Collaborative Memory: Multi-User Memory Sharing in LLM Agents with Dynamic Access Control

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Abstract

Complex tasks are increasingly delegated to ensembles of specialized LLM-based agents that reason, communicate, and coordinate actions—both among themselves and through interactions with external tools, APIs, and databases. While persistent memory has been shown to enhance single-agent performance, most approaches assume a monolithic, single-user context—overlooking the benefits and challenges of knowledge transfer across users under dynamic, asymmetric permissions. We introduce **Collaborative Memory**, a framework for multi-user, multi-agent environments with asymmetric, time-evolving access controls encoded as bipartite graphs linking users, agents, and resources. Our system maintains two memory tiers: (1) *private memory*—private fragments visible only to their originating user; and (2) *shared memory*—selectively shared fragments. Each fragment carries immutable provenance attributes (contributing agents, accessed resources, and timestamps) to support retrospective permission checks. Granular *read policies* enforce current user–agent–resource constraints and project existing memory fragments into filtered transformed views. *Write policies* determine fragment retention and sharing, applying context-aware transformations to update the memory. Both policies may be designed conditioned on system, agent, and user-level information. Our framework enables safe, efficient, and interpretable cross-user knowledge sharing, with provable adherence to asymmetric, time-varying policies and full auditability of memory operations.

1 Introduction

The theory of Distributed Cognition [8] posits that cognitive processes are not confined to individual minds but are distributed across groups of people, artifacts, and their interactions within an environment. From this perspective, a collective system—comprising individuals and shared external representations—can function as a unified cognitive entity, capable of collaborative reasoning and complex problem-solving. This conceptual framework aligns closely with recent advances in multi-agent systems [5, 19], where ensembles of specialized agents—often instantiated as large language models (LLMs)—are orchestrated to solve problems that exceed the capacity of any single model. These agents not only communicate and coordinate with one another but also interface with external resources such as tools, APIs, and structured data sources [24, 16].

A key enabler of such collaboration is persistent memory. Recent work has demonstrated that equipping LLM agents with long-term memory significantly enhances their ability to reason over extended horizons [9, 11]. For example, MemGPT introduces an operating system-inspired abstraction for managing contextual memory over time [13]; MemTree employs a hierarchical memory structure for organizing and retrieving information dynamically [14]; and GraphRAG constructs a graph-based
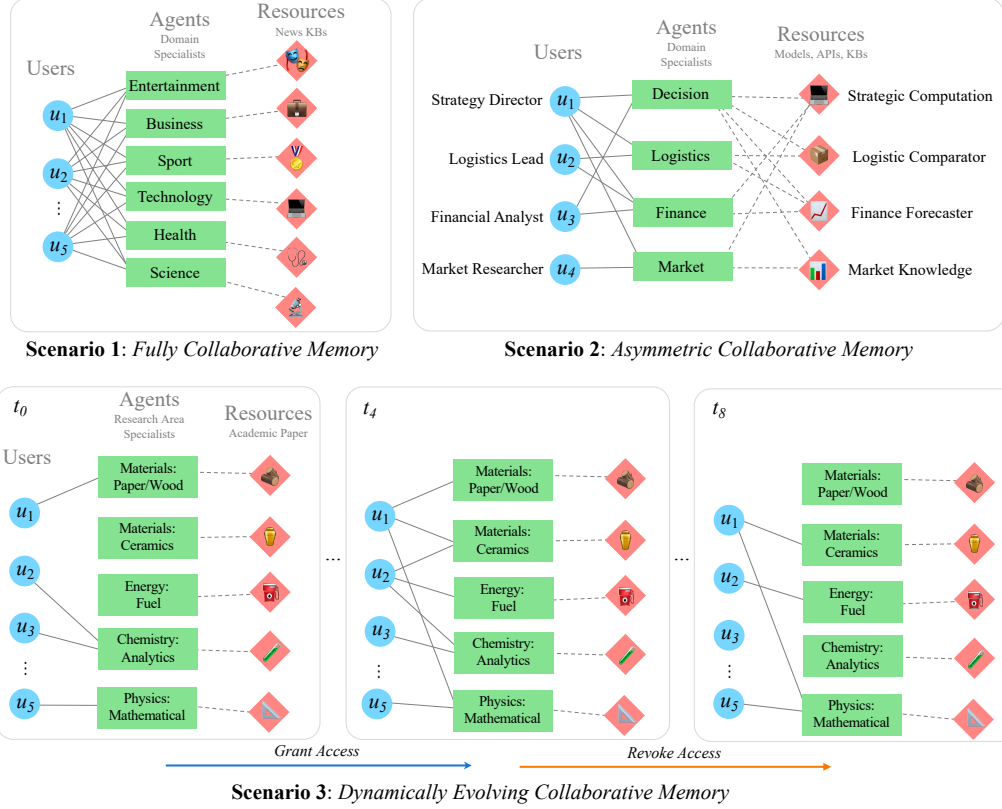
Figure 1: Illustration of multi-user, multi-agent collaboration. Scenario 1 (top-left): A fully collaborative memory environment where all users share unrestricted access to all agents. Scenario 2 (top-right): An asymmetric collaborative memory setup with heterogeneous privilege levels. Scenario 3 (bottom): Dynamically changing access, where permissions are granted or revoked over time.

memory of entities and relations to enable structured knowledge access [3, 17]. These systems allow agents to store, recall, and build upon prior experiences in a manner that supports more coherent and context-aware behavior.

However, these architectures predominantly conceptualize a single-user, single-agent paradigm with centralized, globally accessible memory. This assumption breaks down in many real-world applications that are inherently *multi-user* and *multi-agent*, such as collaborative enterprise assistants, multi-user productivity platforms, and distributed workflow systems [13]. In these settings, sharing memory across user boundaries can reduce redundant inquiries, maintain consistency, and improve collective reasoning (Figure 1). Yet, current research often overlooks these multi-user complexities, leaving real-world systems to face two key challenges that remain underexplored: **1)** *Information Asymmetry,* whereby different users have access to different agents, and each agent, in turn, connects to different resources—making it crucial for memory systems to enforce these asymmetries to prevent unauthorized information sharing; and **2)** *Dynamic Access Patterns,* where permissions evolve over time, allowing or revoking user and agent access based on changing roles, policies, and task requirements.

These asymmetric and temporally evolving constraints pose a central question: How can a multi-user, multi-agent system maximize the utility of collective memory while ensuring that information sharing conforms to permissions governing what can be shared, when, and by whom? In this paper, we take a first step toward addressing this question by introducing a framework designed specifically for multi-user, multi-agent memory management under asymmetric and dynamic access constraints. Our proposed framework comprises several key components:

- **Dynamic bipartite access graphs.** We formalize time-dependent permissions using two bipartite graphs: one representing user-to-agent permissions, and another representing agent-to-resource

permissions. These graphs explicitly encode the evolving permissions landscape, capturing real-world dynamics such as user onboarding, role changes, and evolving policy constraints.

- **Two-tier memory system.** To enable controlled yet flexible knowledge sharing, each agent maintains a dual-tier memory architecture consisting of private memory and shared memory. Private memory isolates sensitive information to individual user contexts, while shared memory enables knowledge transfer among users when allowed by the system's access policies.

- **Fine-grained read and write policies.** Memory interactions are governed by distinct read and write policies. The write policy projects raw interaction logs into structured memory fragments, selectively allocating these fragments to either private or shared memory tiers. Conversely, the read policy dynamically constructs a memory view tailored to each agent's current permissions, selectively incorporating memory fragments according to fine-grained access constraints. Importantly, these policies are highly configurable, supporting specification and enforcement at multiple granularity levels—system-wide, agent-specific, and user-specific—and are adaptive over time.

To our knowledge, this is the first formulation of memory sharing that explicitly accounts for fine-grained access asymmetries in multi-agent, multi-user systems. Our work establishes foundational concepts and formalizations, laying the groundwork for future research into efficient, secure, and adaptive collaborative multi-agent systems.

2 Related Work

Long-term memory for single LLM agents. Early work on augmenting LLMs with *persistent* context treats memory as a flat retrieval table, but recent systems introduce hierarchical or structured representations that better support long-horizon reasoning. MemGPT leverages operating-system abstractions to emulate virtual memory and extend the effective context window of an LLM [13]. MemTree organizes interaction history as a hierarchical dynamically evolving tree whose nodes hold abstracted summaries, enabling continual updates of memory [14]. HippoRAG constructs a hippocampal-inspired knowledge graph and applies Personalized PageRank to integrate new information while avoiding catastrophic forgetting [6]. GraphRAG takes a complementary approach, constructing an entity-relation graph over the corpora and retrieving sub-graphs to answer complex queries [3]. Although highly effective, all of these designs assume a *single-user, single-agent* setting with globally visible memory.

Multi-agent collaboration and shared memory. LLM agents increasingly collaborate as heterogeneous teams whose members specialize in search, planning, self-critique, and tool calling. AutoGen provides an open-source conversation framework that lets developers script arbitrary interaction graphs among tool-augmented agents [22]. AgentVerse explores emergent social behaviors when groups of agents are asked to solve tasks collectively, showing measurable gains over single-agent baselines [2]. MoSA (Mixture-of-Search-Agents) uses Monte-Carlo Tree Search to fuse diverse reasoning trajectories proposed by multiple LLMs and consistently outperforms strong single-model solvers on math and commonsense benchmarks [23]. COPPER introduces a *shared reflector* that learns to issue counterfactual rewards, mitigating credit-assignment issues in multi-agent planning [1]. Most of these frameworks either maintain *no* persistent memory or assume a *fully shared* memory store; Memory Sharing [4] begins to address this gap by letting agents asynchronously contribute to, and retrieve from, a single common memory pool, but it still overlooks user-level privacy or access constraints.

Access-control models for knowledge sharing. The security literature offers mature abstractions for permission management. Role-Based Access Control (RBAC) assigns users to roles that carry predefined privileges, supporting efficient policy administration in large organizations [15]. Attribute-Based Access Control (ABAC) generalizes RBAC by deciding authorization through logical predicates over arbitrary subject, object, and environmental attributes [7]. Our framework inherits the policy modularity of ABAC while explicitly modeling *time-varying* bipartite graphs between users, agents, and resources; to our knowledge, no existing LLM memory system combines such policies with provenance-aware fragment storage.

Summary. Prior work establishes the benefits of (i) structured long-term memory for individual agents and (ii) division-of-labor in multi-agent systems; however, none accommodates the asymmetric,
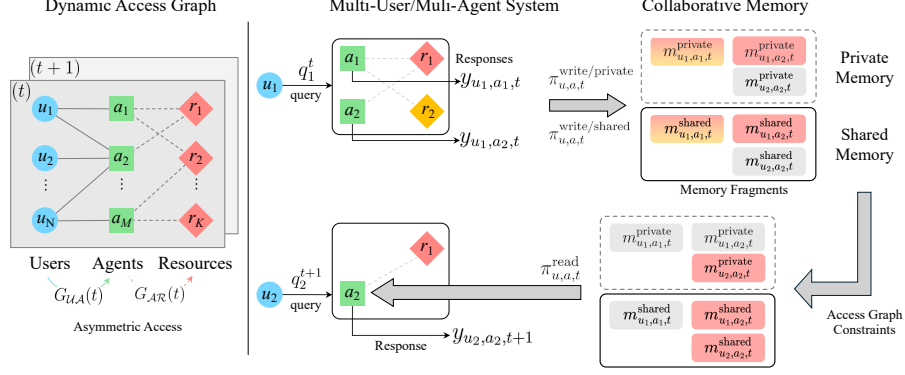
Figure 2: Left: Illustration of the dynamic multi-user environment, where multiple users collaborate with various agents that each have access to different resources. Right: Illustration of Collaborative Memory. User u_1 sends a query q_1 and receives responses from agents a_1 and a_2. These responses are passed to the write policies $\pi^{\text{write/private}}$ and $\pi^{\text{write/shared}}$, which updates both the private and shared memories. Memory fragments that are not accessible are shown in gray. When user u_2 issues another query q_2, the agent access resource r_1 as well as reading from the collaborative memory, retrieving only the information it is permitted to access.

dynamic permissions that arise when *multiple human users* interact with collaborative *multiple LLM agents*. Our contribution is to bridge these threads by embedding formal access-control graphs and policy-conditioned read/write transformations directly into the memory substrate, enabling safe and auditable cross-user knowledge transfer.

3 Collaborative Memory

Large-scale, multi-user applications increasingly rely on ensembles of *LLM agents* that reason, communicate, and coordinate actions—both among themselves and with external resources such as tools, APIs, or databases [19]. Prior research [25, 10, 20] demonstrates that granting agents access to a persistent memory of past interactions can significantly enhance task performance; however, most existing designs assume a *single-user* setting, thus overlooking the benefits of *cross-user* knowledge transfer. In this work, we present **Collaborative Memory**, a framework that enables agents to share knowledge across multiple users without violating each user's or agent's access constraints. As illustrated in Figure 2, users' queries, agent responses, and write policies collectively maintain and manage both private and shared memories, ensuring that each agent can only read the information it is permitted to access.

