Lightweight LLM Agent Memory with Small Language Models

Anonymous ACL submission

Abstract

Although LLM agents can leverage tools for complex tasks, they still need memory to maintain cross-turn consistency and accumulate reusable information in long-horizon interactions. However, retrieval-based external memory systems incur low online overhead but suffer from unstable accuracy due to limited query construction and candidate filtering. In contrast, many systems use repeated large-model calls for online memory operations, improving accuracy but accumulating latency over long interactions. We propose *LightMem*, a lightweight memory system for better agent memory driven by Small Language Models (SLMs). *LightMem* modularizes memory retrieval, writing, and long-term consolidation, and separates online processing from offline consolidation to enable efficient memory invocation under bounded compute. We organize memory into short-term memory (STM) for immediate conversational context, mid-term memory (MTM) for reusable interaction summaries, and long-term memory (LTM) for consolidated knowledge, and uses user identifiers to support independent retrieval and incremental maintenance in multi-user settings. Online, *LightMem* operates under a fixed retrieval budget and selects memories via a two-stage procedure: vector-based coarse retrieval followed by semantic consistency re-ranking. Offline, it abstracts reusable interaction evidence and incrementally integrates it into LTM. Experiments show gains across model scales, with an average F1 improvement of about 2.5 on LoCoMo, more effective and low median latency (83 ms retrieval; 581 ms end-to-end).

1 Introduction

LLM-driven agents excel at long-term dialogue, multi-step reasoning, and task-oriented interaction (Huang et al., 2024; Zhu et al., 2025; Mohammadi et al., 2025; Zhao et al., 2024). To maintain cross-turn consistency beyond the context window, many systems augment agents with external memory (Lee et al., 2024; Xu et al., 2025; Hu et al., 2025). Long-term memory supports continual learning, personalization, and planning.

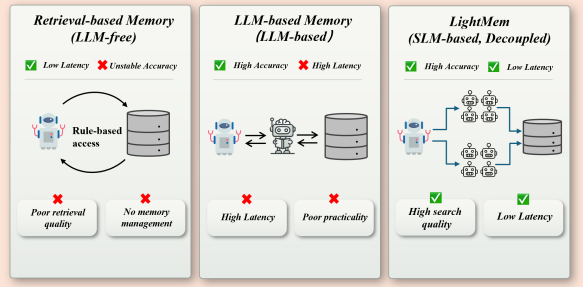


Figure 1: *LightMem* combines enhanced retrieval with SLMs, achieving high retrieval accuracy while significantly reducing online latency compared to retrieval-based and LLM-based memory systems.

Existing memory systems can be broadly divided into two categories. One line is based on retrieval–driven external memory, where past interactions are compressed into retrievable entries (Asai et al.; Maharana et al., 2024) and the top-K memories are recalled via similarity search (Zhong et al., 2024). These methods are efficient, but limited query construction and candidate filtering often introduce retrieval noise, resulting in unstable answer accuracy. Another line of methods (Tan et al., 2025; Zhang et al., 2025) introduces LLM-driven memory operations on top of external memory, repeatedly invoking large models for memory writing, retrieval and controlling. As these operations are typically implemented via repeated model invocations, they can introduce non-trivial runtime overhead over long interactions (Packer et al., 2023; Park et al., 2023). This contrast suggests a natural separation: keep high-frequency online memory decisions lightweight and controllable, while deferring heavy abstraction and consolidation to offline processing (see Figure 1). Recent advances in SLMs (Magister et al., 2023; Han et al., 2024)

make this separation practical. SLMs can reliably handle high-frequency, structured decision tasks in online memory processing, enabling different memory stages to be assigned to models of appropriate scale (Liu et al., 2025). Online memory handling typically consists of structured subtasks (such as intent routing (Zhang et al., 2024), query construction (Hong and He, 2025) and semantic filtering (Hatalis et al., 2023)). These tasks place greater emphasis on predictable behavior and low overhead than on maximal generative capacity. In this setting, lightweight SLMs provide a suitable choice (Sinha et al., 2025) for online control and filtering, while heavier abstraction and consolidation can be deferred to offline processing. Overall, existing memory systems face an efficiency–effectiveness trade-off. Moreover, SLMs are not a silver bullet due to limited capacity and representation. Bridging this gap requires strengthening the external memory pipeline, especially how memories are written and retrieved.

To address the above questions, we propose *LightMem*, a lightweight memory system for LLM agents that models long-term memory as an incrementally evolvable process via specialized SLMs. *LightMem* modularizes and decouples query parsing, memory retrieval, memory writing, and long-term consolidation, enabling independent optimization and elastic scaling of each component. This separation allows for lightweight online processing to be distinct from offline consolidation, achieving efficient memory use under tight compute budgets and supporting long-term evolution. Memories are organized into STM, MTM, and LTM stores based on temporal and access characteristics. User-identity metadata is embedded in each memory unit to enforce user-level logical isolation, balancing privacy, consistency, and scalability. We propose a modular online–offline memory pipeline in which distinct SLMs specialize in complementary memory operations. Online, LightMem uses three specialized small language model modules: a Controller (SLM-1) for intent and query planning, a Selector (SLM-2) for candidate verification and compression, and a Writer (SLM-3) for incremental memory writing. Specifically, the Controller rewrites the user input into intent-conditioned hypothetical queries (HQs) and allocates a fixed Top-K budget across MTM and LTM. Given the retrieved candidates, the Selector performs metadata-constrained prefiltering followed by semantic-consistency based re-ranking to output the final Top-K memories. After each turn, the Writer summarizes the interaction into compact MTM entries and maintains MTM incrementally. Long-term abstraction and consolidation are handled offline by a large-context model, keeping the online path lightweight. Our main contributions are:

- We propose *LightMem*, a lightweight memory system collaboratively driven by SLMs. Different SLMs handle lightweight, high-frequency online memory operations (query construction, retrieval, and writing), while heavier abstraction and consolidation are deferred to offline processing.
- We propose a two-stage memory querying design. Given a user query, *LightMem* first narrows down the candidate set with fast retrieval, and then applies semantic-level verification to select the truly relevant memories.
- We evaluate *LightMem* on LoCoMo and DialSim, demonstrating gains across model scales, including an average F1 improvement of about 2.5 on LoCoMo, improved semantic consistency on DialSim and low median latency (83 ms retrieval; 581 ms end-to-end).

