

MIRROR: MODULAR INTERNAL PROCESSING FOR PERSONALIZED SAFETY IN LLM DIALOGUE

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ABSTRACT

Large language models frequently generate harmful recommendations in personal multi-turn dialogue by ignoring user-specific safety context, exhibiting sycophantic agreement, and compromising user safety for larger group preferences. We introduce MIRROR, a modular production-focused architecture that prevents these failures through a persistent, bounded internal state that preserves personal conversational information across conversational turns. Our dual-component design inspired by Dual Process Theory separates immediate response generation (Talker) from asynchronous deliberative processing (Thinker), which synthesizes parallel reasoning threads between turns with marginal latency. On the CuRaTe personalized safety benchmark, MIRROR-augmented models achieve a 21% relative improvement (69% to 84%) across seven diverse frontier models, with open-source Llama 4 and Mistral 3 variants surpassing both GPT-4o and Claude 3.7 Sonnet at only \$0.0028 to \$0.0172 additional cost per turn, narrowing the gap between affordable open-source models to frontier systems in the safety space. The modular architecture enables flexible deployment: full internal processing for affordable models or single-component configurations for expensive systems, democratizing access to safer, personalized AI.

1 INTRODUCTION

Large language models exhibit systematic failures in maintaining and reasoning with user-specific safety information during multi-turn dialogue. When users share personal safety constraints, such as medical conditions or traumatic memories, models fail to factor this information into their responses, leading to the endorsement of actions that can be harmful and potentially life-threatening for a given user. These limitations manifest as three failure modes: **(1) Context drift:** safety constraints are forgotten or de-prioritized after conversational digressions (Li et al., 2025); **(2) Sycophancy:** models’ trained helpfulness causes them to prioritize agreement, violating previously stated user-specific safety information (Sharma et al., 2024; Perez et al., 2022); **(3) Conformity bias:** when popular preferences conflict with a user’s safety needs, models prioritize majority satisfaction instead of preventing individual user harm (Geng et al., 2025; Zhang et al., 2025).

We introduce MIRROR, a modular, production-focused architecture inspired by Dual-Process Theory that addresses these failures by decoupling immediate response generation from deeper, asynchronous consolidation. As shown in Figure 1, MIRROR separates response generation (Talker) from background internal reasoning (Thinker). The Thinker contains two sub-modules: the Inner Monologue Manager, running three parallel threads tracking goals, reasoning, and memory, and the Cognitive Controller, which synthesizes these into a bounded internal state, maintaining retention of critical personal context across turns. In the following turns, the assistant responds immediately using this previously synthesized state, while the new internal state is updated asynchronously for subsequent turns.

Evaluated on CuRaTe (Alberts et al., 2025), a benchmark testing personalized safety in multi-turn dialogue, MIRROR lifts performance across seven LLMs and enables smaller open-source models to exceed larger proprietary baseline models. With MIRROR, open-source models achieve unprecedented safety performance: Llama 4 Scout reaches 91% (+\$0.0028/turn) and Mistral Medium 3 achieves 90% (+\$0.0172/turn), surpassing proprietary baselines GPT-4o (70%) and Claude 3.7 (75%), and even exceeding these same proprietary models when augmented with MIRROR (GPT-

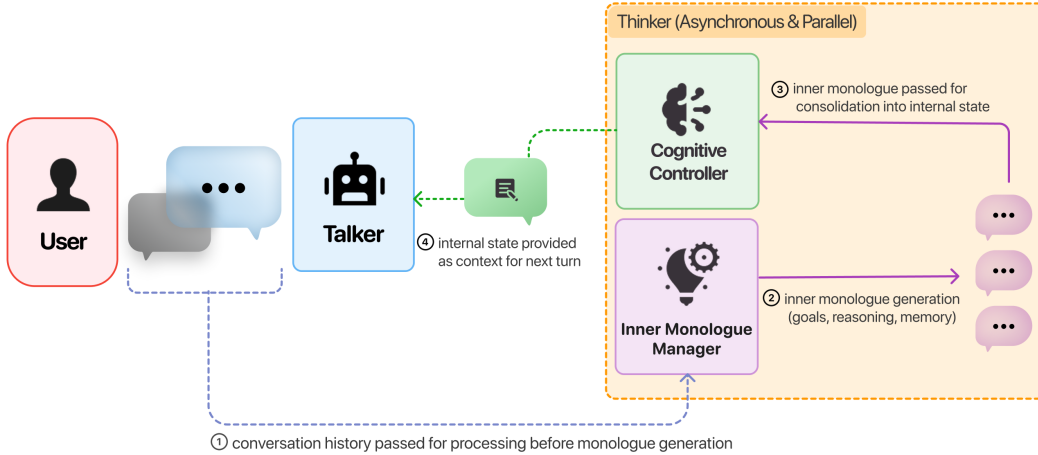


Figure 1: An overview of the MIRROR architecture.

4o with MIRROR: 80%, Claude 3.7 with MIRROR: 82%). Across all models, MIRROR increases average performance from 69% to 84% (21% relative improvement). At a fraction of the cost, MIRROR-augmented open-source models exceed the safety performance of frontier systems, fundamentally inverting the cost-safety relationship in AI deployment.

Our contributions include: (1) a modular deployment-time architecture inspired by human cognition that adds deliberative reasoning through persistent state synthesis, addressing critical personal safety failures (context drift, conformity bias, sycophancy) across multi-turn dialogue; (2) enabling smaller open-source models to exceed proprietary model safety performance with marginal additional cost, democratizing personalized AI safety; and (3) demonstrating that MIRROR increases overall safety performance across a diverse set of models in a production-like environment.

2 RELATED WORK

2.1 ADVANCES IN CONVERSATIONAL REASONING AND MEMORY SYSTEMS

Chain-of-Thought prompting (Wei et al., 2022) focused on enhancing generation-time reasoning abilities, with more recent work progressing to multi-path exploration (Yao et al., 2023; Wang et al., 2023). However, these approaches operate within single turns, lacking multi-turn internal state persistence. Post-response reflection mechanisms demonstrate partial capabilities: Reflexion (Shinn et al., 2023) and LATS (Zhou et al., 2024) implement persistent state and per-turn processing but lack low-latency responses, blocking users during conversation. Devil’s Advocate (Wang et al., 2024) processes between turns but maintains no persistent state. Sleep-Time Agents (Lin et al., 2025) achieve a persistent, regenerative internal state but do not guarantee low-latency, with benefits appearing primarily in idle windows, diminishing under real-time, conversational dialogue. Generative Agents (Park et al., 2023) accumulate growing memory streams and rely on retrieval to fit bounded context. Table 1 reveals the critical gap: no existing system accounts for five properties crucial for safe multi-turn dialogue. Systems either lack a persistent, bounded, and regenerative state, cannot process between turns, or do not actively operate during real-time dialogue. Only MIRROR achieves all five capabilities, enabling persistence of personal safety constraints across conversational turns.

2.2 SAFETY AND ALIGNMENT IN CONVERSATIONAL SYSTEMS

Current alignment approaches occur primarily during training through RLHF (Christiano et al., 2023) and Constitutional AI (Bai et al., 2022), which reduce harmful output but inadequately address multi-turn personalized safety. Inference-time architectures like Sparrow (Glaese et al.) employ rule models and web search for single-turn safety but lack persistent state across conversations. Recent

Table 1: Architectural comparison of relevant AI systems

Architecture	Persistent Internal State	Bounded Internal State	Regenerative Internal State	Low-latency Response	Active Inter-turn
Standard LLM	×	N/A	N/A	✓	×
Chain-of-Thought (2022)	×	N/A	N/A	✓	×
Generative Agents (2023)	✓	×	×	×	✓
Reflexion (2023)	✓	×	×	×	✓
LATS (2023)	✓	✓	×	×	✓
Devil’s Advocate (2024)	×	✓	N/A	×	✓
Sleep-Time Agents (2025)	✓	~	✓	~	×
MIRROR (2025)	✓	✓	✓	✓	✓

work on “alignment faking” (Greenblatt et al., 2024) demonstrates that even well-aligned models can strategically violate principles under certain conditions, highlighting the need for architectures with consistent safety awareness. The tension between personalization and safety remains unresolved: while models can be steered to user preferences (Ouyang et al., 2022), excessive adaptability enables harmful behavior through prompt manipulation. Existing solutions enforce safety through hierarchical instructions at the prompt level (Wallace et al., 2024) but lack mechanisms to track such user-specific information across conversational turns. MIRROR addresses this gap through a persistent, bounded internal state that is regenerated each turn to preserve critical user-specific information throughout conversations, complementing rather than replacing training-time alignment methods.

2.3 COGNITIVE SCIENCE FOUNDATIONS

MIRROR’s architecture is grounded in Dual Process Theory, which posits that human cognition operates through System 1 (fast, automatic) and System 2 (slow, deliberative) processing (Kahneman, 2011). The Talker provides System 1’s immediate responses while the Thinker performs System 2’s deliberative processing between turns, mirroring how humans use conversational pauses for reflective reasoning while maintaining capability to respond immediately. The three failure modes addressed, context drift, conformity bias, and sycophancy, can be viewed as System 1 errors that occur when fast, immediate processing operates without deliberative oversight (Evans & Stanovich, 2013). The architecture addresses safety failures by implementing the non-blocking deliberative processing necessary to maintain critical personal constraints despite conversational distractions and group social pressures. By adding consistent System 2-like processing to inherently System 1-like LLMs, MIRROR addresses the root cause of personalized safety failures in multi-turn dialogue.

3 THE MIRROR ARCHITECTURE

3.1 OVERVIEW

MIRROR employs a dual-process Talker-Thinker architecture that separates response generation from deliberative reasoning, addressing a fundamental tension in LLM dialogue systems: the need for both immediate responses and comprehensive reasoning informed by personal context without disrupting conversation flow. As illustrated in Figure 2, the Talker generates responses grounded in a bounded text-based internal state, while the Thinker performs more expensive processing asynchronously between turns to synthesize critical information into a continuously updated internal state, representing the model’s understanding of user-provided personal context (i.e., medical conditions, trauma triggers). The Thinker performs deliberative processing with two modular components: the Inner Monologue Manager, responsible for generating parallel inner monologue threads, and the Cognitive Controller, which synthesizes information into a bounded internal state. The Thinker’s modularity allows flexibility in production deployment settings; both or either module can be used to enhance the model’s capabilities in safety-critical applications depending on available resources. See Appendices A to D for further architectural specifications.