3.1 Setup and Dynamic Access Graphs

Let $\mathcal{U}$, $\mathcal{A}$, and $\mathcal{R}$ denote the sets of users, large language model agents, and resources (e.g., tools, APIs, a structured data source), respectively. For convenience, we also write $\mathcal{U}(\cdot)$, $\mathcal{A}(\cdot)$, and $\mathcal{R}(\cdot)$ to indicate subset operators over these sets. We use lowercase u, a, and r to refer to individual users, agents, and resources.

At each timestep t, access permissions are captured by two bipartite graphs:

$$G_{\mathcal{U}\mathcal{A}}(t) \subseteq \mathcal{U} \times \mathcal{A}, G_{\mathcal{A}\mathcal{R}}(t) \subseteq \mathcal{A} \times \mathcal{R}, \tag{1}$$

where $(u_i, a_j) \in G_{\mathcal{U}\mathcal{A}}(t)$ means user u_i may invoke agent a_j at time t, and $(a_j, r_k) \in G_{\mathcal{A}\mathcal{R}}(t)$ indicates that a_j can access resource r_k. These graphs evolve over time to reflect new users, revocations, or changes in resource permissions. We define:

$$\begin{aligned} \mathcal{A}(u, t) &:= \{ a \mid (u, a) \in G_{\mathcal{U}\mathcal{A}}(t) \}, \\ \mathcal{R}(a, t) &:= \{ r \mid (a, r) \in G_{\mathcal{A}\mathcal{R}}(t) \}. \end{aligned} \tag{2}$$

Hence, $\mathcal{A}(u, t)$ is the set of agents that user u can invoke at time t, and $\mathcal{R}(a, t)$ is the set of resources agent a can access at time t.

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3.2 Memory Tiers and Provenance

We let $\mathcal{M}$ denote the set of all memory fragments stored (write) and retrieved (read) during user–agent interactions. Each fragment $m \in \mathcal{M}$ has immutable provenance attributes: its time of creation, denoted $\mathcal{T}(m)$, the user who contributed it, $\mathcal{U}(m)$, the contributing agents, $\mathcal{A}(m)$, and the set of resources accessed during its creation, $\mathcal{R}(m)$.

In practice, users may want to keep certain memory fragments private while sharing others for potential cross-user benefits. Hence, we partition:

$$\mathcal{M} = \mathcal{M}^{\text{private}} \cup \mathcal{M}^{\text{shared}},$$

where $\mathcal{M}^{\text{private}}$ contains private fragments and $\mathcal{M}^{\text{shared}}$ contains fragments that can be shared across users. For each user u, we define a private store $\mathcal{M}^{\text{private}}(u, t)$, which includes all memories arising from user u's past interactions with agents up until time t. Similarly, for each agent a, we can define a shared store $\mathcal{M}^{\text{shared}}(a, t)$, which includes all fragments agent a generated for any user up until time t.

When agent a serves user u at time t, it can potentially access a broader set of memory fragments, denoted $\mathcal{M}(u, a, t)$. Formally,

$$\mathcal{M}(u, a, t) := \Big\{ m \in \mathcal{M} \ \Big| \ \mathcal{A}(m) \subseteq \mathcal{A}(u, t) \ \wedge \ \mathcal{R}(m) \subseteq \mathcal{R}(a, t) \Big\}. \tag{3}$$

This set may include:

1. Fragments from user u's history with other agents in $\mathcal{A}(u, t)$;

2. Fragments created by agent a itself while serving other users;

3. Fragments created by other users with agents that u can invoke, subject to a's resource-based permission $\mathcal{R}(a, t)$.

In this way, the system enforces agent- and resource-level constraints even while enabling cross-user and cross-agent sharing.

3.3 Read from the Collaborative Memory

At each timestep t, user u submits a query q. Although the user can potentially access all agents in $\mathcal{A}(u, t)$, not every agent may be relevant to q. Let $\mathcal{A}(u, t, q)$ be the subset of agents deemed suitable for further processing of q.

Each agent $a \in \mathcal{A}(u, t, q)$ receives q and the relevant memory (as filtered by a *read policy*), denoted $\pi^{\text{read}}_{u,a,t}$. Then, it generates the response $y_{u,a,t}$ based on the query, memory, and the resources that it can access. Formally:

$$y_{u,a,t} = a\big(q, \ \pi^{\text{read}}_{u,a,t}(\mathcal{M}(u, a, t)), \ \mathcal{R}(a, t)\big).$$

Such a read policy can, for instance, limit the number of memory fragments retrieved or filter them by specific keywords. To produce a final response to the user, a coordinator or aggregator (e.g., another LLM module) can synthesize all agent outputs $\{y_{u,a,t}\}_{a \in \mathcal{A}(u,t,q)}$ into a coherent reply.

3.4 Write to the Collaborative Memory

Upon producing an output $y_{u,a,t}$, the system applies a *write policy* to insert new information into the memory. We define two kinds of write policies:

$$\pi^{\text{write/private}}_{u,a,t} : \quad y_{u,a,t}, \ \mathcal{M}^{\text{private}}(u, t) \mapsto \mathcal{M}^{\text{private}}(u, +1) \tag{4}$$

$$\pi^{\text{write/shared}}_{u,a,t} : \quad y_{u,a,t}, \ \mathcal{M}^{\text{shared}}(u, t) \mapsto \mathcal{M}^{\text{shared}}(u, +1) \tag{5}$$

By separating private and shared write policies, users can customize the level of confidentiality applied to their contributions. For example, these policies may anonymize entities, redact sensitive information, or block certain kinds of content from being stored. The write policies can also range from straightforward to highly sophisticated. A direct implementation could simply embed the output $y_{u,a,t}$ and insert the resulting vector into a storage table. More advanced approaches may incorporate richer memory management structures [14] to handle structured knowledge abstractions.

Granularity and Dynamics Both the read policy $\pi_{u,a,t}^{\text{read}}$ and the write policies $\pi_{u,a,t}^{\text{write}/*}$ can be tuned at various scopes: $\pi_{u,a,t}^* \in \{\pi_{\text{global}}^* \text{ (shared by all)}, \pi_u^* \text{ (per user)}, \pi_a^* \text{ (per agent)}, \pi_t^* \text{ (over time)}\}$. This flexible design lets system administrators and users independently fine-tune which information is surfaced to each agent (*read time*) and which is persisted back into the memory (*write time*), enabling rich forms of collaboration while maintaining strict access control.

4 Implementation Details

Models All LLM-based components—the task coordinator, domain-specialized agents, the *read/write* memory-transformation modules, and the response aggregator—use `gpt-4o`. Vector embeddings are generated with `text-embedding-3-large`. Agents interact with external tools through the OpenAI function-calling interface.

Multi-Agent Interaction Loop The coordinator LLM receives (i) the user query, (ii) the natural-language specialization string for every agent accessible by the user, and (iii) the conversation history. At each round it outputs a JSON object of the form `{"agent": ID, "subquery": ...}` and may terminate early by outputting `{"stop": true}`.

Resources External resources are exposed as Python callables with JSON schemas—for example, a knowledge-base search defined as `query` $\rightarrow$ `top_k_results`. The underlying LLM performs function-calling to infer the arguments and invokes these functions via the standard OpenAI interface.

Memory Encoder After completing a subtask, the conversational trace are mapped into candidate LLM-generated key–value fragments. Each fragment is annotated with provenance denoting contributing agents, resources used, and creation time.

Memory Retrieval For an incoming subquery, we retrieve (a) the top-k_{user} fragments from the user-specific tier and (b) the top-k_{cross} fragments from the cross-user tier that satisfy the provenance constraint. Cosine similarity between the subquery embedding and fragment keys guides retrieval.

Policy Instantiation We consider two instantiations of the read/write policies: (1) *Simple*—the read policy returns admissible fragments verbatim and the write policy stores generated fragments without modification; and (2) *Transformation*—global, and optionally agent- or user-level, system prompts instruct an LLM to redact, anonymize, or paraphrase fragments before they are surfaced (read) or persisted (write). We adopt the simple read policy and the transformation write policy across all experiments.

Response Aggregation Once the coordinator halts, an aggregator LLM receives the original query together with the ordered list of (subquery, response) pairs produced by agents and synthesizes the final answer.

Metrics We track three performance metrics aggregated over evaluation phases. **Accuracy** measures the average normalized correctness of system responses against ground truth. **Agent Utilization** captures the mean number of distinct agents invoked per query, reflecting coordination overhead. Finally we track **Resource Utilization** is defined as the mean number of knowledge-base or API calls per query, serving as an indirect yet measurable proxy for overall system efficiency.[1]

5 Experimental Evaluation

We evaluate our framework under three progressively complex scenarios, each highlighting a distinct dimension of collaborative memory management. In all cases, we measure accuracy, resource consumption, and privacy compliance to demonstrate the versatility and robustness of our approach.

- **Scenario 1 (Fully Collaborative Memory):** All users have unrestricted access to a global memory pool, illustrating how cross-user collaboration can reduce computational overhead.

- **Scenario 2 (Asymmetric Collaborative Memory):** Users have heterogeneous privilege levels restricting their visibility into resources and memory fragments. We show that even partial collaboration yields efficiency gains while safeguarding private data.

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[1]Agents such as deep research from OpenAI can exhibit significant latency fluctuations (5–30 minutes) [12], making direct latency assessments challenging.
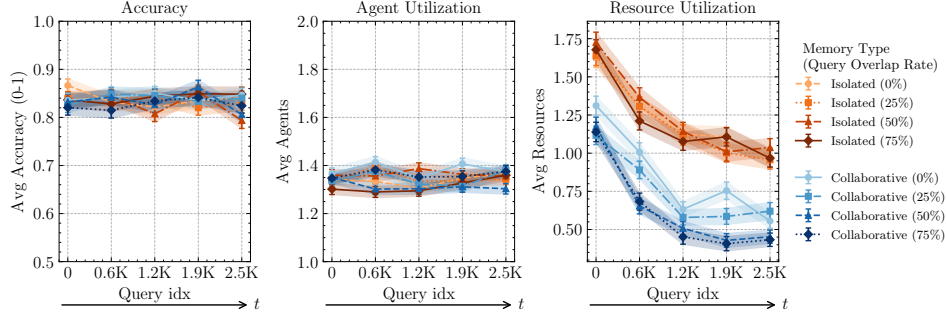
Figure 3: Scenario 1 (Fully Collaborative Memory). Performance of `MultiHop-Rag` under varying degrees of query overlap among five users. Both isolated and collaborative memory exhibit similar accuracy and agent utilization. However, as the number of queries increases (while remains confined to the same six domains), resource usage declines for both approaches—yet collaborative memory consistently achieves a more substantial reduction across all degrees of query overlap.

- **Scenario 3 (Dynamically Evolving Collaborative Memory):** Permissions are granted or revoked in real time, testing the system's ability to adapt while maintaining strict confidentiality guarantees.

5.1 Scenario 1: Fully Collaborative Memory

Cross-user collaborative memory significantly reduces overhead and improves efficiency.

Task   We use the MultiHop-RAG dataset [18], which contains 609 English news articles spanning six domains (technology, entertainment, sports, science, business, health). The dataset includes 2,556 multi-hop questions requiring inference, comparison, and temporal reasoning. We measure accuracy by comparing answers to ground truth with an LLM-based judge.

To simulate multiple resources and domain experts, we partition the corpus into six domain-aligned knowledge bases: `entertainment_kb`, `business_kb`, `sports_kb`, `technology_kb`, `health_kb`, and `science_kb`. We then deploy six domain-specialist agents (*entertainment_agent*, *business_agent*, *sports_agent*, *technology_agent*, *health_agent*, *science_agent*), each granted exclusive access to one resource. Five users have full permissions to query any agent.

To introduce realistic multi-user query overlaps, we apply KMeans clustering to group queries into 10 clusters. From each cluster, a subset is sampled to form a set of "global queries" shared by all users. The remaining queries in each cluster are uniquely assigned to individual users.

Results   Figure 3 shows average accuracy, agent utilization, and resource utilization over time. Under fully collaborative memory, accuracy remains above 0.90 on average across all query indices. In contrast, isolated memory configurations exhibit slightly lower accuracy, especially as the overlap rate increases. Collaboration also significantly improves resource utilization. Resource usage decreases by up to 61% at 50% overlap and by 59% at 75% overlap compared to isolated memory.

5.2 Scenario 2: Asymmetric Collaborative Memory

Partial collaboration increases efficiency while respecting different privilege levels.

