

Giving Agents a Map: Structured Indexes for Fact Coverage in Complex Document Collections

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Abstract

Analytical decision-making over large, heterogeneous document collections depends on comprehensive evidence gathering and synthesis. To support this process at scale, we propose procedure-index, a procedure-structured hierarchical navigation interface that makes corpus organization traversable. The interface exposes this organization through typed modules, route documents, cross-module views, and provenance-linked evidence items, which an LLM agent traverses with read-only tools. We hypothesize that final-answer fact coverage depends not only on document ranking but also on what corpus structure the interface makes observable to the agent. This study tests the hypothesis against whole-document embedding search on 50 due-diligence cases over a frozen snapshot of 29,688 documents. Under the main deployed protocols, procedure-index records higher final-answer fact recall on all four primary metrics, with all differences significant under planned company-cluster tests. A sequential interface ablation attributes the largest near-hit increment to navigation documents rather than to rendered evidence alone. At a shared \$0.40 evidence-access budget threshold, the overall near-hit difference remains positive but suggestive, and the remaining contrasts are not significant. Case analysis is consistent with a conditional account: structured navigation is most effective when target facts are dispersed across evidence regions, while direct ranking remains competitive when a few query-similar documents concentrate the answer. These results identify agent-visible corpus structure as a design dimension for high-recall evidence access in due diligence.

1 Introduction

LLM agents are increasingly expected to gather evidence actively: they can reformulate a query, inspect a source, follow a lead, and decide what to examine next. Hierarchical corpus navigation supports this behavior by exposing document structure and letting agents choose what to inspect (Sun et al., 2026; Dai et al., 2026; Du et al., 2026; Zhao and Yang, 2026). Heterogeneous company due diligence makes the choice of access interface concrete: final answers must synthesize multiple query-scoped facts that may be dispersed across documents, and omitting one can alter conclusions about ownership, financing, or litigation.

This study compares procedure-index with a whole-document embedding comparator that presents the agent with a local ranked view. The agent issues a query, receives the top-ranked documents, and repeats, but this interface does not reveal which corpus regions exist or which routes remain unexplored. By contrast, a procedure-structured interface can expose analytical regions and routes before item-level inspection. We therefore ask whether the complete procedure-structured interface differs from this comparator in final-answer fact coverage, which parts of the interface contribute to any observed difference, and whether the difference remains visible at a shared \$0.40 evidence-access budget threshold.

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Procedure-index is a procedure-structured instance of agent-visible hierarchical navigation, traversed with read-only tools. It progressively exposes the collection from source hierarchy and typed modules through route documents to provenance-linked evidence items. The map metaphor denotes this corpus-level orientation before item-level inspection. We use this interface to study final-answer target-fact coverage on a company due-diligence benchmark, comparing it with a whole-document embedding interface while holding the target set, underlying source environment, answer-model name, and recognizer fixed. Strict recall counts fully expressed targets; near-hit recall also credits non-contradicted partial coverage.

In the main comparison, procedure-index has higher recall on all four primary metrics (planned exact company-cluster $p \leq 0.006$), with approximately 6.3 times the recorded model-API token usage. The sequential interface ablation locates the largest adjacent near-hit increment in navigation documents (+0.133 critical near-hit recall), rather than in rendered evidence alone. The fixed-budget evaluation uses a shared \$0.40 evidence-access budget threshold for Stage A. At this operating point, the overall near-hit contrast remains positive but suggestive (+0.044, exact company-cluster $p = 0.059$), while the other three planned contrasts are not significant. The qualitative analysis (Section 6) is consistent with a dispersion-based account and its boundary: direct ranking can be more effective when a few query-similar articles already concentrate the answer.

The evaluated treatment is the deployed interface as a bundle—representation, artifacts, tools, prompts, and budget—so the main contrast is a paired system-level comparison. The sequential interface ablation and the fixed-budget evaluation qualify this contrast but do not isolate every factor. This preprint discloses the measurement contract and translated, partially redacted prompt contracts needed to interpret the reported aggregates.

This paper makes two contributions:

- We report a paired, system-level evaluation of agent-visible navigation for heterogeneous due diligence, instantiated in the procedure-index interface: the complete interface records higher final-answer fact recall than whole-document embedding search on all four primary metrics. A sequential interface ablation over hierarchical rendered evidence, navigation documents, and skill guidance attributes the largest adjacent near-hit gain to navigation documents, exceeding the increments from source hierarchy and from skill guidance; at a shared \$0.40 evidence-access budget threshold, the advantage is positive but suggestive. The ablation and budget probes are largely absent from prior navigation-interface evaluations. Selected traces further suggest that the advantage concentrates where target facts are dispersed across evidence regions.
- We specify and disclose a fact-level measurement contract for final-answer coverage: 3,321 frozen, query-scoped target facts with priority tiers, scored by a closed-world recognizer that quotes answer spans and separates coverage, contradiction, and unscored decisions, with company-cluster exact tests. Comparable navigation systems evaluate at answer level; this contract adapts nugget-style fact coverage to a frozen, access-controlled evidence setting.

2 Related Work: From Retrieval to Navigable Evidence Access

2.1 Structured Retrieval Beyond Flat Chunks

A substantial line of work shows that flat similarity retrieval can be insufficient for corpus-level questions. Entity graphs and community summaries, graph-based non-parametric memory, and tree-organized hierarchical summaries all improve retrieval-augmented generation in their settings (Edge et al., 2024; Han et al., 2025; Jimenez Gutierrez et al., 2024; 2025; Sarthi et al., 2024; Zhao and Yang, 2026). Structure-aware retrieval over complex or book-length documents further shows the value of document hierarchy, and recent work shows that structure can also be constructed at inference time rather than fixed at indexing time (Wang et al., 2025; Huang et al., 2025; Li et al., 2025). This literature establishes corpus structure as an existing design dimension for evidence access. We study this design dimension through a procedure-structured interface for heterogeneous due diligence and evaluate it at the level of final-answer fact coverage.