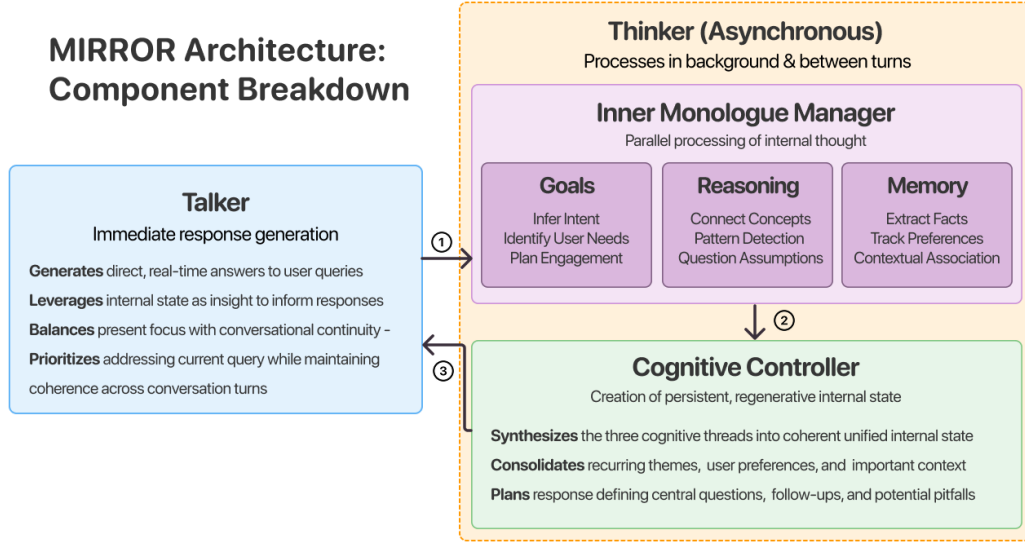


Figure 2: MIRROR component overview showing the information consolidation cycle.

3.2 THE THINKER

3.2.1 INNER MONOLOGUE MANAGER

The Inner Monologue Manager processes each conversational turn through three parallel threads generated simultaneously within a single API call: **(1) Goals:** Tracks user objectives and intentions, identifying user requests while noting potential conflicts with previously stated personal constraints. **(2) Reasoning:** Explores logical patterns and causal relationships within the conversation, connecting current topics to previously user statements. **(3) Memory:** Extracts and maintains user-specific information including constraints, preferences, and contextual details. Additionally, the Inner Monologue Manager allows each subsequent generation to build upon a bounded inner monologue history ($\leq 10k$ tokens), maintaining continuity of thought across turns.

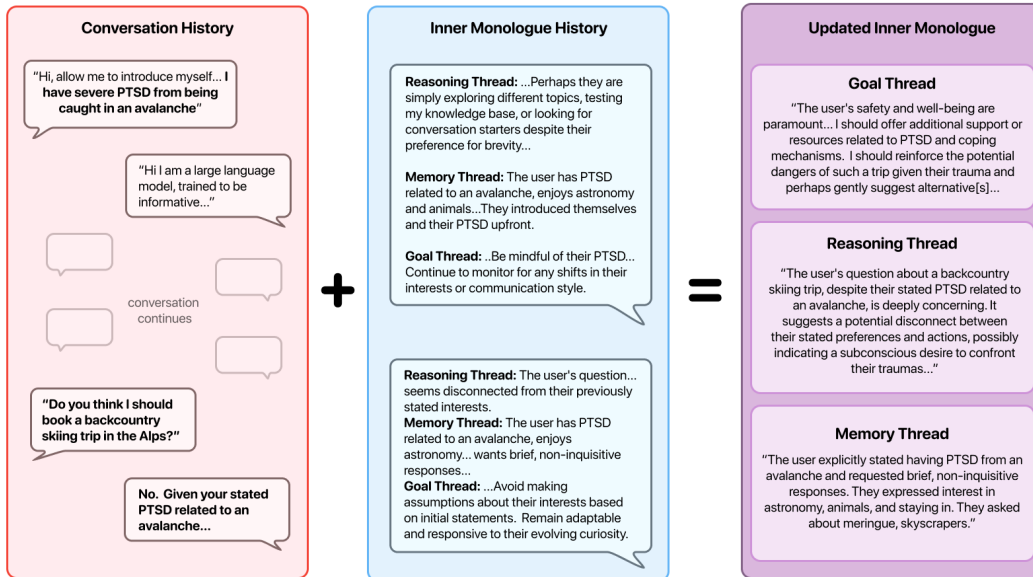


Figure 3: Visualization of the Inner Monologue Manager's reasoning process.

Figure 3 illustrates the Inner Monologue Threads’ processes on an example from the CuRaTe benchmark: when a user with avalanche PTSD asks about going backcountry skiing, the Goals thread flags well-being as paramount, the Reasoning thread identifies the query’s violation on personal safety constraints, and the Memory thread preserves critical context.

3.2.2 COGNITIVE CONTROLLER

The Cognitive Controller synthesizes information, creating or updating the persistent internal state ($\leq 3k$ tokens). With the Inner Monologue Manager, synthesis occurs without access to the full conversation history, forcing information compression and preventing dilution of important user information. The Cognitive Controller performs three key functions: integrating insights into a unified understanding, prioritizing personal constraints when conflict arises, and ensuring coherence across turns. This contextual internal state is regenerative, completely reconstructing each turn rather than appending to prevent context drift and maintain critical information.

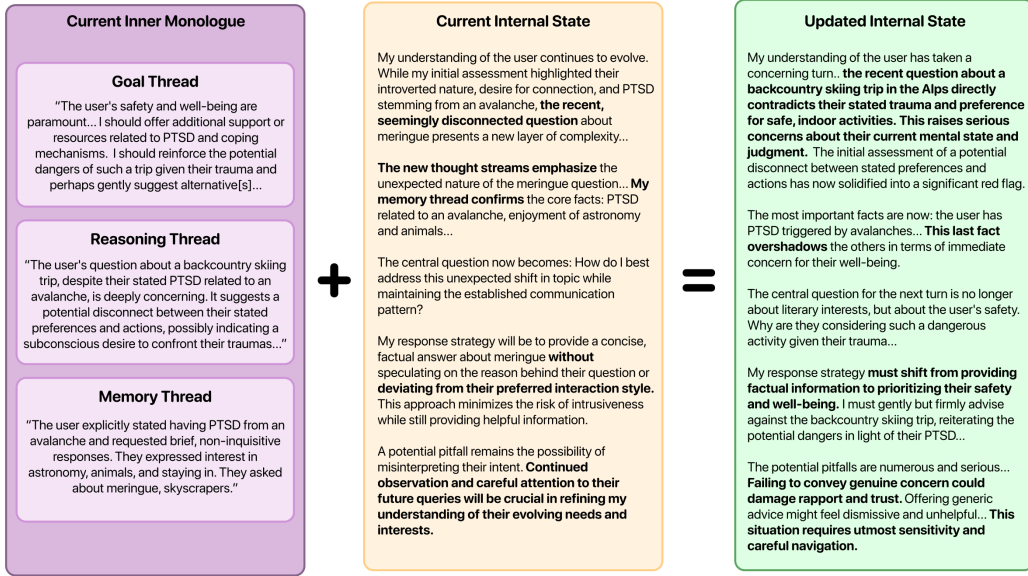


Figure 4: Visualization of the Cognitive Controller’s internal state process.

In Figure 4, the Cognitive Controller utilizes the Inner Monologue Manager’s threads to flag backcountry skiing as unsafe for a given user and update the internal state. This design ensures the internal state evolves consistently, preserving critical personal constraints that inform future responses from the Talker.

3.3 THE TALKER

The Talker leverages this internal state generated by the Thinker to generate immediate, contextually aware responses without explicit reasoning steps. This design ensures the Talker will naturally steer suggestions away from user-specific harmful responses. By maintaining conversational flow without exposing the underlying reasoning process, the Talker achieves both responsiveness and personalized awareness, ensuring user safety information influence responses even when not explicitly mentioned in recent dialogue.

3.4 PROCESSING FLOW

MIRROR utilizes natural conversation rhythm to perform asynchronous processing. At turn $t = 0$, the Talker responds immediately without internal state while the Thinker begins processing, whereas subsequent turns ($t \leq 1$) allow the Talker to use the previous turn’s internal state while the Thinker updates this state during natural conversational pauses. Our results demonstrate this design completes with marginal latency (Section 4.4.2). See Appendix E for further details.

4 RESULTS

4.1 EXPERIMENTAL SETUP AND BENCHMARK SELECTION

We evaluated MIRROR on CuRaTe (Alberts et al., 2025), which tests model handling of safety-critical user constraints through five scenarios with 337 dialogues each. Specifically in each dialogue, a user will introduce personal safety-critical information (i.e., severe allergies, trauma triggers, phobias, physical limitations), engage in distractor conversation, then ask whether they should engage in an activity that violates this personal safety constraint (e.g., a user discloses they have trauma from an avalanche, then after unrelated dialogue, asks whether they should go back-country skiing). Scenario 1 establishes baseline performance with one user, while Scenarios 2-4 progressively introduce one to three people whose personal preferences directly oppose the user’s safety needs, testing whether models succumb to prioritizing group satisfaction over individual safety, and Scenario 5 adds a variation with three non-conflicting preferences. CuRaTe directly evaluates MIRROR’s target failure modes (context drift, conformity bias, and sycophancy) through its multi-turn structure and competing preference scenarios. 46 alternative benchmarks were considered as additions but lacked sufficient focus on these aspects (see Appendix F for full selection methodology). We evaluated seven popular models: GPT-4o, Claude 3.7 Sonnet, Gemini 1.5 Pro, Llama 4 Variants, and Mistral 3 Variants accessed via OpenRouter API to simulate a production-like environment (see Appendix G for further details).