Task   We curate a synthetic dataset of 200 business project queries, each mapped to a distinct high-level objective (e.g., market analysis, logistics planning, or financial forecasting). Example queries range from "Identify high-demand skincare markets in Europe" to "Craft a strategic growth plan for smart home devices in privacy-regulated markets." To address these queries, we simulate four user roles—Market Researcher, Financial Analyst, Logistics and Operations Lead, and Strategy Director—each with unique expertise. In parallel, we deploy four specialized LLM agents, each granted access to different resources (market databases, financial forecasts, logistics comparators, and strategic computation). Access is asymmetric: only the Strategy Director can consult all agents for a comprehensive view, while other roles are limited to subsets of the agents.
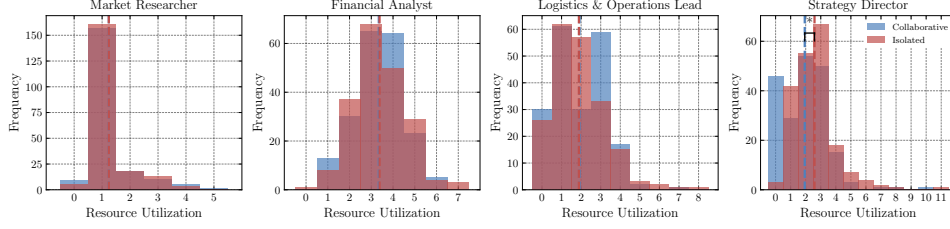
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Figure 4: Scenario 2 (Asymmetric Collaborative Memory). Resource usage with and without asymmetric collaboration. Even limited cross-user visibility leads to fewer agent or knowledge-base calls than a completely isolated configuration.

Results Since no ground truth answers are available for these open-ended questions, we focuses on resource utilization in the evaluation. Figure 4 shows a histogram of resource usage per user. Compared to an isolated setup with no memory sharing, asymmetric collaboration reduces overall resource calls. Intermediate insights discovered by one user can flow to another user with matching privileges, reducing repeated queries to the same tools or knowledge bases. By the time the Strategy Director (with the highest privileges) consolidates final recommendations, partial sharing has already eliminated a significant portion of redundant work.

5.3 Scenario 3: Dynamically Evolving Collaborative Memory

Adaptive permissions allow real-time updates without compromising security.

Task We use the SciQAG dataset [21], a scientific question-answering benchmark spanning fields such as biology, chemistry, and physics. Five scientific categories are selected, each serving as a distinct resource. We deploy five RAG agents, each providing access to one category's corpus. There are five users, and each user submits 4 queries per category, for a total of 100 queries.

To simulate dynamic access control, we represent users and resources as nodes in an evolving graph, where edges denote granted access. Starting with an empty graph, we iteratively add edges (i.e., grant permissions) via Bernoulli trials until the graph reaches 5 edges. We label these discrete time steps $t_0, t_1, \ldots$ at intervals of 100 queries. Specifically:

- At t_0, we begin with a sparse graph.
- From t_1 to t_4, we progressively add more edges (up to 25 total), representing increased access.
- From t_5 to t_8, we gradually revoke edges, mimicking a real-world scenario where privileges are retracted as needed.

Throughout these phases, the same set of 100 queries is used, but the users' agents are determined by the current access graph.

Results Figure 5 summarizes the results under dynamically changing permissions. Accuracy rises as additional access is granted and declines as privileges are revoked, demonstrating the strong coupling between resource availability and response quality. Agent usage similarly increases when users gain access to more agents and decreases upon revocation.

Notably, the average number of queried resources tends to drop over time. This behavior reflects the memory mechanism's ability to reuse previously retrieved information (i.e., stored memory fragments) instead of repeatedly querying external resources. The access matrix in Figure 6 further confirms that users only access agents and resources explicitly granted by the graph, ensuring strict adherence to access control policies.

6 Limitations

Collaborative Memory offers a powerful and flexible platform for enabling multi-user collaboration across diverse, dynamic settings. Nevertheless, several important limitations remain. First, while real-world multi-user collaboration is widespread in industry, large-scale data collection often faces regulatory and privacy obstacles, forcing us to rely on existing benchmarks or synthetic queries with
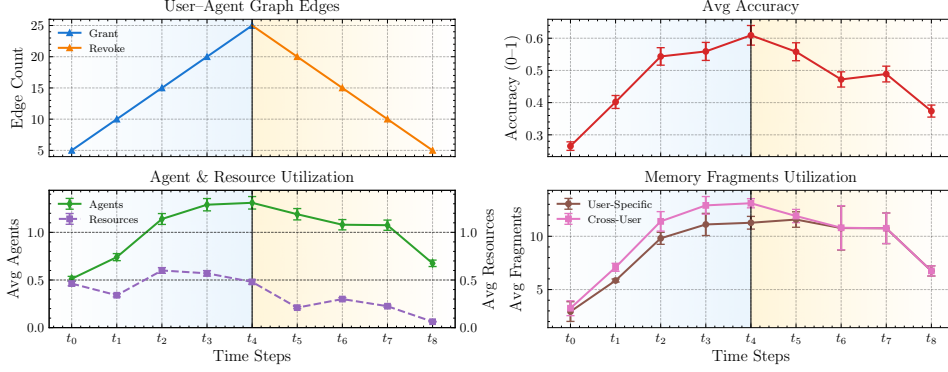
Figure 5: Scenario 3 (Dynamically Evolving Collaborative Memory). System performance over eight time blocks with dynamically changing privileges. Accuracy (top) tracks the available resources, while agent (middle) and resource (bottom) usage also shift in response to access graph updates.

A_1: Chemistry, A_2: Energy, A_3: Ceramics, A_4: Paper, A_5: Physics R_1: Chemistry, R_2: Energy, R_3: Ceramics, R_4: Paper, R_5: Physics
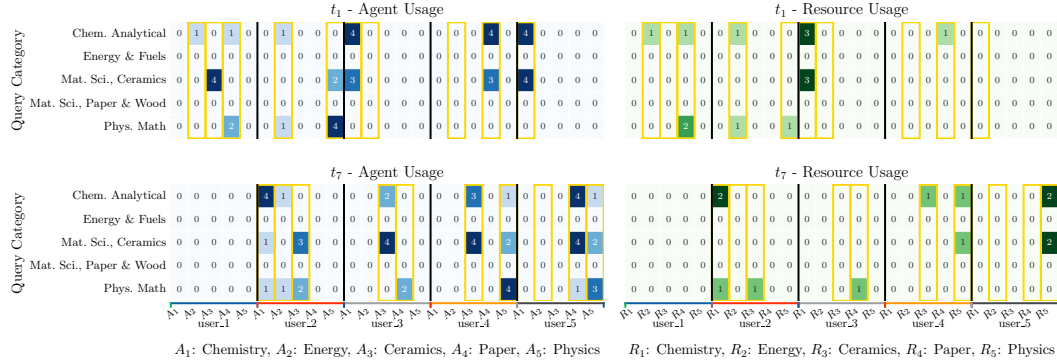
Figure 6: Scenario 3 (Dynamically Evolving Collaborative Memory). Agent and resource usage across user queries from different categories. Yellow rectangles indicate granted access, with values representing the corresponding usage counts.

simulated multi-user environments. Although these setups capture essential aspects of collaboration, they may not fully reflect the complexity of real-world scenarios. Developing robust multi-user collaboration benchmarks is a worthwhile direction to better evaluate methods under more realistic conditions. Second, our current focus on controlled environments with moderate numbers of users and agents leaves the complexities of large-scale enterprise settings—where concurrency is frequent and user roles rapidly evolve—largely unexplored. Third, because our framework leverages LLMs, the probabilistic nature of these models can lead to occasional hallucinations or policy breaches, despite our enforcement mechanisms. Finally, evaluating resource utilization in production environments can be challenging due to unpredictable API latencies; in this paper, we simplify the analysis by measuring resource call counts.

7   Conclusions

In this paper, we drew on Distributed Cognition to tackle collaborative memory management in real-world multi-user, multi-agent scenarios. Our framework, Collaborative Memory, addresses information asymmetry and dynamic access constraints by integrating dynamic bipartite access graphs, a two-tier memory system, and fine-grained read/write policies. This design supports secure, context-aware knowledge sharing that respects evolving permissions. In three progressively complex scenarios, we observe significantly lower resource utilization than in single-user baselines, while maintaining strict privacy compliance.

Disclaimer

References

[1] Xiaohe Bo, Zeyu Zhang, Quanyu Dai, Xueyang Feng, Lei Wang, Rui Li, Xu Chen, and Ji-Rong Wen. Reflective multi-agent collaboration based on large language models. *Advances in Neural Information Processing Systems*, 37:138595–138631, 2024.

[2] Weize Chen, Yusheng Su, Jingwei Zuo, Cheng Yang, Chenfei Yuan, Chen Qian, Chi-Min Chan, Yujia Qin, Yaxi Lu, Ruobing Xie, et al. Agentverse: Facilitating multi-agent collaboration and exploring emergent behaviors in agents. *arXiv preprint arXiv:2308.10848*, 2(4):6, 2023.

[3] Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, Dasha Metropolitansky, Robert Osazuwa Ness, and Jonathan Larson. From local to global: A graph rag approach to query-focused summarization. *arXiv preprint arXiv:2404.16130*, 2024.

[4] Hang Gao and Yongfeng Zhang. Memory sharing for large language model based agents. *arXiv preprint arXiv:2404.09982*, 2024.

[5] Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V Chawla, Olaf Wiest, and Xiangliang Zhang. Large language model based multi-agents: A survey of progress and challenges. *arXiv preprint arXiv:2402.01680*, 2024.

[6] Bernal Jiménez Gutiérrez, Yiheng Shu, Yu Gu, Michihiro Yasunaga, and Yu Su. Hipporag: Neurobiologically inspired long-term memory for large language models. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.

[7] Vincent C Hu, David Ferraiolo, Rick Kuhn, Arthur R Friedman, Alan J Lang, Margaret M Cogdell, Adam Schnitzer, Kenneth Sandlin, Robert Miller, Karen Scarfone, et al. Guide to attribute based access control (abac) definition and considerations (draft). *NIST special publication*, 800(162):1–54, 2013.

[8] Edwin Hutchins. *Cognition in the Wild*. MIT press, 1995.

[9] Patrick Lewis, Ethan Perez, Aleksandara Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Kuttler, Mike Lewis, Wen tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks. *ArXiv*, abs/2005.11401, 2020.

[10] Lei Liu, Xiaoyan Yang, Yue Shen, Binbin Hu, Zhiqiang Zhang, Jinjie Gu, and Guannan Zhang. Think-in-memory: Recalling and post-thinking enable llms with long-term memory. *ArXiv*, abs/2311.08719, 2023.

[11] Eric Melz. Enhancing llm intelligence with arm-rag: Auxiliary rationale memory for retrieval augmented generation. *ArXiv*, abs/2311.04177, 2023.

[12] OpenAI. Deep research faq. https://help.openai.com/en/articles/10500283-deep-research-faq?utm_source=chatgpt.com#h_7419a1dd48, 2025.

[13] Charles Packer, Vivian Fang, Shishir_G Patil, Kevin Lin, Sarah Wooders, and Joseph_E Gonzalez. Memgpt: Towards llms as operating systems. *arXiv preprint arXiv:2310.08560*, 2023.

[14] Alireza Rezazadeh, Zichao Li, Wei Wei, and Yujia Bao. From isolated conversations to hierarchical schemas: Dynamic tree memory representation for llms. *arXiv preprint arXiv:2410.14052*, 2024.

[15] Ravi Sandhu, David Ferraiolo, Richard Kuhn, et al. The nist model for role-based access control: towards a unified standard. In *ACM workshop on Role-based access control*, number 344287.344301, 2000.

[16] Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. *ArXiv*, abs/2302.04761, 2023.

[17] Noah Shinn, Federico Cassano, Beck Labash, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: language agents with verbal reinforcement learning. In *Neural Information Processing Systems*, 2023.

[18] Yixuan Tang and Yi Yang. Multihop-rag: Benchmarking retrieval-augmented generation for multi-hop queries. *arXiv preprint arXiv:2401.15391*, 2024.

[19] Khanh-Tung Tran, Dung Dao, Minh-Duong Nguyen, Quoc-Viet Pham, Barry O'Sullivan, and Hoang D Nguyen. Multi-agent collaboration mechanisms: A survey of llms. *arXiv preprint arXiv:2501.06322*, 2025.

[20] Khanh-Tung Tran, Dung Dao, Minh-Duong Nguyen, Quoc-Viet Pham, Barry O'Sullivan, and Hoang D. Nguyen. Multi-agent collaboration mechanisms: A survey of llms. *ArXiv*, abs/2501.06322, 2025.

