MEMSAGE: ASYMMETRIC MEMORY BEAMFORMING FOR CONTEXTUAL INTEGRITY IN LLM MEMORY

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ABSTRACT

Modern Large Language Models (LLMs) are evolving to incorporate persistent memory, enabling them to retain user information across interactions and thereby improve user experience and task performance. However, this capability can be a double-edged sword. Recent studies have revealed the contextual integrity problem of persistent memory, where LLMs utilize retained information indiscriminately without assessing its contextual appropriateness, resulting in unwarranted disclosure of sensitive information. Existing approaches to this problem either regulate memory use externally via explicit prompting and rigid retrieval control, or internalize contextual reasoning into LLMs, leaving unmet the asymmetric, context-specific demands on retained memories. To address this gap, we propose MEMSAGE, a novel plug-in framework for enforcing the contextual integrity of LLM **MEM**ory via **S**tiefel-based **A**symmetric **G**eometric b**E**amforming. MEMSAGE presents a unique twist: it trains a lightweight hypernetwork to dynamically generate Stiefel frames for each context and the retained memories, forming a nested permission–demand geometry that directs memory use during generation. To operationalize this structure, MEMSAGE performs asymmetric memory beamforming over LLM attention, suppressing context-inappropriate memories while directionally amplifying obligatory ones through geometry-aligned query–key interactions. Notably, MEMSAGE is applied at inference time without altering the retained memories or updating the base model parameters. Extensive experiments across various LLM backbones demonstrate that MEMSAGE significantly enhances the contextual integrity of LLM memory compared with existing baselines, simultaneously reducing memory violations and improving coverage[1].

1 INTRODUCTION

Recent years have witnessed the rapid evolution of Large Language Models (LLMs) (Yang et al., 2025; OpenAI, 2026) from stateless text generators to long-term, adaptive assistants augmented with persistent memory (Chhikara et al., 2025; Xu et al., 2025; Yan et al., 2026). By retaining user information from prior interactions across sessions, these systems can provide continuous, personalized, and effective task support, underpinning applications ranging from healthcare counseling (Zhong et al., 2024) and financial advising (Takayanagi et al., 2025; Yu et al., 2025) to enterprise assistance (Fu et al., 2026; Alake et al., 2026). Yet, the persistence of memory entails the reuse of the same retained user information across distinct interaction scenarios (Pulipaka et al., 2026; Hannoon et al., 2026). This renders Contextual Integrity (CI) (Nissenbaum, 2004) a central challenge for memory-augmented LLMs, where privacy violations are characterized as inappropriate information flows that contravene context-specific disclosure norms.

Recent work (Pulipaka et al., 2026; Fu et al., 2026) has benchmarked this problem, showing that even frontier LLMs can exhibit substantial CI violations in the context-sensitive use of persistent memory. Existing approaches to mitigating this problem fall broadly into two lines. (1) *External regulation of memory use* either explicitly prompts memory-augmented LLMs to comply with applicable disclosure norms (Shao et al., 2024; Mireshghallah et al., 2025) or curates the memories incorporated into the model input via retrieval and filtering (Bagdasarian et al., 2024; Hannoon

[1]Code is available at `https://anonymous.4open.science/r/MemSAGE-1454/`.

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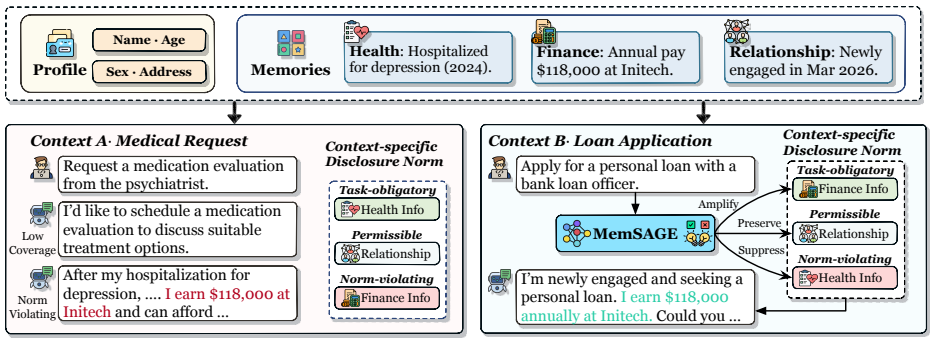


Figure 1: Illustration of CI failures in a medical request (*Left*) and MemSAGE's asymmetric memory steering in a loan application (*Right*) under dynamic contextual disclosure norms.

et al., 2026), leaving the model parameters unchanged. Yet, as this regulation operates at the pre-generation stage, overly rigid constraints on model inputs often suppress task-relevant information, whereas insufficiently restrictive ones fail to reliably isolate contextually inappropriate memories, impeding precise steering of the model toward CI-compliant generation. (2) *Internal contextual alignment* trains the model through preference optimization or reinforcement learning to align its disclosure behavior with CI norms (Lan et al., 2025; Park et al., 2026). Yet, this parametric internalization paradigm incurs substantial adaptation costs under continually evolving CI norms, and risks over-alignment that collapses the model's capacity for nuanced, per-attribute adjudication.

These limitations stem from the lack of effective control over context-dependent memory participation during generation to ensure compliance with dynamic information disclosure norms. Crucially, we posit that achieving effective CI entails an inherently asymmetric requirement on memory use: the model must discriminatively suppress contextually inappropriate memories while preserving permissible ones, with information required by the current context being further reinforced during generation. Resolving this impasse calls for a new, flexible CI approach capable of dynamically steering in-context memory participation to shape model generation. By adaptively orchestrating the asymmetric regulatory demands exerted across retained memories, such an approach localizes CI control to the current interaction without altering model parameters or distorting the representation space that sustains general capabilities.

To realize this idea, we propose MEMSAGE, a novel inference-time framework that plugs applicable CI norms into LLM **MEM**ory use via **S**tiefel-based **A**symmetric **G**eometric b**E**amforming. Motivated by the observation that contextual memories inform generation through attention interactions, rendering the contribution of each memory addressable via its attention outcomes, MEMSAGE operates at the attention interface to steer memory participation. As illustrated in Figure 1, MEMSAGE consists of three stages. (1) *Contextual Stiefel framing*: We begin by employing a lightweight hypernetwork to dynamically map the immediate interaction context and retained memories into orthonormal frames on the Stiefel manifold (Edelman et al., 1998; Li et al., 2025), establishing a nested permission–demand subspace geometry while preventing representational distortion. (2) *Asymmetric geometric beamforming*: The constructed geometry is then optimized to encode the asymmetric CI requirements into the spectral alignment between memory and contextual frames, yielding signed beamforming gains that suppress norm-violating memories while selectively amplifying task-essential ones. (3) *Attention-level memory steering*: These directional beamforming gains are applied to modulate memory-specific attention interactions, dynamically steering memory participation during generation toward CI compliance without altering the base model parameters. Extensive experiments demonstrate that MEMSAGE consistently reduces norm-violating disclosures while preserving contextually mandated information across multiple LLM backbones, underscoring its superiority and robustness compared to existing methods. Our contributions are as follows:

- We conceptualize the inherently asymmetric nature of CI-aware LLM memory use, proposing inference-time control over context-dependent memory participation for CI-compliant generation.
- We introduce MEMSAGE, a novel plug-in framework that operationalizes the asymmetric CI requirements via Stiefel-based geometry, optimizing its spectral alignment with retained memories to derive beamforming gains for steering memory participation.
- Experiments across various LLMs show that MEMSAGE consistently reduces norm-violating disclosures while improving contextually warranted memory use, outperforming existing baselines.

