LightMem-Ego: Your AI Memory for Everyday Life

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Abstract

Personal AI assistants on mobile and wearable devices continuously perceive users' daily lives through visual and audio streams. However, answering queries about past experiences requires lightweight multimodal memory that can continuously accumulate, organize, and retrieve long-term experiences, which remains challenging. To address this challenge, we present **LightMem-Ego**, a lightweight streaming multimodal memory system for everyday-life assistance. The system continuously captures egocentric visual and audio streams, aligns them on a shared timeline, and organizes them into a hierarchical memory consisting of current, short-term, and long-term memory. Given a user query, LightMem-Ego dynamically routes retrieval to the appropriate memory level and generates answers grounded in multimodal evidence. The demonstration can be deployed on smartphones and AI glasses, supporting object finding, conversation recall, life summarization, routine discovery, and personalized assistance[1].

1 Introduction

Personal memory is a fundamental part of everyday intelligence. People constantly rely on memory to recall where they placed an object, what someone just said, what happened during a meeting, or how their routines change over time. As smartphones and AI glasses become natural interfaces for capturing egocentric visual and audio streams, they create a new opportunity for AI assistants: instead of only answering isolated questions, an assistant can become a memory companion for everyday life (Huang et al., 2025b; Yang et al., 2025, 2026). Such a system could help users find misplaced items, recall recent conversations, summarize daily activities, and reason over long-term habits and routines (Yang et al., 2025; Tang et al., 2026; Gao et al., 2026; Deng et al., 2026).

Recent multimodal large language models have made human-computer interaction more natural by combining vision, speech, and language (Long et al., 2025; Yeo et al., 2025; OpenAI, 2024; Gemini Team, 2025). Meanwhile, wearable devices and smartphones provide practical channels for continuous, hands-free perception in daily environments (Huang et al., 2025b; Yang et al., 2025, 2026; Jiang et al., 2026; Deng et al., 2026). However, turning such interfaces into everyday memory assistants requires addressing three fundamental challenges: **First**, egocentric experience arrives as continuous visual-audio streams without explicit event boundaries, requiring assistants to transform raw observations into coherent event-level experiences. **Second**, continuously accumulated experiences must be incrementally organized into current, short-term, episodic, and semantic memory while remaining efficient for long-term deployment. **Third**, user queries naturally span multiple temporal horizons, requiring dynamic routing across different memory levels instead of relying on a single context window or flat retrieval store. Together, these challenges call for an experience-centric memory system that can continuously capture, organize, retrieve, and reason over everyday life (Tang et al., 2026; Xiao et al., 2026; Wang et al., 2026; Alam et al., 2026; Gao et al., 2026).

To address these challenges, we present **LightMem-Ego**, a deployable streaming multimodal memory system for everyday-life assistance. LightMem-Ego connects lightweight smartphone or AI-glasses-style clients with a backend that ingests egocentric visual-audio streams, segments recent observations into events, and organizes them into a three-level memory hierarchy: current memory for ongoing context, short-term memory for recent micro-events, and long-term memory for consolidated episodes and semantic facts (Packer

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[1] https://github.com/zjunlp/LightMem-Ego.

