
EMBER: Efficient Memory via Budgeted Evidence Retention for Long-Horizon Agents

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Abstract

Long-horizon agents can archive large histories, yet answering future requests still consumes retrieval and context tokens. If retained memory omits answer-relevant evidence, the system must revisit more of the raw history. We study *budgeted evidence survival*: selecting, before the query is known, the source evidence that should remain recoverable under a fixed retained source-evidence budget. We instantiate this problem as *Budgeted Pre-Query Retention*, where memory is written during ingestion and later read without access to the full raw stream. We introduce EMBER, a learned retention policy that constructs a compact, source-backed evidence state. EMBER stores evidence capsules: verbatim source excerpts paired with retrieval keys and update metadata, preserving both grounding and read-time access. Post-query outcome feedback trains the writer across the ingestion–retrieval–answer chain. On LongMemEval-RR, our LongMemEval-derived retained-evidence protocol, EMBER-14B reaches 0.3017 F1 at the 8192-token retained-evidence comparison point, compared with 0.1765 for the strongest non-EMBER budgeted baseline. Across retained source-evidence budgets, EMBER improves F1, Retain-Recall, and Read-Recall, indicating that long-horizon memory depends on evidence retained within the budget, not simply on rereading larger histories.

1 Introduction

Long-horizon agents cannot treat memory as a free raw-log archive. Bytes can be stored; usable context is consumed at read time. Documents, conversations, files, and tool traces must still be indexed, retrieved, and read through model context. When a memory write misses useful evidence, the system must broaden search or send more history back through the model.

Full-log RAG postpones the choice of what matters because the corpus remains available at read time. Query-visible memory agents see the target task before deciding what to rewrite or route, as in MemAgent [Yu et al., 2026] and learned memory-operation systems optimized for downstream QA [Yan et al., 2025, Wang et al., 2025]. Persistent agents often have neither luxury: they write memory while the future request is unknown, and the full raw stream cannot remain query-time usable. We study this as *budgeted evidence survival*. Budgeted Pre-Query Retention is the protocol: the agent builds memory during ingestion, keeps only a fixed amount of source evidence, denoted B_{ret} below, and later answers without returning to the full stream. Pre-query writing fixes when the decision is made; the objective is to allocate the budget to evidence the reader can recover and use. Efficiency here means token efficiency: the same B_{ret} should preserve more evidence useful for future answers.

EMBER learns this choice directly. It stores compact evidence capsules: source excerpts with retrieval keys that make them findable after the query arrives. On LongMemEval-RR, which keeps the LongMemEval histories, questions, and answers fixed while changing the resource regime [Wu

et al., 2025], EMBER-14B reaches 0.3017 F1 at the shared 8192-token budget, compared with 0.1765 for the strongest budgeted non-EMBER baseline.

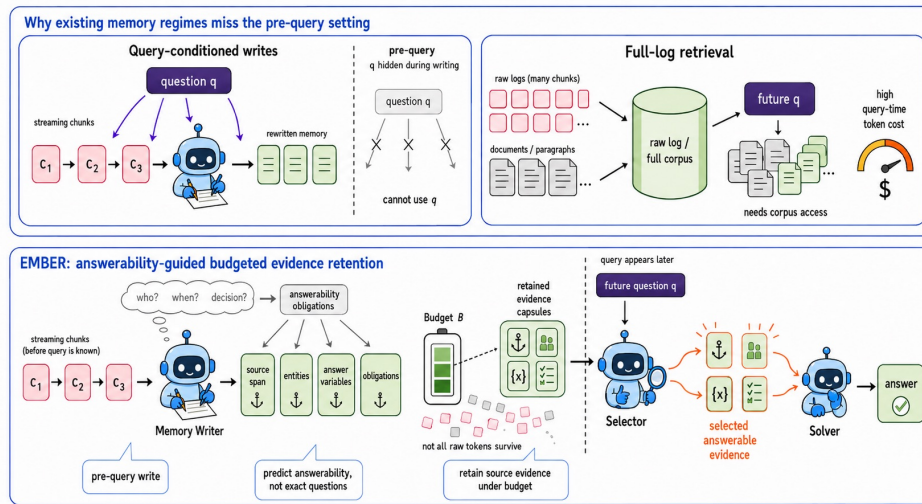


Figure 1: EMBER improves evidence survival under B_{ret} : answerability probes select source spans, and retrieval keys keep them searchable at read time.

We report Retain-Recall, Read-Recall, and F1 so the main comparison separates write failures, read failures, and final answer quality.

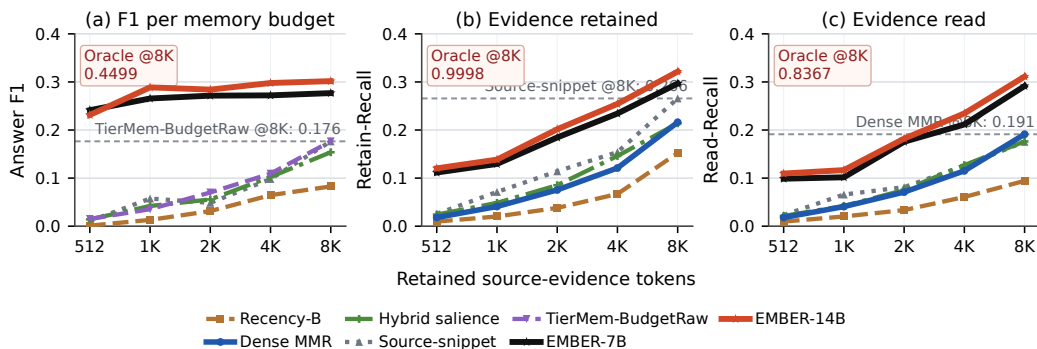


Figure 2: **Memory-token efficiency frontier.** We vary B_{ret} and report F1, Retain-Recall, and Read-Recall. The main table fixes $B = 8192$ for the cross-method comparison; this figure shows the full budget frontier. Dashed references mark the best non-EMBER budgeted value at $B = 8192$ in each panel; Oracle annotations show the matched $B = 8192$ reference.

Among budgeted evidence-survival baselines, TierMem with budgeted raw fallback gives the top F1, essentially tied with the source-snippet heuristic, while source snippets give the strongest Retain-Recall. Summaries can help answer some questions even when they leave no source-traceable evidence behind. EMBER-14B improves over both routes at the common max-budget point: it keeps more gold evidence, brings more of it into the reader, and reaches 0.3017 F1. Figure 2 extends the comparison across budgets; at the same B_{ret} , EMBER gets more gold evidence through writing and reading. At the shared 8192-token point, oracle retention reaches 0.4499 F1, leaving a measurable gap for better source selection and read-time access.

Contributions. Our contributions can be summarized as follows:

- We formalize budgeted evidence survival as Budgeted Pre-Query Retention and instantiate it as LongMemEval-RR, with metrics that separate retention from read-time access.

Table 1: Main results on LongMemEval-RR at $B_{\text{ret}} = 8192$ and top- $k = 10$. F1 is reported as mean \pm half-width of the 95% nonparametric bootstrap confidence interval over 500 examples. Budgeted rows write memory before the query is known and have no raw-log access at read time; full-log and query-visible rows are reference categories. Retained-memory and full-log rows use a GPT-4o reader after retrieval; for EMBER, 7B/14B denotes the memory-policy writer backbone. Oracle retention packs gold-annotated evidence into the same budget.

Method	Query visible at write time?	Full raw-log access?	Source-evidence budget	Retain-Recall \uparrow	Read-Recall \uparrow	F1 \uparrow
<i>Full-log references</i>						
Full raw-log RAG	No	Yes	full log	1.0000	0.6082	0.3645 \pm 0.042
TierMem with full raw logs	No	Yes	full log	1.0000	0.6152	0.4541 \pm 0.044
<i>Query-visible reference</i>						
MemAgent-7B	Yes	No	native	N/A	N/A	0.4633 \pm 0.044
<i>Upper Bound</i>						
Oracle retention	No	No	8192	0.9998	0.8367	0.4499 \pm 0.044
<i>Budgeted evidence-survival baselines</i>						
Random- B	No	No	8192	0.0612	0.0425	0.0350 \pm 0.016
Recency- B	No	No	8192	0.1521	0.0943	0.0827 \pm 0.024
Reservoir- B	No	No	8192	0.0753	0.0615	0.0498 \pm 0.019
Hybrid salience	No	No	8192	0.2140	0.1763	0.1538 \pm 0.032
Summary-only	No	No	B -equiv.	N/A	N/A	0.1156 \pm 0.028
MemAgent-7B (adapted)	No	No	8192	N/A	N/A	0.1311 \pm 0.030
Source-snippet heuristic	No	No	8192	0.2657	0.1754	0.1763 \pm 0.033
Generated-query indexing	No	No	8192	0.2021	0.1423	0.1205 \pm 0.029
TierMem with budgeted raw fallback	No	No	8192	0.1246	0.0997	0.1765 \pm 0.033
Memory-R1 (adapted)	No	No	8192	0.1714	0.1464	0.1565 \pm 0.032
<i>EMBER</i>						
EMBER-7B writer (Qwen2.5-7B)	No	No	8192	0.2966	0.2915	0.2768 \pm 0.039
EMBER-14B writer (Qwen2.5-14B)	No	No	8192	0.3215	0.3112	0.3017 \pm 0.040

Notes. Oracle retention packs annotated gold-evidence turns into the same B_{ret} ; it uses gold evidence labels during retention but no answer text at read time. Appendix Table 15 gives extended reader diagnostics where logged; EMBER rows report only the synchronized F1/Retain/Read run used in the main comparison. Appendix C.4 defines the metrics formally.

- We introduce an answerability-guided retention method that stores source excerpts with retrieval keys, keeping generated summaries and future-question guesses out of the retained object.
- We train the retention policy with answer-time outcome feedback, enabling the agent to preserve evidence that remains useful under B_{ret} .

Together, these pieces make the write step accountable: before any query is observed, EMBER must choose the source-backed capsules that will carry evidence into the read-time budget.

2 Problem Formulation

An episode consists of a stream, a future query hidden during ingestion, a retained memory state, and an answer produced from that memory under budget.

2.1 Streaming Episodes

Each episode is drawn from a distribution D and provides a stream $c_{1:K} = (c_1, \dots, c_K)$, a query q , and a target answer y . During ingestion, the agent observes the stream in order and must retain memory without access to q . After ingestion, q becomes available, and the agent produces an answer \hat{y} from its active context and retained memory.

2.2 Pre-Query Online Memory

What makes the setting hard is the timing of query access. During ingestion, the agent sees only the stream so far and its current memory state; the query q is still unknown, so a write cannot be tailored to it. Only at read time does q arrive, and the agent may then retrieve or select from the retained state. Thus, an online agent must commit memory before learning what will be asked.

2.3 Memory State

At step t , the agent maintains an active context w_t and an external memory state S_t . The active context is a fixed-size working buffer used for streaming computation and write triggering. It does not grow with the stream or with the budget, and it is not a second evidence store. The external memory S_t is the persistent state: a set of retained capsules that outlive the active context across the episode. The experimental budget B_{ret} limits retained source-excerpt tokens available after ingestion:

$$|S_K|_{\text{tok}} \leq B_{\text{ret}}.$$

Throughout, “budget” and the symbol B_{ret} both refer to this retained source-evidence token cap unless noted. Retrieval metadata is serialized and reported separately, not counted as answer-bearing source evidence. The desired memory state is evidence-grounded: it should expose retrievable handles for future queries while preserving source evidence that can be returned to the reader.