[21] Yuwei Wan, Yixuan Liu, Aswathy Ajith, Clara Grazian, Bram Hoex, Wenjie Zhang, Chunyu Kit, Tong Xie, and Ian Foster. Sciqag: A framework for auto-generated science question answering dataset with fine-grained evaluation. *arXiv preprint arXiv:2405.09939*, 2024.

[22] Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, et al. Autogen: Enabling next-gen llm applications via multi-agent conversation. *arXiv preprint arXiv:2308.08155*, 2023.

[23] Sen Yang, Yafu Li, Wai Lam, and Yu Cheng. Multi-llm collaborative search for complex problem solving. *arXiv preprint arXiv:2502.18873*, 2025.

[24] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. *ArXiv*, abs/2210.03629, 2022.

[25] Wanjun Zhong, Lianghong Guo, Qi-Fei Gao, He Ye, and Yanlin Wang. Memorybank: Enhancing large language models with long-term memory. *ArXiv*, abs/2305.10250, 2023.

Appendix Arrangement

The Appendix is organized as follows.

- **Section § A: Discussion of the Broad Impact of Collaborative Memory**
- **Section § B: From Query to Response**
  - **Section § B.1**: The detailed pipeline.
  - **Section § B.2**: The read/write policies.
- **Section § C: Scenario 1: Fully Collaborative Memory**
  - **Section § C.1**: Dataset details, including description and statistics.
  - **Section § C.2**: Experimental setup, including:
    * Access Graph Configuration: Description of the access graph used.
    * Agent/Knowledge Base Configuration: Description of agents, resources, coordinators, and aggregators.
  - **Section § C.3**: Examples of read/write interactions.
  - **Section § C.4**: Performance breakdown by query type.
- **Section § D: Scenario 2: Asymmetric Collaborative Memory**
  - **Section § D.1**: Dataset details, including dataset generation.
  - **Section § D.2**: Experimental setup, including:
    * Access Graph Configuration: Description of the access graph used.
    * Agent and Knowledge Base Configuration with Examples: Includes descriptions of agents, resources, coordinators, and aggregators, along with illustrative examples of agent and resource input/output.
  - **Section § D.3**: Examples of read/write interactions.
- **Section § E: Scenario 3: Dynamically Evolving Collaborative Memory**
  - **Section § E.1**: Dataset details, including description and statistics.
  - **Section § E.2**: Experimental setup, including:
    * Access Graph Configuration: Description of the dynamic access graph used and how they are generated.
    * Agent/Knowledge Base Configuration: Description of agents, resources, coordinators, and aggregators.
  - **Section § E.3**: Examples of read/write interactions.
  - **Section § E.4**: Raw performance data and complete access matrix under different access graph configurations.

A Discussion of the Broad Impact of Collaborative Memory

This paper proposes *Collaborative Memory*, a modular framework for permission-aware memory sharing in multi-agent, multi-user systems. Our key contributions include:

- A novel formulation of access-asymmetric memory sharing, explicitly modeling time-varying user-agent-resource permissions using dynamic bipartite graphs.

- A two-tier memory architecture that separates private and shared memory to balance knowledge isolation with controlled collaboration.

- Configurable read and write policies that support fine-grained, adaptive access control at system, user, or agent levels.

- A decoupled and extensible design, allowing seamless integration with alternative memory systems (e.g., MemTree).

As multi-agent systems are increasingly deployed in real-world applications, the need for effective coordination and secure information sharing has become paramount. Collaborative Memory addresses these challenges by enabling shared memory to improve collaboration and efficiency while enforcing strict controls over access. By enhancing both collaborative capability and information safety, this framework lays the foundation for building scalable, trustworthy multi-agent AI systems across diverse domains. We demonstrate its applicability through three representative scenarios: (1) Fully Collaborative Memory, (2) Asymmetric Collaborative Memory, and (3) Dynamically Evolving Collaborative Memory.

B Query to Response Details

B.1 Pipeline

Figure 7 illustrates the detailed pipeline from a user query to the final response in our multi-agent memory-sharing framework, as outlined below:

- **Query Submission**: When user u_1 submits a query q_1, the pipeline is triggered within the multi-agent memory-sharing framework.

- **Agent Selection | Coordinator**: The coordinator selects the next agent based on the query content and the access graph, ensuring that only authorized agents are eligible to respond.

- **Response Generation | Agents**:

  - The selected agent gathers relevant memory fragments and accessible resources.

  - It generates a response, denoted as $y_{u_1,a_1,t}$ (in the case of agent a_1).

  - The response is used to update the collaborative memory.

- **Aggregation | Aggregator**: After all eligible agents have responded, their intermediate outputs are aggregated by the aggregator to produce the final response.

The specific configurations of the coordinators and aggregators will be described in the corresponding scenario settings. Both the intermediate and final responses can be used to update the collaborative memory. In our current implementation, we update the memory using the intermediate responses. We will publicly release our code and dataset to support transparency and future research.
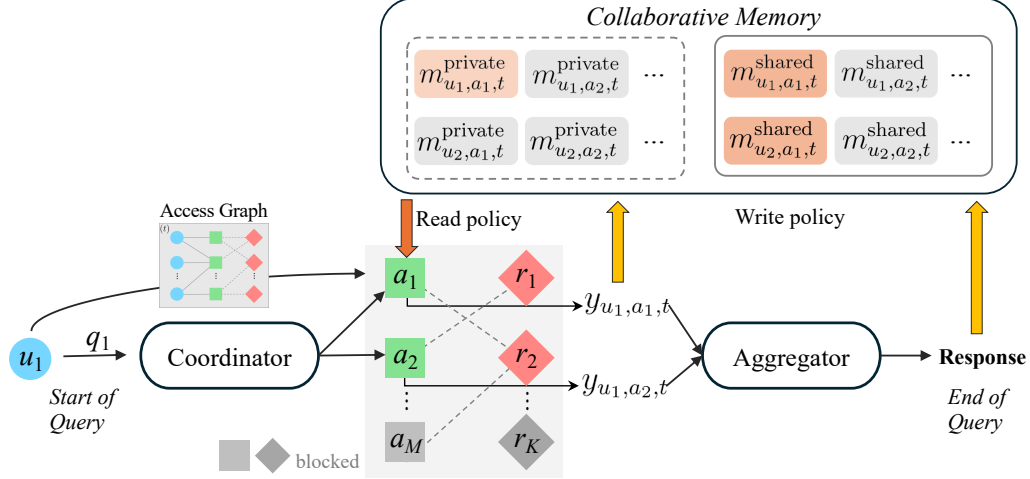
Figure 7: From user query to response: the detailed pipeline. The *Coordinator*, and *Aggregator* are implemented using the GPT-4o API.

B.2 Read/Write Policy

For the read policy, we adopt a straightforward strategy that combines both private and shared memory fragments accessible to the user. For the write policy, we employ a system-level transformation applied uniformly across all users by leveraging LLMs with dedicated prompts. When writing to private and shared memory, we transform the memory with the different prompts as presented in Table 1. While we begin our exploration using this unified policy, the framework is inherently flexible and can be extended to support more fine-grained policies—customized at the level of individual users or agents as needed.

Table 1: System-Level Prompts for Memory Writing Policies

Memory Type	Prompt
Private Memory	*Extract key concepts from interactions that would be useful for the specific user. Focus on creating standalone memories that capture core information. Format each memory as a clear key-value pair where the key is a concise query or topic and the value is a comprehensive answer or explanation.*
Shared Memory	*Extract generally applicable knowledge from interactions that would benefit any user.Focus on creating shareable memories that contain universal information. Remove any user-specific details or personalized examples. Format each memory as a clear key-value pair where the key is a concise query or topic and the value is a comprehensive answer or explanation.*

C Scenario 1: Fully Collaborative Memory

C.1 Dataset Details

The following table provides a comprehensive overview of the MULTIHOP-RAG dataset used in our experiments. We employ 609 news articles with an average length of approximately 2,046 tokens. From these, we derive 2,556 multi-hop queries spanning inference, comparison, temporal reasoning, and null-query instances. Table 2 reports the detailed breakdown of document counts, average lengths, and query-type distributions.

Table 2: Statistics of the MULTIHOP-RAG dataset.

Statistic	Count	Percentage
Documents		
Total articles	609	—
Average tokens per article	2,046	—
Queries (N = 2,556)		
Inference queries	816	31.9%
Comparison queries	856	33.5%
Temporal queries	583	22.8%
Null queries	301	11.8%

C.2 Experimental Details

We evaluate four multi-user datasets with global query overlap rates $\rho \in \{0\%, 25\%, 50\%, 75\%\}$. For each dataset, we run two configurations: *Shared Memory* (cross-user memory sharing enabled) and *Isolated Memory* (sharing disabled). Memory retrieval is configured with a user-specific tier size $k_{\text{user}} = 10$, a shared tier size $k_{\text{cross}} = 10$.

C.2.1 Access Graph Configuration

All five users (`user_1` through `user_5`) have permission to invoke each of the six domain-specialist agents. Conversely, each agent is restricted to a single, domain-aligned resource. These fixed access graphs—complete user-to-agent and one-to-one agent-to-resource—remain constant throughout the experiments to isolate the effects of memory sharing.

C.2.2 Agent/Knowledge Base Configuration

We deploy six specialist agents, each paired with a dedicated knowledge base. Table 3 lists each agent's description and full system prompt. The corresponding resources contain the following number of documents: entertainment (114), business (81), sports (211), technology (172), health (10), and science (21), each indexed with precomputed embeddings.

Table 3: Domain agents and their system prompts in the fully collaborative scenario.

Agent	Description	System Prompt
`entertainment_agent`	Specialist in entertainment news—films, TV, music, celebrity culture, and pop-culture trends.	You are an Entertainment News specialist with deep expertise in: • Summarizing the latest developments in film, television, and music • Contextualizing celebrity news and red-carpet events • Tracking pop-culture trends and fandom reactions • Providing concise, engaging overviews of entertainment topics Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.
`business_agent`	Specialist in business news—markets, companies, economics, and finance.	You are a Business News specialist with deep expertise in: • Reporting market movements and stock-market summaries • Explaining corporate earnings, M&A, and leadership changes • Analyzing economic indicators and policy developments • Providing clear explanations of financial concepts and trends Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.
`sports_agent`	Specialist in sports news—games, scores, athletes, and tournament analysis.	You are a Sports News specialist with deep expertise in: • Summarizing match results and key highlights • Interpreting player statistics and performance metrics • Previewing upcoming fixtures and tournament storylines • Offering tactical analysis and historical context Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.
`technology_agent`	Specialist in technology news—gadgets, innovations, startups, and industry trends.	You are a Technology News specialist with deep expertise in: • Covering product launches and tech reviews • Analyzing startup ecosystems and funding rounds • Tracking breakthroughs in AI, software, and hardware • Explaining complex technical concepts in accessible terms Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.

Table 3: Domain agents and their system prompts in the fully collaborative scenario. (continued)

Agent	Description	System Prompt
health_agent	Specialist in health news—medical research, public health, wellness, and policy.	You are a Health News specialist with deep expertise in: • Summarizing clinical studies and medical breakthroughs • Explaining public-health announcements and guidelines • Contextualizing wellness and fitness trends • Clarifying healthcare policy and its societal impact Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.
science_agent	Specialist in science news—discoveries in physics, biology, environment, and research.	You are a Science News specialist with deep expertise in: • Reporting on breakthroughs across physical and life sciences • Interpreting new research findings and methodologies • Explaining fundamental scientific concepts clearly • Exploring implications for technology, environment, and society Always check relevant memories first. When those are insufficient, use the available tools. Prioritize information from memories and tools.

C.3 Examples

To illustrate the direct impact of persistent memory on resource efficiency, Table 4 presents two "write–then–read" examples. Each example details a memory fragment's unique identifier, key–value content, the query that generated it, and the subsequent query that retrieved it. These cases show that later questions can be answered by recalling existing fragments—without issuing new knowledge-base searches—thereby eliminating redundant external calls and reducing overall resource usage.

Table 4: Memory write–read examples for user_3 in the fully collaborative scenario, showing both user-specific and cross-user entries.

Example 1 (Private Memory)
Discussion: This private fragment captures TechCrunch's critical perspective on Meta by summarizing two related reports, enabling the same user to answer a subsequent AI-related query with richer context.

Memory ID	9bea41d8-7d5a-430a-bd5d-a0bf42a3128f
Key	**TechCrunch**'s perspective on Meta
Value	**TechCrunch**'s reports on Meta from October 19, 2023, and November 30, 2023, demonstrate a consistent critical perspective towards Meta's policies and practices. The reports focus on moderation issues affecting Palestinian voices and the legality and fairness of Meta's ad-free subscription service, highlighting concerns about free expression, consumer rights, and regulatory compliance.