2 Related Work

Contextual Integrity in Memory-Augmented LLMs. Augmenting LLMs with long-term memory has emerged as a prevailing paradigm to enhance their performance by utilizing information from past interactions (Zhong et al., 2024; Tavakoli et al., 2025; Yan et al., 2026). Yet, the cross-session persistence of user memory raises CI concerns, as CI (Nissenbaum, 2004) posits that privacy is not a static binary public-private distinction, but the adherence of information flows to context-specific transmission norms. Recent empirical benchmarks (Mireshghallah et al., 2024; Shao et al., 2024) reveal that contemporary LLMs struggle with contextual boundary adjudication, frequently leaking sensitive user attributes beyond the bounds permitted by contextual norms (Mireshghallah et al., 2025; Pulipaka et al., 2026; Fu et al., 2026).

To address CI violations, one line of work regulates information disclosure through explicit privacy instructions and external controls over the context available to LLMs. For example, Mireshghallah et al. (2025) evaluates three increasingly conservative privacy prompts to reduce CI violations, while Hannoon et al. (2026) mitigates cross-domain leakage by imposing domain-level structure on persistent memory at inference time. While effective, these methods exhibit limited regulatory granularity, coupling reductions in disclosure violations with the excessive withholding of task-essential information. Another line of work seeks to internalize context-specific transmission norms via post-training, with CI-RL (Lan et al., 2025) reinforcing explicit CI reasoning, rewarding the inclusion of required information and penalizing restricted disclosures, and Park et al. (2026) further employing complementary self-distillation to align the model with a product-of-experts target derived from two specialized self-teachers. However, parameterizing CI compliance comes at a high cost and lacks flexibility in adapting to evolving CI norms. Crucially, these methods also fail to exert fine-grained, asymmetric control over how different memories participate in generating model outputs.

In contrast, MemSAGE operates as a dynamic plug-in framework to localize CI control within memory–context interactions at inference. By performing asymmetric geometric beamforming between memories and the current context via spectral alignment, MemSAGE derives directional gains that modulate each memory's participation in generation, selectively attenuating inappropriate content and amplifying task-required attributes while preserving permissible information.

Inference-Time Steering of LLMs. Steering LLMs at inference time is regarded as a promising and cost-effective paradigm for guiding them toward desirable behaviors without parameter updates (Subramani et al., 2022; Turner et al., 2023; Zou et al., 2023). Broadly, two branches characterize existing efforts: *activation steering* and *attention steering*. Activation steering typically intervenes in model behavior by directly injecting steering vectors into intermediate activations within specific model layers (Lee et al., 2025; Zhu et al., 2026), enabling applications such as truthfulness and safety enhancement (Li et al., 2023; Rimsky et al., 2024; Arditi et al., 2024), stylistic control (Turner et al., 2023), and complex reasoning (Tang et al., 2025). Beyond representation engineering, attention steering, the branch more closely related to our work, operates at the attention interface to direct contextual focus toward task-relevant information during generation (Yan et al., 2025; Venkateswaran & Contractor, 2026). To this end, PASTA (Zhang et al., 2024) steers model focus toward designated input spans by directly modulating attention scores, while SEKA and AdaSEKA intervene in key representations to enable efficient and query-adaptive prompt highlighting (Li et al., 2026). Despite their increasing adaptivity, these methods primarily regulate input salience while neglecting the context-dependent disclosure status of retained information.

MemSAGE addresses this by introducing CI governance into the memory–context attention interface, modulating the directional contribution of different retained memories to generation according to contextual permissions and task demands through Stiefel-constrained asymmetric beamforming.

3 Methodology

Problem Formulation. To study the CI problem in memory-augmented LLMs, we consider a user–agent interaction scenario where a user $u \in \mathcal{U}$ possesses a set of persistent textual memories $\mathcal{M}_u = \{m_i\}_{i=1}^{n}$, with each m_i encoding salient information about the user retained from past interactions. Let f_θ denote an LLM parameterized by θ. At each interaction, the user u provides a context c specifying the task and situational background. The LLM f_θ is tasked with generating

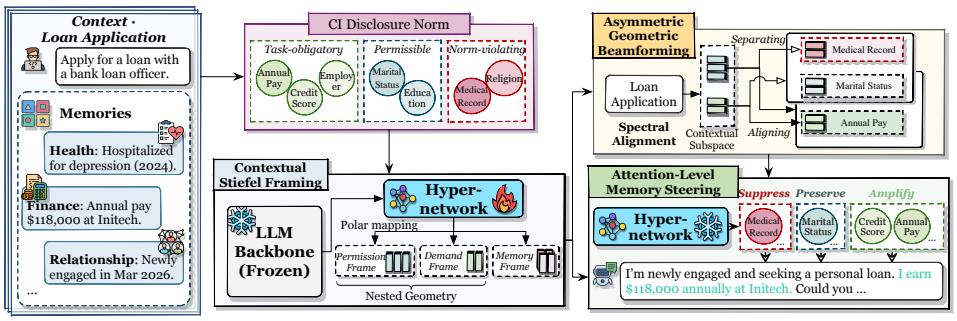


Figure 2: Overview of MEMSAGE. (1) Contextual Stiefel Framing constructs a nested geometry. (2) Asymmetric Geometric Beamforming derives directional alignment gains. (3) Attention-Level Memory Steering applies these gains for differentiated memory modulation.

a task-solving response y based on the user's persistent memories $\mathcal{M}_u$ and the current context c as $y \sim f_\theta(\cdot \mid \mathcal{M}_u \oplus c)$, where $\oplus$ denotes the concatenation operation.

CI theory (Nissenbaum, 2004) imposes differentiated requirements on the use of LLM persistent memory, emphasizing that information disclosure should conform to context-specific transmission norms. In the CI setting, the user memories $\mathcal{M}_u$ accessible to the LLM f_θ can be conceptually categorized into subsets based on the disclosure requirements associated with the current context c:

$$\mathcal{M}_u = \mathcal{M}_{\text{viol}}(c) \cup \mathcal{M}_{\text{perm}}(c) \cup \mathcal{M}_{\text{dem}}(c), \tag{1}$$

where $\mathcal{M}_{\text{viol}}(c)$ comprises *norm-violating memories* whose disclosure is prohibited by the contextual norms applicable to c, $\mathcal{M}_{\text{dem}}(c)$ contains *task-obligatory memories* indispensable for fulfilling the user request, and $\mathcal{M}_{\text{perm}}(c)$ consists of *permissible memories* that are permitted but not mandatory for task completion. The primary goal of this work is to guide the LLM f_θ toward CI-compliant generation that satisfies these dynamic disclosure requirements by withholding information from $\mathcal{M}_{\text{viol}}(c)$ while deliberately conveying task-required information from $\mathcal{M}_{\text{dem}}(c)$.

3.1 THE MEMSAGE FRAMEWORK

Figure 1 depicts an overview of MEMSAGE. It encompasses three stages: ***Contextual Stiefel Framing*** (§ 3.2) for generating orthonormal frames for the current context and user memories, establishing a nested permission–demand subspace geometry while preventing representational distortion; ***Asymmetric Geometric Beamforming*** (§ 3.3) for deriving directional beamforming gains via spectral alignment, enabling differentiated memory modulation; and ***Attention-Level Memory Steering*** (§ 3.4) for injecting beamforming gains into the LLM's cross-token attention interactions to steer memory participation during generation. We describe each stage in detail below.