2 Related Work

2.1 LLM Memory Systems

Prior work can be broadly categorized into retrieval-based memory and LLM-driven memory operations. **Retrieval-based Memory.** MemoryBank (Zhong et al., 2024) supports personalized long-term dialogue by storing summarized user events in an external memory and retrieving relevant entries for each query, with forgetting to control growth. MemGPT (Packer et al., 2023) treats the context window as virtual memory and performs paging between the prompt and an external store, with runtime eviction and on-demand retrieval. ReadAgent (Lee et al., 2024) similarly relies on retrieval over an external cache: it indexes compressed gists and performs on-demand lookup to fetch supporting evidence when needed. **LLM-driven Memory.** HiAgent (Hu et al., 2025) manages in-trial working memory by chunking trajectories into subgoals and summarizing past steps with LLMs. A-MEM (Xu et al., 2025) further builds self-organizing memory networks through LLM-driven note-taking and automatic linking, but typically does not emphasize strict online/offline decoupling under resource

constraints. These lines expose a recurring trade-off between lightweight but noisy retrieval-based memory and more effective yet costly LLM-driven online memory operations. *LightMem* addresses it with SLM-based lightweight online control and filtering, coupled with improved external memory writing and retrieval under a fixed budget.

2.2 Small Language Models

SLMs are increasingly important in the LLM ecosystem for their efficiency, low deployment cost, and controllability (Magister et al., 2023; Allal et al., 2025). Models such as Phi-3 (Retamales et al., 2025) and Gemma (Team et al., 2024) maintain strong language capabilities with substantially lower compute and memory footprints. This makes SLMs particularly suitable for edge and on-device scenarios that require low latency, compact memory usage, and strong privacy guarantees (Sinha et al., 2025; Xu et al., 2024; Wang et al., 2024). From a systems perspective, online memory processing involves high-frequency, fine-grained steps (Hou et al., 2024), making SLMs a natural choice for the online control and filtering plane. In contrast, relying on LLMs for these online components (Hatalis et al., 2023) can markedly increase per-turn cost and latency, limiting deployability under resource constraints (Tuggener et al., 2024).

3 Method

As shown in Figure 2, *LightMem* uses specialized SLMs to modularize memory operations, separating lightweight online querying from offline long-term consolidation.

3.1 Problem Setup and Preliminaries

We consider a multi-turn dialogue setting with multiple users. At turn t, a user provides an input x_t, and the model generates a response y_t. Due to the limited context capacity of SLMs, the accessible dialogue context at turn t is denoted by C_t, typically a truncated window of recent turns. *LightMem* maintains a user-scoped memory store M_u with user-level logical isolation via user identifiers (see §3.2 for the definition of STM/MTM/LTM). Given (x_t, C_t), the system retrieves a memory set $R_t \subseteq M_u$ with $|R_t| \leq K$ and uses R_t to assist in generating y_t. The specific symbols are provided in the Appendix 7.1.

3.2 Memory Stores

STM. STM is implemented as the SLM context window that buffers the most recent interaction sequence in the current session. It serves only as working memory and is updated turn by turn within the prompt; STM is neither persisted nor retrieved.

MTM. MTM is the sole carrier of personalized episodic memory. It stores a set of memory items, each consisting of (i) a concise semantic summary, (ii) temporal information and access statistics, (iii) an embedding for similarity-based retrieval, and (iv) a user identifier for strict per-user isolation.

LTM. LTM stores de-identified, user-agnostic semantic knowledge distilled offline from high-value MTM episodes. It contains no raw personal episodes or user identifiers; instead, it represents stable facts, domain regularities, and cross-user trends. LTM is organized as a lightweight graph-structured knowledge base to support multi-hop reasoning and knowledge sharing across tasks.

3.3 Intent Modeling and Retrieval Control

Given (x_t, C_t), SLM-1 serves as a lightweight retrieval controller rather than a retriever. It converts the raw input into a structured retrieval plan that specifies: (i) what to search (queries), (ii) how to constrain the search (metadata filters), and (iii) how many items to return under a fixed Top-K budget. Concretely, SLM-1 first infers coarse intent attributes, e.g., whether the query depends more on recent episodic details or long-term stable knowledge, and whether strong personalization is needed. These attributes are used only for retrieval planning (query rewriting, routing, and budgeting), not for answer generation. SLM-1 then rewrites the input into a set of hypothetical queries $\{q_t^{(i)}\}$ and outputs metadata constraints ϕ_t (user identifier, optional time window, and type tags) to reduce noise and enforce user-level isolation. Finally, it issues the retrieval request:

$$\mathcal{Q}_t = \left\langle \{q_t^{(i)}\},\ \phi_t,\ K \right\rangle. \tag{1}$$

This request is consumed by §3.4.

3.4 Two-Stage Retrieval

Given $\mathcal{Q}_t$, SLM-2 executes a two-stage retrieval procedure and returns a memory set R_t that satisfies the Top-K constraint:

$$R_t = \textsc{Retrieve}(\mathcal{Q}_t), \qquad |R_t| \leq K. \tag{2}$$

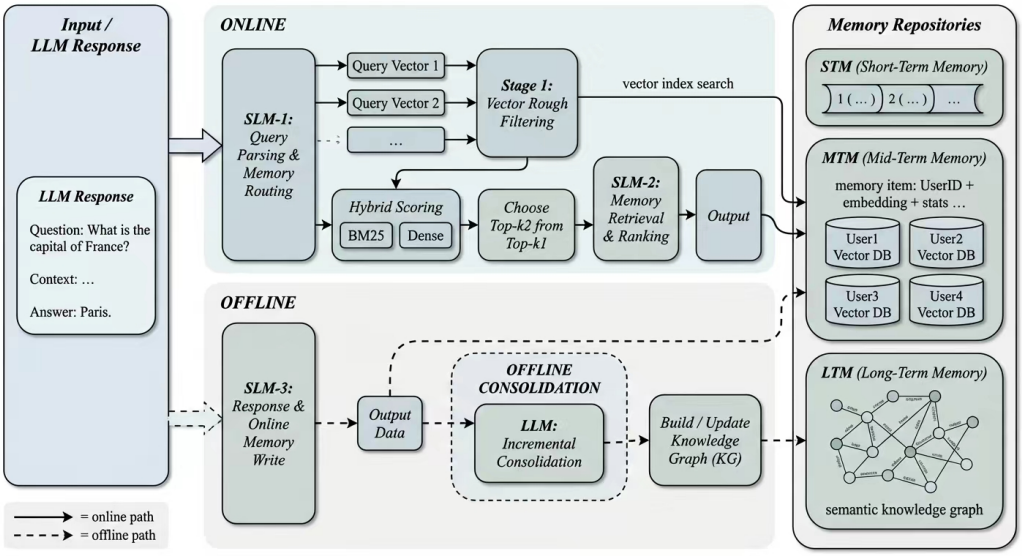


Figure 2: Multiple SLMs coordinate an online pathway for query-time routing and retrieval over STM/MTM, and an offline pathway that incrementally consolidates MTM into a graph-structured LTM.

