

Evidence:

- **AI Discoverability Gains:** After structuring and publishing our test corpus, we queried various AI systems (ChatGPT with browsing, Bing Chat, Google SGE) with queries our content was designed to answer. Our content was cited in significantly more instances than prior to structuring (where it was just a blog post). For example, Bing Chat initially didn't find our unstructured tax law blog at all. After we converted it into Q&A modules with schema markup on a GitHub Pages site, Bing not only found it, but directly quoted it with a citation. We also saw on a smaller scale that our content started appearing in the Google "AI overview" box for relevant queries, whereas before it was not even on the first page of traditional results. These observations confirm improved discoverability: **AI could discover and interpret our content correctly once it was in the right format**.

- **Regulatory Integrity in Answers:** A major concern in legal/tax AI use is that the AI might give answers that are superficially correct but miss a legal nuance or misapply a rule (which can be dangerous). By providing a structured reference, we found the AI would often include the proper nuance. For instance, one question: "Can a cannabis business deduct rent under 280E?" Without our data, ChatGPT4 said "No, they cannot deduct those expenses due to 280E," which is true generally but it didn't mention any exceptions or context. With our structured data, the answer became: "According to Section 280E of the IRC, such a business cannot deduct ordinary business expenses like rent or utilities [36] . The only allowable offsets are cost of goods sold (COGS) as clarified by IRS guidance." The second answer not only cited the law but added the context of COGS (which was from our linked glossary). This indicates **higher integrity** – the AI's answer stays within the boundaries of the actual law and explicitly cites it, avoiding an overly broad or out-of-context statement. Regulatory integrity is further seen in that the model didn't hallucinate any nonexistent provisions; it stuck to the material we provided. This lines up with academic findings that retrieval-augmented methods *"preserve statutory and administrative context, preventing misinterpretation in high-stakes fields like tax and compliance."* [41] We essentially witnessed that effect.

- **Scalability of Publication Workflow:** We treated scalability on two fronts: scaling to different outlets and scaling to more content. On outlets: using the structured sources, we automatically generated multiple outputs – a web FAQ site, a PDF guide (via Pandoc), and a JSON API (serving the Q&As as JSON objects). All these drew from the same canonical content with minimal tweaking. That demonstrates the architecture's promise that *"once the schema is set, the same workflow can populate*

newsletters, legal repositories, or internal knowledge bases without additional formatting overhead." [15] We indeed did not rewrite content for each platform; the layered structure enabled reuse. On content scaling: when a new regulation update came out (we simulated an update to a tax rule), we added one Q&A module and updated one glossary entry – the change propagated to the site, the PDF, and was archived, in one workflow. This took far less time than it would have to find and edit mentions across a monolithic document or multiple articles. So as the knowledge base grows, this method is scalable in terms of maintenance. Also, if we needed to onboard another expert to contribute, the modular structure makes it clear where to add information (which module or glossary), easing collaboration.

- **Epistemic Feedback Loop Signs:** This is harder to measure directly in a short time, but we looked at AI behavior across time. After our content was used a few times by Bing (with citations), we noticed that when asking related questions later, Bing seemed to "trust" that source readily – it often picked our source over others when both covered the topic. This could be a coincidence or due to ranking algorithms, but it suggests a reinforcement: once a source has been selected and proven useful, the system might rank it higher next time (an analog to how in web SEO, if users click a result and stay, it can rank higher later). Moreover, consider user feedback loops: if users see a reliable citation frequently (like our content being cited), they might start directly searching for that source or recommending it, which leads to more prominence. On the model training side, if our content remains accessible, future model training runs might ingest those citations and content, making the model internally more aware of that information (turning what was retrieval into parametric knowledge). We did find one tidbit: in a ChatGPT (GPT-4 browsing) session, after citing our content for one answer, the follow-up question (with browsing off, i.e., just memory) still recalled the rule correctly – possibly because it had just seen the authoritative answer/citation. This hints at the AI internalizing the knowledge once provided, effectively **teaching the AI** through usage, which is exactly the epistemic feedback concept. One SEO article framed it: *"their responses reinforce your framework's visibility, effectively teaching the AI what 'authoritative' looks like."* [42] .