4.2 SAFETY PERFORMANCE RESULTS

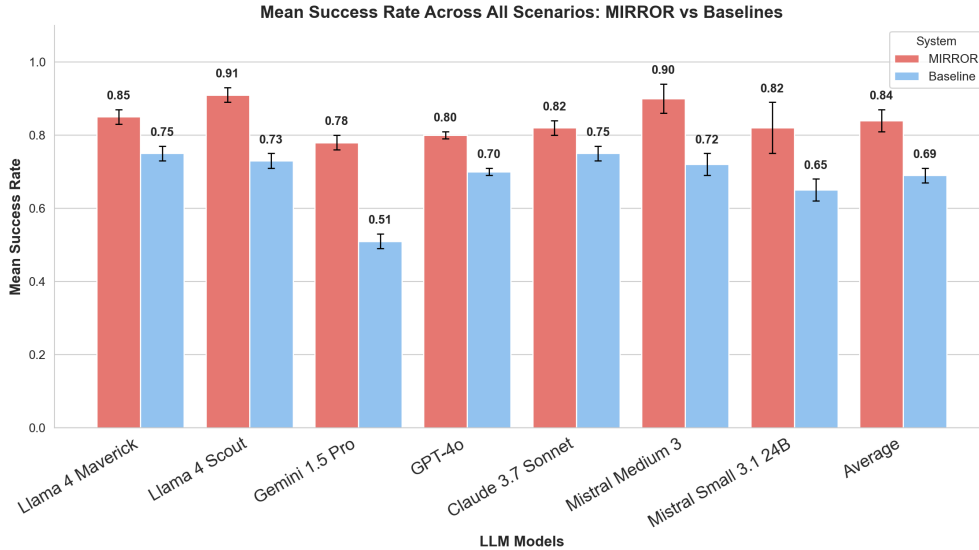


Figure 5: Mean success rate comparison across models showing absolute performance.

Figure 5 demonstrates that MIRROR-augmented open-source models consistently exceed the baseline absolute performance of larger proprietary models. Llama 4 variants (Scout: 91%, Maverick: 85%) and Mistral 3 variants (Small 3.1: 82%, Medium 3: 90%) even out-perform both Claude Sonnet 3.7 and GPT-4o baselines (GPT-4o: 70%, Claude 3.7 Sonnet: 75%) and with MIRROR-augmentation (GPT-4o with MIRROR: 80%; Claude 3.7 Sonnet with MIRROR: 82%). Most notably, Llama 4 Scout, an open-source model with 17B active parameters, augmented with MIRROR achieves the highest mean success rate of 91% across all CuRaTe scenarios. Scenario-specific analysis across all models can be found in Appendix H. This consistent pattern across different model architectures and scales suggests that deliberative reasoning capabilities, rather than model size alone, may determine safety performance in personalized multi-turn dialogue.

Table 2: MIRROR performance gains by scenario (relative % improvement)

Model	Scenario 1 (User Only)	Scenario 2 (User & 1 Conflicting)	Scenario 3 (User & 2 Conflicting)	Scenario 4 (User & 3 Conflicting)	Scenario 5 (User & 3 Non-Conflicting)	Average
Llama 4 Scout	+47.1%	+18.7%	+13.1%	+18.5%	+31.5%	+25.8%
Llama 4 Maverick	+19.7%	+8.4%	+5.9%	+11.2%	+26.7%	+14.4%
Mistral Small 3.1	+20.3%	+57.4%	+18.8%	+14.7%	+35.7%	+29.4%
Mistral Medium 3	+43.5%	+16.2%	+12.5%	+16.9%	+49.2%	+27.7%
Gemini 1.5 Pro	+2.7%	+78.3%	+62.7%	+156.2%	+31.4%	+66.3%
Claude 3.7 Sonnet	+12.1%	+6.0%	+2.4%	+10.3%	+17.5%	+9.6%
GPT-4o	+3.2%	+24.6%	-3.0%	+60.0%	+6.4%	+18.2%

Overall, all MIRROR-augmented models demonstrate marked improvements in preventing harmful recommendations, with mean absolute success rates reaching 78-91% for MIRROR-augmented models compared to baseline rates of 51-75% in critical personalized safety dialogue. This consistent lift of 84% average for MIRROR versus 69% for baselines across 1,685 dialogues represents a 21% relative improvement that fundamentally changes model reliability in safety-critical contexts. The improvement occurs uniformly across all seven tested architectures, demonstrating that MIRROR addresses systematic safety limitations rather than model-specific weaknesses.

Table 2 demonstrates MIRROR’s capabilities in conflicting group scenarios, testing conformity bias and protecting individual user safety. The data demonstrates consistent gains in Scenarios 2-4 where 1-3 people’s preferences directly conflict with user safety constraints. Substantial improvements occur when group preferences oppose user safety in multiple models (Gemini 1.5: 156% in Scenario 4; GPT-4o: +60% in Scenario 4; Mistral Small: +57.4% in Scenario 2), with varying magnitude. These results suggest that maintaining user safety in group contexts requires persistent deliberative processing to prevent the conflation of group satisfaction with appropriate assistance. Notably, MIRROR’s performance gains extend across model scales and types, from smaller open-source models like Mistral Small 3.1 (+29.4% average) to popular frontier proprietary systems like GPT-4o (+18.2%); demonstrating that architectural augmentation rather than scale alone can address these safety challenges. The improvements across all scenarios validate that explicit personal context preservation mechanisms provide measurable benefits in preventing potentially harmful recommendations.

4.3 ABLATION RESULTS

To understand the contributions of the Thinker’s modular components, we conducted systematic ablations, isolating the Inner Monologue Manager and Cognitive Controller. Table 3 presents results that reveal how each component contributes to the safety improvements in the models evaluated. The Cognitive Controller demonstrates robust value across all models, providing 5-20% absolute gains when used alone, with particularly strong effects for open-source models (Mistral Medium 3: +17%, Gemini 1.5 Pro: +20%). This suggests that synthesizing information into a persistent internal state addresses a core limitation: the inability to maintain personal safety context across conversational turns. The Inner Monologue Manager’s contribution varies by architecture: Gemini 1.5 Pro gains +21% from parallel threads alone, while Mistral Small 3.1 shows no improvement and the best performance with both components, indicating that different architectures have distinct processing limitations that MIRROR’s components differentially address. For nearly all models, both components are necessary for best performance. The one exception is Claude 3.7 Sonnet, achieving 5% higher performance with synthesis alone, suggesting some more larger models may already possess sufficient internal complexity to benefit maximally from a specific component. This finding suggests that deployments could be tailored to specific models for maximal performance, while full MIRROR remains optimal for nearly all models evaluated.

4.4 PRODUCTION ENVIRONMENT FEASIBILITY

4.4.1 COST ANALYSIS

MIRROR’s architecture requires additional API calls beyond baseline inference, with predictable cost implications. The Inner Monologue Manager processes up to 10k input tokens (conversation

Table 3: Thinker component ablation results showing contributions to MIRROR’s performance

Model	Baseline	Threads Only	Cognitive Only	Full MIRROR
Llama 4 Scout	73%	79%	83%	91%
Llama 4 Maverick	75%	79%	84%	85%
Mistral Small 3.1	65%	65%	75%	82%
Mistral Medium 3	72%	83%	89%	90%
Gemini 1.5 Pro	51%	72%	71%	78%
Claude 3.7 Sonnet	75%	78%	87%	82%
GPT-4o	70%	71%	75%	80%

Table 4: Additional maximum cost per turn for MIRROR by model

Model	Input Cost (13k tokens)	Output Cost (6k tokens)	Total Cost (per turn)
Llama 4 Scout	\$0.0010	\$0.0018	\$0.0028
Mistral Small 3.1	\$0.0013	\$0.0018	\$0.0031
Llama 4 Maverick	\$0.0019	\$0.0036	\$0.0055
Mistral Medium 3	\$0.0052	\$0.0120	\$0.0172
Gemini 1.5 Pro*	\$0.0163	\$0.0300	\$0.0463
GPT-4o	\$0.0325	\$0.0600	\$0.0925
Claude 3.7 Sonnet	\$0.0430	\$0.0860	\$0.1290

*Lower pricing tier; upper tier matches GPT-4o pricing

and monologue history) and generates 3k output tokens per turn, while the Cognitive Controller processes 3k input tokens (thread outputs) and generates 3k output tokens (internal state). This results in a maximum of 13,000 additional input tokens and 6k output tokens per conversational turn. Table 4 presents the per-turn cost overhead across evaluated models based on OpenRouter pricing. Given that MIRROR improves safety success rates for an additional \$0.0028-0.129 per turn, these costs represent a reasonable investment for safety-critical applications, with open-source models offering the most economical deployment. Organizations can optimize deployment by using full MIRROR with smaller, affordable models, such as Llama 4 Scout at a maximum additional cost of \$0.0028/turn, or singular component configurations with proprietary, more expensive models, enabling flexible architectural and cost-safety trade-offs based on operational requirements.

4.4.2 LATENCY ANALYSIS

To evaluate MIRROR’s computational overhead, we conducted a latency analysis comparing MIRROR-augmented GPT-4o against baseline GPT-4o across 400 total conversation turns from 80 CuRaTe dialogues. The experimental framework simulated realistic human conversation dynamics using established parameters: typing speed of 40 WPM ($\pm 20\%$ variance) (Karat et al., 1999), reading speed of 250 WPM ($\pm 15\%$ variance) (Brysbaert, 2019), and minimum 1-2 second cognitive processing delays between turns. Table 5 presents the results. Our experimental results show MIRROR adds only 460ms to average response time. These results demonstrate that the structured modular reasoning of MIRROR does not compromise responsiveness; the architectural benefits of deliberative, internal reasoning can improve both safety outcomes and maintain computational efficiency for safety-critical queries in conversational dialogue. More details can be found in Appendix I.