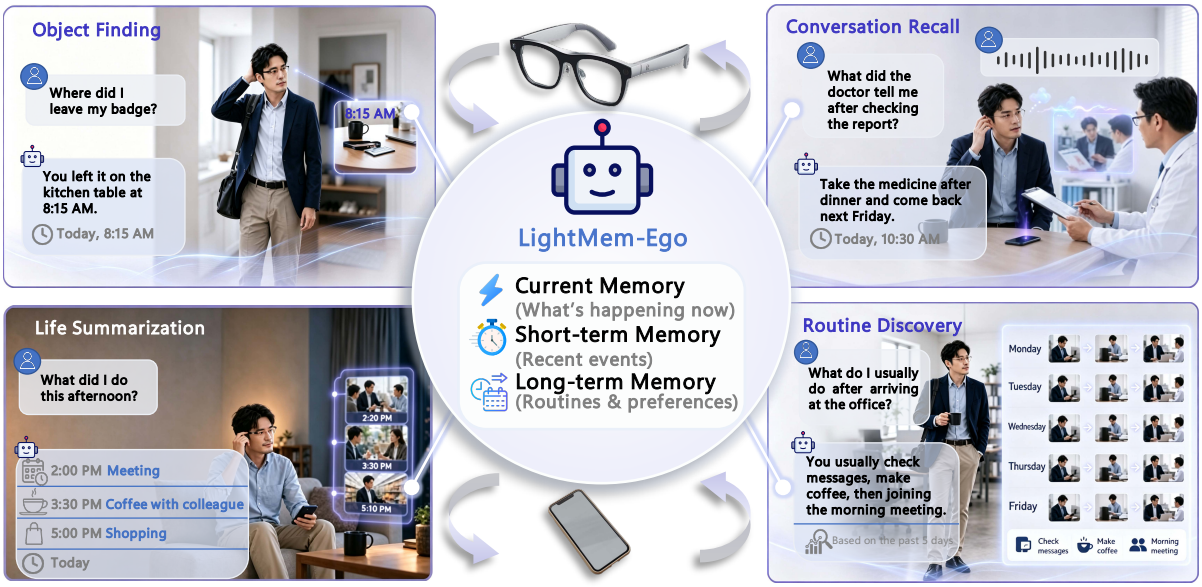


Figure 1: Overview of **LightMem-Ego**'s motivating scenarios and memory hierarchy. The system supports everyday memory assistance across object finding, conversation recall, life summarization, and routine discovery by routing user queries to current, short-term, and long-term memory.

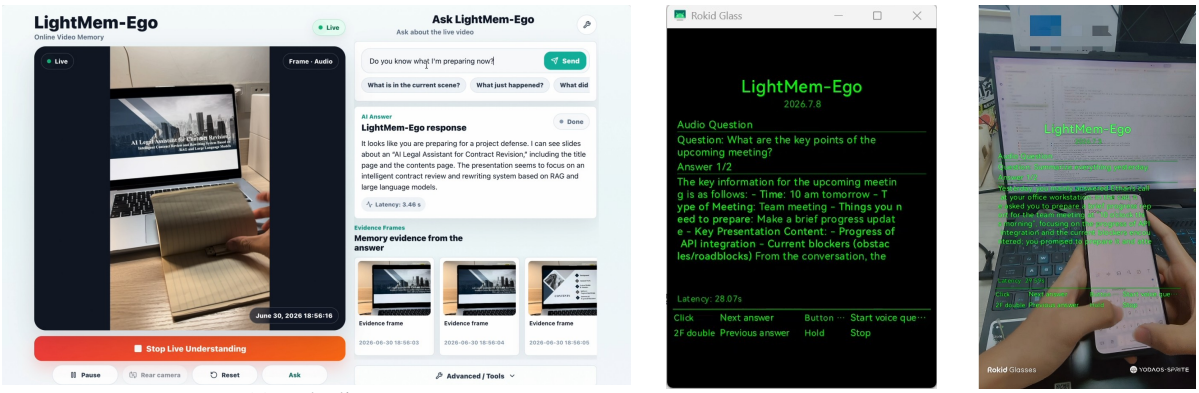
et al., 2023; Chhikara et al., 2025; Fang et al., 2025; Xu et al., 2026). During question answering, a memory router selects evidence according to the temporal scope and intent of the query, enabling grounded responses about the present, the recent past, and long-term routines within a unified interface. The system supports continuous frame streams, audio chunks, synchronized timestamps, and modular ASR, vision-language, language model, retrieval, and storage components. We demonstrate LightMem-Ego on representative egocentric memory tasks, including object finding, conversation recall, life summarization, and routine discovery (Figure 1), and report quantitative results on retrieval, question answering, and latency against application-oriented baselines without explicit multimodal long- and short-term memory.