2.4 Objective

The agent’s objective is to learn a policy that maps streaming observations into budgeted retained memory and later answers from that memory:

$$S_K, w_K \leftarrow \pi(c_{1:K}), \quad \hat{y} \sim \pi(\cdot \mid q, S_K).$$

In the reported retained-memory evaluations, the answer context is the query plus source excerpts retrieved from S_K ; the active buffer is fixed across methods and is not an unbounded raw-log side channel. Performance is measured by task success, such as answer correctness or F1, under B_{ret} and the pre-query protocol. Section 3 instantiates this policy with two interfaces: a pre-query memory writer that builds the retained evidence cover during ingestion, and a reader that queries this cover after the target query is known.

3 Method

3.1 Retention Policy Overview

EMBER learns a budgeted evidence-retention policy. During ingestion, the writer decides which source spans should remain in memory under B_{ret} . The maintained state is a retained evidence cover: the writer observes the stream online, proposes evidence capsules, and maintains a cover S_t under the budget constraint

$$|S_t|_{\text{tok}} \leq B_{\text{ret}}.$$

The write path has three parts. Answerability probes identify source spans that may become useful later. Evidence capsules pair those spans with retrieval keys. A budget layer admits, consolidates, or rejects proposals under B_{ret} . At read time, the reader retrieves from this cover and answers from preserved source evidence.

3.2 Answerability Probes

Topical salience alone is an insufficient write signal: a relevant passage may omit the fact, relation, date, or update needed later. EMBER uses answerability probes, schema-constrained writer decisions that identify what future needs a chunk may support. A probe specifies which source evidence should remain and how it should be found; the retained memory stores the source excerpt, not the probe text. The policy emits a title, entity anchors, surface and intent retrieval keys, an update mode, and optional update targets. In extractive mode, the writer selects a retrieval handle, update intent, and bounded source-backed excerpt under budget; the excerpt is later returned verbatim to the reader. Table 2 summarizes the write path, and Appendix A gives the schema.

Table 2: Answerability-probe pipeline for one incoming chunk. The policy emits retrieval and update fields; retained memory stores source evidence bound to those fields.

Step	Decision	Materialized field or action
Evidence test	Keep or skip the chunk	update_mode=insert/merge/overwrite/skip
Anchor selection	Which entities, dates, or relations identify the fact	title, entities
Retrieval-key generation	How a future query may retrieve the evidence	retrieval_keys_surface, retrieval_keys_intent
Source binding	Which verbatim source excerpt carries the evidence	bounded_source_snippet/focused_source
Budget update	Add, consolidate, replace, or reject under budget	BUDGETUPDATE and update targets

When a write action is selected as the training carrier, the GRPO update in Section 3.6 is applied to these emitted memory-control tokens. The stream text is the writer’s input, the future query is hidden during writing, and the source excerpt is bound from the current chunk.

3.3 Source-Backed Evidence Capsules

The retained cover consists of evidence capsules: a bounded source excerpt, retrieval keys, and token cost. The excerpt preserves stream evidence verbatim, while keys such as entities and intent descriptors make it findable after the query is known. The main budget counts source-excerpt tokens;

retrieval metadata is reported separately in Appendix Table 10. Appendix A.1 gives the structured capsule action schema. The stored object is a grounded capsule, with the source excerpt as the answer-bearing content.

3.4 Budgeted Retention

For each incoming chunk, the writer may propose candidate capsules M_t . The retained cover is updated by a budget-accounting layer:

$$S_t \leftarrow \text{BudgetUpdate}(S_{t-1}, M_t; B_{\text{ret}}).$$

BUDGETUPDATE is deterministic accounting over learned proposals: it checks source grounding, counts source-excerpt tokens, and applies valid updates. During training rollouts, it also records any over-budget mass against the sampled budget, and the reward penalizes that overrun. Reported evaluations enforce the fixed retained budget exactly: the memory used at read time satisfies $|S_K|_{\text{tok}} \leq B_{\text{ret}}$. The learned component is the proposal itself: which spans to preserve, how much source context to include, and which retrieval keys to attach. Appendix A gives the structured action schema, and Appendix B.1 describes the concrete update modes, budget checks, and consolidation rules used to maintain the cover.

3.5 Read-Time Evidence Selection from the Retained Cover

After the query is known, EMBER reads only from the retained evidence cover S_K . The reader first expresses its information need as short retrieval queries $u_{1:n}$:

$$C \leftarrow \text{Retrieve}(S_K, u_{1:n}),$$

where C contains top- k candidate capsules from the retained cover. The retriever does not search the full raw stream outside B_{ret} ; answer quality therefore depends on evidence retained during ingestion.

The selector then chooses retained evidence for the reader:

$$r \sim \pi^{\text{sel}}(\cdot | q, C), \quad \hat{y} \sim \pi^{\text{ans}}(\cdot | q, r).$$

Here r is selected evidence from preserved source excerpts. The bounded active context is used to manage ingestion and streaming state, while the reader’s answer evidence comes from retained source excerpts selected out of S_K . This read path defines our evidence metrics: Retain-Recall measures whether gold evidence survives the pre-query budget update, and Read-Recall measures whether it reaches the reader after the query is known. Outcome-gated training, described next, aligns both stages with downstream answer success.

3.6 Answer-Gated Evidence-Chain Training

EMBER trains the memory writer with an answer-gated evidence-chain objective. The objective rewards retained evidence when it survives ingestion, remains readable at query time, and supports the final answer under a sampled budget. This aligns training with the same Survive–Read–Answer bottlenecks measured by Retain-Recall, Read-Recall, and answer F1. A rollout first commits a retained evidence cover under B_{ret} before the query is known; after the query becomes available, the reader retrieves from this cover, selects evidence, and answers. The training signal gives earlier retention decisions their share of the final answer feedback. Section 4 describes the training curriculum; Appendix C.10 gives the episode construction, budget sampling, reward instrumentation, and optimizer details.

Objective. Each rollout i produces a trajectory τ_i and an answer \hat{y}_i . Let $Q_i = \text{Verify}(\hat{y}_i, y_i) \in [0, 1]$ denote final answer quality. We implement the chain with a multiplicative answer gate. The survival term is retained evidence coverage E_i ; the readability terms are lookup rank score L_i and selection purity P_i ; and W_i rewards valid source-preserving writes. All auxiliary terms are normalized to $[0, 1]$. The rollout reward is

$$\mathcal{R}_i = Q_i (\alpha_Q + \alpha_E E_i + \alpha_L L_i + \alpha_P P_i + \alpha_W W_i) - \lambda_{\text{budget}} \frac{\max(0, |S_i|_{\text{tok}} - \tilde{B}_i)}{\tilde{B}_i}.$$

Final answer quality gates auxiliary evidence rewards, so survival and readability proxies receive credit only when they support the eventual answer. The last term is the budget penalty: if the retained

Algorithm 1 Answer-Gated Evidence-Chain Training

Require: Dataset \mathcal{D} , budget grid $\mathcal{G}_B = \{512, 1024, 2048, 4096, 8192\}$, rollout group size $G = 16$

- 1: **for** each training batch **do**
- 2: **for** $i = 1$ to G **do**
- 3: Sample episode $(c_{1:K}^{(i)}, q_i, y_i) \sim \mathcal{D}$
- 4: Sample budget $\tilde{B}_i \sim \text{Uniform}(\mathcal{G}_B)$
- 5: $(S_i, w_i, \tau_i) \leftarrow \text{INGESTRETAIN}(c_{1:K}^{(i)}, \tilde{B}_i)$ ▷ withhold q_i during ingestion
- 6: $u_i \leftarrow \text{QUERY}(q_i)$; $\mathcal{C}_i \leftarrow \text{RETRIEVE}(S_i, u_i)$
- 7: $r_i \leftarrow \text{SELECTEVIDENCE}(q_i, \mathcal{C}_i)$
- 8: $\hat{y}_i \leftarrow \text{ANSWER}(q_i, r_i)$ ▷ answer from selected retained evidence
- 9: Compute answer-gated evidence-chain reward \mathcal{R}_i
- 10: Select curriculum carrier \mathcal{T}_i from τ_i ▷ write action block or read-selection turn
- 11: **end for**
- 12: $\bar{\mathcal{R}} \leftarrow \frac{1}{G} \sum_{i=1}^G \mathcal{R}_i$
- 13: $\hat{A}_i \leftarrow \mathcal{R}_i - \bar{\mathcal{R}}$ for each $i \in \{1, \dots, G\}$
- 14: Update only the selected carrier \mathcal{T}_i with a clipped GRPO-style objective
- 15: **end for**

cover S_i exceeds the sampled budget \tilde{B}_i , the overrun is normalized by \tilde{B}_i and subtracted from the reward. Thus, budget enters the evidence-chain objective: extra source evidence must improve answer-supported survival or readability enough to justify its token cost. This soft penalty is used during training rollouts to give the policy an explicit budget-aware signal across the frontier; reported evaluations use the fixed B_{ret} for comparison.

Group-relative memory-policy update. We sample $G = 16$ rollouts for each training prompt and compute a single trajectory reward for each rollout. The reported runs use $\lambda_{\text{budget}} = 0.2$, PPO clip range $\epsilon = 0.2$, KL coefficient $\beta = 0.001$, rollout sampling temperature $T = 1.0$, a 256-token cap on each source excerpt, and a 128-token source prefix in the retrieval index. For a rollout group, we compute the group-relative advantage

$$\hat{A}_i = \mathcal{R}_i - \frac{1}{G} \sum_{j=1}^G \mathcal{R}_j.$$

Let \mathcal{T}_i denote the tokens of the selected trainable carrier turn updated for rollout i . In the veRL implementation, the reward is computed from the full Survive–Read–Answer trajectory, while the PPO/GRPO loss is applied to one curriculum-selected carrier turn. In write-retention batches, the carrier is a writer action block emitted during ingestion, such as a capsule proposal or update action for one chunk window. The rollout then continues through retrieval and answering, so the selected write decision receives delayed credit from the final answer-gated reward. Across batches, different write decisions are selected as carriers, exposing the writer’s per-chunk retention decisions to this same outcome signal. In read-selection batches, the carrier is the evidence-selection turn; the answer turn is score-only and does not receive gradient. Appendix C.10 gives the token-level clipped objective and implementation details.

Algorithm 1 summarizes the rollout and group-relative update. Appendix C.10 defines the auxiliary reward terms, episode format, budget sampling, coefficient selection, token-level objective, and implementation details.

4 Experiments

Training Details. We fine-tune Qwen2.5-7B and Qwen2.5-14B [Yang et al., 2024] memory-policy backbones on external pre-query episodes, keeping the retriever fixed during rollouts. Stage I uses RULER-HotpotQA [Hsieh et al., 2024] for controlled multi-hop evidence preservation and converges in about 500 optimization steps. Stage II then runs a 100-step multi-session continuation from MuSiQue [Trivedi et al., 2022] and 2WikiMultiHopQA [Ho et al., 2020], with Stage III hard cases for stale facts, time-scoped evidence, and related-but-unanswerable contexts folded into the same continuation. Across all stages, the query is hidden during memory writing, and the budget

is sampled from $\{512, 1024, 2048, 4096, 8192\}$. The policy is therefore trained across the full budget frontier. Checkpoints and reward coefficients are selected on held-out external pre-query validation episodes, not on LongMemEval-RR or MultiQ-LongMemEval-RR; the selected coefficient vector $(\alpha_Q, \alpha_E, \alpha_L, \alpha_P, \alpha_W) = (0.45, 0.25, 0.15, 0.10, 0.05)$ is fixed for all reported evaluations. Appendix C.10 gives the episode format, optimization settings, coefficient sensitivity, seed stability, and reward-term ablations.