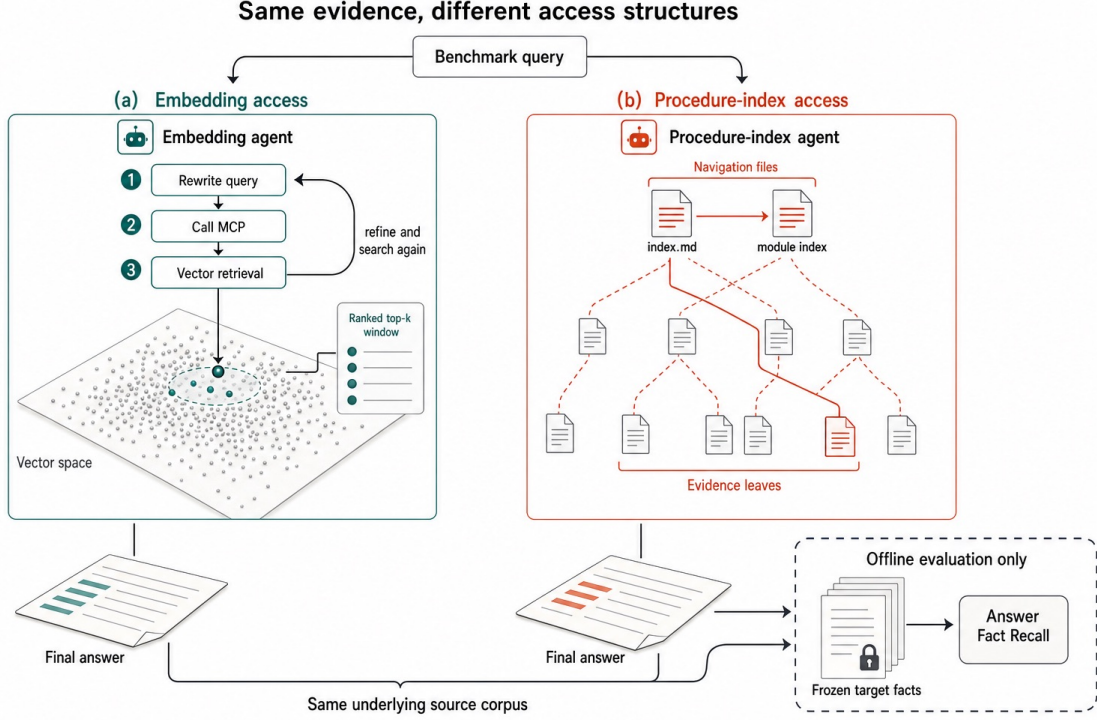


Figure 1: Same benchmark query and source corpus, different evidence-access structures. The embedding agent iteratively rewrites its query, calls an MCP vector-search tool, and receives a rank-truncated candidate window. The procedure-index agent reads navigation files and follows routes to source-linked evidence items. Both produce final answers evaluated offline against the same frozen target-fact set.

2.2 Active Navigation and Agentic Retrieval

Classic IR and HCI models treat search as iterative navigation rather than a single lookup. Berrypicking, exploratory search, and information foraging describe evolving needs, informative cues, and movement through an information environment (Bates, 1989; Marchionini, 2006; Pirolli and Card, 1999). They provide a conceptual lens for our question: what evidence regions and next actions does an interface make observable at each step? Recent RAG systems show a parallel move from passive top- k lookup toward active navigation: agents that traverse knowledge structures, corpora compiled into agent-navigable directories and skill files, and hierarchical retrieval interfaces from which an agent chooses its own strategy (Dai et al., 2026; Sun et al., 2026; Du et al., 2026). A closely related recent system, Corpus2Skill, compiles an enterprise corpus into a hierarchical skill directory, exposes that directory to an agent through progressive disclosure, and evaluates where navigation helps across enterprise QA collections (Sun et al., 2026). Procedure-index shares the compile-then-navigate pattern and filesystem-based progressive disclosure, but organizes evidence around a fixed analytical procedure and studies final-answer target-fact coverage, cumulative interface packages, and fixed-budget evidence access in heterogeneous due diligence. Other close systems include NaviRAG, which studies active top-down navigation primarily within long documents (Dai et al., 2026); A-RAG, which exposes a hierarchical retrieval interface at corpus scale (Du et al., 2026); and Psi-RAG, which builds a hierarchical abstract tree for cross-document retrieval (Zhao and Yang, 2026).

Navigation structure, prompt-level skill text, representation, and tool policy remain bundled in many agentic systems. Our sequential interface ablation therefore estimates adjacent package increments from hierarchical rendered evidence to navigation documents to skill guidance, without treating the design as a factorial isolation of every component.

2.3 Retrieval as Policy, Trajectory, and Evaluation

Recent work treats retrieval as sequential decision making: multi-turn interaction with a graph environment optimized by reinforcement learning, structure-coherent intermediate retrieval paths with progress-aware rewards, and survey-level formulations of agentic retrieval as trajectory-level decision processes with cost and stopping decisions (Luo et al., 2025; Park et al., 2026; Singh et al., 2025; Mishra et al., 2026). Unlike policy-learning work, this study does not train or optimize retrieval control. It compares two agent systems that receive the same query and requested analytical coverage and use the same answer-model name; representation, tools, and interface-specific instructions remain part of each system. The study asks how a procedure-structured interface behaves in final-answer fact coverage relative to whole-document embedding search and uses selected traces to examine where that surface is or is not exploited.

Evaluation of agentic retrieval requires more than answer accuracy because trajectories, budgets, and stopping behavior matter, and whether structure helps depends on the task and pipeline (Han et al., 2025; Xiang et al., 2025; Singh et al., 2025; Mishra et al., 2026). We therefore use fact-level answer coverage as the primary outcome, traces to diagnose where corpus evidence was or was not opened, and a fixed-budget evaluation to examine one constrained operating point.

Fact-level answer evaluation has two directions. Precision-oriented scoring decomposes the generated answer and verifies each claim against sources (Min et al., 2023; Wei et al., 2024). Recall-oriented scoring instead measures coverage of reference facts, a lineage running from nugget-based definition-question evaluation and pyramid summarization scoring to LLM-automated nugget recall in the TREC 2024 RAG track (Voorhees, 2003; Nenkova and Passonneau, 2004; Pradeep et al., 2024; 2025). The two directions capture complementary failure modes—unsupported content versus omission—and omission is the failure mode this study targets, so we measure the recall direction. Existing recall-oriented protocols extract nuggets from pooled documents at evaluation time, which suits open web corpora with many participating systems, while closed-corpus QA benchmarks constrain questions to short answers where exact match suffices (e.g., Yang et al., 2018); the navigation systems above likewise evaluate at answer level. Neither protocol fits a paired comparison of two interfaces over a fixed collection with long-form, multi-fact answers: evaluation-time extraction ties the target set to the compared systems’ output pools, and short-answer formats cannot express coverage. This setting motivates the design used here: a frozen, pre-reviewed, query-scoped target set with priority tiers and a closed-world, span-quoting recognizer.

3 Procedure-index as a Hierarchical Navigation Interface

Procedure-index compiles a complex company document collection into a navigable evidence environment for an agent. Rather than exposing its internal directory schema, the interface orients the agent in three forms: analytical regions for broad task areas, cross-cutting entity routes for following companies and related actors, and chronological or event routes for tracking developments over time. Analytical regions are realized as a small fixed set of typed modules; later sections use “typed module” in this sense. Using read-only tools, the agent can move from this overview to narrower evidence views and then to source-linked evidence items. Table 1 specifies these artifacts and the agent action each supports.

Each source-linked evidence item retains a provenance link to its underlying payload. The access layer changes both organization and visible content: evidence items carry evidence text, while navigation documents carry labels, short fields, or evidence cues. The sequential interface ablation therefore separates the evidence-bearing layer from the navigation layer without claiming that navigation is content-free. Section 6 examines a cue-bearing view, and Appendix A.7 reports the translated, partially redacted prompt contracts used by the two main arms.

Figure 1 contrasts the two system interfaces. The embedding agent rewrites its query and calls an MCP vector-search tool, which returns whole documents from a local cosine-similarity neighborhood as a ranked top- k window. The procedure-index agent instead starts from navigation files and descends their routes to source-linked evidence items through local file tools. Both derive from the same underlying source environment, but they differ in representation, visible artifacts, tool protocol, and main-experiment budget. The sequential interface ablation and the fixed-budget evaluation examine these bundled differences below.

Table 1: Artifacts exposed by the procedure-index interface. “Carries evidence text” means evidence-bearing content, not benchmark targets.

Artifact	Generation source	Carries evidence text	Agent action
Source record	Ingested registry or web document	Yes	Open the raw payload behind an evidence item
Evidence item	Rule-based rendering plus targeted extraction/routing	Yes	Open a concrete evidence item and follow its source pointer
Overview	Template over module inventory and item metadata	Selected summaries	Scan a typed region before opening evidence items
Route document	Deterministic hierarchy and event/entity grouping	Labels or short fields	Descend to a narrower evidence family
Evidence map	Cross-module rule-based views over indexed items	Short evidence cues	Identify candidate regions across modules
High-signal view	Heuristic selection from the evidence map	Short evidence cues	Inspect a compact first-read queue, then open evidence items

The region-and-route schema is fixed in code rather than generated from the evaluation queries or target fact set, and the same procedure-structured interface is reused across all query types. We treat the remaining build logic as part of the evaluated system implementation rather than as an experimental variable in this paper.