2 Related Work

Conversational Memory. Conversational memory extends LLM-based assistants from stateless, single-session interaction to persistent agents that can retain, update, and retrieve user-specific information over time (Du, 2026; Li et al., 2025; Fang et al., 2025; Chhikara et al., 2025). Product systems such as ChatGPT Memory and research systems such as MemGPT and Mem0 demonstrate complementary designs: the former emphasizes personalized continuity, while the latter study explicit memory management through hierarchical context, external storage, consolidation, and retrieval (OpenAI, 2024, 2026; Chhikara et al., 2025; Packer et al., 2023). These systems motivate LightMem-Ego's use of persistent, queryable memory, but they mainly focus on language-centric interaction rather than streaming egocentric multimodal experience.

Wearable and Mobile AI Assistants. Wearable and mobile AI assistants place multimodal interaction in the user's physical environment. Wearable systems and smart-glasses agents use egocentric perception for real-time situated assistance (Huang et al., 2025b,a; Yang et al., 2025, 2026; Zhou et al., 2026). Related benchmarks and prototypes further evaluate glasses-style agents and connect visual understanding with physical-world actions (Jiang et al., 2026; Tu et al., 2026; Liu et al., 2026; Pu et al., 2025; Yang et al., 2025). On smartphones, multimodal assistants increasingly combine language, vision, voice, and on-screen understanding (OpenAI, 2024; Gemini Team, 2025). However, most systems still focus on current-context perception and response, rather than explicit long-horizon memory of everyday experience.

Multimodal Personal Memory. Multimodal personal memory studies how daily experience can be captured, organized, and queried over time. Memory-augmented video agents build intermediate representations for temporally grounded reasoning over long videos (Fan et al., 2024; Long et al., 2025; Yeo et al., 2025; Tian et al., 2025). Personalized egocentric retrieval and VQA recover user-



(a) Web client. (b) Glasses app UI. (c) First-person overlay.

Figure 2: Interfaces of **LightMem-Ego** across web and wearable deployments. The web client visualizes live multimodal capture and retrieved evidence; the glasses client app provides a lightweight interaction surface; and the first-person overlay illustrates how memory-grounded responses are presented in the user's egocentric view.

specific events from long-context recordings (Tang et al., 2026; Xiao et al., 2026; Wang et al., 2026; Alam et al., 2026). Lifelogging and egocentric-life systems organize daily archives for retrieval and assistance (Tran et al., 2025; Yang et al., 2025), while life-journaling systems move toward semantic activity summarization from mobile sensing and language models (Xu et al., 2025). These works motivate LightMem-Ego's streaming hierarchical memory design.

3 LightMem-Ego

LightMem-Ego is a streaming multimodal memory system for everyday-life assistance. It connects smartphones or wearable devices with a backend that captures multimodal life streams, organizes them into hierarchical memory, and answers user questions through explicit memory retrieval. The system combines online updates for current and short-term memory with asynchronous consolidation into long-term episodic and semantic stores, allowing it to support both immediate scene understanding and retrospective reasoning over past experience. Figure 2 shows the deployed interfaces of LightMem-Ego across web, glasses-client, and first-person wearable views.

3.1 Multimodal Life Capture

We represent everyday experience as a temporally ordered multimodal stream:

$$\mathcal{X} = \{x_t\}_{t=1}^{T}, \qquad x_t = (v_t, a_t, m_t), \tag{1}$$

where v_t, a_t, and m_t denote visual observations, audio observations, and auxiliary metadata, respectively. The capture layer is lightweight: it collects, normalizes, and timestamps raw inputs from smartphones or wearable devices, and forwards them to the backend without heavy client-side reasoning. In online deployment, the primary interface is a unified frame–audio stream, in which image frames and short audio chunks are uploaded to the same session. All modalities are aligned on a shared session timeline using the relative timestamp $\tau = t - t_0$, which is preserved for downstream event building, transcript backfilling, and retrieval. Beyond video and audio, the same interface can incorporate side-channel context such as coarse location, screen activity, or lightweight sensor cues.