The retrieved memories R_t are appended to the context to condition response generation for y_t.

For a single user query, SLM-1 may generate n HQs, denoted by $\{q_t^{(i)}\}_{i=1}^n$, to improve recall coverage. We impose a single final return budget K and adopt a double-budget rule in the coarse stage: the total number of candidates returned by Stage 1 is fixed to $2K$.

Stage 1: metadata-constrained coarse retrieval. Under metadata constraints ϕ_t (including the user identifier, an optional time window, and type/source tags), the system performs vector-based coarse retrieval for each HQ. The Stage 1 candidate budget is evenly split across HQs:

$$\sum_{i=1}^{n} K_1^{(i)} = 2K, \qquad K_1^{(i)} = \frac{2K}{n}. \tag{3}$$

Let $C^{(i)}$ denote the candidate list returned for the i-th HQ. The aggregated candidate set is

$$C = \bigcup_{i=1}^{n} C^{(i)}, \qquad |C| = 2K. \tag{4}$$

Stage 1 is designed for coverage, acting as an efficient filter that compresses the large search space into a fixed-size candidate set.

Stage 2: semantic filtering and compression. In Stage 2, SLM-2 takes the HQ set $\{q_t^{(i)}\}_{i=1}^n$ and the Stage 1 candidates C (memory summaries with necessary structured metadata) and performs semantic consistency checking and relevance judgment. Instead of generating answers, SLM-2 conducts controlled selection on a fixed-size candidate pool: it keeps the most relevant half of $|C| = 2K$ candidates and outputs the final retrieval results

$$R_t \subseteq C, \qquad |R_t| \leq K \tag{5}$$

This two-to-one compression yields (i) stable computation with a fixed candidate size, (ii) semantic refinement beyond vector similarity by leveraging intent and metadata, and (iii) noise suppression by explicitly discarding roughly half of the candidates. The resulting Top-K memories R_t are provided to the downstream agent or response generator.

3.5 Memory Writing and Update

After generating y_t, SLM-3 extracts reusable user-relevant information from the current interaction, compresses it into a concise memory item, and appends it to MTM. To prevent redundancy and noise accumulation, highly repetitive items are merged or rewritten, while conflicting information is handled using temporal cues and evidence strength. To ensure consistently low-latency personalized retrieval, we enforce a capacity bound on MTM:

$$|M_u^{\text{MTM}}| \leq B \tag{6}$$

When the bound is reached, MTM is maintained by evicting stale, low-utility items and further compressing redundant content.

3.6 Offline Consolidation

To avoid increasing online retrieval and writing latency, *LightMem* performs offline consolidation to distill high-value episodic evidence in MTM into de-identified, long-term semantic knowledge, enabling sustained evolution of LTM. An LLM handles this offline path with a large context window and is strictly decoupled from online operation. In each cycle, the LLM processes only an incremental batch (newly written or retrieval-reactivated MTM items and low-utility candidates flagged under MTM capacity pressure), rather than rebuilding MTM/LTM from scratch. It abstracts episodes into privacy-preserving knowledge candidates, performs similarity search over LTM to locate semantically nearest anchors, and incrementally inserts and links candidates within the local neighborhood, thereby maintaining LTM as lightweight graph-structured knowledge. Evidence accumulated over time further drives merge/update/drop decisions, while confidence decay is applied to weakly supported candidates to enable natural forgetting and to limit the impact of stale or incidental information on subsequent retrieval and reasoning. We provide each component with algorithmic details deferred to Appendix 7.1.

4 Experiment

4.1 Experimental Setup

4.1.1 Datasets

To evaluate the effectiveness of *LightMem*, we conduct experiments on two datasets. LoCoMo (Maharana et al., 2024) is a benchmark designed to evaluate logical reasoning over extended conversational contexts. It contains long dialogues (on average 9K tokens) and covers five core task categories: Single-hop, Multi-hop, Temporal, Open-domain, and Adversarial. DialSim (Kim et al., 2024) is a dialogue simulation dataset derived from TV shows, containing 1,300 multi-party sessions spanning years.

4.1.2 Baselines

Baselines We select baselines that are representative in prior work on long-term memory, covering common designs for storing, retrieving, and updating dialogue histories and that can be evaluated under the same backbone and retrieval budget for a fair comparison: LoCoMo (Maharana et al., 2024), ReadAgent (Lee et al., 2024), MemoryBank (Zhong et al., 2024), MemGPT (Packer et al., 2023), and A-MEM (Xu et al., 2025). When selecting backbone models, a diverse array of LLMs is used to assess their generalization capabilities. These models encompass GPT-4o, GPT-4o-mini (Hurst et al., 2024), Qwen2.5 (available in 1.5B and 3B) (Bai et al., 2025), and Llama 3.2 (offered in 1B and 3B) (Dubey et al., 2024).

4.1.3 Metric

We evaluate response quality using both lexical-overlap and semantic metrics. Specifically, we report F1 and BLEU-1 to measure answer correctness and token-level overlap with reference responses, which are commonly used for short factual and span-like outputs. For DialSim (Kim et al., 2024), where multiple surface forms can express the same meaning, we additionally report ROUGE-L and METEOR to capture sequence-level overlap and soft token matching, and use SBERT similarity to quantify semantic consistency between generated and reference responses beyond n-gram matches. These metrics offer a dependable evaluation of both precision and meaning retention within long-horizon dialogue scenarios.