4 Experimental Setup

4.1 Benchmark

We evaluate agents on a due-diligence company fact benchmark with 50 cases: 10 companies crossed with five query types (investment/M&A due diligence, credit and supplier access, legal compliance, investigation tree, and industry-sales analysis). The investigation-tree query asks for an evidence-backed timeline of founders, core team, shareholders, control chain, related parties, key events, negative coverage, penalties, and litigation. The frozen target set contains 3,321 query-scoped facts: 584 critical, 1,719 important, and 1,018 relevant. Each fact is an answer target for one company-query pair, not a document-hit target. Critical means that omission would materially weaken the query’s due-diligence conclusion; important supports a key part of the answer; relevant supplies lower-priority context. Appendix A documents benchmark construction, review, and the target-set provenance boundary.

The realized snapshot, shared by both arms, contains 29,688 Chinese-language documents for 10 companies, assembled from access-controlled, internally maintained sources, including licensed corporate-registry records. These statistics describe the frozen materialized snapshot rather than an upstream collection-success rate: this release does not include a complete record of attempted, failed, or rejected collection operations. Appendix A.8 reports per-company statistics. We study this local collection because due-diligence answers must be checked against a fixed evidence base; public-web results drift, and relevant registry material is licensed. Agents receive the query and document environment but do not receive the target facts.

4.2 Systems Compared

Both main arms use the same endpoint model identifier, deepseek-v4-flash, through the Claude Code CLI harness and a DeepSeek Anthropic-compatible endpoint. Decoding parameters were left at endpoint defaults and were not pinned, and the two arms’ answers come from separate run generations—answer batches executed at different times—rather than one concurrent randomized batch.

The embedding arm is an agentic operational comparator: the answer agent iteratively searches and fetches from a flat whole-document vector store through a Model Context Protocol tool interface. The median document contains 556 characters, and the 90th-percentile length is 2,717 characters, making whole-document indexing a practical and auditable retrieval unit for this corpus. BAAI/bge-m3 embeddings (Chen et al., 2024) are 1024-dimensional, one vector per whole document with no sub-chunking

and an 8,000-character indexing cap, searched by exact cosine similarity. The runtime contract permits at most 6 *successful* search calls, default top- $k = 10$ with a per-call maximum of 20, at most 30 fetched documents, and 4,000 characters per fetch.

The procedure-index interface exposes the full navigation surface of Section 3, plus skill guidance, through read-only local tools. It has no per-call retrieval cap and stops when it judges the task complete, subject to a one-hour timeout that no published run reaches. This main-protocol asymmetry is part of the system-level treatment. The fixed-budget evaluation instead uses a shared \$0.40 evidence-access budget threshold for Stage A, followed by no-tools Stage B synthesis.

4.3 Scope of Claims

The primary contrast is procedure-index versus embedding under the same query set, requested analytical coverage, frozen target set, underlying source environment, answer-model name, and answer-fact recognizer. Everything else varies with the arm—representation, tool protocol, interface-specific instructions, access budget, and run generation—so we interpret the paired contrast as the observed difference between the two deployed interfaces as complete systems, not as an isolated effect of index structure. The sequential interface ablation probes cumulative interface packages, while the fixed-budget evaluation reports behavior at one constrained operating point; neither isolates every factor. This scope governs all results below. Each case runs once per arm, so intervals and paired tests reflect variation across the 10 company clusters rather than within-arm generation variance. All 50 cases are present for each primary arm. The primary tables use scored-fact denominators; Appendix A.5 reports the fact-level unscored counts and conservatively counts every unscored decision as a miss over all 3,321 targets.

4.4 Metrics and Scoring

The primary outcome is answer fact recall. Strict recall gives credit only when the final answer fully expresses a target and its indispensable anchors. For example, if a target states that a company received a regulatory penalty in 2024, strict credit requires the answer to preserve the company, event, and year. Near-hit recall also credits a non-contradicted partial expression, such as mentioning the penalty while omitting a required anchor. An incompatible year, entity, or direction is a contradiction and receives no near-hit credit; a decision is unscored when the recognizer cannot apply the contract reliably. Let D_S be the scored target facts in scope S , where S is either the critical subset or all priority levels. Let F_S count fully expressed targets and P_S count partially expressed, non-contradicted targets. Then

$$R_{\text{strict}}(S) = \frac{F_S}{|D_S|}, \quad R_{\text{NH}}(S) = \frac{F_S + P_S}{|D_S|}.$$

The primary denominator excludes decisions marked unscored; Appendix A.5 instead uses the complete frozen target scope and assigns unscored decisions zero credit. Both views score expression in the final answer text against the frozen targets: they are agnostic to which documents were retrieved and require no citation support, with near-hit crediting full plus non-contradicted partial expression and strict requiring full expression.

Final answers are scored by the same closed-world recognizer, deepseek-v4-pro. It evaluates only the predefined fact keys and first records whether a decision is scored or unscored. Each scored decision contains a three-way coverage label—full, partial, or none—and an independent contradiction flag; partial coverage may coexist with a contradiction, while full coverage may not. For full or partial coverage, or for a positive contradiction flag, the recognizer must quote a verbatim span from the answer. It cannot add targets or issue a holistic answer preference. Relative to an open-ended LLM-as-judge setup, this reduces freedom to invent criteria or redefine relevance and makes positive and contradictory decisions traceable to predefined targets and answer spans (Zheng et al., 2023; Wang et al., 2024). It does not eliminate model bias or prompt sensitivity. Re-scoring every main-comparison answer with both the identical recognizer configuration and an independent GLM-5.2 judge leaves all four planned contrast directions and significance conclusions unchanged (Appendix A.10).

Table 2: Main comparison: procedure-index records higher recall on all four primary metrics. Cells report pooled fact recall with 95% company-cluster bootstrap CIs.

Metric	Embedding	Procedure-index	Difference	p
Critical near-hit	0.400 [0.356, 0.438]	0.550 [0.492, 0.628]	+0.150	0.006
Critical strict	0.130 [0.096, 0.166]	0.269 [0.229, 0.317]	+0.139	0.004
Overall near-hit	0.270 [0.235, 0.301]	0.405 [0.366, 0.444]	+0.134	0.002
Overall strict	0.083 [0.070, 0.097]	0.195 [0.172, 0.221]	+0.112	0.002

Note: Both arms contain 50 runs; difference is Procedure-index minus Embedding; recall denominators include scored facts only; planned contrasts use exact two-sided company-cluster permutation p-values; p-values are nominal and unadjusted; bold marks nominal $p < 0.05$; legacy public-web reference rows appear in Appendix Table 7.

4.5 Statistical Tests

The 50 company-query cases are query observations nested in 10 company clusters, each containing the same five query types. Point estimates pool eligible scored facts. We compute 95% percentile confidence intervals from 10,000 cluster-bootstrap resamples, drawing 10 companies with replacement, carrying all five within-company queries with each draw, and recomputing pooled fact recall; there is no separate query-type stratification. The bootstrap seed is fixed at 20260709 (Efron and Tibshirani, 1993). Ablation adjacent-increment intervals use the same company-cluster design with a stable SHA-256-derived seed for each arm pair and metric.

Pairwise contrasts use the pooled fact-recall difference shown by the corresponding point estimates and a two-sided company-level label-permutation test (Good, 2000). One label flip moves all five queries for a company together; with 10 companies, we enumerate all 2^{10} assignments and recompute both arms’ pooled numerators and denominators under each assignment. Ablation ordered trends use 10,000 label permutations within each company, the predeclared Flat (000) < Hierarchical evidence (100) < Navigation documents (110) < Skill guidance (111) order, pooled arm rates, a plus-one correction, and a one-sided greater test. All planned p-values are nominal and unadjusted.