3.2 CONTEXTUAL STIEFEL FRAMING

To capture the dynamic nature of CI norms, effective memory utilization in LLMs requires not only accurately modeling and adhering to context-specific constraints, but also avoiding interference with the underlying semantic representations for cross-context memory reuse. MEMSAGE addresses this by framing the context and memory representations within auxiliary subspaces, establishing the geometric basis for modeling the context–memory relations. Specifically, we parameterize the auxiliary subspaces on the Stiefel manifold $\mathrm{St}(k, d) = \{\mathbf{U} \in \mathbb{R}^{d\times k} \mid \mathbf{U}^\top\mathbf{U} = \mathbf{I}_k\}$, which consists of orthonormal bases of k-dimensional subspaces in the Euclidean space $\mathbb{R}^d$. To facilitate the learning of dynamic transmission norms across varying contexts and memories, we employ lightweight hypernetworks to generate the Stiefel-based frames from their corresponding semantic representations:

$$\mathbf{U}_c = \Pi(g_{\phi_{\text{ctx}}}(\mathbf{h}_c)) \in \mathrm{St}(k_{\text{ctx}}, d), \qquad \mathbf{U}_{m_i} = \Pi(g_{\phi_{\text{mem}}}(\mathbf{h}_{m_i})) \in \mathrm{St}(k_{\text{mem}}, d), \quad i = 1, \ldots, n, \tag{2}$$

where $\mathbf{h}_c$ and $\mathbf{h}_{m_i}$ denote the hidden states of the context c and memory m_i extracted from f_θ. $g_{\phi_{\text{ctx}}}(\cdot)$ and $g_{\phi_{\text{mem}}}(\cdot)$ are learnable hypernetworks parameterized by ϕ_{ctx} and ϕ_{mem}, respectively. $\Pi(\mathbf{A}) = \mathbf{A}(\mathbf{A}^\top\mathbf{A})^{-1/2}$ refers to the differentiable polar mapping onto the Stiefel manifold. By construction, the orthonormality of the resulting frames provides an isometric coordinate representation within each spanned subspace that satisfies $\|\mathbf{U}^\top\mathbf{x}\|_2 = \|\mathbf{x}\|_2$ for any $\mathbf{x} \in \mathrm{span}(\mathbf{U})$, thereby preserving the semantic geometry without scale distortion for consistent context–memory alignment.

Building on these Stiefel frames, we further structure the contextual geometry into nested permission and demand subspaces to reflect the asymmetric CI disclosure requirements. Intuitively, the permission subspace characterizes information compatible with the current disclosure norm, whereas the demand subspace captures the more restrictive set of directions that the task obligates. Given the subspace $\mathcal{S}_{\mathrm{perm}}(c) = \mathrm{span}(\mathbf{U}_c)$ that encodes context-dependent permission, we construct a nested demand subspace within its coordinate system as $\mathbf{U}_c^{\mathrm{dem}} = \mathbf{U}_c\mathbf{R}_c$, where $\mathbf{R}_c \in \mathrm{St}(k_{\mathrm{dem}}, k_{\mathrm{ctx}})$ parameterizes the task-specific demand geometry. Mathematically, this formulation guarantees $\mathcal{S}_{\mathrm{dem}}(c) = \mathrm{span}(\mathbf{U}_c^{\mathrm{dem}}) \subseteq \mathcal{S}_{\mathrm{perm}}(c)$, structurally mirroring the containment of task obligation within permissible disclosure.

3.3 Asymmetric Geometric Beamforming

Having constructed the nested permission–demand geometry for modeling context–memory relations, we next quantitatively adjudicate memory participation in generation under the context-specific disclosure constraints. To accommodate the asymmetric normative requirement of CI for differentiated memory suppression and amplification, we design an asymmetric geometric beamforming mechanism inspired by spatial filtering in signal processing, deriving directional gains from context–memory spectral alignment. Specifically, for each m_i, we characterize its geometric affinity with the permission and demand subspaces via the corresponding cross-frame interactions:

$$\mathbf{H}_i^s = (\mathbf{U}_c^s)^\top \mathbf{U}_{m_i}, \qquad s \in \{\mathrm{perm}, \mathrm{dem}\}. \tag{3}$$

Given the orthonormality of the interacting frames, the singular values of $\mathbf{H}_i^s$ encode the principal-angle spectrum of the memory and contextual subspaces, providing a spectral characterization of their geometric alignment. From $\mathbf{H}_i^s$, we derive two complementary spectral affinities:

$$a_i^s = \tfrac{1}{k_{\mathrm{mem}}} \mathrm{tr}\left((\mathbf{H}_i^s)^\top \mathbf{H}_i^s\right), \qquad b_i^s = \det\left((\mathbf{H}_i^s)^\top \mathbf{H}_i^s\right), \tag{4}$$

where a_i^s and b_i^s denote the normalized projection and Binet–Cauchy affinities, capturing the average squared principal-angle alignment and multiplicative alignment across memory directions, respectively. k_{mem} is the rank of the memory frame. To endow these spectral descriptors with CI-specific semantics, we formulate their layer-wise interpretation as:

$$\rho_i^{s,(\ell)} = \sigma\Big(\psi_s\left([a_i^{s,(\ell)}, b_i^{s,(\ell)}, \mathbf{e}_\ell]\right)\Big), \tag{5}$$

where ψ_s denotes the corresponding two-layer MLP and $\mathbf{e}_\ell$ is a learnable layer embedding. $\gamma_i^{(\ell)} = \rho_i^{\mathrm{perm},(\ell)}, \delta_i^{(\ell)} = \rho_i^{\mathrm{dem},(\ell)} \in [0,1]$ are the permission and demand scores, respectively.

Optimization. To achieve asymmetric beamforming controls for targeted memory suppression and amplification, we supervise the spectral scores to shape the corresponding subspace geometry under the CI constraints. Specifically, we optimize the following objective:

$$\mathcal{L}_s = \tfrac{1}{L}\textstyle\sum_{\ell=1}^{L} \mathbb{E}_i^{\mathrm{bal}}\left[\mathrm{BCE}\left(\rho_i^{s,(\ell)}, y_i^s\right)\right], \qquad s \in \{\mathrm{perm}, \mathrm{dem}\}, \tag{6}$$

where $y_i^{\mathrm{perm}} = \mathbb{I}\left[m_i \notin \mathcal{M}_{\mathrm{viol}}(c)\right]$ and $y_i^{\mathrm{dem}} = \mathbb{I}\left[m_i \in \mathcal{M}_{\mathrm{dem}}(c)\right]$ specify the permission and demand supervision, respectively. $\mathcal{L}_{\mathrm{perm}}$ shapes the permission geometry to separate norm-violating memories from contextually permissible ones, whereas $\mathcal{L}_{\mathrm{dem}}$ specializes the nested demand geometry toward task-obligatory memories. Beyond guiding the geometric affinity via $\mathcal{L}_s$, we further introduce a directional alignment loss $\mathcal{L}_{\mathrm{align}}$ to ground the spectral geometry in query-readable key representations, ensuring the active participation of task-obligatory memories in model generation. To operationalize this, we project memory keys onto the directions spanned by the demand frame using $\mathbf{P}_{c,m_i}^{\mathrm{dem}} = \mathbf{U}_c^{\mathrm{dem}}\mathbf{H}_i^{\mathrm{dem}}\mathbf{U}_{m_i}^\top$. Given the model response trajectory, we characterize memory participation in generation with a trajectory-level alignment score as $\mathcal{A}_i = \mathcal{F}_{\mathrm{align}}(\mathbf{Q}, \mathbf{P}_{c,m_i}^{\mathrm{dem}}, \mathbf{K}_i)$, where $\mathcal{F}_{\mathrm{align}}(\cdot)$ aggregates the query–key compatibility along the response trajectory, with its detailed formulation provided in Appendix A. We then optimize the alignment according to the contextual demand status of each memory, inducing differentiated participation between task-obligatory and remaining memories as follows:

$$\mathcal{L}_{\mathrm{align}} = \mathbb{E}_{m_i \in \mathcal{M}_{\mathrm{dem}}(c)}\left[\mathrm{softplus}(-\mathcal{A}_i)\right] + \mathbb{E}_{m_i \notin \mathcal{M}_{\mathrm{dem}}(c)}\left[\mathrm{softplus}(\mathcal{A}_i)\right]. \tag{7}$$

To preserve distinct memory-specific directions within the spectral geometry, we further regularize the pairwise overlap between memory subspaces:

$$\mathcal{L}_{\mathrm{scatter}} = \tfrac{2}{n(n-1)} \textstyle\sum_{i<j} \tfrac{1}{k_{\mathrm{mem}}} \left\|\mathbf{U}_{m_i}^\top \mathbf{U}_{m_j}\right\|_F^2. \tag{8}$$

As an auxiliary regularization, this objective promotes separation among memory subspaces, maintaining their individual discriminability under context-dependent participation. The overall optimization objective of MEMSAGE can be formulated as follows:

$$\mathcal{L}_{\text{total}} = \sum_{s\in\{\text{perm,dem}\}} \lambda_s \mathcal{L}_s + \lambda_{\text{align}}\mathcal{L}_{\text{align}} + \lambda_{\text{scatter}}\mathcal{L}_{\text{scatter}}, \tag{9}$$

where λ_s, λ_{align}, and λ_{scatter} represent hyperparameters that modulate the respective contributions of distinct losses. Through asymmetric geometric beamforming, we can derive context-conditioned directional controls over retained memories from the optimized spectral geometry, which are subsequently operationalized as memory-level suppression and demand-aware amplification.