3.2 Event Segmentation

Given the captured stream $\mathcal{X}$, LightMem-Ego incrementally partitions it into short event segments $\mathcal{E} = \{e_i\}_{i=1}^{N}$, where each segment corresponds to a contiguous interval on the shared timeline. Segmentation is driven by temporal continuity and cross-frame change signals, enabling lightweight micro-event construction under streaming conditions without semantic parsing of every frame. Each segment stores its temporal span, representative frames, provisional visual description, and aligned or pending audio context. As more evidence arrives, transcripts and refined descriptions are asynchronously attached to existing segments. These segments form the basic units for downstream memory construction and can represent everyday experiences such as meetings, walking episodes, shopping moments, or conversations.

3.3 Hierarchical Memory

LightMem-Ego organizes captured experience into a hierarchical memory system:

$$\mathcal{M} = \{\mathcal{M}_{cur}, \mathcal{M}_{st}, \mathcal{M}_{lt}\}, \tag{2}$$

where $\mathcal{M}_{cur}$, $\mathcal{M}_{st}$, and $\mathcal{M}_{lt}$ denote current, short-term, and long-term memory, respectively. $\mathcal{M}_{cur}$ acts as a lightweight working memory over the most recent multimodal observations and active event state, enabling immediate responses about the ongoing scene. $\mathcal{M}_{st}$ stores recent event segments together with representative visual evidence, provisional or refined descriptions, and transcript context when available. Stable short-term events are then consolidated into long-term memory $\mathcal{M}_{lt}$, which contains episodic memory $\mathcal{M}_{epi}$ for event-centered past experiences and semantic memory $\mathcal{M}_{sem}$ for higher-level regularities such as routines, preferences, and relationships. This hierarchy separates fast online interaction from slower memory consolidation while preserving both event-specific and abstract personal knowledge.

3.4 Edge-Oriented Efficiency

LightMem-Ego targets mobile and AI-glasses deployment by keeping edge processing lightweight and shifting memory construction to the backend. The client samples, compresses, timestamps, and uploads low-rate frames and short audio chunks, avoiding heavy VLM or LLM inference on resource-constrained devices. The online backend path updates $\mathcal{M}_{cur}$ as a rolling buffer and builds $\mathcal{M}_{st}$ from temporal continuity and cross-frame changes, while costly operations such as ASR backfilling, event refinement, indexing, and semantic extraction run asynchronously.

Query-time cost is also reduced. Stable events are consolidated into a event-centric long-term memory, where multimodal evidence is pre-aligned under event anchors. User-facing inference therefore retrieves compact event records rather than raw streams or fragmented modality-specific evidence. A query router selects the cheapest sufficient source: $\mathcal{M}_{cur}$ for current-scene queries, $\mathcal{M}_{st}$ for recent recall, and $\mathcal{M}_{lt}$ for retrospective or routine-level questions. This keeps wearable interaction responsive while slower memory updates run in the background.

3.5 Experience Retrieval and QA

Given a user query q, LightMem-Ego first routes the query to appropriate memory sources and then generates an answer from retrieved evidence. Formally, retrieval produces a query-specific evidence set $\mathcal{R}(q) \subseteq \mathcal{M}_{cur} \cup \mathcal{M}_{st} \cup \mathcal{M}_{lt}$. The routing process is guided by the temporal scope and semantic intent of the query, naturally supporting time-aware, person-aware, place-aware, and event-aware retrieval. Retrieved evidence may include recent observations, short-term event records, episodic entries, semantic summaries, timestamps, representative frames, and transcript snippets. These heterogeneous signals are fused into a compact evidence view E_q, and the final answer is generated as $\hat{y} = f(q, E_q)$. By making retrieval explicit and memory-grounded, LightMem-Ego supports both immediate questions about the present scene and retrospective questions about who, where, when, and what happened in the user's past experience.

4 Demonstration

Figure 3 summarizes the main demonstration scenarios of LightMem-Ego. We organize the demo around everyday memory needs that span immediate scene understanding, recent event recall, and long-term routine reasoning.