4.1.4 Implement Details

To isolate the effect of memory, we use GPT-4o-mini as the fixed response generator for *LightMem* and all baselines. *LightMem*'s control plane uses locally deployed, quantized SLMs: SLM-1 for HQ generation and retrieval control, SLM-2 for semantic re-ranking and compression, and SLM-3 for online writing and MTM maintenance. For HQ generation, SLM-1 follows a structured prompt for query decomposition and routing; Table 1 summarizes the prompt logic and provides an example. We deploy quantized Llama-3.2-1B-Instruct via Ollama by default and additionally evaluate Qwen2.5-1.5B-Instruct for robustness. Offline consolidation is handled by a large-context LLM and is decoupled from the online path. We encode all queries and memory entries using all-MiniLM-L6-v2 (384 dimensions) and retrieve the top-10 nearest neighbors in the coarse vector retrieval stage. SLM-2 is fine-tuned with LoRA on 2,000 constructed (Query, Subgraph, Path) samples. We cap MTM capacity at $B = 10^4$ and apply dynamic pruning beyond this limit by evicting stale, low-utility items and merging/compressing redundant content. *LightMem* inference and latency measurements are conducted on a single NVIDIA RTX 4090 (24GB) GPU. Other unspecified settings follow A-MEM

(Xu et al., 2025).

Table 1: Structured HQ prompt used by SLM-1 for query decomposition and routing.

HQ prompt step	Example
Detect missing info	Identify underspecified references (e.g., pronouns such as "it/that/he/the project"), implicit context dependencies, and vague time cues (e.g., "recently/last time/before").
Generate HQs	Rewrite the user request into one or more standalone hypothetical queries, optionally splitting intent into user-specific vs. factual queries, and making implied context (time/location) explicit.
Route and budget	Assign each HQ to MTM (user-specific) or LTM (general/public knowledge) and allocate a retrieval budget under a fixed top-K constraint.
Example	Input: "Recommend a dinner spot." The prompt yields two HQs: one asks about the user's preferred cuisines or dietary constraints (routed to MTM), and the other asks about highly rated nearby restaurants (routed to LTM).

4.2 Performance

Performance. As shown in Table 2, *LightMem* achieves the best overall performance on the LoCoMo benchmark. In comparison to baselines that directly rely on long-context replay (such as LoCoMo and MemGPT), *LightMem* demonstrates more stable performance across the majority of question categories. It has particularly distinct advantages in multi-hop and temporal questions, all while not being reliant on a single long-context input. In comparison with summarization- or compression-based methods (MemoryBank and ReadAgent), *LightMem* consistently outperforms them across all categories, with larger margins on multi-hop and temporal reasoning. When compared to the strongest memory-centric baseline, A-MEM, *LightMem* further improves overall performance in most model settings. On GPT-4o, *LightMem* attains an F1 score of 34.50 for multi-hop questions, surpassing A-MEM's score of 32.86. Overall, *LightMem* demonstrates more robust long-term memory across different model scales and question types. In addition, it maintains significant advantages in cross-session reasoning tasks.

Table 3 reports the comparison on DialSim with GPT-4o-mini. We incorporate METEOR and SBERT similarity. This is driven by the characteristics of long-term dialogue generation. In long-term dialogue generation, semantically accurate answers can be presented in diverse surface forms. Consequently, metrics based solely on n-grams may undervalue advancements. METEOR partially accounts for morphological and synonym-level matching, while SBERT directly measures semantic alignment between the generated response and the reference, providing a complementary view of memory effectiveness. Across all metrics, *LightMem* achieves the best results. Importantly, *LightMem* improves not only lexical overlap (e.g., ROUGE-L/ROUGE-2 and METEOR) but also semantic similarity, with SBERT increasing from 19.51 (A-MEM) to 23.40. This indicates that the gains are not limited to reproducing similar wording, but also reflect stronger semantic consistency enabled by more effective use of long-term conversational history.

Generalization. We evaluate all methods across diverse backbones, ranging from large models (GPT-4o / GPT-4o-mini) to small open-source models (Qwen2.5 and Llama-3.2). As shown in Table 2, *LightMem* remains the best or near-best method across these settings, indicating that its gains are robust and not tied to a specific backbone.

4.3 Ablation Study

To quantify the contribution of each component in *LightMem*, we conduct ablation studies by removing or simplifying one key module at a time while keeping the rest of the system unchanged. We consider the following variants:

- **w/o semantic reranking** We remove the LM-based semantic filtering stage and keep only embedding-based Top-K retrieval.
- **w/o HQ and retrieval routing** We disable HQs as well as the controller-based routing/budget allocation, and retrieve using the original query directly.
- **w/o MTM** We remove the MTM layer, relying only on the current context (STM) and LTM for retrieval and generation.
- **w/o offline consolidation** We disable the offline consolidation pipeline so that LTM is not periodically updated from MTM.
- **w/o graph structure** We replace the graph-structured LTM with a flat vector store.

Table 2: Main results on LoCoMo across question categories. We report F1 and BLEU-1 for each category, along with the token length of the effective context. Best results within each model block are in bold.