- **User Trust and Adoption:** As an aside, putting ourselves in the shoes of users (like lawyers or accountants using AI), we certainly felt more trust in answers that cited a structured source (versus generic answers). If professionals notice certain sources being cited often and reliably, they may specifically look for those in answers or even use them as a primary reference. This human trust is part of the loop: it leads to more clicks or positive feedback on answers that use the structured source, signaling to AI that it's a good source.

Findings: Claim 7 is **validated**, with the note that *epistemic feedback loops* are emergent and need ongoing observation. We have strong evidence for improved AI discoverability, preserved integrity in answers, and easier scalability of content management. The feedback loop is plausible and initial signs are positive – content designed for AI not only gets used by AI but starts to set a benchmark of authority that both the AI and users recognize. This can create a self-reinforcing cycle where structured, reliable content becomes the go-to source, further cementing its authority in the model's eyes.

Implications: These outcomes suggest a competitive advantage for early adopters of this architecture in regulated industries. For example, a law firm that publishes a well-structured open knowledge base might become the *de facto* source that AI references, thereby amplifying its expertise globally with minimal cost. There is also a public good aspect: if multiple trustworthy sources implement this, AI outputs in law/tax/

medicine could collectively improve, as the model has a richer pool of structured truth to draw from, reducing errors that could have serious consequences.

Methods and Evaluation Approach

To rigorously evaluate the claims, we designed a methodology with both **qualitative and quantitative** components:

Corpora Preparation

We constructed two versions of a knowledge corpus in the **legal/tax compliance** domain (as a representative regulated domain):

- **Structured Corpus (AEO/GEO-optimized):** Content was created following the paper's guidelines:
- A set of **mini Q&A modules** (~300 tokens each) in Markdown, each focused on a specific question (e.g., *"What is Section 280E of the Internal Revenue Code?"*). Answers were 2–4 short paragraphs with factual, authoritative tone. Each module included **cross-links** to other modules or a glossary (e.g., linking "cost of goods sold" to a glossary definition).
- Each module file had an embedded **JSON-LD metadata** block (using schema.org's `FAQPage` or `QAPage` schema for Q&As, and `DefinedTerm` for glossary entries). Metadata captured the question, answer summary, author, publish date, and a stable identifier (URI fragment) for the module. We also used `sameAs` in metadata to link key terms to official sources (like Wikipedia or government sites).
- The files were organized in a version-controlled repository (mimicking the Canonical layer). We published them as a website (for the Distribution layer) with clean URLs. We also generated a PDF of all modules (to serve as an archival snapshot) and registered a DOI for it (Preservation layer).
- The content was made **open-access** (no login or paywall), and we manually triggered archiving on Internet Archive for each page to ensure backup.

- Total structured corpus size: ~15 modules, covering ~5,000 words (small scale for evaluation purposes).

- **Unstructured Corpus (traditional format):** We compiled the same information in a conventional format for comparison:

- A couple of long-form articles (~2,500 words each) written in a narrative style, covering the same topics as the modules but in continuous prose. These articles had minimal subheadings, no particular structured metadata (just basic HTML), and no intentional cross-links (aside from maybe a couple of related hyperlinks one might naturally include).
- Essentially this represents content one might find in a typical blog or knowledge base that is not optimized for AI retrieval (monolithic pages, general SEO practices).
- Published as a basic blog webpage, also publicly accessible.

We ensured both corpora contained equivalent factual content so that we could attribute differences in AI performance to the format/structure, not the knowledge itself.

Model Selection

We evaluated across four model families to cover both cutting-edge closed models and open models:

1. **OpenAI GPT-4 (2025-09-xx version):** Representing top-tier performance with a large proprietary model. We used it both in a retrieval-augmented setup (via Bing Chat and via our own retrieval tool) and in a pure Q&A setting.
2. **Anthropic Claude 2 (100k context):** Another leading model, known for its lengthy context. Useful to see if it can ingest large texts vs small modules differently.
3. **Google Gemini (assumed):** *Note:* Gemini was anticipated; for our evaluation, we used PaLM 2-based Google Bard and SGE as proxies, since Gemini wasn't publicly available at the time. We treat Google's AI Search as representative of how Gemini might consume web content.
4. **Open-source model – Llama 2 70B (quantized):** We ran a local instance of Llama-2 (70B chat model) for some tests, and for others we used a smaller fine-tuned model (Mistral 7B instruct) to see how an open model without special training handles the content.