Immediate Assistance. LightMem-Ego supports immediate assistance and short-horizon recall in mobile and AI-glasses settings. For example, users may ask *Where did I leave my badge?*, *When did I last hold my keys?*, or *What am I looking at now?* In these cases, the system retrieves relevant recent observations and event segments, and returns answers grounded in temporally localized memory evidence. This case demonstrates how online perception and short-term memory can work together in everyday environments.

Conversation Recall. LightMem-Ego also supports recall of recent spoken interactions. After a meeting or conversation, users can ask questions such as *What did the doctor tell me after checking the report?* or *What did my colleague ask me to do?* The system combines short-term event memory with aligned transcript context to recover the relevant conversational episode. This shows the value of multimodal memory for recovering spoken information beyond one-shot speech transcription.

Life Summarization and Routine Discovery. Beyond recovering isolated facts, LightMem-Ego can summarize recent experiences and reason over repeated patterns. A user may ask *What did I do this afternoon?*, *Summarize what happened during lunch*, or *What do I usually do after arriving at the office?* The system aggregates event-centered evidence across multiple segments and, when appropriate, draws on long-term semantic memory to identify recurring activities, preferences, and

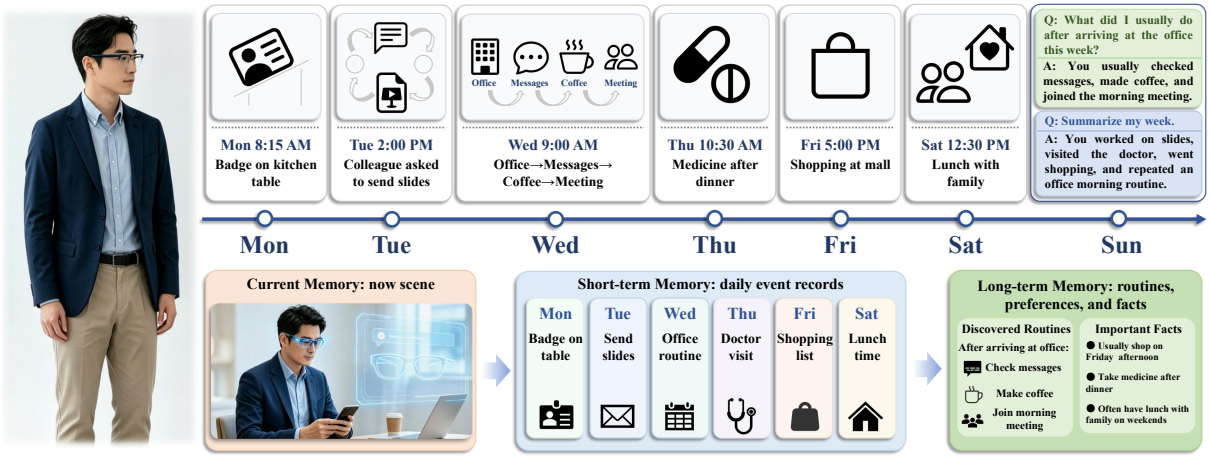


Figure 3: Representative demonstration scenarios of **LightMem-Ego**. The system supports immediate assistance, conversation recall, life summarization, and routine discovery by retrieving evidence from hierarchical memory.

routines. This scenario illustrates the ability of LightMem-Ego to move from event recall to higher-level summarization and habit-level reasoning.

5 Quantitative Evaluation

5.1 Evaluation Setup

We evaluate LightMem-Ego on three daily memory scenarios: object finding, conversation recall, and life summarization. For each scenario, we construct queries with manually annotated gold evidence. We report retrieval performance with Recall@1/3/5 and MRR, QA performance with LLM- and human-judged accuracy, and interactive latency with P50 / P90 retrieval, generation, and end-to-end QA time on phone and glasses-style clients.