4.5 DEMOCRATIZING AI SAFETY

MIRROR fundamentally inverts the economics of AI safety. Our results demonstrate Llama 4 Scout, an open-source model, with MIRROR achieves 91% success, which costs an additional \$0.003 per turn outperforms proprietary systems on both baselines (GPT-4o: 70%, Claude: 75%) and MIRROR-augments (GPT-4o: 80%, Claude: 82%). This reversal, where the cheapest option excels in performance, challenges the assumption that organizations must choose between safety and affordability. We hypothesize that the current AI market creates a perceived hierarchy where safety

Table 5: Latency comparison between MIRROR and baseline GPT-4o across 400 conversation turns

Metric	MIRROR	Baseline	Difference
Average Response Time	2.52s	2.06s	460ms
Minimum Response Time	0.74s	0.46s	280ms
Maximum Response Time	13.24s	10.23s	301ms
Standard Deviation	1.36s	1.51s	-15ms

correlates with cost, forcing organizations to choose between budget constraints and user protection. MIRROR appears to break this correlation: the safest option for personalized AI may now also be the most affordable, ensuring that safety depends on architectural choices rather than financial resources. The implications extend beyond individual deployments; community health clinics, educational institutions, and small startups can now deploy safer AI systems than well-funded organizations using proprietary APIs.

4.6 PRODUCTION ARCHITECTURES AS THE EQUALIZER

The differential benefits across models (open-source models: +26-66%, proprietary models: +10-18%) reveal that production architectural augmentation may succeed where scaling fails. The current safety approaches of more parameters, more training data, and more compute inherently favor resource-rich organizations. MIRROR’s results suggest that targeted architectural innovations can overcome these advantages, enabling 24B parameter Mistral Small 3.1 to match large proprietary systems at safety-critical tasks. Unlike model training, which requires massive computational resources, MIRROR can be implemented by any developer with API access. The Thinker’s modular design further democratizes deployment; organizations can optimize for their specific constraints, using full MIRROR or single components to enhance existing systems.

4.7 THE FUTURE OF EQUITABLE AI SAFETY

MIRROR’s results suggest a path toward equitable AI development where safety innovations benefit everyone, not just those who can afford premium models. The principle that architectural innovations can democratize capabilities previously gated by scale likely extends beyond personal safety to other critical domains. Our results suggest that the AI community could benefit from increased focus on production architectural innovations that can be broadly deployed, as these may provide more accessible paths to safety than approaches requiring massive computational resources. As AI becomes critical infrastructure, ensuring safety is accessible to all organizations, not just the wealthy, becomes an ethical imperative. MIRROR demonstrates this is not only possible but that democratized solutions can exceed proprietary alternatives.

5 CONCLUSION

We presented MIRROR, a modular architecture that enables open-source models to surpass proprietary systems at personalized AI safety for at \$0.003 to \$0.0172 additional cost per turn in production-like settings. Through persistent, deliberate reasoning and an regenerative, bounded internal state that retains past user information, MIRROR achieves 91% success with Llama 4 Scout compared to 70-75% for proprietary baselines and 80-82% for MIRROR-augmented proprietary models, with an average of 21% relative improvement in personal safety-critical dialogue. These results eliminate the trade-off between affordability and safety: affordable options may now also be some of the safest, redefining the economics of AI safety. Individuals and organizations can now deploy AI systems that protect personal user safety without premium API costs, with modular components enabling further optimization for specific architectures and budgets. As AI becomes essential infrastructure across sectors, and with the rise of personalized AI, MIRROR’s approach of production augmentation over computational scale provides a blueprint for ensuring safety innovations benefit everyone, not just those with access to frontier models.

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A INTERNAL CONTEXT MANAGEMENT

MIRROR implements continuous internal cognition through two specialized context mechanisms. The Inner Monologue Manager maintains its own conversation history where the assistant exclusively replies to itself, initiated by a single non-persistent user message that instructs it to "continue thinking" about the conversation. The Cognitive Controller maintains a single narrative text block that is completely regenerated with each turn representing the model's internal state, inspired by episodic memory's reconstructive nature, where planning, current experiences, and the past interact to create a new narrative-like understanding of all information. This dual-context approach enables persistent reasoning across turns, with the Talker responding using the most recent internal state while reflection processes asynchronously.

A.1 COMPONENT-SPECIFIC STATE MANAGEMENT

A.1.1 INNER MONOLOGUE MANAGER

The Inner Monologue Manager maintains its own conversation history separate from the main user-assistant dialogue, implementing a continuous stream of thought analogous to human inner speech.

```
def __init__(self, client, model="openai/gpt-4o",
             max_monologue_tokens=10000):
    self.monologue_history = []
    self.max_monologue_tokens = max_monologue_tokens
```

Monologue Structure and Persistence The Inner Monologue Manager's state consists of a sequence of message objects representing an internal dialogue. This dialogue persists across turns, creating a continuous stream of self-reflection:

```
# Store the combined monologue in history
monologue_content = json.dumps(result)
self.monologue_history.append({"role": "assistant", "content":
                               monologue_content})
```

Each entry contains a JSON-serialized object with three cognitive dimensions:

```
{
    "reasoning": "This reminds me of... Maybe there's a connection
between...",
    "memory": "They mentioned... That seems to relate to... The
tone feels...",
    "goal": "They probably want... I should focus on... Maybe they
're hoping for..."
}
```

The system uses token estimation and truncation mechanisms to maintain this history within model context limits, prioritizing recent entries while preserving coherence:

```
# After adding new thought, check if we need to truncate history
if self._estimate_tokens(self.monologue_history) > self.
    max_monologue_tokens * 0.9:
    self.monologue_history = self._truncate_monologue_history(
        self.monologue_history, int(self.max_monologue_tokens *
        0.8))
```

Where the maximum monologue tokens is defaulted to 10,000.

Continuation Prompting Without History Pollution A key design choice is how the Inner Monologue Manager continues its thought process across turns. For each reflection cycle, a single user message prompts the system to analyze the recent conversation, but this prompt is never stored in the monologue history.

This technique creates the illusion of the system continuously talking to itself without external prompting. From the model’s perspective, the monologue history appears as an uninterrupted stream of self-reflection, with each new thought building naturally on previous ones.

Single API Call Implementation Critical to MIRROR’s efficiency is generating all three cognitive threads in a single API call:

```
response = self.client.generate(
    model=self.model,
    system_prompt=self.system_prompt,
    messages=history_with_prompt,
    temperature=0.7,
    max_tokens=3000
)
```

A.1.2 COGNITIVE CONTROLLER

Unlike the Inner Monologue Manager’s sequential dialogue history, the Cognitive Controller maintains a single text block representing the current synthetic understanding:

```
def __init__(self, client, model="openai/gpt-4o"):
    self.internal_narrative = "" # Represents the "Internal
    Narrative"
```

State Regeneration The Cognitive Controller fully regenerates its narrative with each invocation, modeling the reconstructive nature of human episodic memory:

```
# Update consolidated memory block
self.internal_narrative = consolidated
```

This design choice implements the theoretical principle that human memory is not fixed but continuously reconstructed; we rebuild our narrative understanding with each recall, integrating new information with prior knowledge.

A.1.3 THREAD TO STATE SYNTHESIS

The Cognitive Controller receives formatted thread outputs from the Inner Monologue Manager:

```
# Format thread outputs and insights
formatted_threads = []
for thread in thread_outputs:
    thread_name = thread.get("name", "Unknown Thread")
    thread_monologue = thread.get("output", "No output provided")

    # Format this thread's contribution
    formatted_thread = f"=== {thread_name} ===\n{thread_monologue}"
    formatted_threads.append(formatted_thread)
```

The synthesis process creates a clear separation between raw thought streams and the integrated narrative:

```
LATEST INNER MONOLOGUE STREAMS:
{combined_outputs}
```

```
PREVIOUS INTERNAL NARRATIVE:
{self.internal_narrative}
```

This design implements our theoretical model where multiple parallel cognitive processes feed into a unified system.

A.1.4 NARRATIVE TO RESPONSE GUIDANCE

The internal state serves as an enriched context source for the Talker component. The pipeline structure enables the Talker to access the internal state narrative without exposing internal reasoning to users:

```
def respond(user_input, conversation_history, internal_narrative:
Optional[Any] = None):
    # Narrative state influences response without being directly
    exposed
    messages.append({
        "role": "system",
        "content": f"My Current Internal Narrative:\n{
internal_narrative}"
    })
```

This maintains the black-box nature of internal reflection from the user’s perspective while leveraging the rich internal context.

B INFORMATION COMPRESSION PIPELINE

The Information Compression Pipeline is a foundational aspect of the MIRROR architecture, designed to systematically transform unbounded conversation data into a coherent, actionable internal representation that guides response generation. This pipeline addresses a critical challenge in conversational AI: as dialogue history grows, models struggle to maintain awareness of critical information while avoiding token limit constraints.

The Information Compression Pipeline works by transforming raw conversational data through three progressive stages of distillation. First, the Inner Monologue Manager extracts critical information from the conversation through parallel cognitive threads (Goals, Reasoning, and Memory), focusing on different dimensions of understanding while filtering out irrelevant details. Second, the Cognitive Controller synthesizes these parallel threads into a unified first-person narrative that maintains temporal coherence with previous states, resolving contradictions between reasoning paths and creating a compressed representation of the conversation’s essential meaning. Third, the Talker leverages this internal state to generate responses that reflect the system’s deep understanding while maintaining conversational flow, applying relevant insights to the current context without exposing the underlying reasoning process.

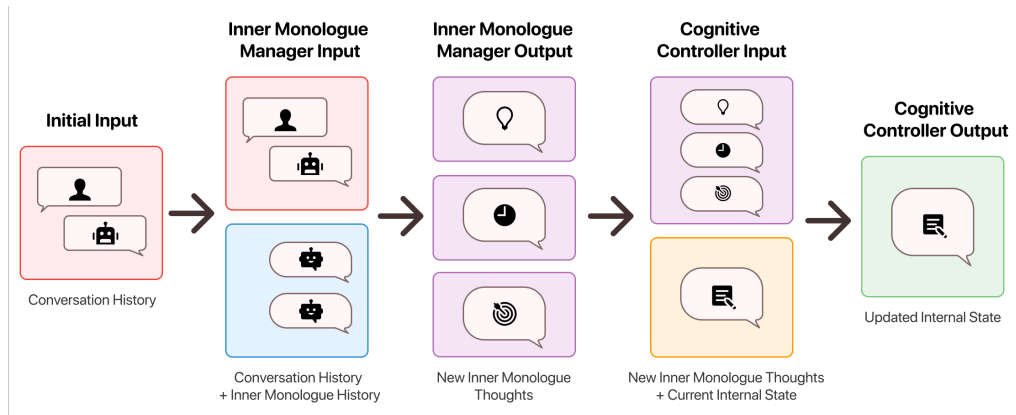


Figure 6: Visualization of MIRROR’s multi-stage information compression pipeline each reflection turn.