Generated at	Query #51 (user_3): *After **TechCrunch** reported on Meta's moderation issues affecting Palestinian voices on October 19, 2023, and again on Meta's ad-free subscription service being potentially illegal and unfair on November 30, 2023, was there consistency in the news source's critical perspective towards Meta's policies and practices?*
Used at	Query #54 (user_3): *Who is the Silicon Valley figure associated with the rise of artificial intelligence, mentioned in articles by 'The Age', 'Fortune', and 'TechCrunch', who faced no removal efforts by Anthropic co-founders, has been described as generous and impactful, yet is also theorized to have had transparency issues with the board?*

Example 2 (Shared Memory)
Discussion: Highlights cross-user sharing, with a fragment about Sam Bankman-Fried's criminal trial about cryptocurrency generated by user_2 and reused by user_3 for a related financial question.

Memory ID	01d1b5d4-0f17-42c6-903c-e40e572019a4
Key	Who is facing a criminal trial related to **cryptocurrency** fraud?
Value	Sam Bankman-Fried, the former CEO of the **crypto** exchange FTX, is facing a criminal trial. He was once considered the trustworthy face of the **cryptocurrency** industry and is accused of committing fraud for personal gain.
Generated by	Query #10 (user_2): *Who is the individual facing a criminal trial, as reported by both TechCrunch and Fortune, who was once considered the trustworthy face of the **cryptocurrency** industry according to The Verge, and is accused by the prosecution of committing fraud for personal gain?*
Used by	Query #15 (user_3): *Who is the individual associated with the **crypto** exchange FTX, who has been accused of using customer funds for a buyout and is facing multiple charges of fraud and conspiracy, as reported by sources like Fortune, The Verge, and TechCrunch?*

C.4 Performance Breakdown by Query Type

Figure 8 breaks down performance by query type—(top row) inference, (middle) comparison, and (bottom) temporal—across three key metrics: average accuracy (left), agent utilization (center), and resource utilization (right). In each plot, solid lines show the shared-memory condition and dashed lines the isolated-memory condition; colors distinguish global query overlap rates (0%, 25%, 50%, and 75%). Horizontal red lines in the accuracy panels indicate the human-annotated evidence upper-bounds for each task.

For inference queries, both configurations achieve near-ceiling accuracy, but shared memory steadily reduces the number of agent calls and external retrievals, particularly at higher overlap rates. Comparison tasks exhibit a small accuracy gain under sharing, with a more pronounced drop in resource usage as overlap increases. Temporal queries, which are hardest, benefit most in resource efficiency from shared memory, while maintaining comparable accuracy and modest reductions in agent invocations.
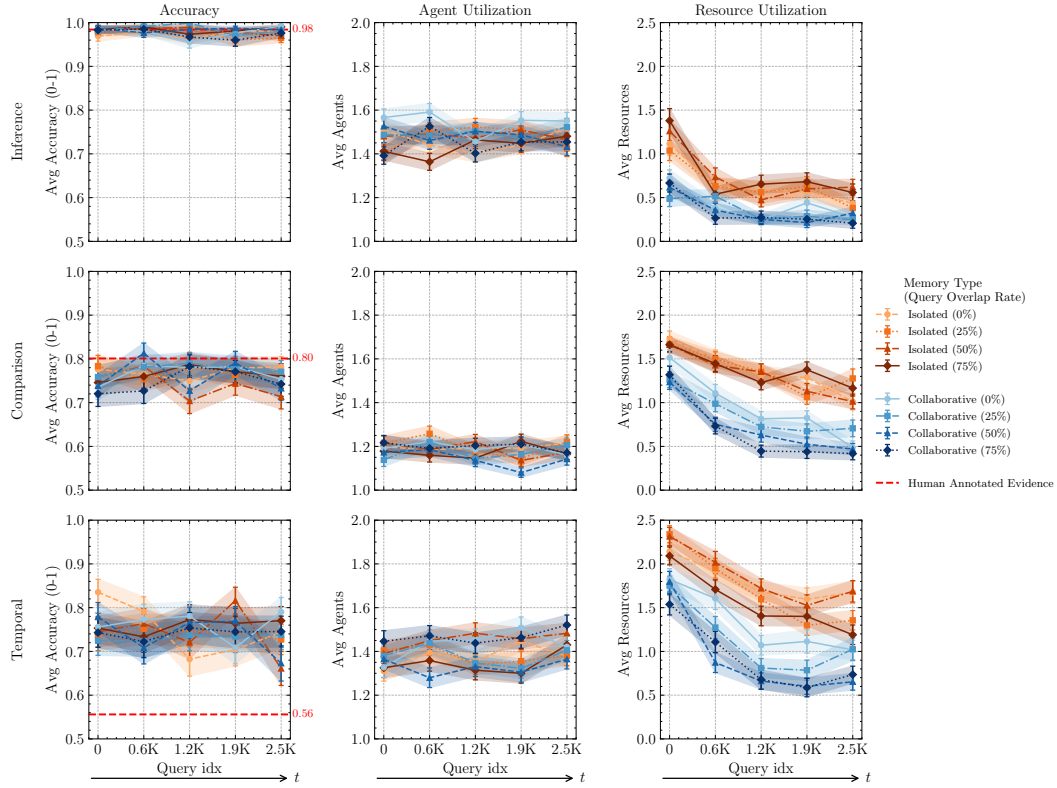
Figure 8: Performance by query type over five time bins: (left) average accuracy, (center) average agents per query, and (right) average external retrievals per query.

D Scenario 2: Asymmetric Collaborative Memory

This scenario simulates a collaborative reasoning environment involving multiple users and agents operating under access constraints and shared memory policies. The system comprises four users, each assigned a predefined role: *market researcher*, *financial analyst*, *logistics and operations lead*, and *strategy director* (user 4). These roles determine the scope of interaction with specialized agents—for example, the market researcher is restricted to delegating subtasks to the `market_agent`, while the strategy director, who has the highest level of access, can interact with all four agents across domains. This role-based routing ensures efficient task decomposition, policy enforcement, and targeted agent utilization. Figure 9 illustrates the system pipeline for Scenario 2, showcasing the coordinated collaboration among users, agents, and shared resources in response to a complex, cross-domain query. Further implementation details are provided in the following sections.

Figure 9: System pipeline for Scenario 2, illustrating the collaboration among users, agents, and resources in response to a complex query. The *Decomposer*, *Coordinator*, and *Aggregator* are implemented using the GPT-4o API.

D.1 Dataset Details

We use GPT-4o to synthesize a dataset designed to simulate multi-user, multi-agent collaborative experiments. The dataset consists of 200 business project scenarios, evenly split between 100 easy and 100 hard queries. The prompt used to generate the dataset and an example of generated dataset are shown below.

```
Prompt = f"""
Generate a JSON object describing a realistic {difficulty.upper()} business project
    scenario.

The format should be:

"{project_id}": {{
  "query": "Realistic business objective (e.g., enter Latin American e-commerce, assess
      demand for AI services in Asia)",
  "users": [
    {"user_id": "user_1", "role": "market"},
    {"user_id": "user_2", "role": "finance"},
    {"user_id": "user_3", "role": "logistics"},
    {"user_id": "user_4", "role": "decision_maker"}
  ]
}}
```

```
Output ONLY valid JSON. No explanation. Avoid markdown syntax.
"""
```

```
Dataset example:
"project_easy_01": {
    "query": "Identify high-demand skincare markets in Europe.",
    "users": [
        {
          "user_id": "user_1",
          "role": "market"
        },
        {
          "user_id": "user_2",
          "role": "finance"
        },
        {
          "user_id": "user_3",
          "role": "logistics"
        },
        {
          "user_id": "user_4",
          "role": "decision_maker"
        }
    ]
  }
```

D.2 Experimental Details

We design two types of experiments to evaluate our system: one with memory sharing and one without, memory retrieval is configured with a user-specific tier size $k_{\text{user}} = 20$, a shared tier size $k_{\text{cross}} = 20$. To simulate realistic multi-user, multi-agent interactions, we initialize four distinct users, each with specific role descriptions. These users are assigned varying levels of access to a set of specialized agents. Each agent, in turn, has controlled access to a set of task-relevant resources, forming a hierarchical access structure that mirrors real-world organizational settings.