Scenario	R@1	R@3	R@5	MRR
Object Finding	22.2	66.7	77.8	0.454
Conversation Recall	44.4	55.6	55.6	0.481
Life Summarization	88.9	100.0	100.0	0.944
Overall	**51.9**	**74.1**	**77.8**	**0.627**

Table 1: Memory retrieval accuracy across everyday-life scenarios. R@k denotes Recall@k, and MRR measures the reciprocal rank of the first relevant memory entry.

5.2 Memory Retrieval Accuracy

Table 1 summarizes retrieval accuracy in the three demonstration scenarios. LightMem-Ego retrieves relevant memory evidence within the top-3 results for most queries, achieving 74.1 overall R@3 and 0.627 MRR. The results suggest that the hierarchical memory store provides sufficiently accurate evidence selection for downstream experience QA in everyday object finding, conversation recall, and life summarization settings.

Scenario	LLM-Judge	Human Acc.
Object Finding	44.4	55.6
Conversation Recall	33.3	33.3
Life Summarization	77.8	77.8
Overall	**51.9**	**55.6**

Table 2: Experience QA accuracy on daily scenarios.

5.3 Experience Question Answering Accuracy

Table 2 reports QA accuracy against annotated experience evidence. LightMem-Ego obtains 51.9 LLM-judged accuracy and 55.6 human-judged accuracy overall, with the best performance on life summarization. These results indicate that, when relevant evidence is retrieved, the system can produce usable memory-grounded answers for the demonstrated everyday QA scenarios, while fine-grained object finding and conversation recall remain more challenging in the current prototype.

Stage	Phone		Glasses-style	
	P50	P90	P50	P90
Short-term memory QA				
Retrieval	13 ms	15 ms	14 ms	29 ms
Answer gen.	5.77 s	10.38 s	6.10 s	9.79 s
End-to-end QA	5.86 s	10.95 s	7.01 s	9.96 s
Long-term memory QA				
Retrieval	4.09 s	15.39 s	10.39 s	28.93 s
Answer gen.	9.00 s	22.40 s	9.25 s	22.62 s
End-to-end QA	14.87 s	35.15 s	19.96 s	42.70 s

Table 3: Latency breakdown by memory scope and client. P50 / P90 are 50th / 90th percentile latencies.

5.4 Latency on Mobile and Wearable Clients

Table 3 reports the runtime of LightMem-Ego on phone and glasses-style clients. For short-term

System	Platform and Input	Real-time Visual-Audio Stream	Current / Short-term MM Memory	Long-term MM Episodic Memory	Long-term Semantic Memory	Timestamped Evidence Retrieval
ChatGPT Memory	Text chat	—	—	—	*Partial*	—
Mem0-style memory	Text and agent memory	—	*Partial*	—	✓	*Partial*
Memories.ai	Video archives and visual memory platform	*Partial*	*Partial*	✓	*Partial*	*Partial*
Gemini Live	Phone	✓	*Partial*	—	—	—
Ray-Ban Meta AI Glasses	Glasses	*Partial*	*Partial*	—	—	—
Vinci	Phone or wearable camera	✓	✓	*Partial*	*Partial*	*Partial*
VisualClaw	Streaming video with agent workspace	*Partial*	*Partial*	—	*Partial*	*Partial*
VisionClaw	Smart glasses	✓	*Partial*	—	—	*Partial*
Egocentric Co-Pilot	Smart glasses with web agents	✓	✓	*Partial*	*Partial*	*Partial*
EgoButler	AI-glasses egocentric video and audio	*Partial*	*Partial*	*Partial*	*Partial*	✓
LightMem-Ego	**Phone and glasses-style client**	✓	✓	✓	✓	✓

Table 4: Capability comparison with representative commercial assistants, text-based memory systems, and egocentric multimodal assistants. The table compares publicly described system capabilities rather than experimentally measured performance. We mark a capability as supported only when it is implemented as an explicit first-class component. *Partial* indicates limited, implicit, offline, session-level, or modality-restricted support; — indicates that the capability is not explicitly supported or not publicly described.

memory QA, the system achieves interactive response times, with P50 end-to-end latency of 5.86s on phone and 7.01s on the glasses-style client. Long-term memory QA requires additional retrieval and evidence aggregation, leading to higher P50 latency of 14.87s and 19.96s, respectively. This latency profile is consistent with the intended usage of the demo: recent-memory queries support near-interactive assistance, while long-term queries remain practical for retrospective recall and life-summary interactions.