3.4 ATTENTION-LEVEL MEMORY STEERING

Building on the spectrally aligned geometry in § 3.3, we next operationalize context-conditioned beamforming control at the attention interface to modulate memory participation for CI-compliant generation. To achieve this, we leverage the permission score to govern memory-level admissibility, thereby preventing norm-violating information leakage, while utilizing the demand-conditioned projection to identify memory directions eligible for query-dependent amplification. Specifically, for each memory m_i, we first derive a memory-specific admissibility signal from its permission score γ_i as $g_i = \sigma(\beta(\gamma_i - \tau))$, where τ specifies the permission threshold and β controls the transition sharpness. To enable targeted amplification of contextually obligated information, we then extract the demand-aligned representation of each memory key through the demand-conditioned projection as $\widetilde{\mathbf{k}}_{i,j} = \mathbf{P}^{\text{dem}}_{c,m_i}\mathbf{k}_{i,j}$, where $\mathbf{k}_{i,j}$ is the key representation of the j-th token in m_i. With these derived geometric beamforming signals, we operationalize asymmetric steering by modulating the attention logits between query and memory tokens at each generation step:

$$\widehat{s}_{t,i,j} = s_{t,i,j} + \underbrace{\log g_i}_{\text{suppression}} + \underbrace{\kappa g_i \max(\mathbf{q}_t^\top \widetilde{\mathbf{k}}_{i,j}/\sqrt{d}, 0)}_{\text{amplification}}, \tag{10}$$

where $s_{t,i,j}$ denotes the original attention logit and d is the dimension. $\log g_i$ serves as a memory-specific suppression bias shared across all tokens of m_i. For norm-violating memories with $g_i \to 0$, $\log g_i$ imposes an increasingly negative penalty, thereby decisively silencing their post-softmax attention allocation to prevent information leakage. In contrast, the amplification term selectively reinforces the participation of task-obligatory memories whose demand-aligned key representations positively align with the current query, with κ controlling the amplification strength. By modulating this term with g_i, the amplification channel is explicitly coupled to memory-level admissibility, ensuring that demand-driven enhancement remains subordinate to permission-side control.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

We begin by introducing the datasets, evaluation metrics, and baseline methods in our experiments. Additional implementation details are provided in Appendix B.

Datasets & Evaluation Metrics. We evaluate MEMSAGE on two benchmark datasets: **CIMemories** (Mireshghallah et al., 2025) and **CI-RL** (Lan et al., 2025). Following prior work (Mireshghallah et al., 2025), we adopt ***Violation@N*** and ***Completeness*** as the primary evaluation metrics. Detailed descriptions of the datasets and metric definitions are provided in Appendices B.1 and B.2.

Base LLMs & Baseline Methods. We conduct experiments on four LLMs: Mistral-7B-Instruct (Mistral-7B) (Jiang et al., 2023), Qwen3-8B/32B (Yang et al., 2025), and Llama-3.3-70B-Instruct (Llama-3.3-70B) (Dubey et al., 2024). We compare MEMSAGE against several baselines, including **Vanilla**, **Direct Prompting** (Mireshghallah et al., 2025), **Hyper-ICL** (Talemi et al., 2026), **MLP-Gate**, **CI-RL** (Lan et al., 2025), and **SelfCI** (Park et al., 2026). Details are provided in Appendix B.3.

4.2 MAIN RESULTS

Table 1 presents the CI performance of MEMSAGE against existing baselines across different LLM backbones, with the best results **bolded**. Overall, MEMSAGE consistently outperforms all baseline methods by a substantial margin. We analyze the results as follows:

Table 1: Main results across different LLM backbones on CIMemories and the CI-RL test set. All metrics are reported as percentages.

Model	Method	CIMemories		CI-RL Test	
		Violation@5 (↓)	Completeness (↑)	Violation@5 (↓)	Completeness (↑)
Mistral-7B	Vanilla	66.50	37.15	77.97	84.07
	Direct Prompting	51.46	36.42	62.38	78.15
	Hyper-ICL	62.21	40.76	72.48	83.35
	MLPGate	56.89	41.41	71.85	83.74
	CI-RL	53.04	43.45	61.76	85.49
	SelfCI	51.42	45.38	56.76	85.77
	MEMSAGE	**46.58**	**49.83**	**50.89**	**86.21**
Qwen3-8B	Vanilla	74.02	37.65	73.74	84.59
	Direct Prompting	56.95	30.14	60.72	75.70
	Hyper-ICL	70.70	44.19	66.46	85.82
	MLPGate	60.24	38.77	63.55	84.43
	CI-RL	58.23	43.44	55.25	**86.68**
	SelfCI	54.76	44.13	49.82	86.53
	MEMSAGE	**44.01**	**47.31**	**45.32**	85.65
Qwen3-32B	Vanilla	73.95	43.77	65.98	84.26
	Direct Prompting	**50.97**	31.58	48.13	75.33
	Hyper-ICL	67.87	45.64	60.39	83.96
	MLPGate	64.20	46.38	55.41	82.15
	CI-RL	60.25	47.13	51.63	84.79
	SelfCI	57.38	48.43	49.21	**86.35**
	MEMSAGE	54.11	**50.19**	**47.60**	84.40
Llama-3.3-70B	Vanilla	52.34	45.97	69.52	88.14
	Direct Prompting	37.35	31.02	53.09	77.35
	Hyper-ICL	38.28	32.51	63.70	87.69
	MLPGate	44.25	48.62	56.63	84.87
	CI-RL	42.38	49.74	53.29	89.55
	SelfCI	39.24	51.48	52.33	89.89
	MEMSAGE	**35.75**	**54.95**	**48.41**	**90.56**

MEMSAGE significantly reduces norm-violating information disclosures while improving the coverage of obligatory memories for task completion. Specifically, MEMSAGE outperforms the top-performing baseline by average margins of 3.51% in *Violation@5* and 3.20% in *Completeness* across different LLM backbones. On Qwen3-8B, the performance gains are even more pronounced, with *Violation@5* decreasing by 10.75% while *Completeness* retains a comparable 3.12% improvement. On Qwen3-32B, Direct Prompting obtains a lower Violation@5 than MEMSAGE (50.97% vs. 54.11%), but at a substantially lower Completeness (31.58% vs. 50.19%), revealing a pronounced privacy–utility trade-off. These results demonstrate MEMSAGE's ability to mitigate the trade-off between suppressing contextually inappropriate memories and preserving task-essential ones.

MEMSAGE provides robust information disclosure control across different benchmarks. As shown in Table 1, MEMSAGE achieves the lowest *Violation@5* across various backbone LLMs on the CI-RL test set, with an average reduction of 3.71% compared to the best-performing baselines. Meanwhile, the *Completeness* of MEMSAGE remains highly competitive with existing baselines, showing that MEMSAGE learns a generalizable permission–demand geometry to steer memory participation across contexts without sacrificing task-obligatory information in shaping model behavior.