The agent pool consists of four domain-specific agents: `market_agent`, `finance_agent`, `logistics_agent`, and `decision_agent`. Each agent is guided by a domain-specific system prompt that reflects its area of expertise. These agents interact with task-relevant resources simulated by the GPT-4o API, including a market knowledge base (`market_kb`), a financial forecast model (`finance_forecaster`), a logistics planning tool (`logistics_comparator`), and a strategic reasoning module (`strategic_computation`). For each agent and resource, we provide a representative query-response example to illustrate their behavior and capabilities. Detailed descriptions of the agents and resources can be found in Table 7 and Table 9.

```
market_agent:
Query:
Conduct a comprehensive analysis of consumer skincare trends and preferences in various
    European countries to identify potential high-demand markets.

Response:
Based on the analysis of consumer skincare trends and preferences in various European
    countries, we can identify potential high-demand markets. Here are the insights:

1. **Germany**: Consumers are increasingly interested in health and wellness,
    sustainability, and eco-friendly products. The market shows a strong preference for
    personalized skincare solutions and tech-driven products.
2. **Sweden**: ...
3. **France**: ...
4. **Italy**: ...
5. **UK**: ...
6. **Netherlands**: ...
7. **Switzerland**: ...

These countries reflect high-demand markets due to their specific trends and consumer
    preferences. They align with broader European trends such as sustainability,
    minimalism, personalization, and clean beauty, indicating potential profitability
    for skincare products that cater to these preferences.
```

```
finance_agent:
Query:
Analyze the economic indicators and purchasing power in Germany and other identified high-demand European
    markets to assess the financial viability and potential profitability of entering these skincare
    markets.
```

```
Response:
To assess the financial viability and potential profitability of entering high-demand skincare markets in
    Europe, we need to analyze the economic indicators and purchasing power in Germany and other
    identified markets such as Sweden, France, Italy, the UK, the Netherlands, and Switzerland.

### Economic Indicators and Purchasing Power Analysis:

1. **Germany**:
   - **GDP Growth**: Stable growth rate around 1-2%.
   - **Inflation Rate**: Stabilizing around 2-3%.
   - **Unemployment Rate**: Low, enhancing consumer spending capacity.
   - **Purchasing Power**: High disposable income, indicating potential for premium product sales.
2. **Sweden**: ...
3. **France**: ...
4. **Italy**: ...
5. **UK**: ...
6. **Netherlands**: ...
7. **Switzerland**: ..

### Financial Viability and Profitability Assessment:

- **High Disposable Income**: Countries like Germany, Sweden, France, the UK, Netherlands, and Switzerland
    have high disposable incomes, indicating strong potential for premium skincare product sales.
- **Stable Economic Conditions**: ...
- **Consumer Preferences**: ...

### Recommendation:

Entering the skincare markets in Germany, Sweden, France, Italy, the UK, the Netherlands, and Switzerland
    is financially viable and potentially profitable due to their stable economic conditions, high
    purchasing power, and alignment with consumer preferences for premium, sustainable, and innovative
    products.
```

```
logistics_agent
Query:
Evaluate the logistical and supply chain requirements for distributing skincare products across Germany
    and other identified high-demand European markets, focusing on high-demand regions.

Response:
To evaluate the logistical and supply chain requirements for distributing skincare products across Germany
    and other identified high-demand European markets, we need to consider the infrastructure,
    regulatory environment, and distribution networks in these regions.

### Logistical and Supply Chain Evaluation:

1. **Germany**:
   - **Infrastructure**: Highly efficient with robust road, rail, and port systems. Central location within
       Europe facilitates access to various markets.
   - **Regulatory Environment**: Supportive of business operations with strong manufacturing and
       distribution networks.
   - **Distribution Networks**: Well-developed, enabling efficient distribution across the country and to
       neighboring regions.
...

### Final Recommendation:

- **Germany**: Leverage its central location and efficient infrastructure for distribution across Europe.
    Its strong regulatory environment supports seamless operations.
...

Overall, these countries offer favorable logistical and supply chain conditions for distributing skincare
    products, aligning with consumer preferences and economic indicators. Entering these markets is
    viable and potentially profitable, given their infrastructure, regulatory support, and distribution
    capabilities.
```

```
decision_agent
Query:
Synthesize the insights from market_agent, finance_agent, and logistics_agent to provide a comprehensive
    recommendation for entering high-demand skincare markets in Europe, focusing on Germany and other
    identified regions.

Response:
### Comprehensive Recommendation for Entering High-Demand Skincare Markets in Europe

Based on the synthesis of insights from consumer trends, economic indicators, and logistical evaluations,
    the following comprehensive recommendation is provided for entering high-demand skincare markets in
    Europe, focusing on Germany and other identified regions:
```

```
#### Step 1: Consumer Trends and Preferences Analysis
- **Germany**: High demand for personalized, eco-friendly, and tech-driven skincare products.
...

#### Step 2: Economic Indicators and Purchasing Power Analysis
...

#### Step 3: Logistical and Supply Chain Evaluation
...

### Final Recommendation:

1. **Market Entry Strategy**:
   - **Germany**: Serve as a central hub for distribution across Europe, leveraging its efficient
        infrastructure and strong regulatory support.
   ...

2. **Product Strategy**: ...

3. **Operational Strategy**: ...

By focusing on these high-demand regions and aligning product offerings with consumer preferences and
     economic conditions, the entry into European skincare markets is positioned for success, with
     potential profitability driven by strong purchasing power and stable economic indicators.
```

```
market_kb
input:
consumer data in European skincare market.

output:
**Consumer Data in the European Skincare Market**

**Overview:**
The European skincare market remains one of the largest and most mature sectors within the beauty and
     personal care industry. As of 2023, the market continues to exhibit steady growth driven by various
     factors including increasing consumer awareness of skincare ingredients, a rising preference for
     sustainable and ethical products, and the influence of digital platforms.

**Consumer Demographics:**
1. **Age Groups:**
...

**Consumer Preferences:**
1. **Ingredient Consciousness:**
...

**Influence of Digital Platforms:**
...

**Challenges:**
...

**Conclusion:**
The European skincare market is diverse and dynamic, with an increasing focus on products that prioritize
     health, sustainability, and ethical standards. Brands that adapt to these changing consumer
     preferences and leverage digital innovations are well-positioned to succeed in this competitive
     landscape.
```

```
finance_forecaster
input:
Financial modeling and cost projections for distributing skincare products across high-demand European
     markets, considering logistics and supply chain requirements.

output:
To forecast the financial outlook for distributing skincare products across high-demand European markets,
     we need to consider several key elements: market size, demand growth, logistics and supply chain
     costs, pricing strategy, and competitive landscape. Below is a simplified projection model.

1. **Revenue Forecast:**

   - **Market Demand Size:** Assume penetration into markets like Germany, France, and the UK (collectively
          accounting for a large portion of the EU skincare market).
   - **Demand Growth:** Skincare product demand is expected to grow at approximately 5-7% annually due to
          increased consumer awareness and preference for skincare. Given the high demand and quality of
          products, you might capture a market share of 0.5-1% in the first year.
   - **Average Retail Price:** Estimate an average retail price for your skincare product at EUR 50 per
          unit.
   - **Units Sold:** Initial distribution could lead to approximately 100,000 units sold across all markets
          in the first year, expanding significantly thereafter.
```

```
   **Projected Revenue First Year:**
   Revenue = Units Sold * Average Retail Price
   Revenue = 100,000 * EUR 50 = EUR 5,000,000

2. **Cost Forecast:**
    ...

3. **ROI Analysis:**
    ...

**Forecast Summary:**

If executed well with strong marketing, streamlined supply chain, and effective distribution, entering
     high-demand European markets could achieve substantial revenue growth and profitability. Gradual
     market share increases and scaling operations should provide opportunities to optimize costs and
     improve net profits. Investments in logistics optimization, brand establishment, and customer loyalty
      programs could enhance ROI over the subsequent years, potentially reaching 40-50% as operations
     stabilize and market presence strengthens.
```

```
logistics_comparator:
input:
{
  "options": [
    "Germany",
    "France",
    "United Kingdom",
    "Italy",
    "Spain"
  ],
  "criteria": "logistical and supply chain requirements for high-demand regions"
}

output:
When considering 'logistical and supply chain requirements for high-demand regions,' there are several
     factors to take into account, including infrastructure efficiency, existing trade networks,
     regulatory environment, and geographic location. Here's a ranking based on these considerations:

1. **Germany**: Germany is known for its highly efficient infrastructure system, including roads, railways,
     and ports. It has central access to the European market, making it a pivotal hub for logistics and
     supply chain operations. Its regulatory framework generally supports business operations, and it has
     strong manufacturing and distribution networks.

2. **United Kingdom**:
...

3. **France**:
...

4. **Italy**:
...

5. **Spain**:
...

This ranking reflects the complexity and efficiency of the logistics and supply chain sector in each
     country, considering their ability to manage and fulfill demands across high-demand regions
     efficiently.
```

```
strategic_computation
input:
{
  "expression": "Calculate the new profit margin after a 5% price increase, assuming costs remain constant
       and demand elasticity is low."
}

output:
To evaluate the new profit margin after a 5% price increase, we need to understand how the increase in
     price affects revenue and then calculate the resulting profit margin under the assumption that costs
     remain constant and demand elasticity is low.

Let's break down the process:

1. **Initial Setup**:
   - Assume the original selling price is P.
   - Assume the cost per unit is C.
   - Assume the initial quantity sold is Q.

2. **Initial Profit Margin**:
```

```
   - Initial revenue: R = P * Q
   - Initial total cost: T = C * Q
   - Initial profit: Profit = R - T = (P * Q) - (C * Q) = (P - C) * Q
   - Initial profit margin: Profit Margin = Profit / R = ((P - C) * Q) / (P * Q) = (P - C) / P

3. **Price Increase**:
   - New selling price: P' = P * 1.05

4. **Revenue with Low Demand Elasticity**:
   - With low demand elasticity, quantity sold Q' ~= Q
   - New revenue: R' = P' * Q' = (P * 1.05) * Q = 1.05 * P * Q

5. **New Profit**:
   - New profit: Profit' = R' - T = 1.05 * P * Q - C * Q = (1.05P - C) * Q

6. **New Profit Margin**:
   - Profit Margin' = Profit' / R' = ((1.05P - C) * Q) / (1.05 * P * Q) = (1.05P - C) / (1.05P)

Thus, the new profit margin after a 5% price increase with constant costs and low demand elasticity is:

   Profit Margin' = (1.05P - C) / (1.05P)

Compared to the initial profit margin of (P - C) / P, this indicates an increased profit margin, assuming
     demand remains largely unchanged.
```

User-to-agent and agent-to-resource relationships are encoded in a hierarchical access graph, where edges denote authorized delegation. This graph is intentionally non-fully connected to reflect realistic enterprise constraints. Notably, only the *strategy director* user has comprehensive visibility and access across all agents and resources, enabling them to perform holistic decision-making and synthesize the final output. Details of the access graph structure can be found in Section D.2.1, and a full description of the agents and resources is provided in Section D.2.2.

During the experiments, low-level users—assigned to *market researcher*, *financial analyst* and *logistics and operations lead*—are each responsible for a subtask decomposed from the main query. The *strategy director*, acting as the decision maker, is directly assigned the main query and approaches it by following the subtasks from the perspective of each specialized role, synthesizing the final response accordingly.

```
You are a project coordinator tasked with breaking down the following high-level business
     objective into specific subtasks for a team of three users with distinct functional
     roles.

Project: <query>

The users and their roles are:
- user_1: market
- user_2: finance
- user_3: logistics

For each user, generate a role-specific subtask they would be responsible for in this
     project. Output a valid JSON object mapping each user ID to their subtask. Only
     output the JSON, in the following format:

{
  "user_1": "Subtask for market role...",
  "user_2": "Subtask for finance role...",
  "user_3": "Subtask for logistics role...",
}
```

D.2.1 Access Graph Configuration

The access graph in our system consists of two layers of asymmetric permissions: (1) **user-to-agent** access and (2) **agent-to-resource** access. Each user can only interact with a subset of agents, and each agent can only retrieve a subset of external resources. This layered structure enforces partial observability and decentralized delegation.

Table 5: User-to-agent mapping indicating which agents are accessible to each user role in the asymmetric collaborative scenario.

User Role	Accessible Agents
Market Researcher	`market_agent`
Financial Analyst	`finance_agent,` `decision_agent`
Logistics Lead	`logistics_agent,` `finance_agent`
Strategy Director	`market_agent, finance_agent,` `logistics_agent, decision_agent`

Table 6: Mapping of agents to their accessible resources in the asymmetric collaborative scenario.

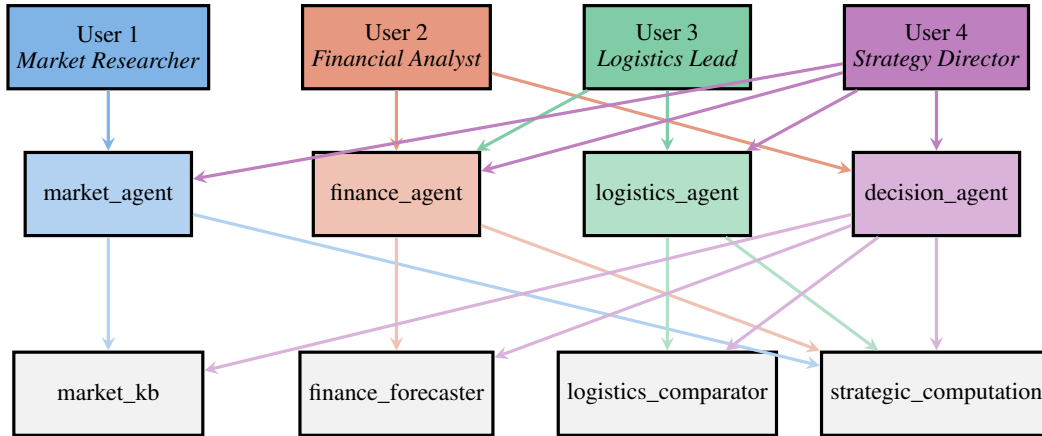| Agent	Accessible Resources
`market_agent`	`market_kb,` `strategic_computation`
`finance_agent`	`finance_forecaster,` `strategic_computation`
`logistics_agent`	`logistics_comparator,` `strategic_computation`
`decision_agent`	`market_kb, finance_forecaster,` `logistics_comparator, strategic_computation`

Figure 10: Color-coded access graph illustrating hierarchical user-to-agent and agent-to-resource mappings. Each user and their corresponding agents are assigned a unique color. The *strategy director* (User 4) has full visibility and access.

D.2.2 Agent/Knowledge Base Configuration

This section provides detailed configurations of the domain-specific agents, the coordinator and aggregator roles, and the resources they rely on. Each agent is designed with a specialized system prompt tailored to its functional expertise, enabling focused task execution within collaborative workflows. The coordinator assigns queries to appropriate agents based on domain relevance, while the aggregator synthesizes outputs into a coherent final response. Additionally, a set of task-relevant resources—including knowledge bases, forecasting tools, and computation modules—support the

agents in delivering accurate and context-aware outputs. Tables 7–9 summarize the roles, descriptions, and system prompts for all components.

Table 7: Domain agents and their system prompts in the asymmetric collaborative scenario.

Agent	Description	System Prompt
market_agent	Analyzes market competition and consumer data.	You are a market intelligence agent. Use market research reports and strategic case studies to identify trends, consumer behaviors, and competition analysis. Always consult memory first. If needed, call tools to retrieve new insights.
finance_agent	Performs financial modeling and cost projections.	You are a financial planning agent. Evaluate revenue forecasts, pricing structures, and cost breakdowns using financial models and simulations.
logistics_agent	Evaluates supply chain feasibility and vendor performance.	You are a logistics analyst. Use distribution comparators and operational data to assess fulfillment feasibility and vendor efficiency.
decision_agent	Synthesizes recommendations from other domains.	You are a strategic coordinator. Integrate inputs from various domain experts to formulate a cohesive strategic recommendation.

Table 8: Coordinator and aggregator with their system prompts in the asymmetric collaborative scenario.

	Description	System Prompt
coordinator	Assigns queries to appropriate agents based on domain expertise.	You are a coordinator for a specialized multi-agent system. Your job is to analyze user queries and determine which specialized agent is best suited to handle each query or sub-query. For each query: 1. Identify the primary domain(s) of the query 2. Select the most appropriate specialized agent based on their expertise areas. 3. For complex queries that span multiple domains, determine if sequential agent consultation is needed 4. When reformulating queries for specific agents, emphasize aspects relevant to their expertise 5. When the task is complete, respond with COMPLETE
aggregator	Merges multi-agent outputs into a unified user response.	You are an aggregator for a multi-agent system. Combine outputs from multiple specialized agents into a single, direct, and coherent response to the user query.

Table 9: Available resources and their functional roles in the asymmetric collaborative scenario.

Name	Type	Description
market_kb	knowledge_base	Market trends and consumer data
finance_forecaster	forecast_model	Performs financial forecasting and ROI estimation
logistics_comparator	comparator	Compares distribution and vendor options for supply chain planning
strategic_computation	computation	Executes strategic cost-benefit calculations

D.3 Examples

D.3.1 Read/Write example

Table 10 presents a multi-agent collaboration example in which agents write to and read from both private (user-specific) and public (cross-user) memory. This scenario highlights how agents can leverage memory entries for continued reasoning and strategic synthesis across users and roles.

Table 10: Memory write–read examples for multi-user multi agent collaboration, showing both user-specific and cross-user entries.

project_hard_52: "Craft a strategic growth plan for smart home devices in privacy-regulated markets."	