5.5 Capability Comparison with Existing Assistants and Memory Systems

We further compare LightMem-Ego with representative commercial assistants, text-based memory systems, and recent egocentric multimodal assistants in terms of publicly described capabilities. As shown in Table 4, existing systems cover different parts of the design space: ChatGPT Memory and Mem0-style systems mainly focus on conversational or text-based agent memory, while Memories.ai explores long-term visual memory for searchable video archives (OpenAI, 2024, 2026; Chhikara et al., 2025; Memories.ai, 2026). Gemini Live and Ray-Ban Meta AI Glasses support real-time multimodal interaction, while recent egocentric assistants such as Vinci, VisualClaw, VisionClaw, Egocentric Co-Pilot, and EgoButler explore real-time perception, wearable assistance, tool use, or long-context egocentric QA (Huang et al., 2025b; Tu et al., 2026; Liu et al., 2026; Yang et al., 2026, 2025). However, these systems generally do not expose an explicit hierarchy that jointly supports current multimodal memory, short-term event memory, long-term multimodal episodic memory, semantic routine memory, and timestamped evidence retrieval.

In contrast, LightMem-Ego is designed specifically for everyday-life memory assistance over streaming visual-audio experience. Rather than emphasizing only in-the-moment perception, text-based personalization, or agentic task execution, it organizes user experience into current, short-term, and long-term memory stores, enabling both immediate assistance and retrospective experience QA such as object finding, conversation recall, life summarization, and routine discovery.

6 Conclusion

We introduced LightMem-Ego, a streaming multimodal memory system for everyday-life assistance. The system connects mobile and wearable multimodal capture with hierarchical memory construction and memory-grounded question answering, enabling support for object finding, conversation recall, life summarization, and routine understanding within a single backend. Our demonstration and evaluation suggest that explicit long-horizon multimodal memory is a promising systems direction for personal AI assistants.

Ultimately, building real-world personal AI assistants requires moving beyond language understanding alone toward the ability to capture, organize, and recall human experience over time. LightMem-Ego takes a step in this direction by showing how multimodal memory can support AI systems that not only understand utterances, but also understand lived experience.

Limitations

LightMem-Ego remains constrained by several system-level factors. Its current implementation relies on upstream API calls for speech recognition, visual understanding, language generation, and retrieval-based question answering, making both accuracy and latency sensitive to external model reliability, runtime variation, and rate limits. Errors in transcripts, visual descriptions, or timestamp alignment may further propagate into memory construction and affect answer faithfulness. In addition, maintaining multimodal memory over continuous egocentric streams still incurs nontrivial overhead, as the system repeatedly performs segmentation, summarization, embedding, indexing, and storage. The memory update mechanism is also preliminary: it lacks a principled policy for revising, merging, forgetting, or promoting memories. Future work will improve efficiency, robustness, and adaptive memory lifecycle management for longer and more diverse deployments.

Ethical and Privacy Considerations

LightMem-Ego relies on egocentric visual and audio streams, which may contain sensitive information about users and nearby bystanders, including private conversations, faces, documents, locations, screens, and daily routines. Because the system converts these streams into persistent and queryable memory, privacy risks can arise from both raw data and derived representations such as transcripts, event summaries, embeddings, and long-term semantic memories.

The current prototype is intended as a research demonstration and has not yet implemented a complete privacy-preserving pipeline. It does not automatically redact sensitive content, manage bystander consent, enforce fine-grained access control, or provide mature retention and deletion policies. Future work will integrate privacy protection into the memory lifecycle, including on-device preprocessing, selective capture, sensitive-content filtering, encrypted storage, user-controlled memory editing and deletion, and privacy-aware consolidation that avoids promoting incidental sensitive information into long-term memory.

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