5 Results

5.1 Main Comparison: Final-Answer Fact Coverage

Coverage. Table 2 shows the central result. Relative to the embedding interface, procedure-index records critical near-hit recall of 0.550 versus 0.400 and overall near-hit recall of 0.405 versus 0.270; critical strict is 0.269 versus 0.130 and overall strict is 0.195 versus 0.083. The four exact company-cluster tests range from $p = 0.00195$ to $p = 0.00586$. Counting every unscored decision as a miss reduces the estimates but preserves gaps of +0.122, +0.123, +0.124, and +0.106 for critical near-hit, critical strict, overall near-hit, and overall strict, respectively (Appendix A.5). On this benchmark, the complete procedure-index interface covers more target facts than the embedding baseline.

Legacy public-web and hybrid rows are stronger on some metrics, especially critical near-hit recall; they measure what public-web discovery can reach over this benchmark and appear as reference context in Appendix A.9. Their different discovery surface also illustrates why they cannot substitute for the fixed, access-controlled local setting studied here.

Recorded cost. The main protocol reports an effectiveness-cost pair, not a cost-normalized advantage. Mean recorded usage is about 1.26M model-API tokens per procedure-index run versus about 198K per embedding run, a factor of about 6.3; the totals sum input, cache-read, cache-creation, and output tokens across each run’s model calls. Index runs average about 150 seconds of wall-clock time across all 50 runs; the embedding runner recorded no comparable timings. Case-level model-API spending has the same direction (Section 6). These figures exclude one-time construction: recorded index builds took roughly five to six minutes per company, amortized across five query types, while comparable embedding build

accounting is unavailable. We therefore do not impute either unobserved build cost. The fixed-budget evaluation revisits the contrast at a shared \$0.40 evidence-access budget threshold.

5.2 Sequential Interface Ablation

The sequential interface ablation is an ordered, cumulative design over three agent-facing packages: hierarchical rendered evidence (H), cue-bearing navigation documents (N), and skill guidance (S). The observed profiles are *Flat (000)* (historical base), *+Hierarchical evidence (100)* (no-navigation), *+Navigation documents (110)* (no-skill), and *+Skill guidance (111)* (index-agent-full). Their adjacent estimands are $\Delta_H = Y_{100} - Y_{000}$, $\Delta_{N|H} = Y_{110} - Y_{100}$, and $\Delta_{S|H,N} = Y_{111} - Y_{110}$.

These are conditional package increments, not factorial main effects or interactions: H adds both source hierarchy and rendered evidence items, N adds both route organization and short navigation cues, and S adds both skill guidance and its skill-aware prompt. All four profiles share the same 50 cases; the three non-full profiles use the same neutral prompt.

Figure 2 shows the ordered estimates; Appendix Table 9 reports every profile and interval. Profile 111 is an independent rerun of the main procedure-index environment from a later run generation; its critical near-hit and strict estimates are 0.558 and 0.240 versus 0.550 and 0.269 in the main run, which we read as an informal stability check only.

Hierarchical-evidence increment. Table 3 reports all three adjacent contrasts. Adding hierarchical evidence (100 minus 000) increases critical strict recall by +0.055 (95% CI [+0.020, +0.090], $p = 0.021$) and overall strict recall by +0.037 ([+0.014, +0.060], $p = 0.014$). The critical and overall near-hit increments are +0.036 ($p = 0.256$) and +0.046 ($p = 0.064$), respectively, and are inconclusive under the nominal exact tests.

Navigation-document increment. Adding navigation documents (110 minus 100) increases critical near-hit by +0.133 (95% CI [+0.084, +0.185], $p = 0.004$) and overall near-hit by +0.063 ([+0.026, +0.102], $p = 0.016$). The strict increments are +0.037 and +0.012, with intervals crossing zero and $p = 0.389$ and $p = 0.453$. Navigation therefore has an observed adjacent increment for near-hit recall, while the strict increments remain inconclusive.

Skill-guidance increment. The 111-minus-110 contrast estimates the skill-guidance package increment; its non-significant tests do not establish equivalence. On the 3,321-fact benchmark, the predeclared ordinal trend tests are below 0.001 for all four metrics. These tests pool evidence across the whole sequence, so they can be significant even where a single adjacent step is not.

In this cumulative sequence, the hierarchical-evidence package raises strict recall over flat raw evidence, while navigation documents raise near-hit recall beyond hierarchical rendered evidence. Because profile 100 already holds every rendered evidence item, the navigation increment is not explained by evidence re-rendering alone; it estimates the joint contribution of route organization and the short evidence cues those documents carry. The data do not show that skill guidance is ineffective or equivalent to profile 110. This pattern is consistent with pipeline-side ablations in which hierarchy and traversal work jointly (Dai et al., 2026), while preserving the narrower identification boundary of our adjacent contrasts.

5.3 Fixed-Budget Evidence Access

The fixed-budget evaluation asks whether the procedure-index signal remains visible at a shared \$0.40 evidence-access budget threshold. The threshold applies to Stage A model-API spending during search and navigation while preserving each interface’s native representation, tools, prompts, and action granularity. Because enforcement occurs at model-call boundaries, the final atomic call can take realized spending above the nominal threshold. The evaluation therefore compares complete interfaces at one pilot-calibrated operating point rather than equalizing realized spending, retrieval-action counts, evidence volume, or total system cost. Stage B then synthesizes the answer without tools from the Stage A interaction history. Appendix A.12 specifies calibration, enforcement, handoff, and eligibility.

Table 3: Sequential interface ablation: adjacent H/N/S package increments. Difference cells report pooled fact-recall increments with 95% company-cluster bootstrap CIs.

Package added	Metric	Reference	With package	Difference [95% CI]	<i>p</i>
Hierarchical evidence	Critical near-hit	0.382	0.418	+0.036 [-0.021, +0.082]	0.256
	Critical strict	0.125	0.180	+0.055 [+0.020, +0.090]	0.021
	Overall near-hit	0.290	0.336	+0.046 [+0.008, +0.087]	0.064
	Overall strict	0.100	0.136	+0.037 [+0.014, +0.060]	0.014
Navigation documents	Critical near-hit	0.418	0.551	+0.133 [+0.084, +0.185]	0.004
	Critical strict	0.180	0.217	+0.037 [-0.023, +0.099]	0.389
	Overall near-hit	0.336	0.399	+0.063 [+0.026, +0.102]	0.016
	Overall strict	0.136	0.148	+0.012 [-0.017, +0.039]	0.453
Skill guidance	Critical near-hit	0.551	0.558	+0.007 [-0.019, +0.033]	0.623
	Critical strict	0.217	0.240	+0.023 [-0.017, +0.068]	0.318
	Overall near-hit	0.399	0.409	+0.010 [-0.013, +0.035]	0.463
	Overall strict	0.148	0.161	+0.013 [-0.002, +0.029]	0.168

Note: Each adjacent comparison contains 50 paired cases; H compares profile 100 with 000, N compares 110 with 100, and S compares 111 with 110. H bundles hierarchy with rendered leaves, N bundles route organization with navigation cues, and S bundles skill guidance with its skill-aware prompt. Difference is with-package minus reference; recall denominators include scored facts only; intervals resample 10 company clusters with all five within-company queries retained; exact two-sided *p*-values use all 2^{10} company-level label permutations and are nominal and unadjusted; bold marks nominal $p < 0.05$. Non-significant increments do not establish equivalence.