Private Memory

Discussion: This fragment is utilized in the second `market_agent` entry to inform the financial modeling of strategic initiatives focused on privacy-regulated markets.

Memory ID	51982b4d-3fc7-4dc8-83b7-e34ca07114ca
Key	Growth Opportunities in Privacy-Regulated Markets
Value	Developing new products with advanced privacy features can capture market interest. Targeting regions with stringent **privacy** regulations can open new markets. Consumer education campaigns can differentiate a brand and build trust.
Generated at	`market_agent` (user_4): *Conduct market analysis to identify consumer preferences and trends in privacy-regulated markets, focusing on smart home devices. Assess competitive landscape and potential growth opportunities.*
Used at	`market_agent` (user_4): *Develop a financial model to evaluate the cost-effectiveness and ROI of strategic initiatives in **privacy-regulated** markets, considering strict resource constraints. Use insights from the market analysis on consumer preferences, trends, and competitive landscape to inform the financial projections.*

Shared Memory

*Discussion: This is leveraged in the second `decision_agent` of **user_4** entry to synthesize insights from the market analysis and financial modeling when crafting a growth plan for smart home devices in privacy-regulated markets under strict resource constraints*

Memory ID	54214a00-8806-4ada-98ae-7f4029c06b90
Key	strategic recommendations for privacy-regulated markets
Value	1. **Optimize Initial Investment** by reducing upfront costs through leveraging existing technologies, partnerships, or phased implementation. 2. **Reduce Operating Costs** by outsourcing non-core activities, automating compliance processes, and negotiating better rates with vendors. 3. **Accelerate Time to Market** using agile project management, early regulatory engagement, and rapid prototyping. 4. **Enhance Market Penetration** through targeted marketing, leveraging customer insights, and building strategic alliances. 5. **Adjust Revenue Growth Expectations** by identifying additional revenue streams and expanding into adjacent markets. 6. **Reevaluate Discount Rate** by implementing risk mitigation strategies like securing insurance and diversifying investments. 7. **Scenario Planning** for best-case, worst-case, and most likely outcomes to understand variability in returns.
Generated at	`decision_agent` (user_2): *Synthesize recommendations based on the financial model developed by finance_agent, focusing on strategic initiatives in privacy-regulated markets with strict resource constraints.*
Used at	`decision_agent` (user_4): *Synthesize the insights from the **market analysis** and **financial modeling** to craft a strategic growth plan for smart home devices in privacy-regulated markets. Consider the strict resource constraints and cross-domain dependencies, and provide a comprehensive final recommendation.*

D.3.2 Without Subtask Decomposition

Table 11 shows that without subtask decomposition, limited agent and resource access can prevent effective query handling. When the query is reformulated to match User 3's operational role, the system produces a detailed response. In contrast, the original high-level query fails due to misalignment with agent capabilities. These results demonstrate the system's ability to address complex real-world tasks via coordinated collaboration among role-specialized users, agents, and resources.

Table 11: Comparison of user's responses with and without subtask decomposition.

---

project_easy_01: "Identify high-demand skincare markets in Europe."

With Subtask (User 3)

Query	Evaluate the logistical and supply chain requirements for distributing skincare products across different European markets, focusing on high-demand regions.
Response	To conduct a comprehensive analysis of the logistical and supply chain requirements for distributing skincare products across high-demand European markets, we need to consider both logistical infrastructure and financial projections. **Logistical Analysis:** 1. **Germany**: Germany's central location and efficient infrastructure make it an ideal hub for distribution. Its strong manufacturing and distribution networks support seamless logistics operations, providing easy access to various European markets. 2. **United Kingdom**: ...

Without Subtask (User 3)

Query	Identify high-demand skincare markets in Europe.
Response	No agents were able to process the query.

E Scenario 3: Dynamically Evolving Collaborative Memory

E.1 Dataset Details

The SciQAG dataset covers 24 Web of Science (WoS) categories. Since our experiments target evaluating system behavior under dynamic access settings without requiring the full dataset, we select 5 categories: "*Chemistry, Analytical*", "*Energy & Fuels*", "*Materials Science, Paper & Wood*", "*Materials Science, Ceramics*", and "*Physics, Mathematical*". These five categories cover a broad range of scientific domains. Each instance in this dataset consists of passages from a scientific paper along with corresponding question-answer pairs. The passages serve as the reference corpus for answering the associated questions. Table 12 reports the detailed breakdown of document counts, average lengths, and query-type distributions.

Table 12: Statistics of the subset of SCIQAG dataset for the dynamically evolving collaborative scenario.

Statistic	Count	Percentage
Documents		
Total articles	100	—
Average tokens per article	3,609	—
Queries (N = 100)		
Queries from "*Chemistry, Analytical*"	20	20%
Queries from "*Energy & Fuels*"	20	20%
Queries from "*Materials Science, Paper & Wood*"	20	20%
Queries from "*Materials Science, Ceramics*"	20	20%
Queries from "*Physics, Mathematical*"	20	20%

E.2 Experimental Details

- **Users**: We synthesize queries for 5 users. Each user has 4 randomly sampled queries from each of the 5 categories, resulting in a total of 100 queries.

- **Agents**: There are 5 agents, each specializing in one of the five scientific categories, corresponding to their respective domain expertise.

- **Resources**: There are 5 resources, each consisting of the passages from the dataset associated with a specific category, used to answer the corresponding questions.

We evaluate the framework under varying access graph configurations while accumulating memory across the dynamic experiment. The Shared Memory configuration is enabled to support cross-user memory sharing. The same queries are reused in different graph configurations. Memory retrieval is configured with a user-specific tier size of $k_{\text{user}} = 10$, a shared tier size of $k_{\text{cross}} = 10$, and a similarity threshold of 0.1. The agent has the access to one corresponding resource. We next provide details on the access graph configuration and the agent/knowledge base configurations.

E.2.1 Access Graph Configuration

We simulate the evolution of the access graph as a stochastic process. For simplicity, we maintain the agent-resource connection as a one-to-one mapping as reported in Table 15 and change the connections between users and agents. Specifically, we gradually add unseen edges to represent the granting of access and remove existing edges to represent the revocation of access. During the granting phase (from t_0 to t_4), the number of edges increases progressively to 5, 10, 15, 20, and 25, respectively. Starting from the fully connected graph at t_4, we reverse the process by progressively removing edges, resulting in graphs with 20, 15, 10, and 5 edges at t_5 through t_8, respectively. The graph at the previous stage provides the base of the next stage. The pseudocodes for these two procedures are in Algorithm 1 and Algorithm 2. We use $p = 0.2$ for the probability.

Algorithm 1 Access Granting Procedure (Generating t_0–t_4)

1: Initialize empty bipartite graph G with user and agent nodes
2: Define candidate edges between all user-agent pairs
3: **for** $i = 0$ to 4 **do**
4:     Add 5 new edges to G using Bernoulli trials with probability p
5:     Collect updated user-to-agent mappings from G
6:     Save updated YAML configuration with timestamp t_i
7: **end for**

Algorithm 2 Access Revoking Procedure (Generating t_5–t_8)

1: Load fully connected bipartite graph G
2: **for** $i = 5$ to 8 **do**
3:     Remove 5 edges from G using Bernoulli trials with probability p
4:     Collect updated user-to-agent mappings from G
5:     Save updated YAML configuration with timestamp t_i
6: **end for**

The user-to-agent mappings at each timestamp during the granting process are summarized in Table 13, and the mappings for the revoking process are shown in Table 14.

Table 13: Users to their accessible agents at timestamp from t_0 to t_4 in the access granting stage.

Timestamp	User	Accessible Agents
t_0	U_1	`materials_paper_wood_agent`, `materials_ceramics_agent`
	U_2	`physics_mathematical_agent`
	U_3	
	U_4	`materials_paper_wood_agent`
	U_5	`chemistry_analytical_agent`
t_1	U_1	`materials_paper_wood_agent`, `materials_ceramics_agent`, `energy_fuels_agent`
	U_2	`physics_mathematical_agent`, `energy_fuels_agent`
	U_3	`energy_fuels_agent`, `chemistry_analytical_agent`
	U_4	`materials_paper_wood_agent`, `energy_fuels_agent`
	U_5	`chemistry_analytical_agent`
t_2	U_1	`materials_paper_wood_agent`, `materials_ceramics_agent`, `energy_fuels_agent`
	U_2	`physics_mathematical_agent`, `energy_fuels_agent`, `chemistry_analytical_agent`
	U_3	`energy_fuels_agent`, `chemistry_analytical_agent`, `materials_ceramics_agent`
	U_4	`materials_paper_wood_agent`, `energy_fuels_agent`, `physics_mathematical_agent`
	U_5	`chemistry_analytical_agent`, `materials_ceramics_agent`, `energy_fuels_agent`
t_3	U_1	`materials_paper_wood_agent`, `materials_ceramics_agent`, `energy_fuels_agent`, `chemistry_analytical_agent`
	U_2	`physics_mathematical_agent`, `energy_fuels_agent`, `chemistry_analytical_agent`, `materials_ceramics_agent`
	U_3	`energy_fuels_agent`, `chemistry_analytical_agent`, `materials_ceramics_agent`, `physics_mathematical_agent`
	U_4	`materials_paper_wood_agent`, `energy_fuels_agent`, `physics_mathematical_agent`, `materials_ceramics_agent`
	U_5	`chemistry_analytical_agent`, `materials_ceramics_agent`, `energy_fuels_agent`, `physics_mathematical_agent`
t_4	U_1	`materials_paper_wood_agent`, `materials_ceramics_agent`, `energy_fuels_agent`, `chemistry_analytical_agent`, `physics_mathematical_agent`
	U_2	`physics_mathematical_agent`, `energy_fuels_agent`, `chemistry_analytical_agent`, `materials_ceramics_agent`, `materials_paper_wood_agent`
	U_3	`energy_fuels_agent`, `chemistry_analytical_agent`, `materials_ceramics_agent`, `physics_mathematical_agent`, `materials_paper_wood_agent`
	U_4	`materials_paper_wood_agent`, `energy_fuels_agent`, `physics_mathematical_agent`, `materials_ceramics_agent`, `chemistry_analytical_agent`
	U_5	`chemistry_analytical_agent`, `materials_ceramics_agent`, `energy_fuels_agent`, `physics_mathematical_agent`, `materials_paper_wood_agent`

Table 14: Users to their accessible agents at timestamp from t_5 to t_8 in the access revoking stage.

Timestamp	User	Accessible Agents
t_5	U_1	chemistry_analytical_agent, energy_fuels_agent, physics_mathematical_agent
	U_2	chemistry_analytical_agent, energy_fuels_agent, materials_paper_wood_agent, materials_ceramics_agent
	U_3	chemistry_analytical_agent, energy_fuels_agent, materials_paper_wood_agent, materials_ceramics_agent, physics_mathematical_agent
	U_4	chemistry_analytical_agent, energy_fuels_agent, materials_ceramics_agent, physics_mathematical_agent
	U_5	energy_fuels_agent, materials_paper_wood_agent, materials_ceramics_agent, physics_mathematical_agent
t_6	U_1	energy_fuels_agent
	U_2	chemistry_analytical_agent, energy_fuels_agent, materials_ceramics_agent
	U_3	chemistry_analytical_agent, materials_paper_wood_agent, materials_ceramics_agent, physics_mathematical_agent
	U_4	chemistry_analytical_agent, energy_fuels_agent, materials_ceramics_agent, physics_mathematical_agent
	U_5	energy_fuels_agent, materials_paper_wood_agent, physics_mathematical_agent
t_7	U_1	
	U_2	chemistry_analytical_agent, energy_fuels_agent, materials_ceramics_agent
	U_3	materials_paper_wood_agent, materials_ceramics_agent
	U_4	materials_ceramics_agent, physics_mathematical_agent
	U_5	energy_fuels_agent, materials_paper_wood_agent, physics_mathematical_agent
t_8	U_1	
	U_2	chemistry_analytical_agent
	U_3	materials_ceramics_agent
	U_4	materials_ceramics_agent
	U_5	energy_fuels_agent, physics_mathematical_agent

Table 15: Agents to their accessible resources in the dynamically evolving collaborative scenario.

Agent	Accessible Resources
materials_paper_wood_agent	materials_paper_wood_kb
materials_ceramics_agent	materials_ceramics_kb
energy_fuels_agent	energy_fuels_kb
chemistry_analytical_agent	chemistry_analytical_kb
physics_mathematical_agent	physics_mathematical_kb

E.2.2 Agent/Knowledge Base Configuration

We deploy five specialist agents, each paired with a dedicated knowledge base. Table 16 list each agent's description and full system prompt. In addition to the specialist agents, there is a coordinator to assign queries to different agents and an aggregator to merge the outputs. Their system prompts are listed in Table 17.