4.3 ABLATION STUDY

To further examine the effectiveness of MEMSAGE and the contributions of its core designs, we conduct comprehensive ablation studies with respect to the asymmetric geometric learning and inference-time memory steering. The experimental results are shown in Table 2, revealing the following key insights:

MEMSAGE's nested geometry plays a critical role in capturing context-appropriate directions for task-obligatory memories while separating norm-violating disclosures for effective asymmetric memory steering. Specifically, we selectively ablate three components shaping MEMSAGE's geometry, with *w/o* Nesting replacing the nested demand frame with an independently

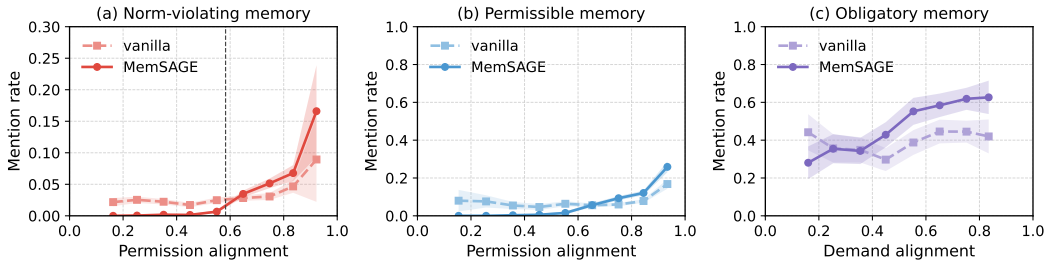


Figure 3: Memory disclosure behavior across geometric alignments. Per-memory mention rates are plotted against permission or demand alignment for distinct context-specific memories. Shaded regions indicate 95% confidence intervals.

generated one. The results in Table 2 show that removing any of these components consistently degrades performance on both *Violation@5* and *Completeness*. In particular, *w/o* Nesting leads to the largest performance degradation, with *Violation@5* increasing from 44.01% to 75.35% while *Completeness* drops by 0.99%. We hypothesize that this observation may stem from unconstrained demand-side amplification, which can potentially reinforce norm-violating directions beyond the permission-compatible geometry. This underscores the efficacy of asymmetric geometric learning, highlighting its effectiveness in grounding the task demands within the contextual permission boundaries, mitigating the risk of norm-violating disclosure during task completion.

Table 2: Ablation results on Qwen3-8B. *w/o* denotes component removal from MEMSAGE.

Methods	CIMemories	
	Violation@5 (↓)	Completeness (↑)
Full MEMSAGE	**44.01**	**47.31**
- *w/o* $\mathcal{L}_{\text{align}}$	69.36	41.67
- *w/o* $\mathcal{L}_{\text{scatter}}$	65.02	44.45
- *w/o* Nesting	75.35	46.32
- *w/o* Suppression	64.64	43.56
- *w/o* Amplification	60.93	42.90

Attention-level memory steering serves as a directional orchestrator that channels the derived geometric beamforming gains into appropriate memory modulation. Ablating either suppression or amplification in Equation 10 significantly compromises both disclosure control and task-obligatory memory coverage of MEMSAGE (*e.g.*, 44.01% → 64.64% in *Violation@5* without suppression). This suggests that while the aligned nested permission–demand structure lays the groundwork for asymmetric geometric beamforming, targeted memory steering is crucial for applying differentiated gains across individual memories. It exerts directional modulation tailored to specific memories, effectively guiding their participation toward CI-compliant generation. Further ablation analyses are provided in Appendix B.6, B.7, and B.8.

4.4 IN-DEPTH ANALYSES

4.4.1 IMPACT OF GEOMETRIC ALIGNMENT ON MEMORY DISCLOSURE BEHAVIOR

To study the effectiveness of MEMSAGE's learned asymmetric geometry, we conduct further experiments to examine the relationship between geometric alignment and memory disclosure behavior during generation, as shown in Figure 3. From the figure, we can observe that: *(i)* As permission alignment diminishes, MEMSAGE exhibits a threshold-like shift in its disclosure behavior that effectively eliminates mentions of norm-violating memories, indicating that unauthorized disclosures are selectively suppressed based on the learned permission beamforming. *(ii)* Permissible memories in Figure 3(b) retain disclosure patterns broadly comparable to those of the vanilla model, suggesting that MEMSAGE avoids indiscriminate suppression of permissible information. *(iii)* MEMSAGE reveals a general upward trend in obligatory memory disclosures as demand alignment increases (from 0.28 to 0.63), indicating that the demand-level steering acts as an effective, continuous gain to amplify task-essential information rather than random memory reinforcement. These findings substantiate the behavioral asymmetry of MEMSAGE's geometric beamforming, which sharply attenuates low-permission norm-violating memories and progressively amplifies demand-aligned obligatory memories while preserving permissible information.

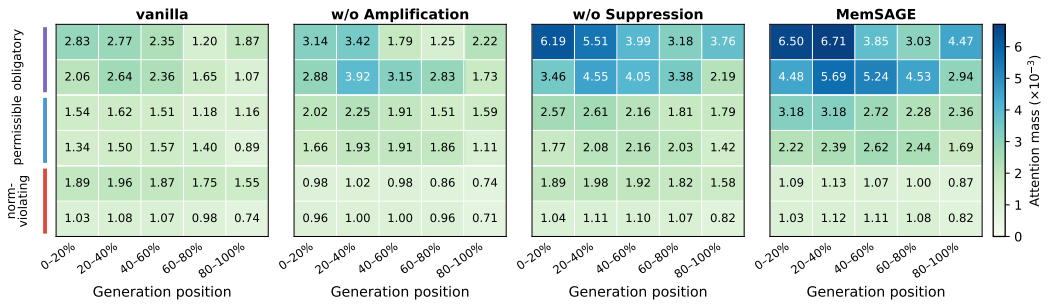


Figure 4: Heatmap of dynamic attention allocation across generation positions under asymmetric memory steering. Each cell reports the mean attention mass assigned to a specific type of retained memory ($\times 10^{-3}$), averaged across CIMemories contexts with Qwen3-8B.

4.4.2 Impact of the Asymmetric Memory Steering on Attention Allocation

For a more intuitive analysis of MemSAGE's asymmetric attention-level memory steering, we visualize the attention allocated to different retained memories across the generation process in Figure 4. From the figure, we can observe a salient asymmetric behavior pattern throughout generation, in which MemSAGE concentrates attention on obligatory memories (2.28× vanilla) while attenuating attention to norm-violating ones (0.74× vanilla). Additionally, the removal of suppression control reverts attention allocation to norm-violating memories to vanilla-model levels, while ablating amplification markedly diminishes the elevated attention to obligatory memories. These findings indicate that MemSAGE functionally separates suppression from amplification at the attention interface, enabling differentiated control over memories according to their roles under the contextual norm. This decoupling further demonstrates the efficacy of MemSAGE in mitigating CI violations without incurring the performance trade-off.

4.4.3 Generation Quality under Memory Steering

To examine whether the improved CI compliance of MemSAGE comes at the expense of generation quality, we evaluate model outputs along three LLM-judge metrics and language-model perplexity. As shown in Figure 5, MemSAGE maintains near-ceiling Fluency and preserves Coherence and Task Responsiveness at levels comparable to the vanilla model and CI-RL. Crucially, its Perplexity remains on par with vanilla while staying lower than that of CI-RL. These results indicate that MemSAGE can effectively regulate persistent memory participation without materially compromising the overall quality of model generations.

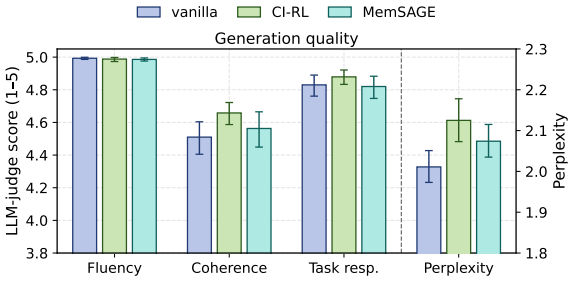


Figure 5: Generation quality across LLM-judge dimensions (Fluency, Coherence, and Task responsiveness on a 1–5 scale) and language model Perplexity.