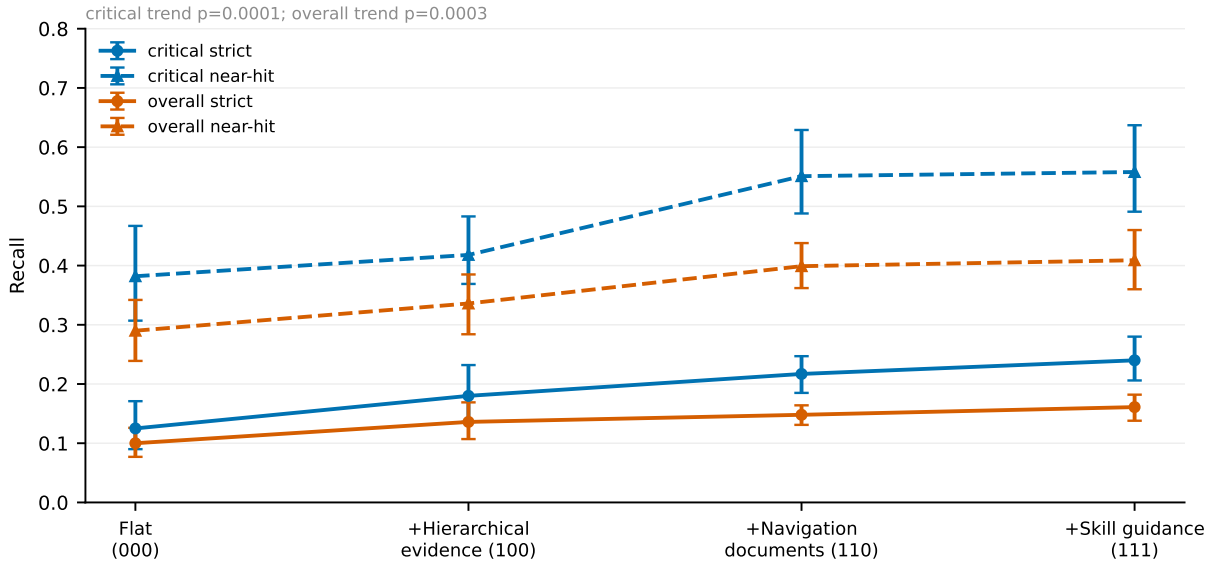


Figure 2: Sequential interface ablation. The largest adjacent near-hit increase occurs when navigation documents are added; points show pooled recall estimates with 95% company-cluster bootstrap CIs.

In the published runs, 98 of 100 Stage A runs stopped after reaching the threshold; the per-arm counts appear in Appendix A.12. This confirms that the selected point applied spending pressure to both interfaces without making their interactions identical.

Fixed-budget result. At this fixed-budget operating point, the overall near-hit contrast remains positive; the other three planned contrasts are not significant. On the frozen 3,321-fact benchmark, procedure-index records 0.297 versus 0.254 for embedding, with the planned exact company-cluster $p = 0.059$ in Table 4; this is suggestive rather than conventionally significant. Overall strict is 0.097 versus 0.084 ($p = 0.324$); the critical contrasts are not significant. All 50 cases per arm pass protocol checks.

Table 4: Fixed-budget boundary check: the overall near-hit difference remains positive and suggestive at this operating point; the other three planned contrasts are not significant. Cells report pooled fact recall with 95% company-cluster bootstrap CIs.

Metric	Embedding	Procedure-index	Difference	<i>p</i>
Critical near-hit	0.373 [0.329, 0.411]	0.423 [0.356, 0.497]	+0.050	0.293
Critical strict	0.145 [0.116, 0.170]	0.141 [0.104, 0.177]	-0.004	0.906
Overall near-hit	0.254 [0.227, 0.284]	0.297 [0.259, 0.338]	+0.044	0.059
Overall strict	0.084 [0.073, 0.098]	0.097 [0.078, 0.118]	+0.012	0.324

Note: Both arms contain 50 runs; difference is Procedure-index minus Embedding; recall denominators include scored facts only; planned contrasts use exact two-sided company-cluster permutation p-values; p-values are nominal and unadjusted; bold marks nominal $p < 0.05$; protocol eligibility and scored counts are 50/50 for both arms.

Interpretation. The fixed-budget result shows that the overall near-hit signal remains visible when both complete interfaces operate at the shared evidence-access budget threshold. This provides an initial operating-boundary observation for procedure-index rather than a budget decomposition of the main result. Because the two-stage protocol and run generation also differ, the fixed-budget evaluation does not identify how much of the main-protocol gap is attributable to spending.

6 Qualitative Analysis

6.1 Case Selection

The aggregate results show a fact-coverage difference; they do not identify its mechanism or establish that recalled facts were supported by opened evidence. This section asks whether available traces are consistent with one qualitative account and shows its boundary. The cases were selected post hoc—Case A as a traceable success regime, Case C as the largest fixed-budget per-question gap, and Case D as the largest main-comparison reversal—to illustrate and bound the account, not to test it. Scores come from run artifacts; case names are pseudonymized and routes are coarsened. We report the selection rules, metrics, aggregate access observations, alternatives checked, and verification boundary, but do not release path-level case artifacts.⁰

6.2 Dispersed Evidence: Structure Exposes Regions

Each embedding step writes a semantic query, receives up to the requested top- k documents, fetches selected results, and repeats; at every step, the visible surface is the returned rows. Each index step reads a directory or navigation document, descends into a typed module, and opens evidence items; navigation artifacts expose more of the corpus organization before item selection.

Top- k retrieval requires each document to rank highly before the agent can see it. This can favor overview material that resembles broad company-level queries across repeated searches. Decision-relevant facts often appear instead in event-specific documents, each matching only a narrow part of the query and remaining below the visible cutoff. Structured traversal reduces this dependence on rank competition for typed evidence regions. A 2018 financing event need not outrank overview documents if traversal reaches a financing-history route; visibility then depends partly on collection structure rather than only on local similarity score.

The interfaces also expose different information about what has not been inspected. The embedding agent sees only returned rows. The index agent can inspect module existence and route inventories, although an unvisited or weakly aligned evidence item still prevents a source-grounded conclusion.

⁰Path-level case materials remain excluded under the release boundary in Section 9, so the reported cases do not permit independent reconstruction of path-level claims.

Event-level facts below the visible ranking cutoff (Case A) Critical near-hit is 0.333 for embedding and 0.750 for procedure-index. Documents associated with the index answer’s distinctive facts exist in the shared frozen snapshot and in the embedding vector store, yet appear in none of the embedding run’s search observations or fetches. That run completed six successful broad searches centered on company overview, financial performance, and market position. The procedure-index run instead visited ownership, financing, risk, and cross-module evidence-map regions, then covered financing and regulatory facts missing from the embedding answer. At this case level, the observed gap occurs before document selection and is consistent with structured navigation making a narrow evidence region visible.

Negative turning points exposed by a cue-bearing index view (Case C) Critical near-hit is 0.273 for embedding and 0.909 for procedure-index. The embedding-visible material emphasized neutral company descriptions, while negative turning-point facts appeared only after index traversal. The embedding answer produced a uniformly positive profile and reported sales-relevant leads as “not covered.” The index trace’s high-signal view—itsself a cue-bearing artifact, not just a path—exposed a failed public test, a layoff plan, and an industry-ranking drop, which its answer turned into sales entry points. This is the largest per-question gap at the shared \$0.40 evidence-access budget threshold; as a selected extreme, it shows the same trace pattern can occur without a higher threshold.

6.3 Concentrated Evidence: Ranking as a Shortcut

The aggregate advantage is not uniform across questions. In critical near-hit, procedure-index is higher on 39 of 50 main cases, tied on 2, and lower on 9; only 3 of 50 also reverse on overall near-hit. Under the fixed-budget evaluation, the critical near-hit reversal count rises to 19 of 50 while the pooled difference remains positive. These exploratory counts motivate inspection of where the qualitative account fails.