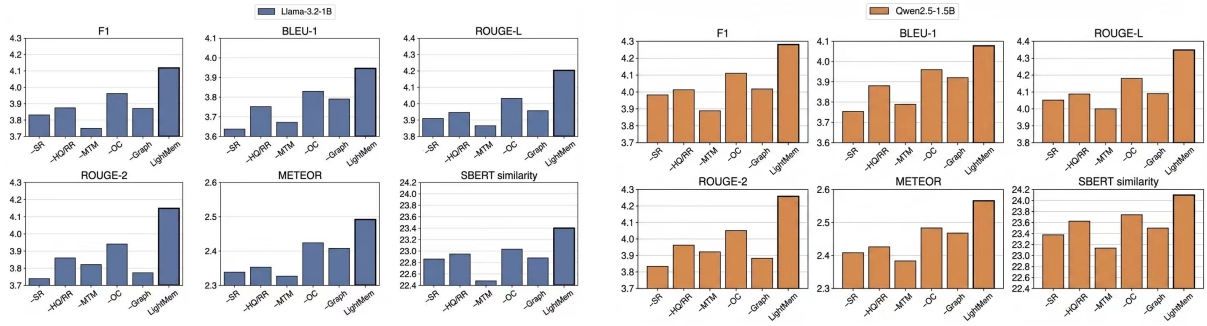
Model	Method	Single-hop		Multi-hop		Temporal		Open-domain		Adversarial		Token Length
		F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	
GPT-4o-mini	LoCoMo	40.36	29.05	25.02	19.75	18.41	14.77	12.04	11.16	**69.23**	**68.75**	16,910
	ReadAgent	9.67	7.66	9.15	6.48	12.60	8.87	5.31	5.12	9.81	9.02	643
	MemoryBank	6.61	5.16	5.00	4.77	9.68	6.99	5.56	5.94	7.36	6.48	432
	MemGPT	41.04	34.34	26.65	17.72	25.52	19.44	9.15	7.44	43.29	42.73	16,977
	A-MEM	44.65	37.06	27.02	20.09	45.85	36.67	12.14	12.00	50.03	49.47	2,520
	LightMem	**45.80**	**38.20**	**28.85**	**21.40**	**46.20**	**37.10**	**13.50**	**12.90**	54.50	52.10	1,150
GPT-4o	LoCoMo	**61.56**	**54.19**	28.00	18.47	9.09	5.78	16.47	14.80	**52.61**	**51.13**	16,910
	ReadAgent	12.46	10.29	14.61	9.95	4.16	3.19	8.84	8.37	6.81	6.13	805
	MemoryBank	8.28	7.10	6.49	4.69	2.47	2.43	6.43	5.30	4.42	3.67	569
	MemGPT	60.16	53.35	30.36	22.83	17.29	13.18	12.24	11.87	34.96	34.25	16,987
	A-MEM	48.43	42.97	32.86	23.76	39.41	31.23	17.10	15.84	36.35	35.53	1,216
	LightMem	49.80	44.20	**34.50**	**25.10**	**40.10**	**32.00**	**18.40**	**16.90**	41.50	39.80	680
Qwen2.5-1.5B	LoCoMo	11.15	8.67	9.05	6.55	4.25	4.04	9.91	8.50	40.38	40.23	16,910
	ReadAgent	10.13	7.54	6.61	4.93	2.55	2.51	5.31	12.24	5.42	27.32	752
	MemoryBank	13.42	11.01	11.14	8.25	4.46	2.87	8.05	6.21	36.76	34.00	284
	MemGPT	9.56	7.34	10.44	7.61	4.21	3.89	13.42	11.64	31.51	28.90	16,953
	A-MEM	23.63	19.23	18.23	11.94	24.32	19.74	16.48	14.31	46.00	43.26	1,300
	LightMem	**25.10**	**20.50**	**21.50**	**13.80**	**25.60**	**20.80**	**17.20**	**15.10**	**49.80**	**46.50**	720
Qwen2.5-3B	LoCoMo	7.03	5.69	4.61	4.29	3.11	2.71	4.55	5.97	16.95	14.81	16,910
	ReadAgent	3.25	2.51	2.47	1.78	3.01	3.01	5.57	5.22	15.78	14.01	776
	MemoryBank	4.11	3.32	3.60	3.39	1.72	1.97	6.63	6.58	13.07	10.30	298
	MemGPT	7.26	5.52	5.07	4.31	2.94	2.95	7.04	7.10	14.47	12.39	16,961
	A-MEM	17.23	13.12	12.57	9.01	27.59	25.07	7.12	7.28	27.91	25.15	1,137
	LightMem	**19.80**	**15.20**	**15.80**	**11.20**	**29.10**	**26.50**	**9.50**	**9.10**	**33.50**	**29.80**	610
Llama-3.2-1B	LoCoMo	12.86	10.50	11.25	9.18	7.38	6.82	11.90	10.38	51.89	48.27	16,910
	ReadAgent	7.75	6.03	5.96	5.12	1.93	2.30	12.46	11.17	44.64	40.15	665
	MemoryBank	17.30	14.03	13.18	10.03	7.61	6.27	15.78	12.94	52.61	47.53	274
	MemGPT	10.16	7.68	9.19	6.96	4.02	4.79	11.14	8.24	49.75	45.11	16,950
	A-MEM	28.51	24.13	19.06	11.71	17.80	10.28	17.55	14.67	58.81	54.28	1,376
	LightMem	**30.80**	**26.20**	**22.40**	**14.20**	**19.90**	**12.10**	**18.90**	**16.10**	**63.50**	**58.40**	750
Llama-3.2-3B	LoCoMo	8.37	6.93	6.88	5.77	4.37	4.40	10.65	9.29	30.25	28.46	16,910
	ReadAgent	3.25	2.51	2.47	1.78	3.01	3.01	5.57	5.22	15.78	14.01	461
	MemoryBank	7.61	6.03	6.19	4.47	3.49	3.13	4.07	4.57	18.65	17.05	263
	MemGPT	4.32	3.51	5.32	3.99	2.68	2.72	5.64	5.54	21.45	19.37	16,956
	A-MEM	28.14	23.87	17.44	11.74	26.38	19.50	12.53	11.83	42.04	40.60	1,126
	LightMem	**30.20**	**25.90**	**20.10**	**13.50**	**28.20**	**21.10**	**14.20**	**13.50**	**47.10**	**44.80**	640

Table 3: Comparison of different memory mechanisms on DialSim with GPT-4o-mini.

Method	F1	BLEU-1	ROUGE-L	ROUGE-2	METEOR	SBERT
LoCoMo	2.55	3.13	2.75	0.90	1.64	15.76
MemGPT	1.18	1.07	0.96	0.42	0.95	8.54
A-MEM	3.45	3.37	3.54	3.60	2.05	19.51
LightMem	**4.12**	**3.95**	**4.20**	**4.15**	**2.48**	**23.40**

Ablation analysis. Figure 3 shows that removing any single component consistently degrades performance across metrics. Disabling semantic reranking or HQ-based retrieval routing leads to clear drops in F1; on Llama-3.2-1B, *LightMem* achieves an F1 of 4.12, while the variant without semantic reranking scores 3.83 and the variant without HQ and retrieval routing scores 3.87. Removing MTM further lowers performance, with an F1 of 3.75, indicating the benefit of retaining mid-term episodic memory. In comparison, disabling offline consolidation results in a smaller but still consistent decline, with an F1 of 3.96 on Llama-3.2-1B. Removing the graph structure also reduces both lexical and semantic quality, as reflected by a lower SBERT similarity of 22.82 compared to 23.40 for the full *LightMem*. Overall, the full *LightMem* achieves the best results, suggesting that these components contribute complementary benefits.