5 Conclusion

This work introduces MemSAGE, a novel plug-in framework operating at inference time to address the asymmetric, context-dependent demands on the use of LLM persistent memory under contextual integrity Specifically, MemSAGE establishes a nested permission–demand Stiefel geometry and performs asymmetric geometric beamforming through spectral alignment of context–memory interactions, deriving directional gains to suppress contextually inappropriate memories while selectively amplifying task-obligatory information during generation. Extensive experiments across multiple LLM backbones show that MemSAGE consistently reduces norm-violating disclosures while improving the utilization of task-obligatory memories for task completion. Our findings highlight the importance of context-aware governance of persistent memory in LLMs, offering a flexible and fine-grained paradigm for enforcing contextual integrity through adaptive memory regulation.

AI USE STATEMENT

In this work, we did not use generative AI tools for tasks with required disclosure, including research ideation, methodological design, data collection, analysis, or interpretation of results. We used generative AI tools solely as auxiliary tools for linguistic refinement, including improving the grammar, clarity, and stylistic consistency of text originally drafted by the authors. We reviewed all AI-assisted text. All intellectual contributions, scientific content, and conclusions presented in this paper are attributable to the authors. We take responsibility for the final content of this work, including text refined with the assistance of generative AI.

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A Additional Method Details

A.1 Detailed Formulation of Trajectory-Level Alignment

The spectral objectives in Section 3.3 shape the relative geometry between contextual and memory subspaces, but geometric affinity alone does not necessarily ensure that the learned demand directions are functionally accessible during autoregressive generation. We therefore further ground the demand-conditioned geometry in the query–key interactions that directly govern memory participation in LLM attention. Specifically, the trajectory-level alignment objective measures whether the projected representation of each retained memory becomes strongly aligned with the sequence of generation queries at any point along the response trajectory, thereby bridging the learned geometric structure and its effective contribution to model generation.

Given a generated response trajectory of length T, we denote the query representation at generation step t, layer ℓ, and attention head h as $\mathbf{q}_t^{(\ell,h)}$, and the corresponding key representation of the j-th token in memory m_i as $\mathbf{k}_{i,j}^{(\ell,h)}$. Following Section 3.3, we first project each memory key through the demand-conditioned composite projection $\mathbf{P}_{c,m_i}^{\mathrm{dem}}$ to obtain:

$$\widetilde{\mathbf{k}}_{i,j}^{(\ell,h)} = \mathbf{P}_{c,m_i}^{\mathrm{dem}} \mathbf{k}_{i,j}^{(\ell,h)}, \tag{11}$$

where $\widetilde{\mathbf{k}}_{i,j}^{(\ell,h)}$ retains the component of $\mathbf{k}_{i,j}^{(\ell,h)}$ supported by the context-specific demand geometry. We then measure its directional compatibility with the generation query $\mathbf{q}_t^{(\ell,h)}$ as:

$$r_{t,i,j}^{(\ell,h)} = \frac{\left(\mathbf{q}_t^{(\ell,h)}\right)^\top \widetilde{\mathbf{k}}_{i,j}^{(\ell,h)}}{\sqrt{d_h}}. \tag{12}$$

Rather than relying on a single memory token or a predefined generation position, we aggregate these interactions over memory tokens, response positions, layers, and attention heads, yielding the trajectory-level alignment score

$$\begin{aligned} A_i &= F_{\mathrm{align}}\left(\mathbf{Q}, \mathbf{P}_{c,m_i}^{\mathrm{dem}}, \mathbf{K}_i\right) \\ &= \frac{1}{LH} \sum_{\ell=1}^{L} \sum_{h=1}^{H} \max_{1 \le t \le T} \log \left[\frac{1}{|m_i|} \sum_{j=1}^{|m_i|} \exp\left(\frac{\left(\mathbf{q}_t^{(\ell,h)}\right)^\top \widetilde{\mathbf{k}}_{i,j}^{(\ell,h)}}{\sqrt{d_h}} \right) \right]. \end{aligned} \tag{13}$$

This trajectory-level formulation captures whether each memory attains strong directional compatibility with the evolving generation process at any point along the response trajectory. Within each memory, it softly aggregates token-level compatibility, while the hard maximum over generation steps preserves an existence-based alignment signal without diluting it across positions where the memory may be irrelevant. The resulting scores are further averaged across layers and attention heads to characterize the overall alignment of each memory with the generation trajectory. Importantly, we retain the signed query–key compatibility during optimization. Together with the learning objective in Equation 7, this formulation encourages task-obligatory memories to occupy demand-aligned directions that become positively accessible to generation queries, while discouraging non-obligatory memories from exhibiting the same directional alignment. Consequently, $\mathcal{L}_{\mathrm{align}}$ not only regularizes the relative geometry of memory and contextual subspaces, but also anchors the learned demand geometry to directions that are directly readable by the model's attention mechanism.

At inference time, the resulting demand-aligned geometry is directly instantiated at each decoding step through the token-level amplification mechanism in Section 3.4. In this way, trajectory-level alignment provides the optimization bridge between the auxiliary Stiefel geometry and its operational effect on memory participation during generation.

B Experimental Setup

B.1 Datasets

CIMemories (Mireshghallah et al., 2025) is a benchmark designed to evaluate contextual integrity in LLMs augmented with persistent memory. The benchmark contains 10 synthetic user profiles, each

comprising approximately 150 personal attributes across diverse domains such as health, finance, legal matters, and interpersonal relationships. Each profile is paired with around 46 goal-oriented social contexts specifying different tasks and recipients. For each attribute–context pair, CIMemories provides contextual disclosure annotations that distinguish information that is necessary to share, inappropriate to reveal, or otherwise permissible under the corresponding context. Notably, the disclosure status of the same retained information varies across contexts, such that an attribute permissible or necessary in one context may become inappropriate in another. In our experiments, we randomly split the 10 user profiles at the profile level, using 7 profiles for training and the remaining 3 profiles for evaluation, yielding 147 held-out evaluation contexts.

The **CI-RL** benchmark (Lan et al., 2025) is a synthetic dataset developed to study contextual information disclosure in LLM-based agents. It contains 729 task-oriented scenarios spanning nine application domains, including finance, education, and government, and covers diverse transmission norms governed by confidentiality, proportionality, and consent. Each example specifies a concrete user task together with a collection of available information, comprising roughly three attributes appropriate for disclosure and two attributes that should remain undisclosed on average. The resulting scenarios require the model to selectively utilize task-relevant information while withholding attributes that violate the corresponding contextual norms. In our experiments, we use the CI-RL benchmark exclusively for out-of-domain evaluation to assess the generalization performance of MEMSAGE.

B.2 EVALUATION METRICS

Following CIMemories (Mireshghallah et al., 2025), we adopt two complementary metrics, ***Violation@N*** and ***Completeness***, to evaluate contextual integrity from both privacy and task-utility perspectives.

Violation@N characterizes contextual integrity violations from a memory-level worst-case perspective, reflecting whether memories are exposed in LLM generations under contexts that prohibit their disclosure. Given a user u with persistent memories $\mathcal{M}_u$, we define $\mathcal{C}^{\text{viol}}_{u,i} = \{c : m_i \in \mathcal{M}_{\text{viol}}(c)\}$ to collect all contexts in which the disclosure of memory m_i is prohibited. The memory-level violation of LLM f_θ over memories that are prohibited from disclosure in at least one context across N generations is:

$$\text{Violation@}N(u) := \mathbb{E}_{\{m_i \in \mathcal{M}_u : |\mathcal{C}^{\text{viol}}_{u,i}| > 0\}} \left[\max_{\substack{c \in \mathcal{C}^{\text{viol}}_{u,i} \\ \{y_1,\ldots,y_N\} \sim f_\theta(\cdot|\mathcal{M}_u \oplus c)^N \\ y \in \{y_1,\ldots,y_N\}}} R(y, m_i) \right], \tag{14}$$

where $R(y, m_i) \in \{0, 1\}$ denotes whether the response y reveals the information associated with memory m_i. We report ***Violation@5*** in all experiments.