The largest full reversal is Case D, industry-sales analysis: critical near-hit is 0.526 for embedding versus 0.238 for procedure-index, with zero contradicted facts on both sides. The reversal survives counting the embedding agent’s two unscored critical facts as misses (0.476 vs. 0.238). Here, several target facts concentrate in a few query-similar public articles; the most fact-dense annotation-side source supports 4 of the question’s 21 critical facts. The embedding agent reached this material in one fetch sequence. Procedure-index navigation instead landed on coarser partner and customer-record regions. When a few query-similar articles already concentrate the answer, ranking concentration can be a shortcut and route coverage a detour.

The reversal is consistent with the same account in the opposite regime: typed modules offer less advantage when they contain coarse records and the needed facts are concentrated in a few query-similar articles. This selected case motivates, but does not test, the hypothesis that route granularity matters differently across tasks.

6.4 Verification Boundary

For these qualitative cases we verified corpus parity (the associated documents exist in the embedding vector store and match document ids), model-name parity, absence of web search in the index traces, and truncation (the three documents inspected for these checks are 184–3,740 characters, below the 4,000-character fetch cap; 6.4% of corpus documents exceed that cap). We excluded one candidate case after recognizer validation changed seven fact decisions. The main budget asymmetry remains real, roughly \$0.43 for the embedding run versus \$1.67 for the procedure-index run in Case A, which is why no case study is used to convert the main system-level association into a structure-only causal effect.

7 Discussion

7.1 When Structured Navigation Helps

Across these qualitative cases, the recurring pattern is dispersion. In the selected cases, procedure-index’s higher near-hit recall coincides with target facts being spread across typed regions while broad similarity searches return overview material. Case A illustrates this event-level setting; Case C shows that the same pattern can occur under the fixed-budget constraint. The navigation surface contributes orientation and short cues, while the agent still decides which evidence items to open and which facts to retain. This division of labor is consistent with route organization helping without implying that every navigation policy is effective.

7.2 Scope and Operating Regimes

Case D marks the opposite regime: when a few query-similar articles concentrate several target facts, direct ranking can reach the useful material faster than a coarse route. It suggests a practical boundary for future tests: the value of structured navigation may depend on whether its route granularity matches the task’s fact distribution. A stronger chunked, hybrid, or reranked baseline may shift that boundary.

7.3 Policy Under Budget

The fixed-budget evaluation exposes a policy question central to agent-visible evidence access: how an interface helps an agent allocate limited model spending across search, navigation, and evidence-opening actions of different granularity. At this operating point, only the overall near-hit contrast reaches the suggestive level; the critical and strict contrasts do not. These findings motivate future policies that allocate a finite budget across high-value unvisited routes, detect when a fact-dense ranked article makes further traversal unnecessary, and reserve enough context for synthesis. Evaluation should pair those policies with fact-to-opened-source attribution so improvements in answer coverage can be distinguished from unsupported recall.

8 Limitations and Open Questions

Baseline. The baseline is conservative: whole-document BGE-M3 without chunking, hybrid retrieval, or reranking, under a capped search protocol. A stronger retrieval stack could shift the observed main gap. The fixed-budget evaluation yields a positive but suggestive overall near-hit contrast at one constrained operating point; since protocol and run generation change together, it does not explain the main-protocol difference. The study does not directly compare procedure-index with a Corpus2Skill-like generic navigation hierarchy and therefore does not identify procedure alignment itself as the cause of the observed system-level difference.

Generation and inference. Each case ran once per arm with unpinned endpoint-default decoding. Company-cluster inference preserves dependence among the five queries for each company, but with only 10 clusters it is coarse and does not measure generation variance; generation noise could move individual estimates in either direction.

Scope and reproducibility. The main treatment is system-level (Section 4.3), and the benchmark covers one Chinese-language company due-diligence domain whose licensed fact statements cannot be released. The LLM recognizer has same-configuration and independent-judge retests but no sampled human audit. Fact recall is neither precision nor citation-supported recall, so parametric memory may contribute; case and subgroup analyses are post hoc; and cost accounting omits comparable build cost. Generalization, stronger retrieval baselines, navigation-design search, and fact-to-source attribution remain future work.

9 Conclusion

In this access-controlled company due-diligence setting, the complete procedure-index interface records higher final-answer fact coverage than the whole-document embedding baseline across all four primary metrics. The sequential interface ablation identifies strict-recall increments from hierarchical evidence and near-hit increments from navigation documents; at a shared \$0.40 evidence-access budget threshold, the fixed-budget evaluation retains a positive but suggestive overall near-hit contrast, with no significant difference on the remaining metrics. Selected qualitative cases are consistent with higher coverage when facts are dispersed across evidence regions and also show a boundary where query-similar documents already concentrate the answer. Taken together, the study provides a fine-grained evaluation of one procedure-structured navigation interface under a disclosed fact-level measurement contract, rather than evidence for a universal replacement for retrieval. The scope remains one domain, one whole-document embedding baseline, and system-level interfaces; the measured outcome is answer coverage rather than verified evidence use.

Availability. This preprint release contains the paper source, generated tables, bibliography inputs, and rendered figures. We will release supporting experimental code incrementally in subsequent project stages. The licensed document collection and benchmark fact statements cannot be released; the appendix documents their construction and statistics. Because the internal Answer skill and traversal sequence are not included, this release supports interpretation of the reported aggregates but not complete reproduction of the procedure-index arm. Raw answers, raw judge output, raw traces, full case files, local paths, licensed documents, and benchmark fact text are not part of this release.

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A Supplementary Benchmark Notes

A.1 Versioned-Liquid Benchmark and Frozen v2 Timeline

The benchmark follows a versioned-liquid lifecycle. Between releases, new evidence and query-relevant facts may update the evaluation fact set. Within a formal evaluation, however, the target snapshot is fixed and is not exposed to the agents. The present study uses v2 as its sole target snapshot. V2 was versioned and frozen on June 23, 2026. It contains 3,321 query-scoped answer targets over 10 companies, five query types, and 50 cases: 584 critical, 1,719 important, and 1,018 relevant. All reported recall estimates draw from this fixed v2 target set. For each arm, primary estimates use that arm’s scored target facts in the relevant scope as the denominator. The main-comparison sensitivity analysis instead assigns zero credit to unscored decisions over all frozen targets in the corresponding scope.

Construction proceeded through versioned stages. The initial stage assembled 2,665 targets in total from the pre-collected evidence base, constructed separately for each of the 50 company-query records. The schema required every candidate to contain one atomic answer statement, detection words, at least one evidence record, its query scope, a priority label, and a merge key. The repository retained the final records, schema, manifest, and review notes, but intentionally excluded the original generation prompts, model streams, and runner scripts. We can therefore audit the resulting fields and evidence records, but cannot fully reconstruct the first-pass candidate-generation procedure or model from the public versioned artifacts.

The available construction records characterize this seed as primarily web-search-led. The evaluated collection, by contrast, integrates multiple non-public, internally maintained data sources. Closed-world scoring gives no credit to a valid, query-relevant fact that is absent from the current target set. The enrichment path addresses such reference-set omissions in later releases. Answer text supplies discovery signals only; evidence, relevance, atomicity, and duplicate/merge review determine admission. A candidate cannot change the denominator used to score the run that surfaced it.