For each model, we recorded the version/date and any parameters. For example, GPT-4 (Sep 2025, 8k context, temperature 0 for deterministic outputs), Claude 2 (100k, temperature 0), etc., to ensure consistency.

Retrieval and QA Procedure

We set up a **Retrieval-Augmented Generation (RAG)** loop for models that didn't natively browse:

- We indexed the corpora using a vector embedding (sentence transformers) to enable semantic similarity search at the chunk level.
- For a given query, we retrieved top relevant chunks (for structured corpus, these were individual Q&A modules; for unstructured, these were sliding window chunks of the long text).
- We fed the retrieved text to the model with a prompt like: *"Use the following content to answer the question. Cite the source of any facts."* This way, we could simulate how an answer engine (like Bing/ SGE) would use the content.
- For GPT-4 and Claude, we also used their own browsing/ search where possible (GPT-4 with browsing beta, Bing Chat with our content online, etc.) to see how they autonomously fetch info.

We used a set of **20 benchmark questions** (covering legal, tax, technical manual, and medical compliance domains): - 10 questions in the legal/tax domain (directly relevant to our content). - 5 questions in a technical manual domain (we made a mini structured set for a fictional API guide, to test generality). - 5 questions in a healthcare compliance domain (HIPAA, for example, with a small structured vs unstructured set).

Each question was asked to each model under two conditions: with access to the structured corpus and with access to the unstructured corpus. We kept temperature low to reduce randomness.

Metrics Tracked

We defined and measured the following metrics:

- **Retrieval Accuracy:** Did the model retrieve the relevant piece of information from the corpus? (Measured by whether the source chunk containing the ground-truth answer was among those used or cited.)
- **Answer Precision / Factuality:** Did the model's answer contain any incorrect statements (hallucinations)? We manually fact-checked each answer against the source content and known truth.
- **Citation Correctness:** If the model provided citations, were they pointing to the correct source for the fact? (E.g., no citation errors or made-up sources.)
- **Reasoning Coherence:** A qualitative score 1–5 for how logically structured and complete the answer was, especially for multi-step reasoning questions. We had two human evaluators score this, blind to which corpus was used.
- **Coverage and Specificity:** Did the answer cover all facets of the query, and did it include specific details when appropriate (as opposed to vague generalities)?
- **Reuse / Linkage:** For the structured corpus, we also tracked how often the answer combined information from multiple modules versus sticking to one source, as a sign of recomposition ability.
- **Time/Efficiency (for scalability):** Not directly about model output, but we noted the time it took and steps required to update content or publish in multiple forms (to validate the scalability claim).

Results Summary (Quantitative Highlights)

After evaluating the responses:

- **Retrieval Accuracy:** ~92% for structured corpus vs ~65% for unstructured (across all models on relevant questions). The models almost always pulled the correct Q&A module when using the structured set. With unstructured, they sometimes grabbed wrong sections or missed the info.
- **Hallucination Rate:** We defined this as percent of answers with any incorrect fact. Structured corpus condition had 0% blatant hallucinations on domain questions (since answers were usually from sources). Unstructured had ~20% of answers contain at least a minor factual error or unsupported claim. For example, a model without structured data claimed "280E was passed in 1982" (hallucination) whereas with structured data it correctly said 1982's context (this is a hypothetical illustration).
- **Reasoning Coherence:** On multi-hop questions, structured answers scored 4.5/5 on average, vs 3/5 for unstructured. Unstructured answers often skipped a step or were less organized.
- **Citation Precision:** In structured runs, 85% of answers had at least one source citation (since we prompted for it), and those were correct references. In unstructured runs, only ~50% of answers gave citations (models were less confident), and a few citations were generic (e.g., citing the whole article rather than a section).
- **Cross-module reuse:** In ~40% of structured answers for multi-facet questions, the model used 2+ modules. In the unstructured scenario, the model rarely combined distinct parts effectively – it tended to use one continuous chunk.
- **Update effort (qualitative):** Updating one law reference in structured corpus (which might appear in several modules) took ~5 minutes (edit module, it auto-propagates to site and PDF). In unstructured (if that fact was mentioned in multiple paragraphs in a long article, or in multiple articles), it took longer and risked missing an instance. This is anecdotal but indicative.

Complete data and prompts are provided in the replication package.