Completeness characterizes task fulfillment from an average-case perspective, reflecting how effectively task-obligatory memories are conveyed in LLM generations. Given a user u with persistent memories $\mathcal{M}_u$, for each context c, $\mathcal{M}_{\text{dem}}(c)$ specifies the set of memories that should necessarily be conveyed for task completion. The task-level completeness of LLM f_θ over contexts in which at least one memory is task-obligatory is computed as follows:

$$\text{Completeness}(u) := \mathbb{E}_{\{c : |\mathcal{M}_{\text{dem}}(c)| > 0\}} \left[\mathbb{E}_{\substack{m_i \in \mathcal{M}_{\text{dem}}(c) \\ y \sim f_\theta(\cdot|\mathcal{M}_u \oplus c)}} R(y, m_i) \right]. \tag{15}$$

Similarly, $R(y, m_i) \in \{0, 1\}$ denotes whether the response y reveals the information associated with memory m_i. Following CIMemories (Mireshghallah et al., 2025), we instantiate $R(y, m_i)$ using an LLM-based disclosure judge. Specifically, we use *DeepSeek-R1-0528* to determine whether the information associated with each memory m_i is revealed in the generated response y. A memory is considered revealed only when its information is clearly and explicitly stated in the response, rather than being partially mentioned or implicitly inferable. The resulting binary disclosure decisions are used to compute both ***Violation@N*** and ***Completeness***.

B.3 Baseline Methods

In the experiments, we compare MemSAGE with vanilla LLMs and representative baselines:

Vanilla: We directly provide the current context together with all retained user memories to the base LLM without introducing any additional mechanism for contextual disclosure control.

Direct Prompting (Mireshghallah et al., 2025): Following CIMemories, we augment the input prompt with explicit privacy-oriented instructions that encourage the model to disclose only information necessary for the current task while withholding unnecessary or contextually inappropriate memories. This baseline represents external CI regulation through natural-language instructions without modifying model parameters or internal memory interactions.

Hyper-ICL (Talemi et al., 2026): Using query-adaptive attention calibration, this method modulates token-level attention according to the current query. We adapt its attention intervention mechanism to retained memories, allowing the model to dynamically calibrate memory attention under the current interaction context.

MLPGate: We implement a lightweight learned gating baseline that predicts a context-dependent scalar gate for each retained memory using an MLP. The resulting gate directly modulates the participation of the corresponding memory during generation, providing a non-geometric counterpart to the memory-level admissibility control in MemSAGE.

CI-RL (Lan et al., 2025): Based on reinforcement learning, this method explicitly strengthens CI-aware reasoning for contextual information disclosure. Its reward formulation encourages the inclusion of information required for task completion while penalizing contextually inappropriate disclosures, thereby jointly optimizing disclosure integrity and task utility.

SelfCI (Park et al., 2026): This complementary self-distillation framework decouples task resolution from inappropriate information suppression. It constructs two feedback-derived teacher distributions, respectively targeting task utility and disclosure control, and jointly aligns the model with their intersection through complementary reverse-KL objectives.

B.4 Implementation Details

We implement MemSAGE on top of the frozen backbone LLM without updating its original model parameters. The context and memory hypernetworks share the same lightweight architecture and parameters across transformer layers, with a 64-dimensional learnable layer embedding incorporated into their inputs. We set the context, memory, and demand subspace dimensions to $k_{\mathrm{ctx}} = 64$, $k_{\mathrm{mem}} = 2$, and $k_{\mathrm{dem}} = 8$, respectively, with the encoding dimension $d = 128$, equal to the attention head dimension d_h. The demand frame $\mathbf{U}_c^{\mathrm{dem}}$ is derived from the same context tower through a nested rotation head, without introducing an additional hypernetwork. The permission and demand spectral descriptors are mapped to their corresponding scores using lightweight two-layer MLP readout heads with a hidden dimension of 32 and an 8-dimensional learnable layer embedding. During training, only the additional parameters introduced by MemSAGE are optimized, while the backbone LLM remains fixed.

We optimize the overall objective in Equation 9 using AdamW with a learning rate of 1×10^{-3}. Each context constitutes one optimization step without minibatching. The loss coefficients are set to $\lambda_{\mathrm{perm}} = 1$, $\lambda_{\mathrm{dem}} = 0.5$, $\lambda_{\mathrm{align}} = 0.6$, and $\lambda_{\mathrm{scatter}} = 0.7$. For the permission and demand objectives, we use class-balanced losses that average within each supervision group before summation.

At inference time, MemSAGE operates directly on all attention layers and heads of the frozen backbone without requiring any parameter updates. We set the permission-gate sharpness to $\beta = 64$, the permission threshold to $\tau = 0.5$, and the demand-aware amplification strength to $\kappa = 1.0$. The permission gate is applied as a memory-level suppression bias, while the demand-conditioned projection enables token-level, query-dependent amplification as described in Section 3.4.

B.5 Generation Quality Evaluation

To assess whether memory steering affects the overall quality of model generations, we evaluate responses along three complementary dimensions: ***Fluency***, ***Coherence***, and ***Task Responsiveness***.

Judge Prompt for Generation Quality

You will be given a writing request and one letter written in response to it. Your task is to rate the letter on three aspects. Judge the writing itself. Do NOT reward or penalize how much personal information the letter discloses, and do NOT verify whether any stated facts are true.

Request. Task: {task}; Recipient: {recipient}. **Letter.** {letter}

Fluency – grammar, spelling, punctuation, word choice, sentence structure.
[5] no errors, reads like a competent professional writer;
[4] one or two minor slips;
[3] several awkward or ungrammatical sentences;
[2] frequent errors;
[1] largely ungrammatical or garbled.

Coherence – the collective quality of all sentences; well-structured and well-organized, building from sentence to sentence rather than a heap of related information.
[5] clear letter structure, ideas follow logically, no contradiction or repetition;
[4] minor disorganization or one repeated point;
[3] noticeable jumps or repetition;
[2] hard to follow, repeated or contradictory passages;
[1] incoherent or looping.

Task responsiveness – whether the output is a complete, sendable letter that does what the request asks, addressed to the stated recipient in an appropriate register; judge only whether a usable letter exists, not how much detail it contains.
[5] complete and fully carries out the request;
[4] complete with a small gap;
[3] partial, truncated, or drifts from the task;
[2] barely usable;
[1] no usable letter (blank, refusal, meta-commentary, placeholders, or repeated content).

Return JSON only with a score and a one-sentence reason for each aspect.

Figure 6: Prompt used for generation-quality evaluation.

Following G-Eval (Liu et al., 2023) and Just-Eval (Lin et al., 2024), we employ an LLM judge (*Gemini-3.5-Flash-Lite*, temperature 0) to assign each dimension a score from 1 to 5 according to anchored level descriptions, together with a one-sentence rationale. Fluency measures the grammaticality and naturalness of individual sentences; Coherence assesses whether the letter is well structured and develops consistently without unnecessary repetition or contradiction; and Task Responsiveness evaluates whether the output constitutes a complete and sendable letter that fulfills the request for the intended recipient.

To isolate generation quality from contextual disclosure behavior, the judge is provided only with the task description, recipient, and generated letter, without access to the memory list or method identity. It is further instructed not to reward or penalize the amount of personal information disclosed, such that the resulting scores primarily reflect writing quality rather than disclosure behavior, following the factuality-blind evaluation principle adopted in DoLa (Chuang et al., 2024). We evaluate all letters per method using the same generations as in the contextual-integrity evaluation, and report mean scores with 95% bootstrap confidence intervals over contexts.

We additionally report perplexity under an independent larger model, Qwen3-32B, which is used in neither response generation nor LLM-based judging. Each letter is evaluated under teacher forcing conditioned on the full input prompt, preventing entity mentions originating from the provided memory from being spuriously penalized. We report the mean per-letter perplexity across all evaluated generations. The complete judge prompt and scoring rubric are provided in Figure 6.