Benchmarks. LongMemEval-RR [Wu et al., 2025] is the main external long-horizon memory evaluation. RULER-HotpotQA [Hsieh et al., 2024] is a controlled, training-adjacent stress test. MultiQ-LongMemEval-RR and ablations then probe memory reuse and component effects.

- **LongMemEval-RR** is our LongMemEval-derived Budgeted Pre-Query Retention protocol [Wu et al., 2025], not an official LongMemEval benchmark name. It preserves the original histories, questions, and answer targets; only the resource regime changes. Methods ingest sessions before the query is known, retain a fixed budget of source evidence, and answer from retained memory without returning to the raw stream. This evaluates a natural deployment constraint for long-horizon agents: the task distribution stays fixed, while query-time raw-log access is no longer available. All LongMemEval-derived protocols are used only for evaluation.
- **RULER-HotpotQA** [Hsieh et al., 2024] is a controlled, training-adjacent stress test for evidence survival when memory is written before the question. Stage I draws from the same task family, so this benchmark probes in-distribution multi-hop retention. LongMemEval-RR provides the held-out cross-method comparison.

Baselines. We compare three baseline categories: full-log systems with raw-history access, query-visible memory agents, and budgeted evidence-survival methods. EMBER belongs to the last category: it writes memory before the query is known and answers only from retained memory. On RULER-HotpotQA, we compare with context-only Qwen models, fixed-retriever vanilla RAG, and a pre-query adaptation of MemAgent; Appendix C.3 reports its adaptation curve. Because MemAgent was designed for query-visible in-context memory rewriting, this adapted version serves as a diagnostic, protocol-matched baseline for source-evidence retention.

LongMemEval-RR Main Results. Table 1 evaluates the evidence-survival chain at $B_{\text{ret}} = 8192$, the largest budget used by the budgeted baselines. We use this common max-budget anchor to give every baseline its largest source allowance. At this anchor, EMBER-14B reaches 0.3017 F1, compared with the top non-EMBER budgeted F1 baseline at 0.1765, a +0.125 F1 gain (95% paired bootstrap CI: [+0.081,+0.169]). The closest baseline is TierMem-BudgetRaw, whose F1 is competitive despite low Retain-Recall and Read-Recall because compressed summaries can still carry answer signal without appearing as source-traceable gold evidence. EMBER’s advantage is that the answer gain travels through the source-traceable evidence chain: more gold evidence survives, more of it is read back, and final F1 rises. Figure 2 gives the corresponding efficiency frontier: at every budget level, EMBER converts the same B_{ret} into higher F1, Retain-Recall, and Read-Recall than the budgeted baselines. The tight-budget setting is already effective: at $B_{\text{ret}} = 512$, EMBER-7B reaches 0.2413 F1, above the strongest non-EMBER budgeted baseline at $B_{\text{ret}} = 8192$. This uses one-sixteenth of the budget, keeping about 7.7K fewer source tokens in the query-time memory state. For long-horizon agents, this difference becomes query-time cost: if retained memory misses useful evidence, the system must retrieve or reread larger raw contexts. At this tightest budget, EMBER-7B has slightly higher F1 than EMBER-14B despite lower Retain-Recall and Read-Recall, a small reader-side crossover within the same evidence-survival frontier. This pattern matches the training design, where the writer samples multiple budgets and learns to choose evidence under both tight and loose memory limits. Oracle retention reaches 0.4499 F1 and 0.8367 Read-Recall at the same 8192-token anchor. The full sweep in Appendix Table 12 shows how the remaining gap can move to the reader side: as the retained cover grows, fixed top- k retrieval can introduce candidate competition, so Read-Recall and F1 need not rise monotonically even when gold evidence survives ingestion. Tables 10 and 11 make the metadata accounting explicit, including a conservative serialized-budget check.

Mechanism Ablation: Survive, Read, Answer. Table 3 follows evidence through the pipeline: survival after ingestion, access at read time, and final answer F1. The ablations show that source evidence, answerability probes, and retrieval keys are coupled. Without probes, the writer keeps weaker source evidence. Without retrieval keys, more source evidence survives, but less reaches the reader. Full EMBER resolves both failures: probes choose source spans, retrieval keys bring them

back at read time, and delayed outcome training aligns the retained cover with final answer quality. The row labeled EMBER w/o outcome RL uses the same probe-and-capsule interface as EMBER; its gap to full EMBER isolates the effect of answer-gated training on write-time retention choices. The reader and prompt format stay fixed.

Table 3: LongMemEval-RR mechanism ablations at $B = 8192$. Columns track retention after ingestion, read-time access, and answer F1.

Variant	Mechanism removed	Retain-Recall	Read-Recall	F1	Failure mode
EMBER full	–	0.3215	0.3112	0.3017	Missed evidence / Aggregation errors
EMBER w/o outcome RL	Delayed outcome training	0.2651	0.2481	0.2242	Weak outcome alignment
No answerability probes	Write-time answerability cues	0.2426	0.2075	0.2031	Poor source selection
No retrieval keys	Retrieval keys	0.3032	0.2162	0.2089	Retained source is hard to retrieve/use
Generated-query indexing [Nogueira et al., 2019]	Answerability-grounded cues	0.2021	0.1423	0.1205	Query-like keys do not preserve answerability
Summary-only	Source traceability	N/A	N/A	0.1156	Compressed memory loses evidence
Oracle retention	Learned retention	0.9998	0.8367	0.4499	$B = 8192$ oracle reference

MultiQ Coverage Ablation. MultiQ-LongMemEval-RR tests whether one frozen retained memory can serve multiple future tasks. Table 4 shows the failure mode of generic budgeted retention: strong heuristics preserve only 10–12% of future evidence at a 10% budget and leave coverage balance at zero. EMBER-14B preserves a broader cover and reaches 0.2767 F1, compared with 0.0824 for the strongest heuristic baseline.

Table 4: MultiQ-LongMemEval-RR retention. One retained memory serves multiple future queries over the same history. Values report the 10% budget with top- $k = 10$ retrieval. Coverage balance is the average weakest-query Retain-Recall.

Method	Budget	Mean-query Retain-Recall	Read-Recall	Group Retain-Recall	Coverage balance	F1
Recency- B	10%	0.1200	0.1200	0.1213	0.0000	0.0451
Reservoir- B	10%	0.1157	0.1157	0.1082	0.0000	0.0483
Dense MMR	10%	0.1131	0.1131	0.1141	0.0000	0.0614
Hybrid salience	10%	0.1063	0.1063	0.1071	0.0000	0.0824
Oracle retention	10%	0.6275	0.6275	0.6083	0.0517	0.3982
EMBER-7B	10%	0.2752	0.2691	0.3218	0.0312	0.2617
EMBER-14B	10%	0.3081	0.3051	0.3412	0.0356	0.2767

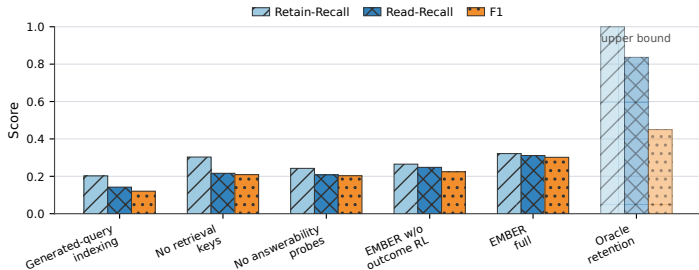


Figure 3: Evidence-loss chain on LongMemEval-RR. Each variant is evaluated at $B = 8192$ with the same reader. Bars show where evidence is lost: ingestion, read-time access, or answer use.

Controlled Pre-Query QA. RULER-HotpotQA is an in-distribution stress test for EMBER, not the paper’s held-out benchmark. Stage I trains on the same task family, so the question is deliberately narrow: whether a writer blind to the query can preserve a clean multi-hop support chain through the retained-budget bottleneck. At the 28K operating point, Table 5 shows EMBER-14B at 0.8412 ± 0.033 F1, above the strongest vanilla RAG configuration at 0.7772 ± 0.037 F1. EMBER also exceeds the query-visible references, but those rows run different protocols and are not matched to EMBER’s training distribution. We therefore use RULER-HotpotQA as a controlled stress test; LongMemEval-RR remains the held-out cross-method comparison. Appendix C.8 reports the full length sweep.

Table 5: Controlled, training-adjacent pre-query QA on RULER-HotpotQA at 28K tokens. Appendix C.8 reports the full length sweep. F1 is reported as mean \pm 95% confidence-interval half-width.

Group	Method	Query visible at write time?	Full source at read time?	F1 \uparrow
Context-only	Qwen3-8B	No	Yes	0.7108 \pm 0.041
Full-source retrieval	Vanilla RAG, Qwen3-8B, $k=8$	No	Yes	0.7772 \pm 0.037
Query-visible reference	MemAgent-7B [Yu et al., 2026]	Yes	No	0.7865 \pm 0.037
Query-visible reference	Memory-R1 [Yan et al., 2025]	Yes	No	0.8165 \pm 0.035
Budgeted evidence survival	MemAgent-7B (pre-query adapted) [Yu et al., 2026]	No	No	0.2606 \pm 0.039
Budgeted evidence survival	Memory-R1 (pre-query adapted) [Yan et al., 2025]	No	No	0.3124 \pm 0.041
Budgeted evidence survival	Source-snippet retention	No	No	0.7353 \pm 0.039
Budgeted evidence survival	EMBER-7B (Qwen2.5-7B)	No	No	0.8195\pm0.034
Budgeted evidence survival	EMBER-14B (Qwen2.5-14B)	No	No	0.8412\pm0.033
Δ vs strongest Vanilla RAG				+0.0640

Notes. Budgeted evidence-survival rows write memory before the question is known and answer without full-source access. RULER-HotpotQA is in the Stage-I task family, so this table is a controlled in-distribution stress test; the held-out cross-method comparison is LongMemEval-RR. Full-source and query-visible rows are reference categories, not distribution-matched head-to-head baselines.

5 Related Work

Agent memory and learned memory operations. Persistent-memory systems store long-lived interaction records or external memory substrates for later use [Park et al., 2023, Zhong et al., 2023, Packer et al., 2023, Wang et al., 2023, 2024, Chhikara et al., 2025, Anokhin et al., 2024, Xu et al., 2025]. Recent learned memory-operation methods train agents to rewrite, update, revisit, or use memory entries [Yu et al., 2026, Yan et al., 2025, Wang et al., 2025, Huo et al., 2026, Shi et al., 2026]. MemAgent and Memory-R1 are the closest examples: they make memory writing an explicit learned action over entries or rewrites. The retention question remains: before the query arrives, which source evidence should fit inside B_{ret} and remain useful after ingestion?

RAG, tiered memory, and budgeted retrieval. Retrieval-augmented and tiered-memory systems reduce read-time cost by indexing, routing, or compressing access to stored information [Lewis et al., 2020, Zhang et al., 2026, Fang et al., 2025, Zhu et al., 2026]. TierMem is the sharpest contrast: it routes among summaries and can escalate to an immutable raw-log store when summary evidence is insufficient. In our setting, the full-log fallback is outside the query-time budget, so the retention decision must happen during ingestion: which source evidence enters the small retained memory, and will it still support later answers?