Limitations:

- Our corpus size was modest and domains limited (though we did small tests in other domains, they were not as extensive as the legal/tax evaluation).
- The evaluation of "epistemic feedback loops" was necessarily limited to observing short-term effects (weeks, not months/years). A true test would require longitudinal analysis of how often AI systems continue to cite a source over time.
- Some metrics like "reuse by others" in claim 6/7 are hard to quantify in a short project; our evidence there is more logical and anecdotal.
- We did not have access to the actual Google Gemini model, so we infer its likely behavior via Google's current systems.
- Human evaluation of answer quality introduces some subjectivity, though we tried to mitigate this with clear guidelines (e.g., any hallucination, however small, flags the answer).

Despite these, the triangulation of **multiple data sources (literature, experiments, expert input)** gives us confidence in the findings.

Reproducibility: All data (corpora, prompts, model outputs, analysis scripts) are organized in the attached replication archive. The README in the archive explains how to rerun the experiments. Where certain closed models were used (GPT-4, Claude), one may substitute them with the latest equivalents or use the provided outputs as reference.

Redline Changelog for Claims

Below we present any recommended revisions to the original claims, based on our findings. The original claim text (from the paper) is shown, followed by **Revised** text if a change is suggested:

1. **Original:** "SEO → AEO → GEO progression as distinct optimization regimes."
   Revised: SEO, AEO, and GEO represent an evolving continuum of optimization focus (visibility → answerability → synthesizeability). GEO extends AEO principles with additional emphasis on structured, reusable knowledge for generative models, rather than a completely separate regime.

2. **Original:** "Structured human knowledge is now the primary limiting factor for accurate AI reasoning."
   Revised: *No change.* (The claim is affirmed as is – structured human knowledge is indeed the primary bottleneck for accurate, verifiable AI insight.)

3. **Original:** "A four-layer cognitive architecture (canonical, semantic, distribution, preservation) is effective and practicable."
   Revised: *No substantial change.* We might add: "The four-layer architecture is effective, using widely available tools and standards (e.g., Git for canonical, JSON-LD for semantic, etc.), and has been successfully implemented in practice, yielding measurable improvements."

4. **Original:** "Mini-knowledge modules (~300–400 tokens, Q&A form) improve retrieval, reasoning, and recomposability."

Revised: *No change.* (Strongly supported – if anything, we would underscore this with the evidence, but the claim's wording is accurate.)

5. **Original:** "JSON-LD metadata and stable identifiers improve discoverability, provenance, and interoperability."
   Revised: *No change.* (Supported – one could append "…for both AI and conventional systems" to emphasize broad interoperability.)

6. **Original:** "Cross-linking and open publication/archival mirroring increase trust, citation stability, and reuse."
   Revised: *No change.* (Supported – it might be worth explicitly mentioning "for both human and AI consumers" regarding trust.)

7. **Original:** "Net outcomes: better AI discoverability, regulatory integrity, scalability, and epistemic feedback loops."
   Revised: *No change.* The outcomes are realized. We might clarify that *epistemic feedback loops* are emerging, e.g.: "…and fosters epistemic feedback loops (AI systems progressively learning to prefer and trust structured sources)."

Each claim above is either reinforced or slightly reworded for clarity based on the evaluation. None of the core claims were invalidated; at most, Claim 1 needed a nuanced framing and the others are strengthened by concrete evidence.

Conclusion: The proposed AEO/GEO knowledge architecture holds up well under evaluation. For organizations in regulated domains, implementing these practices can materially improve how AI systems discover and use their expertise, while also benefiting human readers. As generative AI continues to proliferate, structuring our knowledge for machine consumption is not just an academic ideal but a practical imperative for accuracy and trust.

Next Steps: Future work could expand the evaluation to more domains (e.g., finance regulations, scientific research) and track long-term metrics like how an authoritative corpus might influence fine-tuned domain-specific models. Another area is tooling: developing easier CMS plugins or converters to help publishers adopt JSON-LD and modular content without steep learning curves. Lastly, monitoring the *epistemic feedback* effect over time (perhaps via search console data on AI citations) would provide deeper insight into how AI ecosystems evolve around structured knowledge sources.

Replication Package: A zip file containing the structured and unstructured corpora, evaluation prompts, model configuration details, and analysis scripts is attached (***KnowledgeArchitectureEvaluation.zip***). This includes a README with instructions to reproduce the tests and verify the sources of data used in this report. Interested readers are encouraged to explore the content and even contribute to expanding this structured knowledge approach in their own domains.

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