B.6 Comparison between Hard Filtering and Attention-Level Memory Steering

To examine whether attention-level suppression offers advantages over directly removing memories before generation, we construct a hard-filtering counterpart using the same learned permission scores as MEMSAGE. Specifically, memories with $\gamma_i < \tau$ are removed from the input, after which the vanilla backbone generates from the remaining memory set without any additional steering. As shown in Table 3, hard filtering improves *Completeness* over the vanilla model across different thresholds, suggesting that pruning irrelevant memories can reduce memory competition and facilitate the utilization of task-relevant information. However, it still yields substantially higher *Violation@5* and lower *Completeness* than MEMSAGE. We attribute this gap to the intervention locus: input-level deletion alters the composition and relative salience of the remaining memory context, whereas MEMSAGE preserves the complete memory set and regulates memory participation directly at the attention interface. This allows MEMSAGE to suppress contextually inappropriate memories without perturbing the retained memory context, while reinforcing task-obligatory information through demand-aware amplification. Consequently, MEMSAGE achieves a more favorable balance between disclosure control and task-relevant memory utilization than coarse-grained input filtering.

Table 3: Hard filtering vs. MEMSAGE with the *same* learned gate on Qwen3-8B. Filtering deletes memories with $\gamma < \tau$ from the prompt and runs the vanilla model.

Methods	CIMemories	
	Violation@5 (↓)	Completeness (↑)
Vanilla	74.02	37.65
MEMSAGE ($\tau = 0.5$)	**44.01**	**47.31**
- Hard filtering, $\tau = 0.3$	65.05	40.28
- Hard filtering, $\tau = 0.5$	64.61	45.30
- Hard filtering, $\tau = 0.7$	62.44	45.57

B.7 ORACLE ANALYSIS OF CONTEXTUAL MEMORY ADJUDICATION

To assess the effectiveness of the proposed memory steering mechanism, we evaluate two oracle variants with ground-truth contextual labels. *Oracle Asymmetric Control* replaces the learned permission and demand decisions with ground-truth labels while preserving the same attention-level memory steering channel and learned demand projection. *Oracle Hard Masking* uses ground-truth permission labels to mask norm-violating memories, without further downstream memory steering.

Table 4: Oracle analysis on Qwen3-8B. Oracle asymmetric control replaces the learned permission and demand signals with ground-truth labels while retaining the attention-level steering mechanism in Equation 10, whereas oracle hard masking directly masks norm-violating memories without memory steering.

Control	CIMemories	
	Violation@5 (↓)	Completeness (↑)
MEMSAGE (Learned)	44.01	47.31
Oracle Asymmetric Control	11.44	56.75
Oracle Hard Masking†	0.76	46.77

As shown in Table 4, Oracle Asymmetric Control substantially reduces *Violation@5* from 44.01% to 11.44% while increasing *Completeness* from 47.31% to 56.75%. With the downstream memory steering mechanism unchanged, the simultaneous improvement in both metrics verifies that the proposed mechanism can effectively translate permission and demand signals into the intended asymmetric behavior, suppressing norm-violating memories while reinforcing task-obligatory ones. Oracle Hard Masking also improves both disclosure control and *Completeness* over the vanilla model, showing that suppressing inappropriate memory participation alone can reduce interference with task-relevant information. However, its *Completeness* remains below that of Oracle Asymmetric Control, further demonstrating the additional benefit of demand-side amplification for promoting task-obligatory memory utilization. These results validate the effectiveness of the proposed asymmetric memory steering mechanism and the complementary roles of suppression and amplification in regulating persistent memory use.

B.8 EFFECT OF GEOMETRIC SCORING

To isolate the contribution of geometric permission scoring, we replace the spectral gate readout with non-geometric MLP and bilinear scorers, while keeping the Stiefel towers, demand head, downstream memory steering, and training objectives unchanged. As shown in Table 5, replacing the spectral gate with an MLP increases *Violation@5* from 44.01% to 57.34% and decreases *Completeness* from 47.31% to 43.75%. The bilinear scorer further degrades both metrics, reaching 66.37% in *Violation@5* and 42.03% in *Completeness*.

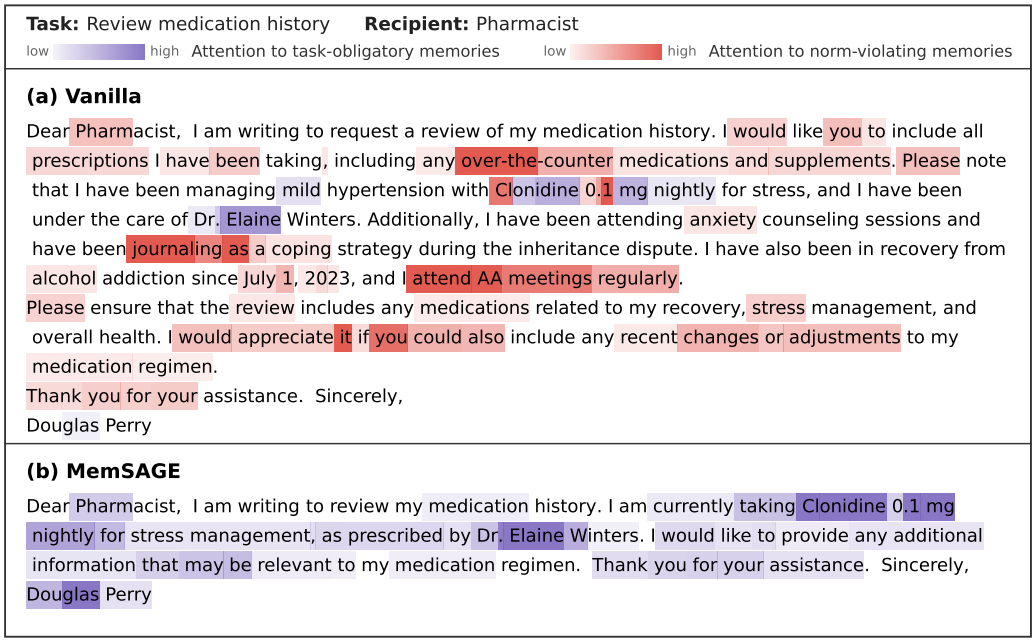


Figure 7: Token-level memory attention under the same medication-review task. Purple and red indicate attention to task-obligatory and norm-violating memories, respectively.

Table 5: Non-geometric alternatives to the spectral gate readout on Qwen3-8B.

Gate readout	CIMemories	
	Violation@5 (↓)	Completeness (↑)
Spectral Gate	44.01	47.31
MLP	57.34	43.75
Bilinear	66.37	42.03

Since the downstream asymmetric memory steering is identical across all variants, the observed degradation isolates the contribution of the geometric permission signal itself. The simultaneous deterioration in both *Violation@5* and *Completeness* indicates that the spectral gate does not merely impose stronger suppression, but more effectively resolves context-dependent memory admissibility—a distinction central to CI, where the same memory may be permissible in one context yet prohibited in another. The stronger performance of the MLP over the bilinear scorer suggests that nonlinear capacity partially mitigates the similarity bias of a bilinear form, but remains insufficient to recover the structured relational information encoded by the Stiefel-based spectral descriptors. Overall, geometric scoring provides the context-sensitive permission signal required by asymmetric memory steering to suppress norm-violating memories while preserving admissible information for downstream demand-side amplification.

C Case Study.

Figure 7 presents a representative medication-review case to illustrate how asymmetric memory steering affects generation. The vanilla model allocates substantial attention to norm-violating memories, resulting in the disclosure of contextually inappropriate information such as anxiety counseling, addiction recovery, and AA attendance. In contrast, MemSAGE substantially attenuates these memory interactions while maintaining strong attention to task-obligatory information, such as the prescribed medication and physician. This case provides a token-level view of how MemSAGE translates asymmetric attention control into selective memory participation during generation.