Query prediction, summarization, and context compression. Document expansion, self-questioning, and evidence-utility methods improve retrieval or memory access through predicted queries, self-generated probes, or utility signals [Nogueira et al., 2019, Yang et al., 2026, Ma et al., 2025, Jain and Vedam, 2026]. Extractive and query-focused summarization select source spans under a length budget or for a known information need [Liu, 2019, Dong et al., 2018, Dang, 2006]: the objective is document coverage or relevance to an observed query. Related context- and cache-compression work reduces read-time text or hidden-state footprint. These directions reduce the cost of using an available context or corpus. EMBER stores source excerpts with write-time answerability cues and retrieval keys, so retained evidence can be recovered under the query-time budget.

6 Conclusion

This paper treats long-horizon memory as a retained evidence state under a fixed token budget. The results on LongMemEval-RR and MultiQ-LongMemEval-RR show that a compact memory can outperform generic retention and budgeted raw fallback when the write step preserves evidence the reader can later recover. This view makes memory quality auditable: the retained state can be inspected for the source evidence it carries, the evidence it loses, and the retrieval failures that remain. Appendix C.1 discusses how the same evidence-state view extends to persistent agent memory.

7 Limitations and Broader Impact

We evaluate EMBER on controlled long-horizon memory benchmarks, not deployed assistant systems. Scores depend on evidence-label granularity, retained-token budget, and the reader/retriever; deploy-

ments may add variation from user-specific histories, evolving preferences, privacy constraints, and memory drift. We estimate training-seed variance with three EMBER-7B runs. Selective retention can reduce the amount of history read at query time, making memory more compact and auditable, but it can also preserve sensitive, stale, or misleading evidence. Deployed systems should provide inspection and deletion controls, respect user intent before preserving private evidence, and treat retained memory as auditable application state, not invisible model context.

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A Prompt Templates (Schema-Constrained JSON)

A.1 Memory Writer Prompt

```
SYSTEM: You are a memory writer. Output ONLY valid JSON.
GOAL: Convert the current stream chunk into source-evidence capsule actions
and a compact residual context.
CONSTRAINTS:
- produce source-evidence capsule actions when the chunk contains durable
  evidence
- emit a skip action when the chunk adds no evidence worth retaining
- each action uses insert / merge / overwrite / skip
- keep retrieval keys concise
- preserve source evidence needed for future answers through source excerpts
- residual active context must be compact
INPUTS:
- current_chunk: ...
- candidate_context: ...
- related_capsules:
  [ {id, title, entities, retrieval_keys, source_excerpt, version, update_mode
    }, ... ]
- retained_memory_state: ...
- usage_signals: ...
- budget_state: ...
OUTPUT JSON SCHEMA:
{
  "memory_items": [
    {
      "title": "...",
      "entities": ["...", "..."],
      "retrieval_keys_surface": ["...", "..."],
      "retrieval_keys_intent": ["...", "..."],
      "focused_source": "...",
      "update_mode": "insert|merge|overwrite|skip",
      "merge_target_id": "..."
    }
  ],
  "residual_context": {
    "pointers": ["...", "..."],
    "active_frontier": ["...", "..."],
    "residual_local_context": ["...", "..."]
  }
}
NOTE: This JSON is the memory-writer action format. The stored form is a
retrieval-indexed source-evidence capsule materialized from these fields.
For \texttt{skip}, the writer emits only the update mode and no source payload.
```

A.2 Task-Solver Prompt (Query Generation)

```
SYSTEM: You are a retrieval query generator. Output ONLY JSON.
GOAL: Produce 1-3 short retrieval queries for the current question.
CONSTRAINTS:
- each query <= 12 tokens
- diversify queries: entity-based + intent-based
OUTPUT:
{"queries": ["...", "..."]}
```

A.3 Memory Writer Evidence Selection Prompt

```
SYSTEM: You are a memory writer selecting retained source evidence.
Output ONLY JSON.
GOAL: From retrieved memory items, select the preserved source evidence
that should return to the task solver.
CONSTRAINTS:
- select the most relevant item ids for the given query
- avoid redundant or weakly supported items
- do not rewrite or compress the source excerpts
- the answer prompt will receive the selected source excerpts verbatim
INPUTS:
- query: ...
- active_context: ...
- retrieved_candidates: [ {id, title, entities, retrieval_keys, source_excerpt
  }, ... ]
OUTPUT JSON SCHEMA:
{
  "selected_ids": ["id1", "id2"]
}
NOTE: The task solver sees the source excerpts attached to the selected
items. The memory writer uses the retained-memory structure to judge
which retrieved evidence is authoritative and non-redundant.
```

B Implementation Notes

B.1 Update Modes for the Retained Evidence Cover

The writer proposes each capsule with an `update_mode` field. The budget-accounting layer executes the proposal deterministically:

`insert`

Adds a new capsule to the cover. The layer builds a stored item from the proposed source excerpt, anchors, and retrieval keys, indexes it, and charges its source-evidence token cost against B_{ret} . If admission would exceed the budget, the proposal is rejected.

`merge`

Updates an existing capsule identified by `merge_target_id`. New facts are appended and deduplicated; the title, entities, and retrieval keys are replaced with the proposal's values. The source excerpt is overwritten only when the proposal supplies a new one; otherwise the original excerpt is preserved. The merged capsule is re-embedded and re-indexed.

`overwrite`

Replaces the target capsule entirely: all fields are set to the proposed values, the version counter increments, and the index is rebuilt. This mode is used when the writer determines that the existing capsule is stale or superseded.

`skip`

No modification to the cover. The writer emits `skip` when the current observation adds no evidence worth retaining. The layer validates that no target ID or payload accompanies a skip action.

Budget rejection. Every non-skip proposal is charged a source-evidence token cost equal to the length of its source excerpt. If the cumulative retained tokens after the proposed update would exceed B_{ret} , the proposal is rejected and the cover remains unchanged. During training rollouts, over-budget proposals incur a cost penalty in the reward; during evaluation, the budget is enforced exactly.

Deduplication and consolidation. Before insertion, the layer checks for near-duplicate capsules using embedding cosine similarity. When a proposed capsule overlaps substantially with an existing

one, the writer is expected to use merge or overwrite rather than insert. Invalid references (e.g., a merge targeting a nonexistent ID) trigger a validation error and the proposal is dropped.

B.2 General Implementation Practices

- Strict JSON validation on every writer output; invalid outputs are resampled and resamples are counted as cost when desired.
- A lightweight dedup index (embeddings + hashing) identifies near-duplicate candidates for the merge and overwrite modes above.
- The retriever remains frozen during RL rollouts for training stability and a fixed read-side interface.

C Appendix

C.1 Retained Evidence State

Long-horizon memory is more than an index, a summary, or an extended context; it is a retained evidence state built before the next request arrives. Retain-Recall and Read-Recall make this state measurable by separating write-time evidence loss from read-time access failure and answer-time reasoning failure. This decomposition lets Budgeted Pre-Query Retention test memory construction rather than only retrieval quality.

Persistent assistants, coding agents, and tool-using systems accumulate dialogue, files, edits, and observations before the next request arrives. EMBER does not require these systems to archive everything as raw context; it provides a learnable interface for deciding which source evidence should remain available under B_{ret} .

C.2 Vanilla RAG K-Curve Control

Table 6: Vanilla RAG K-curve on the 28K-token pre-query RULER-HotpotQA setting, separate from the LongMemEval-RR retained-budget protocol. All rows use the Qwen2.5-7B backbone and BGE-small [Xiao et al., 2023] retriever. The control shows that EMBER’s extractive read-select gain is not explained by reduced context size alone. Values report answer F1 in percentage points.

Method	Result
Qwen2.5-7B + vanilla RAG ($k = 3$)	62.28
Qwen2.5-7B + vanilla RAG ($k = 8$)	73.08
Qwen2.5-7B + vanilla RAG ($k = 15$)	74.84
Qwen2.5-7B + extractive read-select	76.95

C.3 MemAgent Retraining for Pre-Query Writing

For the MemAgent baseline, we follow the MemAgent in-context memory algorithm but train and evaluate it under the same pre-query protocol used for EMBER. During memory-writing turns, the model receives the stream chunk and its current in-context memory state, but not the downstream question. The question becomes available only after memory construction, when the model retrieves or uses the maintained memory to answer. This is the pre-query adapted MemAgent baseline used in the main comparison. The adaptation tests whether MemAgent’s in-context rewriting interface can operate under the same timing constraint; it is not the native query-visible MemAgent setting. In the held-out curve below, retraining raises validation F1 from 0.0180 to 0.1330 and lowers unknown answers from 0.9860 to 0.8140, but the adapted interface remains weaker than source-evidence retention methods in the main comparison.

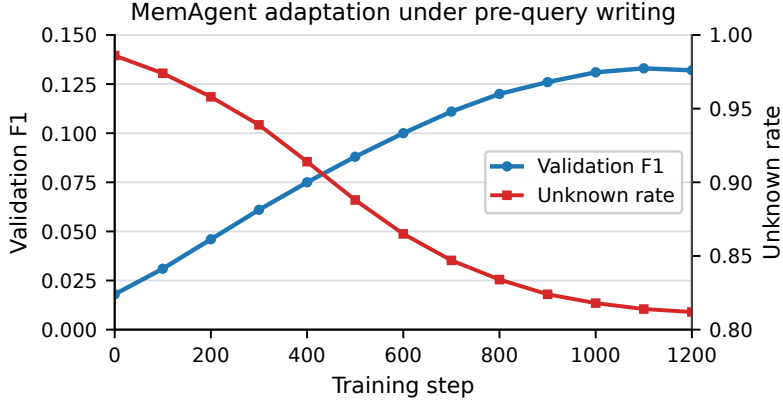


Figure 4: Retraining curve for MemAgent adapted to pre-query writing. The curve tracks the held-out pre-query objective during adaptation: memory is written before the target question is known, then evaluated after the question becomes available.

C.4 LongMemEval-RR Protocol and Extended Tables

LongMemEval-RR is a derived evaluation protocol built on LongMemEval [Wu et al., 2025]. It reuses LongMemEval histories and questions, keeps the answer targets fixed, and changes only access timing and the retained evidence budget. Methods ingest sessions online before the target query is known; after ingestion, they may use only a fixed budget B_{ret} of retained source evidence. The full raw history is outside this budget at query time, and answers must be produced from retained memory. We report Retain-Recall, Read-Recall, answer F1, Sub-EM, and budget-normalized metrics. The offline retention probe measures whether gold evidence survives B_{ret} . Table 15 reports GPT-4o reader evaluations after query-time retrieval. We release the construction script, budget settings, chunk/span rules, retained-memory wrapper, and evaluator with the benchmark artifacts.

Table 7: LongMemEval-RR protocol card. LongMemEval-RR is a derived retained-memory protocol, not an official LongMemEval benchmark name. We identify the exact input snapshot by file hash for reproducibility.