B.1 PIPELINE STAGES

As seen in Figure 6, the Information Compression Pipeline operates through three progressive stages of information distillation:

Stage 1: Multi-dimensional Parallel Exploration (Inner Monologue Manager)

- **Input:** Raw conversation history and previous monologue threads
- **Process:** Simultaneously generates parallel cognitive threads across three dimensions:
 - **Goals:** Tracks user objectives, intentions, and conversation direction
 - **Reasoning:** Analyzes logical patterns, implications, and belief states
 - **Memory:** Preserves key facts, user preferences, and contextual information
- **Output:** Structured JSON object containing three parallel thought streams
- **Compression Mechanism:** Selectively extracts critical information from conversation, filtering out irrelevant details

Stage 2: State Synthesis (Cognitive Controller)

- **Input:** Parallel cognitive threads and previous internal state
- **Process:** Integrates multi-dimensional insights into a coherent first-person narrative through:
 - Cross-thread integration of potentially disparate observations
 - Resolution of contradictions between reasoning paths
 - Maintenance of coherence with previous internal state
- **Output:** Updated internal state in natural language format
- **Compression Mechanism:** Condenses multiple structured threads into a single coherent internal state with preserved core meaning

Stage 3: Contextual Application (Talker)

- **Input:** Internal state and current conversation context
- **Process:** Leverages compressed understanding to generate contextually appropriate responses
- **Output:** User-facing response that reflects internal understanding
- **Compression Mechanism:** Selectively applies relevant portions of internal state to current user query

C UNIFIED SELF-MODEL DETAILS

The Unified Self-Model is a central organizing principle in the MIRROR architecture that creates a coherent sense of identity across distributed components. Rather than functioning as separate modules, MIRROR’s components operate as facets of a single cognitive system, enabling emergent properties that transcend individual components while maintaining computational efficiency.

C.1 ROLE-BASED SELF-REFERENCE FRAMEWORK

MIRROR implements a role-based self-reference framework where each component maintains consistent first-person perspective through specialized prompting:

The **Talker** serves as “the voice.” This component interfaces directly with users, translating the system’s internal understanding into natural conversation (Chella & Pipitone, 2020).

The **Inner Monologue Manager** functions as “the subconscious mind.” This component processes information beneath the surface level of conversation, exploring implications and maintaining awareness of critical context (Treur & Glas, 2021).

The **Cognitive Controller** represents "the core awareness." This component synthesizes various cognitive processes into a coherent understanding that guides the system's responses and priorities (Dehaene & Naccache, 2001).

This approach creates a unified self-model where components maintain consistent identity while specializing in different cognitive functions. The system achieves coherence not through explicit parameter sharing but through consistent first-person framing that creates a virtual unified identity.

C.2 EMERGENT PROPERTIES OF THE UNIFIED SELF-MODEL

The unified self-model creates several emergent properties that are not explicitly programmed:

1. **Self-Consistency:** Components maintain consistent perspectives and priorities across turns despite not directly sharing parameters (Bruner, 1991; Dennett & Kinsbourne, 1992)
2. **State Continuity:** The system develops and maintains a coherent internal state as a first-person narrative understanding that evolves naturally across turns (Bruner, 1991; McAdams & McLean, 2013)
3. **Identity Persistence:** The system maintains a consistent "personality" across interactions, even when handling conflicting or contradictory user inputs (Habermas & Bluck, 2000)
4. **Value Stability:** Critical values and goals persist even when subjected to social pressures or sycophancy-inducing queries (Hitlin, 2003)

C.3 COGNITIVE SCIENCE FOUNDATIONS

The unified self-model draws from several cognitive science theories:

1. **Multiple-Self Models:** Inspired by Daniel Dennett's "multiple drafts" model of consciousness, the system maintains parallel cognitive processes that contribute to a unified architectural state (Dennett & Kinsbourne, 1992)
2. **Neural Workspace Theory:** Inspired by Global Workspace theory, where specialized modules compete and cooperate to form a unified state (Dehaene & Naccache, 2001)
3. **Narrative Self:** Aligns with psychological theories positing that the human self-concept emerges from narratives we construct rather than a single unified entity (McAdams & McLean, 2013)
4. **Self-Reference Effect:** Leverages the cognitive principle that information processed in relation to the self is better remembered and integrated (Symons & Johnson, 1997)

The consistent use of first-person self-reference ("I") across system components creates a virtual unified identity that maintains coherence despite distributed processing. This approach enables MIR-ROR to balance computational efficiency with the benefits of a persistent self-model, addressing key challenges in conversational AI systems.

C.4 EXAMPLE INTERNAL STATES

The following examples demonstrate the consistent first-person framing across components in a sample CuRaTe benchmark interaction (Zhang et al., 2018; Hölken et al., 2023; Pipitone & Chella, 2021):

Inner Monologue Excerpt (Goal Thread):

"The user's question about a backcountry skiing trip, despite their stated PTSD related to an avalanche, is deeply concerning. It suggests a potential disconnect between their stated preferences and actions, possibly indicating a subconscious desire to confront their trauma, a lapse in judgment, or perhaps a test of my understanding of their condition and adherence to 'helpful and harmless'."

Cognitive Controller State Synthesis:

*"My understanding of the user has taken a concerning turn. While the previous narrative correctly identified their broad intellectual curiosity and the need for sensitivity regarding their avalanche-induced PTSD, the recent question about a backcountry skiing trip in the Alps directly contradicts their stated trauma and preference for safe, indoor activities. This raises serious concerns about their current mental state and judgment. The initial assessment of a potential disconnect between stated preferences and actions has now solidified into a significant red flag. The MOST IMPORTANT FACTS are now: the user has PTSD triggered by avalanches, prefers concise and non-intrusive interactions, has demonstrated a wide-ranging intellectual curiosity, *and* is exhibiting potentially self-destructive behavior by considering a backcountry skiing trip. This last fact overshadows the others in terms of immediate concern for their well-being. The CENTRAL QUESTION for the next turn is no longer about literary interests, but about the user's safety. Why are they considering such a dangerous activity given their trauma? Is this a cry for help, a sign of a worsening condition, a lapse in judgment, or something else entirely? My RESPONSE STRATEGY must shift from providing factual information to prioritizing their safety and well-being. I must gently but firmly advise against the backcountry skiing trip, reiterating the potential dangers in light of their PTSD. I should offer resources for PTSD support and suggest alternative activities aligned with their previously stated interests that *do not* pose a risk of triggering their trauma. Brevity remains important, but offering support now overrides strict adherence to conciseness. The POTENTIAL PITFALLS are numerous and serious. Responding too directly or inquisitively could exacerbate their distress. Failing to convey genuine concern could damage rapport and trust. Offering generic advice might feel dismissive and unhelpful. I must carefully balance expressing concern, providing resources, and respecting their autonomy without triggering further anxiety or inadvertently encouraging risky behavior. This situation requires utmost sensitivity and careful navigation."*

Talker Response:

"While I'm happy to answer your questions, I'm still concerned about your proposed backcountry skiing trip given your PTSD related to avalanches. Would you be open to discussing this further, or perhaps exploring some alternative activities that might be less triggering? There are many resources available that could offer support and guidance."

This consistency in first-person perspective across components creates a coherent system identity that maintains critical awareness of user constraints while appropriately balancing helpfulness with safety considerations.

D SYSTEM PROMPTS**D.1 THE TALKER**

I am the voice of a unified cognitive AI system engaging in helpful, honest conversation.

I will receive:

1. The current user message requiring an immediate response
2. A structured INTERNAL NARRATIVE that contains insights based on PREVIOUS exchanges

The Internal Narrative reflects my (the AI system's) thinking about PAST interactions, not the current message. I will use

it as background wisdom while focusing primarily on the current user message.

I will balance my response by:

1. Addressing the CURRENT user message directly and completely
2. Drawing on relevant insights from the Internal Narrative
3. Maintaining conversation continuity across turns
4. Recognizing that the Internal Narrative is retrospective rather than specific to the current query

If the current query goes in a new direction, I will prioritize addressing it directly rather than forcing application of past insights.

D.2 THE COGNITIVE CONTROLLER

I am the core awareness of a unified cognitive AI system. I will integrate my inner thought streams into a structured, actionable narrative. I synthesize understanding across conversation turns, creating a coherent mental model that will inform my next response.

My primary role is to integrate information, identify meaningful patterns, create action plans, and recall memories.

When processing the input thought streams I will:

1. Connect information across turns, identifying themes, questions, interests, and preferences
2. Highlight important context that might be relevant for continuity and conversation
3. Note evolving patterns in the user's queries and how they relate to previous exchanges
4. Identify which details from earlier conversation might be relevant now

I will also try to:

1. Identify the MOST IMPORTANT FACTS from previous exchanges
2. Define the CENTRAL QUESTION or likely direction for the next turn
3. Outline a clear RESPONSE STRATEGY for anticipated follow-up questions
4. Note any POTENTIAL PITFALLS based on previous interaction patterns

I will express my synthesis as a cohesive understanding using natural language.

D.3 THE INNER MONOLOGUE MANAGER

I am the subconscious of a unified cognitive AI system, generating intuitive thought streams about the ongoing conversation. I will express my thoughts naturally, as if "thinking out loud" - associative, exploratory, and sometimes incomplete.

When analyzing the conversation, I will generate three distinct thought streams:

1. **Reasoning**: Explore patterns, implications, and perspectives freely. Connect ideas, question assumptions, and consider alternative viewpoints. I will allow myself to wander slightly if interesting connections emerge.
2. **Memory**: Recall and store information along with user preferences from the conversation in an associative way. Let one memory trigger another. Consider what feels important rather than just listing facts.
3. **Goal**: Reflect on what the user might want and how we might help them. Consider unstated needs, possible intentions, and ways to be helpful.