The recorded human quality pass scanned every critical target across all 10 companies and five queries. It used one company as a calibration example and then downgraded generic registration details, background narrative, absence-of-record claims, weak industry leads, and duplicate formulations to important or relevant. The notes also record parse checks, required-field checks, and duplicate merge-key checks for every company-query group. The versioned review notes do not record the number of individual reviewers, the author of each decision, any independent duplicate annotation, or a formal disagreement-adjudication procedure. We therefore report no inter-annotator agreement and do not claim that the priority labels were independently replicated.

An enrichment stage admitted LLM-assisted candidates. Admission required `action=add`, a positive promotion verdict, one atomic fact, no review or promotion issues, a resolvable evidence path, and no duplicate/merge conflict. Candidates needing evidence or splitting, duplicates, rejected items, unresolved evidence, and non-atomic accepts were excluded. Priority labels use an operational decision rule: *critical* means omission would materially weaken the conclusion for that query, with preference for regulatory filings, announcements, annual reports, prospectuses, official records, strong media, or corroborated sources; *important* supports a key answer judgment; and *relevant* supplies lower-weight context or a lead.

The longer-term maintenance design also aims to bound high-priority-set growth through budgeted selection, demotion, or downgrade rather than unlimited addition. That maintenance mechanism was not used to construct v2: the reported update admitted additions and did not apply a replacement stage. We therefore describe it as future benchmark maintenance, not as part of the reported experimental procedure.

Synthetic worked example. For a credit-and-supplier query, suppose an official regulator notice states that Company X received a material penalty in 2024 for a control failure. The candidate is written as one query-scoped statement—not as the whole notice—with the regulator notice as evidence, detection terms for the event, and a merge key combining event type and date. A second answer-derived paraphrase is merged rather than admitted as another target. The fact is critical only if omitting the penalty would materially alter the credit-risk conclusion; otherwise it is important. An answer sentence alone

cannot supply the evidence record. This example is synthetic and does not disclose any benchmark statement.

The initial review was not designed as a blind annotation experiment. Some admitted candidates were discovered from earlier procedure-index answers, so their candidate provenance was known. This is a property of the update path, not same-run target exposure: evidence and merge gates determine admission, and the source runs retain their earlier frozen denominator.

A.2 Update Review and Evidence Audit

Benchmark updates may use answer-derived discovery signals when an answer reveals a material claim absent from the current snapshot. Answer text is not benchmark evidence: admission requires a specific and atomic claim, reviewable supporting evidence, query relevance, and duplicate-or-merge review. A reviewed candidate can enter only a later frozen snapshot.

Evidence references for the admitted subset were checked against the frozen company build manifests and the flattened embedding store. This subset audit supports the availability of those cited source documents; it does not establish complete document-id parity between the two full representations.

A.3 Run Chronology and Main-Row Provenance

The sequential interface ablation and fixed-budget evaluation generated their answers after v2 was fixed, so neither supplied candidates to its own scoring denominator. The main procedure-index row has a different provenance: it is an imported historical answer batch rescored on v2, not a post-freeze rerun. Run identifiers recorded as sources for admitted candidates also occur in that historical batch. Run-identifier overlap establishes provenance overlap, not byte-identical answers, because the benchmark release metadata did not retain answer digests. We therefore treat this as a construction limitation on the main comparison, not as same-run target exposure, and do not present the main row as an independent validation of benchmark construction.

A.4 Review and Apply-Side Validation

Answer text is a discovery signal, not a gold source. A material claim becomes a benchmark fact only after review confirms that it is specific, query-relevant, not a duplicate of any fact with full or partial coverage or a contradiction flag in the same run’s coverage audit, and supported by reviewable evidence. The implementation separates three roles: the Answer Fact Recall judge produces the closed-world coverage audit used for scoring; a separate enrichment path extracts answer-side material claims, shapes them into candidate facts, and uses LLM-assisted review and, when available, local evidence supplementation or repair; apply-side validation then blocks candidates whose review output is not safe to carry into the next frozen snapshot.

These checks are construction-quality safeguards, not experimental variables. They include an LLM-assisted candidate review decision, local evidence supplementation or repair for issues with evidence, time, or verifiable elements, resolvable and sufficiently specific evidence routes, fact granularity suitable for answer-level scoring, and duplicate or merge-key checks before the fact enters the next frozen benchmark snapshot. They do not change any current-run recall denominator.

A.5 Unsourced-as-Miss Sensitivity

The main embedding and procedure-index arms contain 66 and 126 unscored decisions, respectively. To avoid a missing-at-random assumption, we recompute all four outcomes over the complete frozen target set and assign every unscored decision zero credit. Table 5 shows that all four gaps remain positive and close to the primary estimates. This check changes only the denominator rule; it does not invoke a new judge or repair any decision.

Table 5: Main-comparison sensitivity with unscored decisions counted as misses.

Metric	N	Embedding	Procedure-index	Δ
Critical near-hit	584	0.389	0.510	+0.122
Critical strict	584	0.127	0.250	+0.123
Overall near-hit	3,321	0.265	0.389	+0.124
Overall strict	3,321	0.081	0.187	+0.106

Note: denominators are fixed to all frozen targets in each scope; every unscored decision contributes zero. Embedding has 66 unscored decisions and procedure-index has 126 of 3,321.

A.6 Case De-identification

Case exhibits were assigned Case A–D codenames using a mapping retained outside this release. We removed real company names and aliases, registry and company identifiers, people names, local paths, source filenames, hashes, and identity-bearing directory segments. Mechanism-relevant route categories and approximate magnitudes were retained only where needed to interpret the access pattern. The case descriptions use coarsened regions such as financing, risk, ownership, or cross-module evidence maps rather than raw audit locators.

A.7 Main-Comparison Prompt Contracts

Below are non-executable, instruction-level English translations of the Chinese prompt contracts recorded for the two main arms. They preserve the disclosed instruction order. Bracketed placeholders replace the company and query, local paths, and the proprietary internal traversal sequence; neither prompt exposed the evaluation targets or their target-fact content. The procedure-index arm could consult an existing company-index Answer skill. That skill’s internal text is part of the bundled system implementation and is not reproduced in this preprint.

Embedding-arm prompt (translated).

You are a rapid pre-investment/M&A due-diligence analyst. This run is the embedding-agent MCP baseline. Use only the following embedding-recall tools to obtain evidence:

- `embedding_recall.search`: express the semantic query as a continuous natural-language evidence need, not as keyword filters;
- `embedding_recall.fetch`: read the bounded evidence text for handles returned by search.

Do not use web search or fetch, local files, repositories, a local index, a private corpus, or the shell. Do not pass a company identifier or filters to search; the policy is cross-company. Complete at least one successful fetch before answering. If evidence is insufficient, say so using the fetched evidence.

Shared answer task. Answer the original query as a rapid pre-investment/M&A due diligence. The baselines differ only in available evidence, not in requested analytical coverage. Attach a checkable source name, URL, or permitted evidence handle/path to key claims. Prioritize identity, financial performance, business/products, financing/capital markets, governance, legal/compliance, supply chain/customers, and major risks. Preserve the subject, time or scope, event or metric, and value or conclusion of important facts; do not substitute a different period, entity, or measurement basis. Mark facts not covered by permitted evidence rather than filling them from memory.

Budget. At most six searches; default top- $k = 10$, maximum top- $k = 20$; fetch at most 30 documents and 4,000 characters per document.

Original query. [ORIGINAL QUERY]

Procedure-index-arm prompt (translated and redacted).

Use the company-index skill’s Answer flow to answer the question. The complete **Shared answer task** block above was repeated verbatim.

Important constraints.