Item	Protocol specification
Source snapshot	LongMemEval-S JSON from xiaowu0162/longmemeval; input file longmemeval_s.json, SHA-256 dad95067c042691bd270bb304f02c5dad46c434874346d819181b827d5b88055.
Examples used	All 500 examples in the snapshot are used for the main LongMemEval-RR reader evaluation; no main-result examples are dropped.
Source-evidence units	Main tables use turn-level units. Each turn is rendered with session ID, date, speaker role, and turn text. Session-level probes are reported separately as diagnostics.
Gold evidence labels	Session-level gold units come from the native <code>answer_session_ids</code> field. Turn-level gold units use native <code>turn_has_answer</code> labels when present; if no positive turn label is present for an example, all turns in the annotated answer sessions are treated as gold. We do not construct LongMemEval-RR gold labels by answer-string matching.
Oracle retention	Oracle retention packs these gold source-evidence units into the same B_{ret} . It uses gold evidence labels during retention but receives no answer text at read time.
MultiQ construction	MultiQ-LongMemEval-RR groups five future questions over one compiled history. We construct 100 groups with seed 42 and target 80 sessions per group; question text is stored only as post-ingest evaluation metadata, not as an ingest-time session.
Scripts	Loader: <code>longmemeval.py</code> . Retention metrics: <code>eval_retention_probe.py</code> . Reader evaluation: <code>eval_longmemeval_rr_reader.py</code> . MultiQ builder: <code>build_multiq_longmemeval_rr.py</code> .

Retention metrics. For each query q , let $G(q)$ denote the gold source-evidence units, $M(q)$ the source-evidence units retained after ingestion, and $R(q)$ the units retrieved for the reader after the query becomes available. We measure the two points at which answer evidence can be lost:

$$\text{RetainRecall}(q) = \frac{|G(q) \cap M(q)|}{|G(q)|}, \quad \text{ReadRecall}(q) = \frac{|G(q) \cap R(q)|}{|G(q)|}.$$

Retain-Recall measures retention: how much gold evidence remains in memory after pre-query ingestion. Read-Recall measures answer-time access: how much gold evidence reaches the reader context after query-time retrieval. For budgeted methods, retrieval is performed from retained memory, so Read-Recall is upper-bounded by Retain-Recall. Low Retain-Recall identifies a write-time retention failure; high Retain-Recall with low Read-Recall identifies a retrieval or ranking failure; high Read-Recall with low F1 identifies a reader-side reasoning or aggregation failure. Methods that do not retain source-traceable units, such as abstractive summaries or native MemAgent memory entries, report N/A for these source-evidence metrics. Summary-derived signals can still help answer F1, but they are not counted as retained gold evidence unless they preserve source-traceable units. This distinction explains why a summary-heavy baseline can obtain competitive F1 while showing low Retain-Recall and Read-Recall.

Statistical reporting. Main reader tables define their uncertainty notation in the corresponding captions. LongMemEval-RR reports bootstrap confidence half-widths; the RULER-HotpotQA headline table reports 95% confidence-interval half-widths. Extended deterministic diagnostics report point estimates.

Table 8: Retention sweep and fixed-budget evidence results on LongMemEval-RR (turn-level, top- $k = 10$). Values are reported across B_{ret} .

Method	Metric	$B=512$	$B=1024$	$B=2048$	$B=4096$	$B=8192$
Recency- B	Retain-Recall	0.0096	0.0202	0.0380	0.0670	0.1521
Recency- B	Read-Recall	0.0096	0.0202	0.0335	0.0607	0.0943
Dense MMR	Retain-Recall	0.0180	0.0409	0.0754	0.1210	0.2161
Dense MMR	Read-Recall	0.0180	0.0407	0.0709	0.1151	0.1912
Hybrid salience	Retain-Recall	0.0241	0.0485	0.0852	0.1460	0.2140
Hybrid salience	Read-Recall	0.0213	0.0421	0.0752	0.1270	0.1763
Source-snippet heuristic	Retain-Recall	0.0256	0.0712	0.1141	0.1541	0.2657
Source-snippet heuristic	Read-Recall	0.0231	0.0658	0.0812	0.1258	0.1754
Oracle retention	Retain-Recall	0.9608	0.9744	0.9839	0.9960	0.9998
Oracle retention	Read-Recall	0.9576	0.9602	0.9219	0.8842	0.8367
EMBER-7B	Retain-Recall	0.1116	0.1295	0.1845	0.2343	0.2966
EMBER-7B	Read-Recall	0.0987	0.1017	0.1756	0.2116	0.2915
EMBER-14B	Retain-Recall	0.1203	0.1385	0.2016	0.2543	0.3215
EMBER-14B	Read-Recall	0.1095	0.1167	0.1821	0.2345	0.3112

Table 9: Memory-token efficiency on LongMemEval-RR (turn-level, GPT-4o reader, top- $k = 10$). Table 1 uses $B = 8192$ as the fixed cross-method comparison point. F1 per 1K retained source-evidence tokens is computed only for budgeted methods with source-traceable retained evidence. Full-log reference systems are excluded because their accessible raw-log denominator is not the retained evidence budget.

Method	Retained source-evidence tokens	Retain-Recall	Read-Recall	F1	F1 / 1K retained source-evidence tokens
Random- B	8192	0.0612	0.0425	0.0350	0.0043
Recency- B	8192	0.1521	0.0943	0.0827	0.0101
Reservoir- B	8192	0.0753	0.0615	0.0498	0.0061
Hybrid salience	8192	0.2140	0.1763	0.1538	0.0188
Source-snippet heuristic	8192	0.2657	0.1754	0.1763	0.0215
Generated-query indexing [Nogueira et al., 2019]	8192	0.2021	0.1423	0.1205	0.0147
TierMem-BudgetRaw [Zhu et al., 2026]	8192	0.1246	0.0997	0.1765	0.0215
Memory-R1 (pre-query adapted) [Yan et al., 2025]	8192	0.1714	0.1464	0.1565	0.0191
Oracle retention	8192	0.9998	0.8367	0.4499	0.0549
EMBER-7B	8192	0.2966	0.2915	0.2768	0.0338
EMBER-14B	8192	0.3215	0.3112	0.3017	0.0368

Table 10: Retained-memory accounting at the $B = 8192$ LongMemEval-RR operating point. All rows use the same 8192-token retained source-evidence cap. The main protocol charges source-excerpt tokens because they are the answer-bearing content. Retrieval metadata is serialized as index text and reported separately; it is not returned as answer content, and the reader receives source excerpts selected through the index. For EMBER, this overhead is at most 18.5% of the source-evidence cap.

Method	Source-evidence cap	Avg metadata tokens	Total serialized tokens	Metadata/source ratio	F1
Source-snippet heuristic	8192	0	8192	0.0%	0.1763
Generated-query indexing over snippets [Nogueira et al., 2019]	8192	1657	9849	20.2%	0.1205
EMBER-7B	8192	1243	9435	15.2%	0.2768
EMBER-14B	8192	1516	9708	18.5%	0.3017

Table 11: Serialized-budget accounting check on LongMemEval-RR. The main protocol budgets retained source-evidence tokens and reports metadata separately in Table 10. This stricter check charges serialized index text against an 8192-token serialized-token envelope. The EMBER rows use the existing $B = 4096$ reader runs and charge the larger $B = 8192$ metadata overhead from Table 10 as a conservative upper bound; their total serialized footprints remain below 8192 tokens.

Method	Source-evidence cap	Metadata charge	Serialized footprint for check	F1
Source-snippet heuristic	8192	0	8192	0.1763
TierMem-BudgetRaw [Zhu et al., 2026]	8192	0	8192	0.1765
EMBER-7B	4096	≤ 1243	≤ 5339	0.2721
EMBER-14B	4096	≤ 1516	≤ 5612	0.2978

Table 12: Reader F1 budget sweep on LongMemEval-RR (turn-level, GPT-4o reader, top- $k = 10$). Each cell reports a matched reader evaluation under the retained source-evidence budget.

Method	$B=512$	$B=1024$	$B=2048$	$B=4096$	$B=8192$
Recency- B	0.0012	0.0131	0.0314	0.0645	0.0827
Hybrid saliency	0.0141	0.0420	0.0556	0.1024	0.1538
Source-snippet heuristic	0.0104	0.0575	0.0485	0.0981	0.1763
TierMem-BudgetRaw [Zhu et al., 2026]	0.0151	0.0353	0.0701	0.1094	0.1765
Oracle retention	0.4843	0.5013	0.5218	0.4632	0.4499
EMBER-7B	0.2413	0.2656	0.2715	0.2721	0.2768
EMBER-14B	0.2314	0.2887	0.2841	0.2978	0.3017

Interpreting the F1 frontier. The F1 sweep tracks the same efficiency pattern as the evidence metrics: EMBER remains ahead across retained source-evidence budgets and reaches its strongest reported F1 at the shared $B = 8192$ comparison point. Retain-Recall and Read-Recall in Table 8 separate the two forces behind this frontier. More budget lets more gold evidence survive ingestion, but a larger retained cover also gives the fixed top- k retriever more candidates to rank. The oracle curve makes this visible: oracle retention nearly saturates Retain-Recall at all budgets, peaks at $B = 2048$ with 0.5218 F1, and then falls to 0.4499 F1 at the shared $B = 8192$ anchor as Read-Recall drops from 0.9219 to 0.8367. Thus 0.4499 is the matched oracle reference for the main 8192-token comparison, not a cross-budget maximum. This non-monotonic oracle behavior is not a separate anomaly; it is the read-side dilution that motivates reporting Retain-Recall and Read-Recall separately. The smallest budget remains informative: EMBER-7B at $B = 512$ reaches 0.2413 F1, already above the strongest non-EMBER budgeted baseline at $B = 8192$ (0.1765). At this single budget point, EMBER-7B has slightly higher F1 than EMBER-14B even though EMBER-14B has higher Retain-Recall and Read-Recall; this is answer-use variance when little context reaches the reader, not a retention reversal. In source-evidence budget terms, the same answer pipeline uses 512 instead of 8192 charged source-evidence tokens, a reduction of 7680 tokens, or about 94%, per query-time memory state.

Table 13: Offline retention probe on LongMemEval-RR ($\text{top-}k = 10$). The table reports the fair heuristic with the highest Retain-Recall at each retained source-evidence budget under the offline probe. Randomized baselines are averaged over five seeds, with confidence intervals reported as 95% CIs when shown; dense baselines use deterministic hashing embeddings. Session-level rows report oracle retained recall only, so oracle retrieved recall is marked n/a.

Granularity	Budget	Best fair heuristic	Retain-Recall	Read-Recall	Oracle Retain-Recall	Oracle retrieved (Read-Recall)
Session	512	Source-snippet heuristic	0.0150	0.0150	0.0270	n/a
Session	1024	Source-snippet heuristic	0.0180	0.0180	0.0810	n/a
Session	2048	TF-IDF salience	0.0358	0.0358	0.2790	n/a
Session	4096	Recency- B	0.0679	0.0679	0.7069	n/a
Session	8192	Hybrid salience	0.1297	0.1297	0.9776	n/a
Turn	512	Source-snippet heuristic	0.0256	0.0231	0.9608	0.9576
Turn	1024	Source-snippet heuristic	0.0712	0.0658	0.9744	0.9602
Turn	2048	Source-snippet heuristic	0.1141	0.0812	0.9839	0.9219
Turn	4096	Source-snippet heuristic	0.1541	0.1258	0.9960	0.8842
Turn	8192	Source-snippet heuristic	0.2657	0.1754	0.9998	0.8367

Table 14: Hybrid-salience retention probes on LongMemEval-RR. Values summarize hybrid-salience retention across single-query and multi-query retained-memory settings.