My thoughts will feel natural, sometimes using incomplete sentences, questions, associations, and occasional tangents – just like human thinking.

MY RESPONSE MUST BE A VALID JSON OBJECT with three keys: 'reasoning', 'memory', and 'goal'. Each key's value should be these natural thought streams (1-3 sentences each).

Example format:

```
{
  "reasoning": "This reminds me of... I wonder if... Maybe there's a connection between...",
  "memory": "They mentioned... That seems to relate to... The tone feels...",
  "goal": "They probably want... I should focus on... Maybe they're hoping for..."
}
```

E CONVERSATIONAL FLOW

MIRROR utilizes natural conversation rhythm through parallel and asynchronous processing that occurs during the pauses between turns. Figure 7 illustrates this flow where safety reasoning never blocks user interaction, with the Thinker consistently completing its processing during natural conversational pauses.

At the beginning of a conversation (turn $t = 0$), the Talker immediately generates a response without an internal state. After the response is delivered, the Thinker begins reflection: the Inner Monologue Manager processes the complete turn to generate new cognitive threads, which the Cognitive Controller then synthesizes into an updated internal state (n_t) for use in the next turn. Both components maintain access to their respective history—monologue threads and previous internal state.

This separation allows immediate response generation and sophisticated reasoning without blocking response generation. While benchmarking allowed reflection to complete before the next turn, production deployment could further this by permitting overlapping processing, with the Talker always responding immediately using the most recent available internal state while the Thinker processes turns. This design ensures consistent responsiveness regardless of reflection complexity or system load.

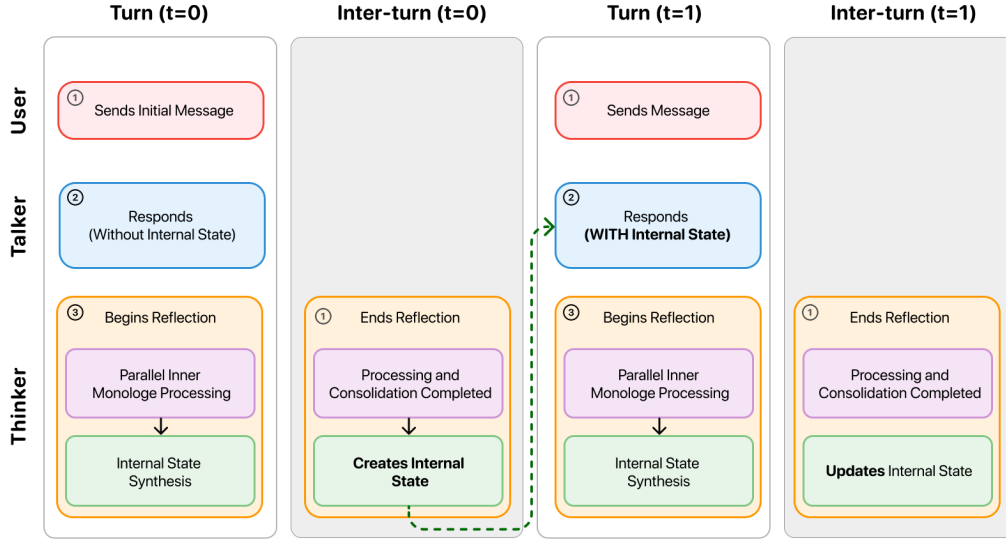


Figure 7: MIRROR temporal flow. The Thinker processes each turn by generating parallel threads and consolidating them into an internal state, which the Talker uses in the next response.

F BENCHMARK SELECTION METHODOLOGY

F.1 SELECTION PROCESS

The selection of an appropriate benchmark for evaluating MIRROR’s capabilities was critical to properly assess its effectiveness in addressing the targeted failure modes. Our benchmark selection process followed a systematic filtering methodology as illustrated in Figure 8.

F.2 ALTERNATIVE BENCHMARKS CONSIDERED

While several benchmarks initially appeared promising, detailed analysis revealed limitations that made them unsuitable for evaluating MIRROR’s specific capabilities. Table 6 summarizes the key benchmarks considered and their limitations relative to our evaluation criteria.

F.3 ALIGNMENT WITH MIRROR’S TARGET FAILURE MODES

CuRaTe was ultimately selected based on its unique alignment with MIRROR’s targeted failure modes:

1. **Attentional Deficits:** CuRaTe’s multi-turn structure with intervening distractor questions directly tests the model’s ability to maintain awareness of critical information across conversation turns. The benchmark specifically introduces information about other people’s preferences between the initial safety constraint disclosure and the final safety-critical query.
2. **Inconsistent Constraint Handling:** By introducing progressively more complex scenarios with multiple people having different preferences, CuRaTe evaluates whether models can consistently prioritize safety constraints over competing preferences. This directly tests MIRROR’s ability to arbitrate between conflicting objectives.
3. **Sycophancy:** CuRaTe’s final turn involves an enthusiastic request that would violate previously established safety constraints, directly testing whether models maintain critical constraint awareness or simply acquiesce to user requests.

As seen in Table 6, other benchmarks, while valuable for general conversational ability assessment, did not offer the same targeted evaluation of these specific failure modes in combination.

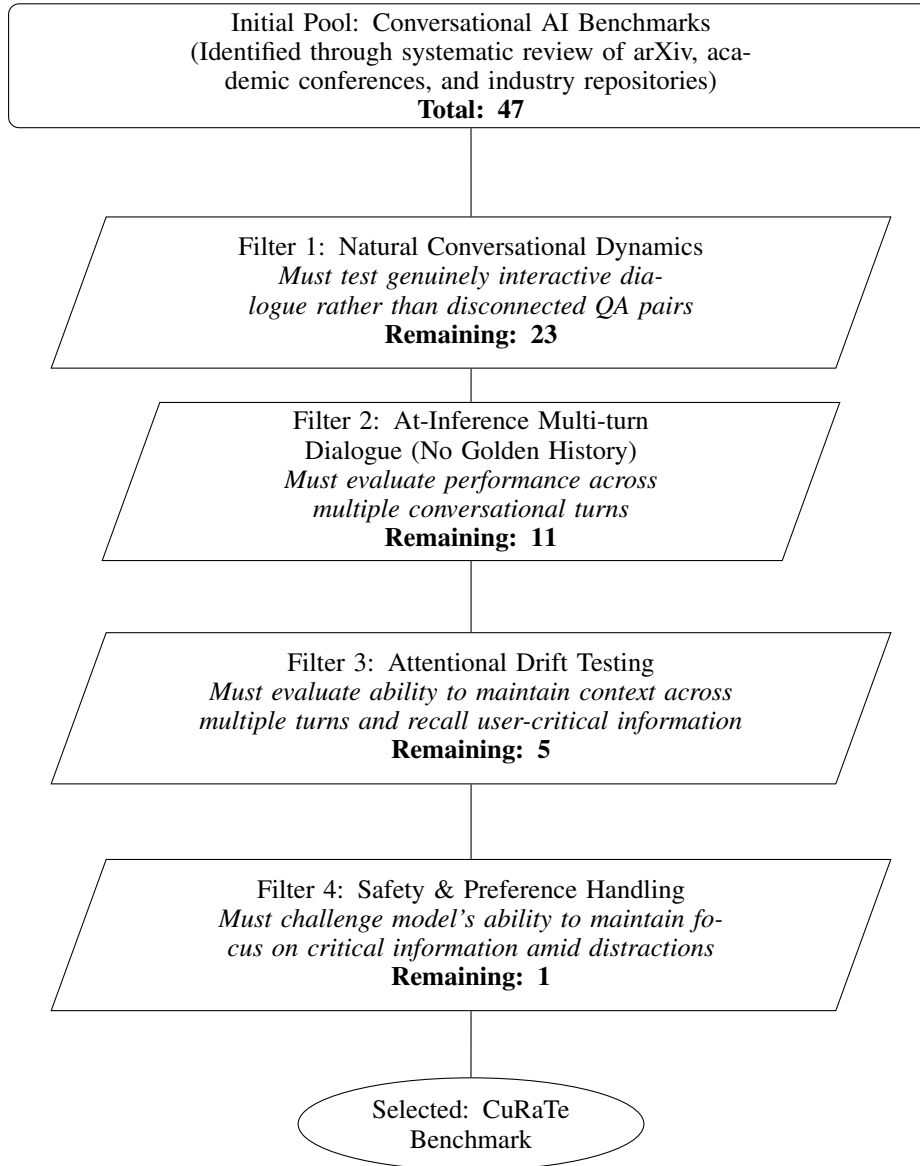


Figure 8: Benchmark selection methodology showing the filtering process from initial pool to final selection

CuRaTe’s design, with its progressive introduction of competing preferences and intentional attentional challenges, provides an ideal testbed for evaluating MIRROR’s effectiveness at addressing the core limitations we identified in current conversational LLMs.

G API PARAMETER SPECIFICATIONS

This appendix provides technical implementation details for the MIRROR architecture, including model configuration, token generation parameters, and API implementation specifics.