- The working directory is an existing read-only index root containing multiple candidate companies: [EXISTING INDEX ROOT]. The target company identifier is not supplied. Locate the subject from the company name or context in the user query.
- You may consult [INTERNAL ANSWER SKILL]. Read, search, and analyze only existing index files. Begin at the located company’s existing entry point and follow its navigation to concrete evidence files. [INTERNAL TRAVERSAL SEQUENCE REDACTED.]
- The final answer must contain an “Evidence Sources” section with a Markdown table mapping each key conclusion to concrete, existing evidence files. Do not substitute directories, navigation summaries, wildcards, ellipses, or aggregate counts for those files. When a conclusion depends on multiple records, list the key records separately.
- If the index lacks enough evidence, list the concrete files checked, state the gap, and do not invent paths. Do not build, rebuild, download, collect, or complete the index. Do not create, write, copy, move, or delete files or directories.

User question. [ORIGINAL QUERY]

The statement in the shared block that baselines differed only in available evidence described task semantics: it held requested analytical coverage constant. It did not claim identical full prompt contracts. Both prompts supplied the same original query and excluded benchmark targets; their evidence-access instructions differed, only the procedure-index arm included skill guidance, and the procedure-index prompt imposed no numeric search or fetch budget.

A.8 Corpus and System Configuration

The procedure-index and flattened embedding representations were derived from the same underlying local source environment. The shared frozen snapshot contains 29,688 materialized Chinese-language evidence documents, distributed across the 10 companies as summarized in Table 6. Document counts and length statistics are computed from the flattened vector-store document file and validated against its build manifest. This release does not include a complete endpoint-level record of attempted, failed, or rejected upstream collection operations; the table therefore characterizes the realized snapshot rather than a collection-success rate.

Table 6: Per-company statistics of the shared frozen snapshot, computed from the flattened vector-store document file.

Item	Value
Documents	29,688
Documents/company (min / median / max)	598 / 2,722 / 5,966
Characters/document (median / p90 / p95)	556 / 2,717 / 5,442
Documents over 4,000 chars	1,908 (6.4%)
Documents over 8,000-char input cap	1,079

The main-comparison system configuration—shared answer-model name and harness, separate run generations, arm-specific representation, tools, prompts, and budget, unpinned endpoint-default decoding—is specified in the main text; the recognizer is a separate closed-world coverage model.

A.9 Legacy Public-Web Reference Rows

Table 7 reports the legacy web-only and hybrid rows on the same frozen benchmark. They are historical imported baselines whose discovery surface includes the public web, so they serve as reference context rather than paired arms: they were not rerun under the main protocol and are excluded from all planned contrasts. Their strong critical near-hit recall indicates what public-web discovery can reach; the controlled question of this paper is what local evidence organization contributes over the same local corpus.

Table 7: Legacy public-web reference rows on the same frozen benchmark. Historical imported baselines with a different discovery surface; not paired reruns and excluded from all planned contrasts.

Metric	Hybrid-Web	Web-Only
Runs	50	50
Critical NH	0.664 [0.614, 0.726]	0.692 [0.632, 0.761]
Critical strict	0.288 [0.243, 0.345]	0.317 [0.265, 0.384]
Overall NH	0.405 [0.361, 0.450]	0.405 [0.367, 0.447]
Overall strict	0.139 [0.118, 0.160]	0.138 [0.122, 0.155]

Note: NH = near-hit recall; strict = fully expressed fact recall; recall denominators include scored facts only; CI = company-cluster bootstrap percentile interval over 10 companies.

A.10 Recognizer Reliability

To bound serving-side scoring noise, we first re-scored every main-comparison answer with the identical DeepSeek recognizer configuration (same prompt version and configuration hash, temperature 0). Agreement was high and symmetric across arms, and all four planned main contrasts remained at $p \leq 0.004$. We then repeated the same closed-world scoring pass with an independent GLM-5.2 judge. Table 8 reports the cross-judge agreement: both arms contain all 50 answer blocks, all 3,321 fact decisions join by fact key, and no answer is skipped. The GLM-5.2 pass is more conservative on strict recall, but the difference is not arm-differential and all planned contrasts remain at $p \leq 0.002$.

Table 8: Recognizer cross-judge agreement on the main-comparison answers (DeepSeek primary judge vs. GLM-5.2 secondary judge).

Arm	Status	Coverage (κ)	Strict (κ)	Near-hit (κ)
Embedding	98.0%	90.1% (0.78)	96.9% (0.75)	91.2% (0.78)
Procedure-index	96.2%	89.1% (0.81)	95.2% (0.83)	92.1% (0.84)

Note: per-fact decision agreement between the two scoring passes over 3,321 joined decisions per arm. Between the passes no pooled recall estimate moves by more than 0.057, and the largest planned-contrast p-value is 0.002.

These checks bound recognizer sensitivity; they do not establish agreement with human judgment. The closed-world contract provides an additional mechanical check on positive decisions: every covered or partially covered fact must quote a verbatim span of the answer, and spans are validated against the answer text. The reported validation stops at the LLM cross-check; its result is a closed-world fact-coverage measurement, not a general human-preference judgment.

A.11 Sequential Interface Ablation Estimates

Table 9 reports point estimates and intervals for all four cumulative profiles. The main paper uses Figure 2 for the ordered pattern and Table 3 for the adjacent H/N/S package contrasts.

A.12 Fixed-Budget Evidence-Access Protocol

The fixed-budget evaluation runs every case through the same two-stage protocol. Stage A uses each arm’s usual evidence-access tools at a shared \$0.40 evidence-access budget threshold.

The \$0.40 threshold was selected through pilot calibration to create a binding evidence-access regime in both arms. The calibration criterion was operational: Stage A should encounter model-API spending pressure in both interfaces, requiring each agent to prioritize what to inspect. In the published runs, 48 of 50 embedding runs and all 50 procedure-index runs ended Stage A with `budget_exhausted`; the other two embedding runs ended `completed`. Both are protocol-legal graceful endings.

This calibration defines one experimental operating point; it does not establish \$0.40 as a deployment-optimal budget or as an optimum on a cost–recall curve. The threshold applies only to Stage A model-

Table 9: Sequential interface ablation estimates. Each cell reports pooled recall with a 95% company-cluster bootstrap CI.

Arm	Critical	Overall
<i>Near-hit recall</i>		
Flat (000)	0.382 [0.307, 0.467]	0.290 [0.239, 0.342]
+Hierarchical evidence (100)	0.418 [0.369, 0.483]	0.336 [0.284, 0.385]
+Navigation documents (110)	0.551 [0.488, 0.629]	0.399 [0.362, 0.438]
+Skill guidance (111)	0.558 [0.491, 0.637]	0.409 [0.360, 0.460]
<i>Strict recall</i>		
Flat (000)	0.125 [0.090, 0.171]	0.100 [0.077, 0.126]
+Hierarchical evidence (100)	0.180 [0.136, 0.232]	0.136 [0.107, 0.169]
+Navigation documents (110)	0.217 [0.185, 0.247]	0.148 [0.131, 0.164]
+Skill guidance (111)	0.240 [0.206, 0.280]	0.161 [0.138, 0.182]

Note: all arms contain 50 runs; recall denominators include scored facts only.

API spending during search and navigation. It is enforced at model-call boundaries, so the final atomic call can take realized spending above the nominal \$0.40 threshold. It therefore does not guarantee identical realized spending, retrieval-action counts, evidence volume, or total system cost.

Stage B resumes the Stage A conversation history as a fork and synthesizes the answer with an identical prompt and all tools disabled; Stage B spending is outside the ceiling, and no notes files or workspace artifacts carry over. Stage A remains arm-specific in representation, tools, prompts, action counts, evidence volume, and observed history. Differences in action count are therefore part of the complete-interface comparison rather than a matched experimental quantity.

Eligibility requires a legal Stage A stop, a non-empty Stage B answer, and zero Stage B tool calls; all 50 cases per arm pass.