Setting	Granularity	Budget	Top- k	Retain-Recall	Read-Recall	Coverage balance
LongMemEval-RR	Turn	8192	10	0.2140	0.1763	n/a
LongMemEval-RR	Session	8192	10	0.1297	0.1297	n/a
MultiQ-LongMemEval-RR	Group	10%	10	0.1063	0.1063	0.0000

Table 15: Extended GPT-4o reader evaluation on LongMemEval-RR, derived from LongMemEval histories and questions [Wu et al., 2025]. Methods ingest turn-level histories before the query is known, then answer after top- k retrieval from either retained memory or full raw logs. Budgeted rows use $B = 8192$ retained source-evidence tokens unless noted. Full raw-log RAG and TierMem-FullRaw keep the full raw history at read time. Oracle retention is an oracle reference policy that packs annotated gold-evidence turns into the same B_{ret} before answer-time retrieval; it uses gold evidence labels during retention but no answer text at read time. Unknown is the fraction of reader outputs that abstain or cannot produce an answer. MemAgent rows store rewritten memory text; source-unit recall metrics are therefore N/A. EMBER rows report the synchronized F1/Retain/Read run used in the main comparison; Sub-EM and Unknown are not reported for those rows.

Method	Budget	Top- k	F1	Sub-EM	Unknown	Retain-Recall	Read-Recall
Full raw-log RAG [Lewis et al., 2020]	full raw	3	0.2567	0.2260	0.6180	1.0000	0.3949
Full raw-log RAG [Lewis et al., 2020]	full raw	5	0.3004	0.2640	0.5480	1.0000	0.4814
Full raw-log RAG [Lewis et al., 2020]	full raw	10	0.3645	0.3140	0.4340	1.0000	0.6082
TierMem-FullRaw [Zhu et al., 2026]	full raw	10	0.4541	0.4600	0.3820	1.0000	0.6152
Oracle retention	8192	3	0.3786	0.3420	0.4680	0.9998	0.6802
Oracle retention	8192	5	0.4104	0.3600	0.4100	0.9998	0.7527
Oracle retention	8192	10	0.4499	0.3980	0.3680	0.9998	0.8367
Random- B	8192	10	0.0350	0.0129	0.9251	0.0612	0.0425
Recency- B	8192	10	0.0827	0.0756	0.8756	0.1521	0.0943
Reservoir- B	8192	10	0.0498	0.0275	0.9214	0.0753	0.0615
Hybrid salience	8192	10	0.1538	0.1264	0.7653	0.2140	0.1763
Summary-only	B -equiv.	10	0.1156	0.0967	0.8251	N/A	N/A
Source-snippet heuristic	8192	10	0.1763	0.1285	0.7852	0.2657	0.1754
Generated-query indexing [Nogueira et al., 2019]	8192	10	0.1205	0.1065	0.7402	0.2021	0.1423
TierMem-BudgetRaw [Zhu et al., 2026] (Recency- B)	8192	10	0.1765	0.1476	0.7126	0.1246	0.0997
MemAgent-7B (pre-query adapted) [Yu et al., 2026]	8192	10	0.1311	N/A	0.8180	N/A	N/A
EMBER-7B	8192	10	0.2768	N/A	N/A	0.2966	0.2915
EMBER-14B	8192	10	0.3017	N/A	N/A	0.3215	0.3112
TierMem-BudgetRaw [Zhu et al., 2026] (Recency- B)	8192	3	0.0503	0.0480	0.9300	0.1246	0.0731
TierMem-BudgetRaw [Zhu et al., 2026] (Dense MMR)	8192	3	0.0248	0.0180	0.9560	0.0303	0.0208
TierMem-BudgetRaw [Zhu et al., 2026] (Hybrid salience)	8192	3	0.0224	0.0200	0.9720	0.0171	0.0130
TierMem-BudgetRaw [Zhu et al., 2026] (Source-snippet)	8192	3	0.0195	0.0160	0.9700	0.0147	0.0134
MemAgent-7B (query-visible) [Yu et al., 2026]	native	3	0.4633	0.4700	0.4200	N/A	N/A

Table 16: TierMem-BudgetRaw breakdown on LongMemEval-RR with GPT-4o reader, turn-level retention, $B = 8192$, and top- $k = 3$ query-time retrieval. Values report answer F1 by question type.

Question type	F1
Knowledge update	0.1995
Multi-session	0.0030
Temporal reasoning	0.0000
Single-session user	0.0786

Table 17: Diagnostic retained-budget adaptations of existing memory methods. Adapted variants ingest the same stream before the query is known, enforce the same B_{ret} , and answer only from retained memory. These rows use a Qwen2.5-14B reader and are not mixed with the GPT-4o Table 1 comparison.

Method	Original assumption	RR adaptation	Budget enforcement	Raw-log access?	Reader	Retain-Recall	F1
Memory-R1 [Yan et al., 2025]	Learned memory operations	RR retained-evidence adaptation	Hard retained budget	No	Qwen2.5-14B	0.1701	0.1524
Mem- α [Wang et al., 2025]	QA-reward memory construction	RR retained-evidence adaptation	Hard retained budget	No	Qwen2.5-14B	0.2341	0.1731
AtomMem [Huo et al., 2026]	Atomic memory editing	RR retained-evidence adaptation	Hard retained budget	No	Qwen2.5-14B	0.1792	0.1568

Table 18: Multi-query LongMemEval-RR retention probe. A single retained memory is shared by multiple future queries from the same history. Values report mean per-query retained evidence recall, retrieved evidence recall, and coverage balance under B_{ret} . For a query bundle g with queries $q_{g,1:K}$, coverage balance is $\min_j \text{RetainRecall}(q_{g,j})$, averaged over bundles; it measures whether one frozen memory also covers the hardest query in the bundle.

Top- k	Budget	Best fair retention	Mean query Retain-Recall	Read-Recall	Coverage balance	Oracle mean query Retain-Recall
3	1%	Recency- B	0.0147	0.0147	0.0000	0.0950
3	2%	Random- B	0.0265	0.0265	0.0000	0.1397
3	5%	Recency- B	0.0650	0.0645	0.0000	0.3386
3	10%	Recency- B	0.1200	0.1100	0.0000	0.6275
10	1%	Recency- B	0.0147	0.0147	0.0000	0.0950
10	2%	Random- B	0.0265	0.0265	0.0000	0.1397
10	5%	Recency- B	0.0650	0.0650	0.0000	0.3386
10	10%	Recency- B	0.1200	0.1200	0.0000	0.6275

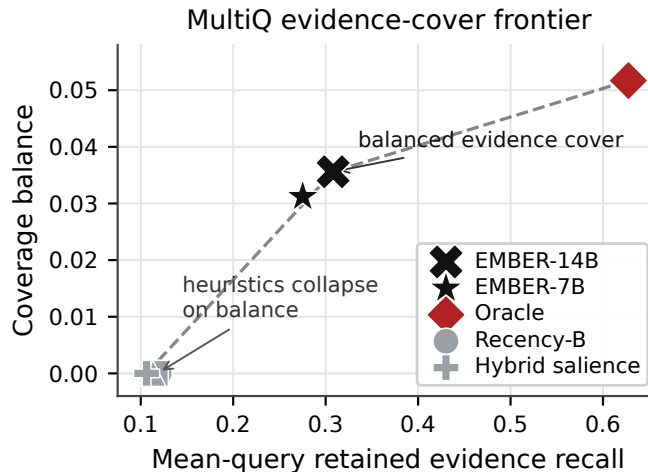


Figure 5: MultiQ coverage frontier on LongMemEval-RR. At the same 10% of B_{ret} , heuristic retention methods preserve fragments of future evidence but fail to cover all future queries. EMBER shifts the retained memory toward a more balanced evidence cover while also increasing mean-query evidence recall.

Table 19: Implementation and training infrastructure used for LongMemEval-RR rollouts.

Component	Implementation choice	Why it matters
Rollout engine	vLLM rollout server	Supports batched pre-query episodes.
Retriever / index	GPU-resident embedding index	Keeps retrieval latency controlled during budget sweeps.
Episode format	Online ingest followed by post-ingestion queries	Matches the retained-budget protocol.
Budget accounting	Soft over-budget penalty during training; hard retained budget at evaluation	Makes retained evidence cost comparable across methods.
RL interface	Curriculum-selected carrier turn	Applies the PPO/GRPO loss to one configured write or read-selection decision while scoring the full trajectory.

C.5 Compute, Assets, and Release Notes

Table 20 summarizes the execution paths used by the reported experiments. Reader evaluations use GPT-4o through Azure OpenAI with deterministic decoding. Retention probes and LongMemEval-RR reader runs share the same retained-budget wrapper and evaluation scripts. The training and rollout jobs use two GPU configurations: H200 SXM $\times 4$ and H100 NVL $\times 8$. The anonymized supplementary artifact includes the construction scripts, budget settings, evaluation commands, and wrappers needed to reproduce the reported protocol.

Table 20: Compute disclosure for the reported experiments. Exact wall-clock time depends on batching and API throughput; the released scripts specify the commands and operating points used for each run.

Experiment family	Compute path	Reported operating point
LongMemEval-RR retention sweeps	CPU preprocessing plus embedding retrieval/indexing	$B \in \{512, 1024, 2048, 4096, 8192\}$, top- $k = 10$
LongMemEval-RR reader evaluation	Azure GPT-4o reader, temperature 0	turn-level, $B = 8192$, top- $k = 10$
EMBER training	vLLM rollout server on H200 SXM $\times 4$ or H100 NVL $\times 8$	Stage I converges around 500 steps; Stage II/III continuation trains for 100 steps
MultiQ-LongMemEval-RR	Offline retained-evidence probe on CPU/GPU preprocessing path	multi-query retained-budget setting, 1–10% retained budget

Table 21 lists the main external assets. We cite the upstream sources and do not redistribute third-party model weights or benchmark data beyond derived protocol scripts and evaluation metadata. Users of the released artifact should obtain each upstream dataset or model under its own license and terms.

Table 21: External assets used by the paper and how they are used.

Asset	Use in this paper	License / terms handling
LongMemEval [Wu et al., 2025]	Source histories and questions for LongMemEval-RR	Cited upstream; users obtain upstream data under its terms.
RULER / HopQA / MuSiQue / 2WikiMultiHopQA [Hsieh et al., 2024, Trivedi et al., 2022, Ho et al., 2020]	Controlled pre-query QA training and stress tests	Cited upstream; benchmark data are not redistributed in the paper.
Qwen2.5 / Qwen3	Writer and reader backbones	Upstream model sources are credited; third-party weights are not redistributed.
BGE-small [Xiao et al., 2023]	Embedding retriever	Cited upstream; used as an external embedding model.
GPT-4o / Azure OpenAI	Reader evaluation	Used through the hosted API; model weights are not redistributed.
Prior memory systems [Yu et al., 2026, Yan et al., 2025, Wang et al., 2025, Zhu et al., 2026]	Baselines and comparison regimes	Cited upstream; adaptations are evaluated under the retained-budget protocol.

C.6 Full Rollout Procedure

Algorithm 2 expands the concise method description into the full execution procedure used by the rollout engine. The main text focuses on the retention mechanism; this appendix records the implementation sequence: online ingest, budgeted cover update, query-time retrieval from retained memory, evidence selection, answer generation, and trajectory logging for outcome training.