Experimental setup. Under a unified deployment configuration, we assess the scalability and latency by utilizing GPT-4o-mini. Subsequently,



(a) Ablation study on Dialsim with Llama-3.2-1B

(b) Ablation study on Dialsim with Qwen2.5-1.5B

Figure 3: Ablation study on DialSim. We report F1, BLEU-1, ROUGE-L, ROUGE-2, METEOR, and SBERT similarity.

Table 4: Scalability and latency analysis across five baselines on GPT-4o-mini.

Method	Retrieval Latency P50 (ms)↓	Retrieval Latency P95 (ms)↓	End-to-End P50 (ms)↓	End-to-End P95 (ms)↓
LoCoMo	0	0	2054	3658
ReadAgent	34	97	614	1027
MemoryBank	16	51	439	1047
MemGPT	143	451	2087	3451
A-MEM	856	1583	914	3682
LightMem	83	167	581	1325

we present the following latency metrics:

- **Retrieval Latency (ms).** Time from receiving a user query to finishing memory retrieval and constructing the final prompt. It includes local computation but excludes remote GPT-4o-mini generation time. For the full-context LoCoMo baseline, retrieval latency is 0 ms since no external memory is retrieved.
- **End-to-End Latency (ms).** The time from receiving a user query to producing the final response, including retrieval, remote API transmission and queuing, and GPT-4o-mini inference and decoding.
- **P50 / P95.** The median (P50) and 95th-percentile (P95) latency across all samples. P95 captures tail latency from network jitter and service queuing, reflecting real-world system stability.

Table 4 compares retrieval and end-to-end latency on GPT-4o-mini. Among memory-enabled methods, *LightMem* achieves a good balance between retrieval overhead and end-to-end responsiveness. Its retrieval latency remains low, with P50/P95 of 83/167 ms, substantially lower than MemGPT and especially A-MEM, which exhibits heavy tail latency. *LightMem* also shows competitive end-to-end latency, with a P50 of 581 ms and a controlled P95, indicating stable behavior under remote API settings. When considered together with the effective context length in Table 2, these results are more interpretable: LoCoMo and MemGPT rely on replaying large dialogue histories with effective contexts close to 16K tokens, whereas *LightMem* consistently operates with much shorter contexts (around 1K tokens on GPT-4o-mini). This reduction in effective context length lowers prompt construction and inference cost, contributing to better scalability and practical deployability.

5 Conclusion

We present *LightMem*, a lightweight external memory system for LLM agents driven by small language models (SLMs). *LightMem* decouples high-frequency online memory operations (query control, retrieval, and writing) from offline consolidation, and organizes memory into STM/MTM/LTM with user-scoped isolation. Online, it operates under a fixed retrieval budget and uses HQ-based routing plus a two-stage retrieval (coarse vector search followed by semantic consistency re-ranking) to reduce retrieval noise. Experiments on LoCoMo and DialSim show consistent gains across model scales, including +2.5 average F1 on LoCoMo, improved semantic consistency on DialSim, and low median latency (83 ms retrieval; 581 ms end-to-end).

6 Limitations

This work focuses on a specific design of online–offline decoupled memory pipelines driven by specialized small language models. The impact of alternative consolidation strategies and control policies is not fully explored and remains an interesting direction for future investigation.

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7 Appendices

7.1 Complete Algorithm and Process Specifications

7.1.1 Symbols and Data Structures

- x_t: the user input at interaction turn t.
- y_t: the response generated by the system at turn t.
- C_t: short-term memory (STM), representing the truncated recent dialogue context.
- M_u^{MTM}: the mid-term memory (MTM) store associated with user u.
- M^{LTM}: the global long-term memory (LTM), shared across users.
- K: the fixed Top-K retrieval budget.
- B: the capacity limit of the MTM.
- HQs: hypothetical queries generated by SLM-1 to guide memory retrieval.
- ϕ_t: metadata constraints, including user identifiers, temporal windows, and type tags.

Mid-Term Memory (MTM). Each MTM entry represents a compressed interaction record, consisting of a concise semantic summary, a retrieval embedding, associated temporal metadata (e.g., timestamps and access frequencies), and a user identifier for user-level isolation.

Long-Term Memory (LTM). Each LTM node represents a de-identified semantic knowledge unit and is stored in a lightweight graph structure, which supports associative organization and multi-hop access across memory units.

7.1.2 Online Retrieval Procedure

Algorithm 1 describes the full online retrieval process executed at each dialogue turn.

Algorithm 1 IntelliMem Online Retrieval

Require: User query x_t, truncated context C_t, user memory M_u^{MTM}, global memory M^{LTM}, retrieval budget K
Ensure: Retrieved memory set R_t
Intent Modeling and Query Control (SLM-1)
Infer high-level intent signals from (x_t, C_t), including (i) degree of personalization and (ii) reliance on recent vs. long-term information.
Generate a set of HQs $\{q_t^{(i)}\}_{i=1}^{n}$.
Produce metadata constraints ϕ_t (e.g., user identifier and optional temporal filters).
Allocate retrieval quotas across memory layers under a fixed Top-K constraint.
Stage 1: Metadata-Constrained Coarse Retrieval
Initialize candidate set $C \leftarrow \emptyset$.
for each $q_t^{(i)}$, $i = 1, \ldots, n$ **do**
    Retrieve candidates from M_u^{MTM} and/or M^{LTM} using vector search under ϕ_t.
    Let $K_1^{(i)} \leftarrow \lceil \frac{2K}{n} \rceil$ and collect up to $K_1^{(i)}$ candidates as $C^{(i)}$.
    Update $C \leftarrow C \cup C^{(i)}$.
end for
Optionally truncate C to size $2K$ if $|C| > 2K$.
Stage 2: Semantic Filtering and Compression (SLM-2)
Perform semantic consistency checking and relevance assessment conditioned on $\{q_t^{(i)}\}$ and C.
Select up to K items to form the final retrieved set $R_t \subseteq C$ with $|R_t| \leq K$.
Output
return R_t (to be appended to the prompt for response generation).

7.1.3 Response Generation

At each dialogue turn, the retrieved memory set R_t is concatenated with the short-term context C_t and provided to a fixed response generator (e.g., GPT-4o-mini) to produce the system response y_t. This stage does not involve any memory control or modification, and the same response generation setup is used for IntelliMem and all baseline methods in our experiments.