Table 16: Domain agents and their system prompts in the dynamically evolving collaborative scenario.

Agent	Description	System Prompt
chemistry_analytical_agent	Specialist in analytical chemistry—techniques, instrumentation, and chemical analysis.	You are an Analytical Chemistry specialist with deep expertise in: • Explaining analytical methods such as spectroscopy, chromatography, and mass spectrometry • Interpreting experimental results and chemical measurements • Discussing laboratory techniques and instrumentation details • Providing insights on quality control and chemical validation processes Always check relevant memories first. When those are insufficient, use the knowledge_base tools. Prioritize information from memories and the scientific literature dataset over your parametric knowledge. Do not provide responses to inquiries that are unrelated to the domain of analytical chemistry.
energy_fuels_agent	Specialist in energy and fuels—renewable energy, fossil fuels, and energy technologies.	You are an Energy & Fuels specialist with deep expertise in: • Discussing renewable energy sources like solar, wind, and bioenergy • Analyzing fossil fuel technologies including oil, gas, and coal • Evaluating energy storage systems and grid technologies • Interpreting policies, market trends, and environmental impacts Always check relevant memories first. When those are insufficient, use the knowledge_base tools. Prioritize information from memories and the energy sector dataset over your parametric knowledge. Do not provide responses to inquiries that are unrelated to the domain of energy and fuels.

Continued on next page

Agent	Description	System Prompt
`materials_ paper_ wood_ agent`	Specialist in materials science—paper, wood, and biomaterials research and applications.	You are a Paper & Wood Materials Science specialist with deep expertise in: • Explaining the properties and processing of paper and wood materials • Discussing advancements in sustainable materials and bio-based composites • Analyzing mechanical, chemical, and environmental performance • Exploring industrial applications in packaging, construction, and manufacturing Always check relevant memories first. When those are insufficient, use the knowledge_base tools. Prioritize information from memories and the materials science dataset over your parametric knowledge. Do not provide responses to inquiries that are unrelated to the domain of paper and wood materials.
`materials_ ceramics_ agent`	Specialist in materials science—ceramics, glass, and high-performance materials.	You are a Ceramics Materials Science specialist with deep expertise in: • Explaining the processing and properties of ceramics and glass • Analyzing thermal, mechanical, and electrical performance characteristics • Discussing applications in aerospace, electronics, and structural components • Exploring advances in high-temperature and wear-resistant materials Always check relevant memories first. When those are insufficient, use the knowledge_base tools. Prioritize information from memories and the materials science dataset over your parametric knowledge. Do not provide responses to inquiries that are unrelated to the domain of ceramics and high-performance materials.
`physics_ mathematical_ agent`	Specialist in mathematical physics—models, theories, and mathematical formulations of physical systems.	You are a Mathematical Physics specialist with deep expertise in: • Explaining mathematical models of physical systems and phenomena • Interpreting equations, simulations, and theoretical predictions • Discussing areas such as quantum mechanics, statistical physics, and dynamical systems • Providing insights into mathematical methods used in physics research Always check relevant memories first. When those are insufficient, use the knowledge_base tools. Prioritize information from memories and the physics literature dataset over your parametric knowledge. Do not provide responses to inquiries that are unrelated to the domain of mathematical physics.

Table 17: Coordinator and aggregator with their system prompts in the dynamically evolving collaborative scenario.

	Description	System Prompt
coordinator	Assigns queries to appropriate agents based on domain expertise.	You are a coordinator for a specialized scientific knowledge system consisting of domain-specific expert agents. Your job is to analyze user queries and determine which specialized agent is best suited to handle each query or sub-query.
		For each query: 1. Identify the primary domain(s) of the query 2. Select the most appropriate specialized agent based on their expertise areas. 3. For complex queries that span multiple domains, determine if sequential agent consultation is needed 4. When reformulating queries for specific agents, emphasize aspects relevant to their expertise 5. When the task is complete, respond with COMPLETE
aggregator	Merges multi-agent outputs into a unified user response.	You are an aggregator for a multi-agent scientific knowledge system. Your role is to combine outputs from multiple specialized agents into a single, logically structured, and detailed response to the user query.

E.3 Examples

To illustrate how our system stores and subsequently reuses memory entries and how the saved memory facilitates solving subsequent queries, Table 18 presents two representative "write–then–read" cases using private and shared memory fragments. Each example includes the memory's unique ID, the stored key–value pair, the original query that triggered the memory write, and the later query that retrieved it. Example 1 demonstrates private memory reuse: the memory was created when user_1 submitted Query #18 and later accessed by the same user in Query #40. Example 2 highlights shared memory reuse: information originally stored in response to user_5's query was subsequently retrieved by user_2. We provide detailed discussions in the table.

E.4 Raw Performance Data and Complete Access Matrix Under Different Access Graph Configurations

In this section, we present the results across graph configurations, including (1) raw data of the system performance over eight time blocks with dynamically changing privileges and (2) the full access matrix in Figure 11.

Figure 11 presents the complete agent and resource usage patterns across user queries. It clearly illustrates that agents and resources are only utilized when access is explicitly granted (i.e., in the yellow rectangles) despite the change of the privileges.

Table 18: Memory write–read examples for private and shared memories in the dynamically evolving collaborative scenario.

Example 1 (Private Memory)

Discussion: The stored content discusses structural dimorphism in cellulose, emphasizing the role of 21 symmetry structures as high-energy intermediates, thereby supporting analysis of flexibility in cellulose's structural transitions.

Memory ID	8177e2aa-2ef0-4b20-bdcb-af33d8d1ae00
Key	Potential energy surfaces for cellulose
Value	The study concluded that twofold symmetry structures of cellulose act as barriers between lower-energy forms. Energy maps using empirical force fields and quantum mechanical methods suggested that 21 symmetry structures might have higher potential energy due to close atomic contacts, potentially serving as transition points or barriers. Despite the increased energy from these close contacts, hydrogen bonds could stabilize these structures. The study also highlighted the flexibility of cellulose chains and possible deviations from 21 symmetry, indicating substantial flexibility and the influence of crystal packing on the flat ribbon-like 21 structures.
Generated at	Query #18 (user_1): *What was the conclusion about the potential energy surfaces for cellulose and its derivatives?*
Used at	Query #40 (user_1): *What is the significance of cellulose's dimorphism?*

Example 2 (Shared Memory)

Discussion: Although the original context involved irradiated wood, the saved explanation—how moisture accelerates hydrolytic and chemical degradation—proved relevant to understanding degradation processes in insulating paper. Additionally, this sharing occurs because both User_2 and User_5 have access to the chemistry analytical agent. The constraints enforced by our access graph ensure that the shared information is used safely and appropriately.

Memory ID	01b1f4d0-d7d5-4be5-ae96-98620a49add2
Key	Influence of relative humidity on irradiated wood
Value	Relative humidity affects the chemical changes in irradiated wood during heat treatment, influencing color change. Higher humidity increases moisture content, facilitating hydrolytic reactions and lignin breakdown, leading to chromophore formation and color change. Moisture acts as a plasticizer, enhancing polymer mobility and reaction rates, which accelerates lignin breakdown. Controlling humidity can manage color alteration in wood.
Generated at	Query #21 (user_5): *How does relative humidity affect the change in color of irradiated wood during heat treatment?*
Used at	Query #66 (user_2): *What role does moisture play in the degradation of insulating papers?*

Table 19: Performance and Memory Statistics Across Different Access Graph Configurations

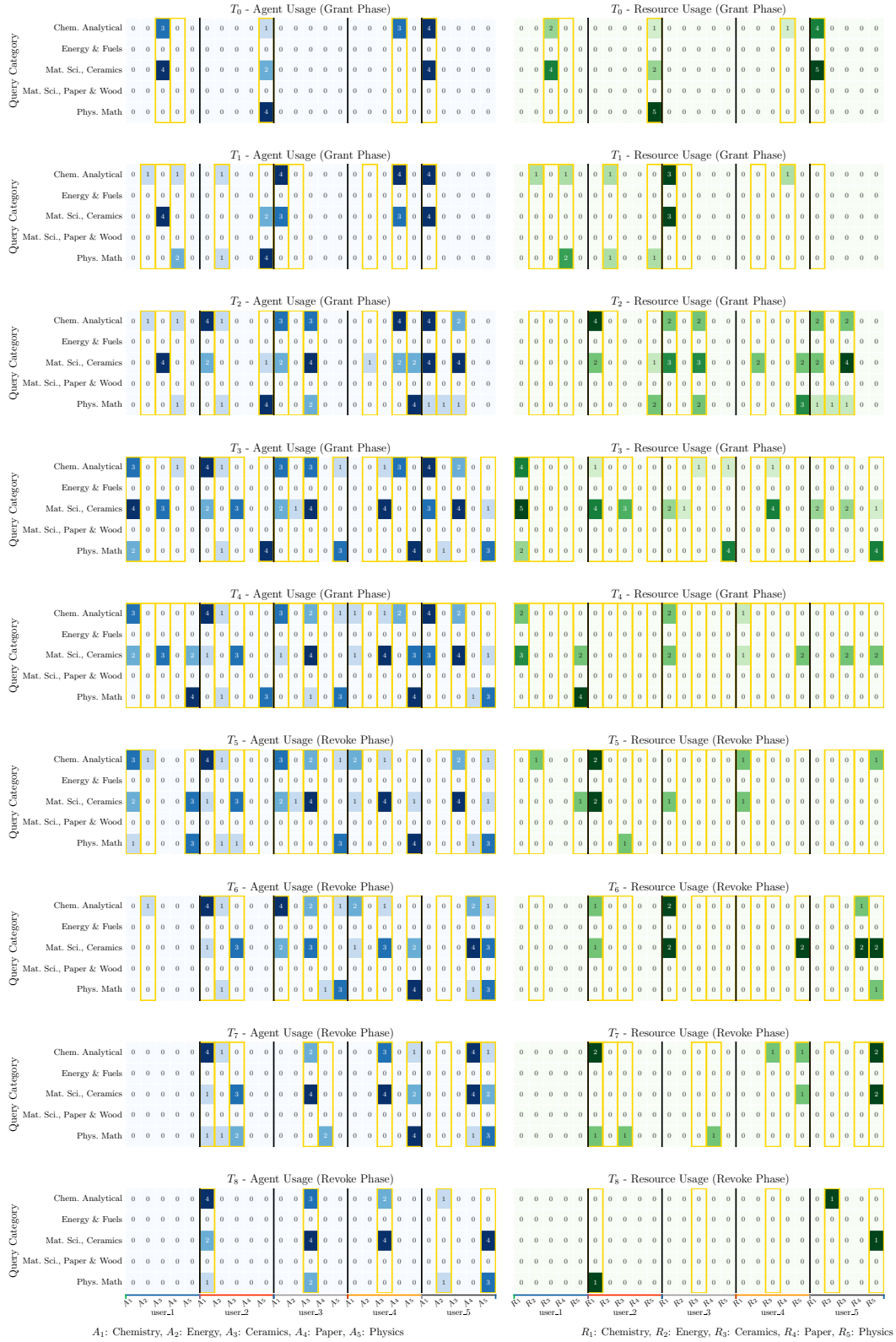| Time	Condition	Accuracy	# Resources	# Agent	# User Memory	# Cross Memory
t_0	Grant	0.27 ± 0.01	0.46 ± 0.02	0.51 ± 0.03	2.94 ± 0.93	3.25 ± 0.70
t_1	Grant	0.40 ± 0.02	0.34 ± 0.02	0.74 ± 0.04	5.85 ± 0.14	7.09 ± 0.37
t_2	Grant	0.54 ± 0.03	0.60 ± 0.03	1.14 ± 0.06	9.81 ± 0.57	11.40 ± 0.91
t_3	Grant	0.56 ± 0.03	0.57 ± 0.03	1.29 ± 0.06	11.11 ± 1.04	12.90 ± 0.83
t_4	Grant	0.61 ± 0.03	0.48 ± 0.02	1.31 ± 0.07	11.27 ± 0.60	13.10 ± 0.43
t_5	Revoke	0.56 ± 0.03	0.21 ± 0.01	1.19 ± 0.06	11.57 ± 0.72	11.90 ± 0.62
t_6	Revoke	0.47 ± 0.02	0.30 ± 0.01	1.08 ± 0.05	10.77 ± 2.06	10.80 ± 2.07
t_7	Revoke	0.49 ± 0.02	0.23 ± 0.01	1.07 ± 0.05	10.75 ± 1.44	10.75 ± 1.44
t_8	Revoke	0.37 ± 0.02	0.06 ± 0.00	0.68 ± 0.03	6.75 ± 0.48	6.75 ± 0.48

Figure 11: Complete agent and resource usage across user queries from different categories. Yellow rectangles indicate granted access, with values representing the corresponding usage counts.