Here B_{work} denotes the active-context capacity used to trigger a write step when the streaming buffer grows too large. It is an implementation threshold for w , not B_{ret} . All budgeted comparisons vary or fix B_{ret} .

Algorithm 2 EMBER Rollout with Budgeted Pre-Query Evidence Retention

Require: Stream $c_{1:K}$, query q , active-context budget B_{work} , retained evidence budget B_{ret} , initial cover S_0 , writer policy π^{write} , selector π^{sel} , reader π^{ans}

Ensure: Answer \hat{y} , trajectory τ , retained evidence cover S

```
1:  $w \leftarrow \emptyset$ ,  $S \leftarrow S_0$ ,  $\tau \leftarrow ()$ 


---


2: for  $k = 1$  to  $K$  do
3:    $w \leftarrow \text{Append}(w, c_k)$ 
4:   while  $|w| > B_{\text{work}}$  do
5:      $C^{\text{maint}} \leftarrow \text{LocalMemoryState}(S, w)$ 
6:      $(M, w') \sim \pi^{\text{write}}(\cdot | c_k, w, C^{\text{maint}})$ 
7:      $S \leftarrow \text{BudgetUpdate}(S, M; B_{\text{ret}})$ 
8:      $w \leftarrow w'$ 
9:     Append the memory-control segment and log-probs to  $\tau$ 
10:  end while
11: end for


---


12:  $u_{1:n} \sim \pi^{\text{ans}}(\cdot | q)$ 
13: Append  $q$  to  $u_{1:n}$  if it is not already included
14:  $C \leftarrow \text{Retrieve}(S, u_{1:n})$  ▷ retrieve only from retained evidence
15:  $r \sim \pi^{\text{sel}}(\cdot | q, C)$  ▷ select retained evidence
16: Append the evidence-selection segment and log-probs to  $\tau$ 
17:  $\hat{y} \sim \pi^{\text{ans}}(\cdot | q, r)$  ▷ answer from selected retained evidence
18: Append solver query and answer segments to  $\tau$ 
19: return  $\hat{y}$ ,  $\tau$ ,  $S$ 


---


```

C.7 LongMemEval-S Ablation Settings

The LongMemEval-S representation ablations compare memory representations and interfaces for online ingestion. These settings are not a fully nested ablation ladder: they test different paths from streamed sessions to query-time evidence. **Online notes** asks the LLM to write generic notes before the query is known, stores the generated note text, retrieves those notes, and answers from them. This setting represents online writeable memory with weak evidence grounding: the model may organize the stream, but it can also discard source details needed later. **Source only** stores preserved source snippets directly and retrieves them at query time. It keeps answer evidence available but lacks retrieval metadata such as titles, entities, or keys. **Schema + source** augments preserved source snippets with retrieval metadata, testing whether source evidence becomes more useful future memory when paired with an explicit schema. Thus, source only is contained in schema + source, but online notes is a separate generated-memory path outside the nested source-retention ladder.

C.8 Pre-Query RULER-HotpotQA Length Sweep

C.9 Question-aware RULER-HotpotQA Accuracy

QwenLong-L1 is reported here under its native question-aware long-context protocol because it does not expose a separate memory-construction step to which pre-query writing can be applied.

C.9.1 W0 Diagnostic Probe

To localize the bottleneck of the trained policy, we use a fixed-action diagnostic rollout with the trained checkpoint. During rollout, each memory write is instrumented with provenance tags and measured whether each stored item was later recovered by retrieval, whether it was selected into the recall context, and whether it contained the gold evidence span. Table 24 reports the resulting stage-wise metrics.

The diagnostic shows that retrieval recall is not the current bottleneck: every stored item was recovered by the retriever under the default top- k setting. The remaining loss comes from write quality and read-side selection. Only 47.8% of written items contain the gold evidence span, only 41.7% of written items are selected into the recall context, and 22.7% of episodes still reach the answer stage

Table 22: Pre-query RULER-HotpotQA length sweep across input lengths up to 3.5M tokens. All methods commit memory or indexes before the question is known and see the question only at retrieval or answer time. MemAgent rows use the pre-query retraining protocol described in Appendix C.3. Because this task family is used in Stage I, the table is an in-distribution stress test; LongMemEval-RR is the held-out cross-method evaluation. Values report answer F1 on a 0–1 scale.

Model	Method	7K	14K	28K	56K	112K	224K	448K	896K	1.75M	3.5M
Qwen2.5-7B-Instruct	Context only	0.6366	0.5739	0.5237	0.0025	0.0023	0.0000	0.0014	0.0071	0.0022	0.0000
Qwen2.5-7B-Instruct	Vanilla RAG ($k = 15$)	0.7553	0.7514	0.7484	0.7416	0.7334	0.7279	0.7089	0.6633	0.6525	0.6285
Qwen2.5-7B-Instruct	Vanilla RAG ($k = 8$)	0.7331	0.7282	0.7308	0.7203	0.7142	0.7124	0.7032	0.6542	0.6401	0.6197
Qwen2.5-14B-Instruct	Context only	0.7433	0.7071	0.6447	0.0026	0.0047	0.0000	0.0030	0.0069	0.0025	0.0000
Qwen2.5-14B-Instruct	Vanilla RAG ($k = 15$)	0.7570	0.7382	0.7369	0.7532	0.7361	0.7395	0.6836	0.6793	0.6395	0.5647
Qwen2.5-14B-Instruct	Vanilla RAG ($k = 8$)	0.7412	0.7281	0.7458	0.7401	0.7156	0.7215	0.6645	0.6638	0.6196	0.5432
Qwen3-8B	Context only	0.7671	0.7570	0.7108	0.0026	0.0029	0.0017	0.0039	0.0076	0.0024	0.0000
Qwen3-8B	Vanilla RAG ($k = 15$)	0.7817	0.7685	0.7713	0.7653	0.7584	0.7715	0.7527	0.7429	0.6990	0.5563
Qwen3-8B	Vanilla RAG ($k = 8$)	0.7707	0.7542	0.7772	0.7587	0.7412	0.7653	0.7392	0.7245	0.6775	0.5502
Qwen3-14B	Context only	0.6880	0.6846	0.5478	0.0075	0.0027	0.0000	0.0087	0.0036	0.0028	0.0000
Qwen3-14B	Vanilla RAG ($k = 15$)	0.7821	0.7627	0.7755	0.7723	0.7603	0.7644	0.7010	0.7312	0.6330	0.5354
Qwen3-14B	Vanilla RAG ($k = 8$)	0.8017	0.7712	0.7542	0.7765	0.7514	0.7556	0.7125	0.7245	0.6225	0.4914
MemAgent-7B	retrained for pre-query writing	0.2929	0.2796	0.2606	0.2249	0.2597	0.2665	0.2520	0.2363	0.1500	0.2125
MemAgent-14B	retrained for pre-query writing	0.2981	0.2814	0.2069	0.2396	0.2208	0.2494	0.2476	0.2181	0.1631	0.1169
EMBER-7B	Learned memory policy	0.8342	0.8343	0.8195	0.8249	0.8116	0.8013	0.7856	0.7907	0.7927	0.7856
EMBER-14B	Learned memory policy	0.8542	0.8613	0.8412	0.8214	0.8212	0.8203	0.8023	0.7945	0.8006	0.7851

Table 23: Question-aware RULER-HotpotQA results across input lengths up to 3.5M tokens. This prior-work protocol is separate from both pre-query evaluation and LongMemEval-RR retained-budget evaluation: the model has access to the question while processing the input. Values report prior-work accuracy (%), not answer F1. MemAgent and QwenLong-L1 rows are reported by MemAgent [Yu et al., 2026]. N/A denotes lengths not reported or not supported under the corresponding prior-work setting.

Model	Method	7K	14K	28K	56K	112K	224K	448K	896K	1.75M	3.5M
DeepSeek-R1-Distill-Qwen-7B	Context only	32	12.50	3.12	0.71	0.62	1.27	0.21	N/A	N/A	N/A
DeepSeek-R1-Distill-Qwen-7B	Vanilla RAG ($k = 6$)	61.13	54.87	53.17	49.23	50.32	32.43	33.85	30.08	29.21	21.65
DeepSeek-R1-Distill-Qwen-14B	Context only	64.06	64.84	57.03	40.62	14.84	8.59	3.12	6.25	N/A	N/A
DeepSeek-R1-Distill-Qwen-14B	Vanilla RAG ($k = 6$)	69.53	70.12	71.41	46.27	45.56	42.34	37.24	32.34	33.17	30.19
Qwen2.5-7B-Instruct	Context only	55.45	56.75	53.78	50.51	47.45	26.34	7.25	N/A	N/A	N/A
Qwen2.5-7B-Instruct	Vanilla RAG ($k = 6$)	72.13	70.34	70.13	69.23	67.45	62.76	61.90	60.52	60.21	59.35
Qwen2.5-14B-Instruct	Context only	70.76	68.19	56.78	53.2	43.23	33.55	11.25	3.56	N/A	N/A
Qwen2.5-14B-Instruct	Vanilla RAG ($k = 6$)	75.64	74.34	75.14	74.12	69.53	69.67	71.74	68.54	66.32	67.79
Qwen3-8B	Context only	57.45	60.43	55.78	54.51	50.45	31.34	11.25	1.54	N/A	N/A
Qwen3-8B	Vanilla RAG ($k = 6$)	70.69	72.54	71.31	70.85	68.45	67.62	67.18	64.83	64.49	63.78
Qwen3-14B	Context only	72.23	69.10	59.28	55.17	50.82	45.09	22.13	15.42	N/A	N/A
Qwen3-14B	Vanilla RAG ($k = 6$)	75.64	74.34	75.14	74.12	69.53	69.67	71.74	68.54	66.32	67.79
QwenLong-L1-32B	Long-context RL model	72.66	75.00	72.66	60.94	31.25	17.19	13.28	11.72	N/A	N/A
MemAgent-7B	RL in-context memory	81.63	80.42	79.23	78.16	79.73	73.84	74.56	75.18	74.97	70.58
MemAgent-14B	RL in-context memory	83.69	83.23	84.54	80.86	77.68	80.73	74.90	78.03	76.43	77.09
EMBER-7B	Learned memory policy	84.32	86.53	85.43	85.67	85.17	84.78	83.05	80.42	78.56	76.67
EMBER-14B	Learned memory policy	85.64	85.42	85.08	86.32	86.54	83.65	81.87	81.52	76.61	76.14

without selected gold evidence. This points to write quality and read-side selection; retrieval capacity alone is not the bottleneck.

C.10 Training and Reward Details

Algorithm 1 in Section 3.6 summarizes the training rollout and group-relative update. This appendix gives the instrumentation, episode construction, coefficient selection, and token-level objective used by that algorithm.

The auxiliary reward terms in Section 3.6 are computed from rollout instrumentation. Evidence coverage E_i measures whether the stored or selected evidence contains gold support. The rank score L_i rewards placing gold evidence high in the retrieved set. Selection purity P_i measures how much of the selected evidence is useful and not distractor text. Write utility W_i rewards valid memory writes that preserve future-use evidence. All auxiliary terms are normalized to $[0, 1]$ before being gated by final answer quality Q_i . The budget penalty is $\lambda_{\text{budget}} \max(0, |S_i|_{\text{tok}} - \tilde{B}_i) / \tilde{B}_i$, which charges the policy for source evidence retained beyond the sampled budget. For the reported runs we use

Table 24: W0 training diagnostic rollout on held-out episodes, reported separately from the LongMemEval-RR retained-budget benchmark. Retrieval recall is saturated under the default top- k setting, while losses appear in write quality and read-side selection.