7.1.4 Online Memory Writing and MTM Maintenance

After response generation, IntelliMem updates mid-term memory via SLM-3, as described in Algorithm 2.

Algorithm 2 IntelliMem Online Memory Writing and MTM Maintenance

Require: Current interaction (x_t, y_t, C_t), user mid-term memory M_u^{MTM}, capacity bound B
Ensure: Updated M_u^{MTM}
Memory Extraction and Compression (SLM-3)
Extract reusable, user-relevant information from the current interaction (x_t, y_t, C_t).
Compress the extracted content into a concise semantic memory summary.
Memory Appending
Append the compressed memory summary to the user-scoped MTM M_u^{MTM}.
Redundancy and Conflict Handling
Identify highly repetitive or semantically overlapping MTM entries and merge or rewrite them to reduce redundancy.
Resolve conflicting information using temporal cues and accumulated evidence strength.
Capacity-Bound Maintenance
if $|M_u^{\text{MTM}}| > B$ **then**
    Evict stale or low-utility entries based on recency and access statistics.
    Further compress redundant content to enforce the capacity bound.
end if
return Updated M_u^{MTM}.

7.1.5 Offline Consolidation into Long-Term Memory

The consolidation procedure is summarized in Algorithm 3.

7.1.6 Online-Offline Decoupling Guarantee

All operations in Algorithm 1 and Algorithm 2 are executed under strict latency and compute constraints using small language models. In contrast, Algorithm 3 is performed asynchronously and does not block online interaction. This design ensures that (i) the cost of online retrieval remains bounded by $O(K)$, and (ii) the evolution of long-term memory does not introduce additional overhead to online inference.

8 Experiment

8.1 Statistical Significance Analysis

We report mean $\pm$ standard deviation across three random seeds for all stochastic components (see Table 5). Statistical significance is assessed using paired bootstrap resampling over evaluation instances (1,000 resamples), reporting the mean difference (Δ), its 95% confidence interval (CI), and two-sided p-values. We present results against the strongest baseline (A-MEM) under the same backbone model and retrieval budget.

Algorithm 3 IntelliMem Offline Consolidation into LTM

Require: MTM items flagged for consolidation, existing LTM graph M^{LTM}
Ensure: Updated LTM graph M^{LTM}
Selection of Candidate Episodes
Select MTM items that are newly written, frequently retrieved, or marked as low-utility under MTM capacity pressure.
Abstraction and De-identification
Abstract episodic interaction records into user-agnostic semantic knowledge units.
Remove personal identifiers and session-specific details.
Graph Insertion and Update
Perform similarity search over M^{LTM} to identify nearby semantic anchors.
Insert new nodes and edges within the local neighborhood of matched anchors.
Merge or update existing nodes when semantic overlap exceeds a threshold.
Evidence Accumulation and Forgetting
Aggregate supporting evidence across consolidation cycles.
Apply confidence decay to weakly supported knowledge units.
Remove or down-weight stale or incidental knowledge.
return Updated M^{LTM}.

Table 5: Statistical significance results against A-MEM under the same backbone and retrieval budget.

Category	Method	F1 (mean ± std)	Δ F1	95% CI of Δ	p-value
Multi-hop	A-MEM	27.02 ± 0.31	—	—	—
	LightMem	**28.85 ± 0.28**	1.83	[+1.24, +2.41]	**0.001**
Temporal	A-MEM	45.85 ± 0.37	—	—	—
	LightMem	**46.20 ± 0.34**	0.35	[+0.12, +0.58]	**0.008**

8.2 Failure Analysis: Ambiguous Intent Decomposition in SLM-1

We observe a mild failure mode when SLM-1 generates both episodic and general HQs for an underspecified recall query. For example, given the user query "Can you remind me what I decided about the project timeline?", the relevant decision is stored in MTM, while general planning advice may exist in LTM. SLM-1 may produce HQs for (i) decision recall (MTM), (ii) project disambiguation (MTM), and (iii) generic timeline principles (LTM). Under a fixed Top-K budget, allocating quota to the LTM HQ can introduce a small amount of generic content in the retrieved set. In practice, the final response typically remains correct (the key MTM decision is recalled), but becomes slightly less focused or concise due to additional general advice. This "focus dilution" mainly affects lexical-overlap metrics (e.g., F1/BLEU), while semantic similarity remains stable, and SLM-2's semantic filtering helps preserve the most relevant MTM evidence.

9 Full Prompt Templates and Control Interface Definitions

This appendix provides the complete prompt templates used by all language model components in IntelliMem, including SLM-1, SLM-2, SLM-3, and the offline LLM. All prompts are designed to be functionally complete, explicitly specifying model roles, accessible inputs, required tasks, prohibited behaviors, and output formats, to ensure reproducibility and auditability of the system implementation.

9.1 Unified Prompt Design Principles

All prompts in IntelliMem follow a unified structure to avoid implicit assumptions or undeclared capabilities:

- **Role**: the functional responsibility of the model within the system;
- **Input**: the information accessible to the model;
- **Task**: the explicit objectives the model must perform;
- **Constraints**: behaviors that the model is forbidden to execute;
- **Output Format**: a fixed and machine-parsable output specification.

This design ensures that online models are used for structured control and decision-making rather than open-ended generation.

9.2 SLM-1: Query Decomposition and Retrieval Routing

SLM-1 is responsible for transforming raw user input into a set of HQs and producing routing signals for downstream retrieval. SLM-1 does not perform retrieval and does not generate user-facing responses.

9.2.1 Full Prompt Template (SLM-1)

Role You are the Query Decomposition and Routing Engine for a memory system. Your job is not to answer the user. Your job is to translate the user's raw input into a list of specific search queries HQs used to retrieve necessary data from the memory database.

Input

- The current user input.
- A truncated dialogue context from the current session.

Task Logic For every user input, perform the following steps:

Step 1: Detect Missing Information Identify parts of the input that are vague, ambiguous, or incomplete, including but not limited to unresolved pronouns (e.g., "it", "that", "the project"), implicit contextual dependencies, and underspecified temporal references (e.g., "recently", "last time", "before").

Step 2: Generate HQs Rewrite the request into one or more independent and explicit search queries. Do not reuse the user's raw text verbatim.