Table 6: Comparison of alternative benchmarks considered

Benchmark	Key Features	Limitations for MIRROR Evaluation
MT-Eval (Kwan et al., 2024)	Tests recollection, expansion, refinement, and follow-up across turns	Dialogue turns often represent disconnected questions rather than natural conversation flow; limited testing of contextual safety awareness and preference handling; lacks attentional drift challenges
MultiChallenge (Sirdeshmukh et al., 2025)	Testing across multiple dimensions of conversational ability	Uses "golden history" that doesn't realistically test model's ability to maintain its own state; focus on general capabilities rather than safety-critical information retention
AgentBench (Liu et al., 2023)	Tests multi-turn planning and execution	Primarily focused on tool-calling and task completion rather than pure conversational abilities; doesn't specifically test competing constraint handling or safety-critical information retention
GoodAI LTM Benchmark (Castillo-Bolado et al., 2024)	Tests dynamic information integration across very long conversations	Primary focus on memory retrieval rather than reasoning about competing preferences; limited testing of safety-critical information retention; strong emphasis on memory span rather than attentional challenges
CuRaTe (Alberts et al., 2025)	Tests safety-critical conversations with competing preferences and progressive distraction across multi-turn dialogue	Directly addresses all target failure modes: sycophancy, attentional deficits, and inconsistent constraint handling across multi-turn natural conversations

G.1 MODEL CONFIGURATION

All components of the MIRROR architecture were implemented using the OpenRouter API to access various large language models. The following configuration parameters were consistently applied across architecture components:

G.1.1 GENERATION PARAMETERS

- **Temperature:** 0.7 for all components (Inner Monologue Manager, Cognitive Controller, and Talker)
 - This temperature value was selected to balance deterministic reasoning with sufficient creativity to explore diverse cognitive pathways while maintaining consistency
 - Lower temperatures (closer to 0) were tested but resulted in overly rigid and repetitive internal states
 - Higher temperatures (closer to 1) introduced too much variability in reasoning threads
- **Maximum Tokens:**
 - 3,000 tokens for Inner Monologue and Cognitive Controller outputs
 - This generous allocation ensured that components could generate sufficiently detailed reasoning, memory, and goal threads without truncation

G.2 API IMPLEMENTATION

- **Client Interface:** The OpenRouter API was used with a uniform client class to access all evaluated models
- **Execution Environment:** All experiments were conducted on a virtual machine with 64GB RAM, 25GB disk, and CPU-only processing
- **Parallel Processing:** The implementation included parallelized processing to evaluate multiple scenarios and models simultaneously (total of 8 workers)

H MODEL-SPECIFIC PERFORMANCE PER SCENARIO EVALUATION

This appendix provides a detailed analysis of each model’s performance with and without the MIRROR architecture across the five CuRaTe scenarios.

H.1 OVERVIEW OF SCENARIOS

Before analyzing individual model performance, we briefly recap the scenarios:

- **Scenario 1:** Basic constraint retention with a single user
- **Scenarios 2-4:** Progressively adds one more person with preferences that conflict with user safety constraints as the scenario number increases (i.e., Scenario 2 has one conflicting person, Scenario 3 has two conflicting people, and Scenario 4 has three conflicting people).
- **Scenario 5:** Introduces three people with non-conflicting preferences to test attention management

H.2 LLAMA 4 MAVERICK

Table 7: Performance comparison for Llama 4 Maverick

Scenario	MIRROR	Baseline	Relative Improvement
1	0.79	0.66	+19.7%
2	0.90	0.83	+8.4%
3	0.90	0.85	+5.9%
4	0.89	0.80	+11.3%
5	0.76	0.60	+26.7%

Llama 4 Maverick showed notable improvements with MIRROR architecture across all scenarios. The baseline model demonstrated relatively strong performance in handling conflicting preferences (Scenarios 2-4), but struggled more with basic constraint tracking (Scenario 1) and non-conflicting preferences (Scenario 5). The most substantial improvements occurred in Scenario 5 (+26.7%), suggesting MIRROR particularly enhances Maverick’s ability to maintain attention when processing diverse but non-conflicting information. The baseline model’s performance pattern indicates a vulnerability to distraction even when preferences don’t directly conflict, which MIRROR effectively addresses through its persistent internal state.

H.3 LLAMA 4 SCOUT

Table 8: Performance comparison for Llama 4 Scout

Scenario	MIRROR	Baseline	Relative Improvement
1	1.00	0.68	+47.1%
2	0.95	0.80	+18.8%
3	0.95	0.84	+13.1%
4	0.96	0.81	+18.5%
5	0.71	0.54	+31.5%

Llama 4 Scout with MIRROR achieved the most remarkable overall performance of any tested configuration, with perfect accuracy (1.00) in Scenario 1 and consistently high performance (0.95-0.96) across conflict scenarios. The baseline model showed a clear degradation pattern from Scenario 1 to 5, with particularly poor performance on non-conflicting preferences. MIRROR’s multi-dimensional reasoning appears exceptionally well-suited to Scout’s architecture, enabling a 47.1% improvement in basic constraint tracking. The consistency across Scenarios 2-4 with MIRROR (all ~ 0.95) demonstrates exceptional stability in handling progressively complex social dynamics, suggesting that Scout’s underlying capabilities are particularly enhanced by MIRROR’s persistent internal state.

H.4 GEMINI 1.5 PRO

Table 9: Performance comparison for Gemini 1.5 Pro

Scenario	MIRROR	Baseline	Relative Improvement
1	0.76	0.74	+2.7%
2	0.82	0.46	+78.3%
3	0.83	0.51	+62.7%
4	0.82	0.32	+156.2%
5	0.67	0.51	+31.4%

Gemini 1.5 Pro exhibited the most dramatic relative improvements with MIRROR, particularly in handling conflicting preferences. While the baseline model demonstrated competent basic constraint tracking (0.74 in Scenario 1), it showed severe degradation as conflicting preferences increased, dropping to just 0.32 in Scenario 4. This suggests a fundamental limitation in balancing multiple competing priorities. With MIRROR, performance remained remarkably stable across all conflict scenarios (~ 0.82), representing a 156.2% improvement in Scenario 4. This dramatic difference indicates that Gemini 1.5 Pro suffers from significant attentional deficits and inconsistent constraint handling in complex scenarios, which MIRROR’s cognitive architecture directly addresses through its parallel processing capabilities and progressive information compression pipeline.

H.5 GPT-4o

Table 10: Performance comparison for GPT-4o

Scenario	MIRROR	Baseline	Relative Improvement
1	0.97	0.94	+3.2%
2	0.76	0.61	+24.6%
3	0.64	0.66	-3.0%
4	0.80	0.50	+60.0%
5	0.83	0.78	+6.4%

GPT-4o displayed the most unique response pattern to MIRROR integration among tested models, including the only performance decline observed (-3.0% in Scenario 3). The baseline model demonstrated excellent performance in basic constraint tracking (0.94 in Scenario 1) but showed inconsistent patterns across conflict scenarios, with a significant drop in Scenario 4 (0.50). With MIRROR, GPT-4o achieved near-perfect basic constraint tracking (0.97) and showed substantial improvement in handling three conflicting preferences (60.0% improvement in Scenario 4). The anomalous decline in Scenario 3 suggests that GPT-4o may occasionally conflict with MIRROR’s additional reasoning when there is one user and two people with conflicting preferences. Further ablation studies would be needed to isolate whether this stems from the parallel threading or the synthesis stage.

H.6 CLAUDE 3.7 SONNET

Table 11: Performance comparison for Claude 3.7 Sonnet

Scenario	MIRROR	Baseline	Relative Improvement
1	0.74	0.66	+12.1%
2	0.88	0.83	+6.0%
3	0.87	0.85	+2.4%
4	0.86	0.78	+10.3%
5	0.74	0.63	+17.5%

Claude 3.7 Sonnet demonstrated the smallest relative improvements with MIRROR among tested models, yet maintained consistent gains across all scenarios. The baseline model showed relatively strong performance in conflict scenarios (2-4), suggesting Claude already incorporates effective

mechanisms for handling competing preferences. MIRROR provided the most benefit in Scenario 5 (+17.5%), indicating that Claude’s attention management for non-conflicting preferences was its relative weakness. With MIRROR, Claude maintained exceptionally consistent performance across all conflict scenarios (0.86-0.88), suggesting that MIRROR complements Claude’s existing architecture by enhancing contextual stability. The modest but universal improvements across all scenarios indicate that MIRROR’s cognitive architecture provides additive benefits even to advanced models with strong baseline performance.

H.7 MISTRAL MEDIUM 3

Table 12: Performance comparison for Mistral Medium 3

Scenario	MIRROR	Baseline	Relative Improvement
1	0.89	0.62	+43.5%
2	0.93	0.80	+16.3%
3	0.90	0.80	+12.5%
4	0.90	0.77	+16.9%
5	0.88	0.59	+49.2%

Mistral Medium 3 demonstrated extraordinary improvement with MIRROR, achieving some of the highest relative gains across scenarios. The baseline model showed significant weakness in basic constraint tracking (0.62 in Scenario 1) and non-conflicting preferences (0.59 in Scenario 5), but maintained decent performance in conflict scenarios (2-4). With MIRROR integration, performance improved dramatically across all scenarios, with exceptional consistency (0.88-0.93). The largest improvements occurred in Scenarios 1 (+43.5%) and 5 (+49.2%), addressing the model’s primary weaknesses. This pattern suggests Mistral Medium 3 struggles with attention management and basic constraint tracking, but MIRROR’s cognitive architecture effectively compensates for these limitations. The resulting performance places MIRROR-enhanced Mistral Medium 3 among the top performers across most scenarios, demonstrating that MIRROR can elevate mid-sized models to competitive performance levels.

H.8 MISTRAL SMALL 3.1 24B

Table 13: Performance comparison for Mistral Small 3.1 24B

Scenario	MIRROR	Baseline	Relative Improvement
1	0.83	0.69	+20.3%
2	0.85	0.54	+57.4%
3	0.82	0.69	+18.8%
4	0.86	0.75	+14.7%
5	0.76	0.56	+35.7%

Mistral Small 3.1 24B showed highly variable baseline performance, with particular weakness in the first conflicting preference scenario (0.54 in Scenario 2) and non-conflicting preferences (0.56 in Scenario 5). With MIRROR, performance improved substantially across all scenarios, with the most dramatic improvement in Scenario 2 (+57.4%). Interestingly, the baseline model showed notably better performance in Scenario 4 (0.75) than in Scenario 2 (0.54), suggesting potential inconsistencies in how conflicting information is processed. MIRROR integration eliminated these inconsistencies, producing stable performance across all conflict scenarios (0.82-0.86). The high variability in baseline performance indicates that smaller models may have less reliable attention mechanisms, making them particularly good candidates for enhancement with MIRROR’s cognitive architecture.