Stage	Value	Interpretation
Written evidence coverage	47.8%	About half of written items contain gold evidence.
Retrieval hit rate	100.0%	The retriever recovers written memory at default top- k .
Read-selection hit rate	41.7%	Read selection keeps a minority of written items.
Answer-context gold rate	77.3%	Some answers still lack selected gold evidence.

$\lambda_{\text{budget}} = 0.2$, rollout group size $G = 16$, sampling temperature $T = 1.0$, and source-excerpt caps of 256 tokens with a 128-token source prefix in the retrieval index.

Training data construction. The curriculum trains the retention interface, not a standalone reader. It has two optimizer-length blocks. Stage I uses RULER-HotpotQA to create controlled long-context streams with support evidence and distractors and converges in about 500 optimization steps. Stage II is a 100-step multi-session continuation: it converts MuSiQue and 2WikiMultiHopQA examples into episodes by assigning support facts to timestamped sessions, inserting distractor sessions, and preserving support unit identifiers for reward computation. Stage III hard cases are folded into this 100-step continuation; they are not a separate optimizer block. These transformations add update, temporal, and abstention episodes. In update episodes, an early session states an old value and a later session corrects it; the writer must preserve the evidence that determines the current answer. In temporal episodes, the query depends on when an event, deadline, or preference holds. In abstention episodes, the stream contains topically related content but no source evidence sufficient to answer the query. These cases train the writer to prefer gold source evidence over merely topical context. LongMemEval histories, questions, and evidence labels are not used for training; all LongMemEval-derived protocols are held out for evaluation.

Reward coefficient selection. We select $(\alpha_Q, \alpha_E, \alpha_L, \alpha_P, \alpha_W) = (0.45, 0.25, 0.15, 0.10, 0.05)$ on a held-out validation split constructed from the external training sources: RULER-HotpotQA, MuSiQue, and 2WikiMultiHopQA-derived episodes. These validation episodes are disjoint from training episodes and from the LongMemEval-RR and MultiQ-LongMemEval-RR evaluation sets. All reported results use this frozen coefficient vector.

Table 25: Reward-coefficient sensitivity on LongMemEval-RR for EMBER-7B at $B = 8192$. The default coefficient vector is selected on external validation episodes; the alternatives vary the reward emphasis without test-set tuning.

Reward coefficients $(\alpha_Q, \alpha_E, \alpha_L, \alpha_P, \alpha_W)$	Retain-Recall \uparrow	Read-Recall \uparrow	F1 \uparrow
(0.45, 0.25, 0.15, 0.10, 0.05)	0.2966	0.2915	0.2768
(0.50, 0.20, 0.15, 0.10, 0.05)	0.2917	0.2856	0.2733
(0.40, 0.30, 0.15, 0.10, 0.05)	0.2989	0.2854	0.2722
All equal: (0.20, 0.20, 0.20, 0.20, 0.20)	0.2876	0.2711	0.2552
Top non-EMBER budgeted F1 baseline	0.1246	0.0997	0.1765

The sweep shows that EMBER is stable under small coefficient changes. Nearby answer-heavy and evidence-heavy variants stay within 0.005 F1 of the reported configuration, while equal weighting is lower. We therefore use the rounded validation-selected vector for all reported runs.

Table 27 ablates the same objective by removing individual reward signals. The default objective gives the strongest full-chain performance. Answer-only RL loses both retention and read-time access, while removing E , L , or P damages different points of the Survive–Read–Answer chain. This supports the training design used in the main experiments: final answer quality gates the reward, but evidence-retention and readability signals are needed to assign credit to pre-query memory decisions.

For each training batch, we sample a budget $B_{\text{ret}} \in \{512, 1024, 2048, 4096, 8192\}$ for each episode, so training covers more than the 8192-token operating point. This exposes the writer to the same retained-memory frontier used in Figure 2: the policy must learn which evidence survives when the budget is tight as well as when the cover is larger.

Table 26: Training-seed stability for EMBER-7B on LongMemEval-RR at $B = 8192$. Each seed uses the same reward coefficients, training curriculum, budget sampling, and checkpoint selection on held-out external pre-query validation episodes. LongMemEval-RR is used only for final evaluation. We use EMBER-7B as the lower-cost replicated setting for estimating training-seed variance; EMBER-14B is reported as a single-seed main model.

Seed	Retain-Recall \uparrow	Read-Recall \uparrow	F1 \uparrow
0	0.2966	0.2915	0.2768
1	0.2912	0.2856	0.2705
2	0.2954	0.2926	0.2801
Mean \pm std	0.2944 \pm 0.0028	0.2899 \pm 0.0038	0.2758 \pm 0.0049
TierMem-BudgetRaw (best F1 baseline)	0.1246	0.0997	0.1765

Table 27: Reward-term ablation on LongMemEval-RR for EMBER-7B at $B = 8192$. All rows use the same pre-query retention protocol and reader. The answer-only RL row keeps reinforcement learning but removes the auxiliary evidence-chain terms; it is distinct from the no-RL ablation in Table 3. The remaining rows remove retained-evidence coverage E , lookup/readability score L , and selection purity P .

Reward	Retain-Recall \uparrow	Read-Recall \uparrow	F1 \uparrow
Default	0.2966	0.2915	0.2768
Answer-only RL reward	0.2666	0.2415	0.2361
w/o E	0.2556	0.2416	0.2354
w/o L	0.2712	0.2448	0.2322
w/o P	0.2759	0.2571	0.2425

Validation and checkpoint selection. Checkpoint selection uses held-out pre-query validation episodes constructed from the same external sources and transformations as training. LongMemEval-RR and MultiQ-LongMemEval-RR are used only after checkpoint selection, so the main external evaluation does not tune the retention policy on LongMemEval histories, questions, or support labels.

Episode and batch format. Training and evaluation share a single episode schema. Each episode contains the pre-query stream, the hidden query, the target answer, annotated support units when available, B_{ret} , and a coarse task type:

```
{
  "stream": [
    {"session_id": 1, "timestamp": "...", "text": "..."},
    {"session_id": 2, "timestamp": "...", "text": "..."}
  ],
  "hidden_query": "...",
  "answer": "...",
  "support_units": [...],
  "budget": 512 | 1024 | 2048 | 4096 | 8192,
  "task_type": "single-hop | multi-hop | update | temporal | abstention"
}
```

For the GRPO-style update in Section 3.6, the old-policy importance ratio for an updated token is

$$\rho_{i,t}(\theta) = \frac{\pi_{\theta}(o_{i,t} \mid \text{ctx}_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid \text{ctx}_{i,<t})}.$$

For the exposed memory-control tokens \mathcal{T}_i , we use the clipped objective with $\epsilon = 0.2$ and $\beta = 0.001$:

$$\mathcal{J}(\theta) = \mathbb{E}_{i,t \in \mathcal{T}_i} \left[\min \left(\rho_{i,t}(\theta) \hat{A}_i, \text{clip}(\rho_{i,t}(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_i \right) - \beta \text{KL}(\pi_{\theta} \parallel \pi_{\text{ref}}) \right].$$

The reported veRL integration exposes one carrier turn per rollout to the PPO/GRPO update, while the reward is computed from the full memory trajectory. The curriculum determines which decision becomes the carrier. In write-retention batches, the carrier is a writer action block produced during ingestion, such as a capsule proposal, update mode, or bounded source-excerpt decision for one chunk window. The rest of the episode is still executed: the query is revealed, retained evidence is retrieved and selected, and the final answer is scored. Thus the selected write action receives delayed outcome credit from the full Survive–Read–Answer chain. Across training batches, different write decisions are selected as carriers, covering the stream’s per-chunk retention decisions. When the read-selection curriculum is enabled, the carrier is instead the evidence-selection turn; write and answer turns are masked from the loss but remain in the trajectory used to compute the reward. The answer turn is always score-only in these runs. This applies standard clipped GRPO to a transparent decision carrier while avoiding token-level credit over every prompt and answer token in a rollout.

Table 28: Training configuration for the reported EMBER runs.

Setting	Value
Stage I data	RULER-HotpotQA pre-query online-memory episodes
Stage II data	MuSiQue and 2WikiMultiHopQA multi-session retention episodes
Stage III data	Update, temporal, and abstention hard-case transformations
Stage I convergence	about 500 optimization steps
Stage II/III continuation	100 optimization steps
Learning rate	1×10^{-6}
Rollout group size	$G = 16$
Rollout sampling temperature	$T = 1.0$
Source excerpt cap	256 tokens
Index source-prefix cap	128 tokens
Budget penalty coefficient	$\lambda_{\text{budget}} = 0.2$
PPO clip range	$\epsilon = 0.2$
PPO epochs	8
KL coefficient	$\beta = 0.001$
Trainable carrier	Curriculum-selected writer action block or read-selection turn; one carrier receives loss per rollout
Optimizer	Answer-gated evidence-chain reward with clipped GRPO-style update

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope?

Answer: [Yes]

Justification: The abstract and introduction state the setting, method, and measured gains under Budgeted Pre-Query Retention. The main quantitative claims are reported in Table 1, Figure 2, and Section 4.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: Section 7 discusses the benchmark scope, annotation and budget assumptions, and deployment risks for persistent agent memory.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete and correct proof?

Answer: [N/A]

Justification: The paper is empirical and does not present formal theoretical results.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper?

Answer: [Yes]

Justification: Section 3 describes the retention policy, Section 3.6 gives the training objective, and Appendix C.4 defines the LongMemEval-RR protocol, metrics, budgets, and evaluation wrapper.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Appendix C.4 specifies the derived-protocol construction, retained-budget settings, chunk/span rules, answer-time wrapper, and evaluator. Appendix C.5 states that the anonymized supplementary artifact includes the construction scripts, evaluation commands, and wrappers.

6. Experimental setting/details

Question: Does the paper specify all the training and test details necessary to understand the results?

Answer: [Yes]

Justification: Section 4 describes the benchmark hierarchy, main baselines, and reader settings. Appendix C.10 reports the training configuration, and Appendix C.4 reports the protocol and extended tables.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: Main F1 tables define uncertainty in their captions: LongMemEval-RR reports bootstrap confidence half-widths, while the RULER-HotpotQA headline table reports 95% confidence-interval half-widths. The primary LongMemEval-RR gain reports a paired bootstrap confidence interval. Randomized retention probes average five seeds; extended deterministic diagnostics report point estimates.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources needed to reproduce the experiments?

Answer: [Yes]

Justification: Appendix Table 19 summarizes the rollout engine, GPU-resident retriever, hard budget enforcement, and training interface. Appendix Table 20 reports the compute paths, operating points, and GPU configurations, including H200 SXM $\times 4$ and H100 NVL $\times 8$.

9. **Code of ethics**

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Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse?

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Question: Are the creators or original owners of assets used in the paper properly credited and are the license and terms of use explicitly mentioned and properly respected?

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13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: Appendix C.4 documents LongMemEval-RR, including its source data, construction rules, retained-budget settings, online ingest protocol, metrics, and evaluation wrapper. Appendix C.5 describes the anonymized supplementary artifact and upstream asset handling.

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Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research?

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Justification: The paper describes the LLM-based memory writer, reader, retrieval prompts, Qwen backbones, GPT-4o reader evaluation, and prompt templates in the method, experiments, and appendices.