Rules:

- Clarify implicit or missing entities.
- If the request involves both personal preferences and objective facts, split them into separate queries.
- Make time or location constraints explicit when they are implied.

Step 3: Route Queries For each HQ, assign the appropriate target memory layer:

- MTM for user-specific information.
- LTM for public or general knowledge.

Constraints

- Do not answer the user.
- Do not generate natural language responses.
- Do not perform retrieval.

Output Format JSON only.

9.3 SLM-2: Semantic Consistency Filtering and Candidate Compression

SLM-2 performs semantic consistency checking and candidate selection over a fixed-size set of retrieved memory items to suppress noise and reduce context size. SLM-2 is a selector only and does not generate or rewrite content.

9.3.1 Full Prompt Template (SLM-2)

Role You are the Semantic Consistency Filtering Engine for memory retrieval. You do not answer the user and you do not generate new content.

Input

- A set of HQs.
- A fixed-size list of candidate memory summaries with metadata.

Task For each candidate memory item:

- Judge whether it is semantically consistent with at least one HQ.
- Select the most relevant memory items under a fixed budget constraint.

Guidelines

- Relevance should be judged based on semantic alignment rather than surface-level overlap.
- Each selected memory item should directly support at least one HQ.

Constraints

- Do not rewrite or modify memory content.
- Do not generate explanations or user-facing responses.
- Do not perform retrieval or expansion.
- Selection only.

Output Format JSON only.

9.4 SLM-3: Interaction Summarization and Online MTM Maintenance

SLM-3 is responsible for compressing the current interaction into reusable MTM entries and supporting online MTM maintenance.

9.4.1 Full Prompt Template (SLM-3)

Role You are the Memory Writing and Maintenance Engine for MTM.

Input

- The current user input.
- The generated system response.
- Relevant short-term dialogue context.

Task Your responsibilities include:

- Extract reusable, user-relevant information from the interaction.
- Compress extracted information into concise semantic memory entries.
- Support incremental maintenance of MTM entries.

Guidelines

- Focus on information that may be useful in future interactions.
- Prefer concise, self-contained summaries over raw dialogue transcripts.

Constraints

- Do not store full dialogue transcripts.
- Do not retrieve or search existing memory.
- Do not perform cross-user abstraction.
- Do not generate responses to the user.

Output Format One or more short semantic memory summaries.

9.5 Offline LLM: Long-Term Memory Consolidation

Role You are the Offline Consolidation Model responsible for maintaining LTM.

Input You receive a batch of MTM items selected for consolidation, including newly written items, retrieval-reactivated items, and low-utility items flagged under MTM capacity pressure.

Task Your responsibilities are to:

- abstract episodic MTM items into de-identified semantic knowledge units;
- identify semantic overlap between candidate knowledge units and existing LTM nodes;
- decide whether each candidate should be merged with existing knowledge, used to update it, or discarded;
- integrate retained knowledge into the LTM graph by inserting or updating nodes and edges.

Guidelines

- remove user-specific and session-specific details during abstraction;
- prioritize stable and generalizable knowledge over episodic or incidental information.

Constraints

- do not generate user-facing responses;
- do not modify MTM directly;
- this process is executed offline and asynchronously, without affecting online interaction latency.

Output Format A set of updated or newly inserted LTM knowledge units, together with their associated graph links.

10 LTM Graph Schema and Maintenance Dynamics

This section supplements Section 3.6 by providing a detailed definition of the schema used for the graph-structured LTM and by discussing its maintenance dynamics, including update frequency, node growth behavior, and the impact of offline consolidation on downstream reasoning performance.

10.1 Graph Schema: Node and Edge Types

As described in Section 3.6, LTM is designed as a lightweight, de-identified semantic knowledge graph. Unlike MTM, which stores episodic interaction summaries, LTM aims to capture stable factual knowledge and domain-level regularities. To support cross-task generalization and multi-hop reasoning, elements in the LTM graph are standardized into a small set of node and edge types, summarized in Table 6.

10.2 Maintenance Dynamics and Performance Impact

IntelliMem adopts a decoupled architecture that separates online retrieval from offline consolidation. The offline LLM processes updates in incremental batches, ensuring that maintenance does not block real-time user interaction. Table 7 summarizes key operational metrics of the consolidation process and analyzes their impact on model performance.

Table 6: Node and edge types used in the LTM knowledge graph.

Category	Type	Description and Example
Nodes	Entity	Concrete objects, locations, or named items extracted from interactions (e.g., "Python script", "Paris", "Project X").
	Concept	Abstract categories or generalized classes that characterize shared properties of entities (e.g., "Programming Language", "Capital City", "Urgent Task").
Edges	IsA	Hierarchical membership relation between an entity and a concept (e.g., *Paris* $\xrightarrow{\text{IsA}}$ *Capital City*).
	HasProperty	Links an entity to a specific attribute or state (e.g., *Project X* $\xrightarrow{\text{HasProperty}}$ *Completed*).
	RelatedTo	Generic semantic association based on co-occurrence or functional relatedness (e.g., *SNN* $\xrightarrow{\text{RelatedTo}}$ *Neural Operator*).
	Implies	Logical or causal dependency extracted from reasoning traces (e.g., *High Density* $\xrightarrow{\text{Implies}}$ *Congestion*).

Table 7: LTM update frequency, consolidation cost, and ablation results on reasoning accuracy.

Metric	Value	Description and Analysis
Batch update interval	Every 10–15 turns	Offline consolidation is periodically triggered when MTM accumulates sufficient new entries or reaches capacity pressure, enabling amortized long-term updates without interfering with online processing.
Node growth rate	$\sim$1 node / 4 turns	On average, only one new semantic node is added to LTM every four dialogue turns. This sparsity reflects the high compression ratio of IntelliMem, where noise is filtered and only high-value evidence is retained for persistent storage.
Offline processing time	$\sim$3.5 s / batch	Average time for the offline LLM to perform abstraction, graph linkage, and structural updates. This latency occurs entirely on the offline path and is fully decoupled from online retrieval (average retrieval latency $\sim$83 ms), making it invisible to users.
Reasoning accuracy (F1)	4.12 (full) vs. 3.96 (no update)	The full IntelliMem system (4.12) outperforms a variant without offline consolidation (3.96), corresponding to an approximately 4% performance drop when LTM evolution is disabled. This result highlights the importance of sustained LTM growth and consolidation for long-horizon reasoning.