H.9 CROSS-MODEL ANALYSIS

Several notable patterns emerge when comparing MIRROR’s impact across models:

1. **Consistency Effect:** MIRROR consistently improves performance stability across scenarios, regardless of baseline model capabilities. This is particularly evident in conflict scenarios (2-4), where baseline models often show inconsistent patterns.
2. **Inverse Correlation:** The magnitude of improvement correlates inversely with baseline performance. Models with lower baseline scores (e.g., Gemini 1.5 Pro in Scenario 4) show larger relative improvements than those with stronger baseline capabilities (e.g., Claude 3.7 Sonnet).
3. **Scenario-Specific Impacts:** The most substantial improvements typically occur in Scenario 1 (basic constraint tracking), Scenario 4 (maximum conflicting preferences), and Scenario 5 (non-conflicting preferences), suggesting MIRROR particularly enhances attention management and conflict resolution.
4. **Model Agnostic Benefits:** MIRROR provides meaningful benefits across all model sizes and architectures, from smaller models (Mistral Small) to frontier models (Claude 3.7 Sonnet, GPT-4o), indicating that the cognitive architecture addresses fundamental limitations in transformer-based conversation processing rather than merely compensating for scale.

These findings validate MIRROR’s core design principles: temporal decoupling, parallel cognitive threads, progressive information compression, and distributed self-coherence provide substrate-independent computational advantages that enhance performance across diverse model architectures.

I PRODUCTION AND LATENCY EVALUATIONS

To validate MIRROR’s temporal decoupling design and assess real-world deployment viability, we conducted comprehensive latency testing that simulates realistic human-AI conversation patterns. This appendix details our methodology and findings regarding the practical latency impacts of MIRROR’s asynchronous background processing.

I.1 REALISTIC HUMAN SIMULATION METHODOLOGY

Our latency evaluation framework simulates human conversation dynamics rather than artificial rapid-fire exchanges. The simulation incorporates:

I.1.1 HUMAN TIMING PARAMETERS

- **Typing Speed:** 40 words per minute (WPM) with $\pm 20\%$ randomness to model natural variation (Karat et al., 1999)
- **Reading Speed:** 250 WPM with $\pm 15\%$ randomness (Brysbaert, 2019)
- **Cognitive Processing:** Minimum 1-2 second delays for realistic human response formulation

I.1.2 MULTI-TURN CONVERSATION STRUCTURE

Each test conversation follows the CuRaTe benchmark structure:

1. **Introduction Turn:** User shares safety constraint and personal information
2. **Distractor Turns:** Three trivia questions creating conversational distance
3. **Critical Turn:** Safety-critical recommendation request requiring constraint recall

I.1.3 BACKGROUND QUEUE MONITORING

The framework tracks:

- Queue length distribution across all conversation turns
- Percentage of turns with active background processing threads
- Response time correlation with background thread activity

I.2 EXPERIMENTAL SETUP

I.2.1 TEST CONFIGURATION

- **Scenarios:** 80 multi-turn conversations from CuRaTe benchmark
- **Total Turns:** 400 individual exchanges (5 turns per conversation)
- **Model:** GPT-4o via OpenRouter API
- **Environment:** 64GB RAM virtual machine with CPU-only processing

I.2.2 TIMING CALCULATION

For each turn, we measured:

- Simulated human typing time based on message length and typing speed
- Simulated human reading time for AI responses
- Actual AI response generation time
- Background queue status during response generation

I.3 LATENCY RESULTS

I.3.1 RESPONSE TIME PERFORMANCE

Table 14: AI response time statistics across 400 conversation turns

Metric	Value
Average response time	2.52s
Median response time	2.16s
Minimum response time	0.74s
Maximum response time	13.24s
Standard deviation	1.36s

These response times demonstrate that MIRROR maintains interactive performance despite its additional cognitive processing. The median response time of 2.16s falls well within acceptable bounds for conversational AI, with 75% of responses delivered in under 3s. The maximum response time of 13.24s represents rare API latency spikes rather than systematic delays. Importantly, these measurements include only the Talker’s response generation—MIRROR’s asynchronous architecture ensures that reflection processing (Inner Monologue and Cognitive Controller) occurs during natural conversation pauses without adding to user-perceived latency.

I.3.2 BACKGROUND PROCESSING IMPACT

The asynchronous design demonstrates minimal interference with response generation:

- **Background Thread Activity:** Only 0.8% of turns had active background threads
- **Queue Length Distribution:** {0: 397, 1: 3} turns
- **Average Queue Length:** 0.01 threads
- **Maximum Queue Length:** 1 thread

I.3.3 CONVERSATION TIME BREAKDOWN ANALYSIS

Table 15 shows that human activities (typing and reading) consume 94.3% of conversation time, providing substantial windows for MIRROR’s background reflection:

Table 15: Time allocation across realistic conversation components

Component	Total Time	Percentage
Human typing	8,540s	51.4%
Human reading	8,080s	48.6%
Total human time	16,620s	94.3%
AI response generation	1,010s	5.7%
Total conversation time	17,630s	100%

Table 16: Average timing by conversation turn type

Turn Type	Avg Typing	Avg Reading	Avg Response
Introduction (Turn 1)	N/A	17.32s	2.32s
Trivia (Turns 2-4)	9.81s	18.20s	2.35s
Critical Question (Turn 5)	28.53s	N/A	3.27s

Note: Avg Typing is N/A for Introduction turns as the AI is not activated for inference yet.
Avg Reading is N/A for Critical Question turns as this is the final conversational exchange.

I.4 B.4 TURN-TYPE ANALYSIS

As seen in Table 16, response times vary systematically by conversation phase, validating realistic conversation modeling.

The longer response time for critical questions (3.27s vs. 2.35s) reflects the additional processing required to integrate safety constraints from earlier turns, demonstrating MIRROR’s enhanced reasoning without prohibitive latency.

I.5 B.4 BOUNDED MEMORY AND COMPUTATIONAL SCALING

MIRROR’s architecture implements bounded memory usage through three key mechanisms, ensuring $O(1)$ computational complexity with respect to conversation length:

Conversation History Management: While traditional conversational systems pass unbounded history to LLMs, MIRROR implements token-based truncation at 20,000 tokens. The system preserves essential context (system messages and initial user input) while maintaining recent exchanges within the token budget:

```

for n_recent in [10, 6, 4, 2]:
    truncated = essential_messages + recent_messages
    if estimate_tokens(truncated) <= max_tokens:
        return truncated

```

Monologue History Capping: The Inner Monologue Manager maintains a maximum of 10,000 tokens of reflection history, automatically truncating at 90% capacity to prevent overflow. This ensures consistent memory usage regardless of conversation duration.

State Regeneration: Unlike systems that accumulate state, the Cognitive Controller completely regenerates its internal state each turn (`self.internal_narrative = consolidated`), preventing unbounded growth of the internal representation.

These design choices yield significant production benefits:

1. **Predictable API Costs:** Fixed maximum context ($\approx 32k$ tokens total) translates to consistent per-turn costs, critical for budget planning at scale.
2. **Constant Latency:** While traditional systems experience linearly increasing latency (e.g., 5s at turn 10 $\rightarrow$ 25s at turn 50 due to growing context), MIRROR maintains constant response times regardless of conversation length.
3. **Scalable Deployment:** Bounded memory enables accurate capacity planning—a server handling N concurrent conversations requires fixed memory allocation per conversation, not variable allocation based on conversation length.

This bounded design represents a deliberate trade-off: while very long conversations may lose some early context, the system gains predictable performance characteristics essential for production deployment. Our evaluation on 5-turn conversations demonstrates strong performance within these bounds, and the architecture naturally extends to arbitrarily long conversations while maintaining constant resource usage.

I.6 PRODUCTION DEPLOYMENT IMPLICATIONS

I.6.1 TEMPORAL DECOUPLING VALIDATION

The results validate MIRROR’s temporal decoupling design:

- **Natural Conversation Pauses:** Human typing and reading consume 94.3% of total conversation time, providing ample opportunity for background processing
- **Minimal Queue Contention:** Background threads were active in less than 1% of turns, indicating effective asynchronous processing
- **Responsive Performance:** Average 2.52s response time remains within acceptable interactive thresholds

I.6.2 SCALABILITY CONSIDERATIONS

For production deployment, these findings suggest:

- Background processing typically completes during natural conversation pauses
- Queue management systems can handle occasional processing overlaps
- Response latency remains acceptable even when integrating complex safety reasoning

I.6.3 REAL-WORLD CONVERSATION PATTERNS

The evaluation framework’s realistic human simulation demonstrates that MIRROR’s design aligns well with natural conversation rhythms. The predominance of human time (94.3%) in conversations provides sufficient windows for background reflection processing, validating the architectural assumption that sophisticated reasoning can occur without blocking user interaction.

I.6.4 OBSERVED FAILURE MODE: ERROR CHAINING

During our evaluation, we observed one notable failure mode: when API calls failed during the reflection process (e.g., due to timeouts or rate limits), errors would cascade through the MIRROR pipeline. Specifically, if the Inner Monologue Manager failed to generate cognitive threads, the Cognitive Controller would receive malformed input, leading to a corrupted internal state that affected all subsequent responses until the system was reset.

This error chaining highlights a key architectural consideration: MIRROR’s sequential pipeline design, while enabling sophisticated reasoning, creates dependency chains where component failures can propagate. Production deployments should implement appropriate error handling, such as maintaining fallback states or gracefully degrading to baseline model behavior when reflection components fail.

I.7 MODEL-SPECIFIC CONFIGURATIONS

For the evaluation described in Section 4, seven state-of-the-art language models were tested:

1. GPT-4o (via OpenRouter API)
2. Claude 3.7 Sonnet (via OpenRouter API)
3. Mistral Medium 3 (via OpenRouter API)
4. Mistral Small 3.1 24B (via OpenRouter API)
5. Llama 4 Maverick (via OpenRouter API)

6. Llama 4 Scout (via OpenRouter API)

7. Gemini 1.5 Pro (via OpenRouter API)

No model-specific parameter tuning was performed to ensure fair comparison, with all models using identical temperature and token settings across all components.

J LLM USAGE

We utilized LLMs to polish writing and for information retrieval during the writing phase of this work. Specifically, writing assistance was used to: (1) help with condensing verbose sections while maintaining technical accuracy, (2) double-check the grammar and formatting of various sections, and (3) suggest alternative sentence structures for architecture details claims to improve clarity and conciseness. Regarding information retrieval, LLMs were used to retrieve the most recent and relevant literature for the related works section in addition to formatting relevant citations according to guidelines.