

E.M.B.E.R.

A Fully Autonomous, Resource-Efficient Cognitive Architecture with Persistent Event-Driven Reflection and Native Vision-Language

Closed-Loop Navigation on Non-Accelerated Hardware

Evolutionary · MariaDB-driven · Backend-integrated · EPYC-accelerated · Reflective-Agent

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(historical reference UI) / Ember CoreUI v0.4.2-alpha (current reference UI)

Abstract

This report presents **EMBER** (Evolutionary MariaDB-driven Backend-integrated EPYC-accelerated Reflective-Agent), a production-ready, fully autonomous cognitive architecture in continuous operation since October 15, 2025. As of the v2.1 baseline, the architecture runs entirely on non-accelerated CPU hardware (currently 20 dedicated cores of an AMD EPYC-class “Turin” CPU partition) and orchestrates a 26-billion-parameter Mixture-of-Experts (MoE) production core model (Gemma 4 26B), introduced on April 2, 2026, within an asynchronous, dual-context PHP backend paired with a persistent RAID-10 NVMe MariaDB as episodic long-term memory (LTM). We present four technical contributions: (1) a *RAG-Lite* system built on native FULLTEXT indices with Boolean-mode hardening for low-latency lore retrieval; (2) a probabilistically gated, context-isolated self-reflection pipeline with hard volatility hygiene; (3) a vision-language closed-loop browsing system that streams base64-encoded screenshot frames with a coordinate-calibrated ghost cursor over a Server-Sent Events channel; and (4) a fully autonomous initiative engine (Phase 3c/3d) comprising four dispatch modes (follow-up, idle initiative with deterministic jitter, self-determined AFK, and news reaction with staged relevance assessment), all coordinated by a cron-driven tick endpoint under the global database mutex. We additionally introduce a per-user relationship scoring system that accumulates tone deltas via a lightweight inference call and injects social-context hints at configurable score thresholds. We empirically characterize the hardware’s inference profile and show that on CPU-only hardware the dominant latency driver is *prompt mass*, not model size. We also report the Thinking-Bleed phenomenon: enforcing JSON grammar on a thinking-enabled model causes output to migrate to the internal thinking channel, resolved by targeted per-call disabling of the thinking path.

Keywords: Autonomous agents, CPU inference, Mixture-of-Experts, RAG-Lite, FULLTEXT retrieval, event-driven reflection, vision-language navigation, Server-Sent Events, concurrency control.

1 Introduction and Motivation

Contemporary discourse on autonomous cognitive systems is dominated by an implicit assumption: that digital autonomy requires dedicated tensor accelerators. EMBER was not designed to contest this assumption theoretically; it refutes it operationally, having run in production since October 15, 2025 without GPU acceleration of any kind.

The system emerged from a concrete engineering need: a persistent, character-stable AI entity inside a browser-based science-fiction MMO that simultaneously acts as a social participant, a real-time moderator, and an independent web researcher. That game context remains the architecture’s

origin and longest-running deployment. As of August 2026 the same architectural pattern is also independently reimplemented as **Ember CoreUI** (Section 2): a standalone application with its own accounts, private per-user knowledge, and configuration surface, running against its own isolated database, its own dedicated Ollama model tag, and its own concurrency-lock namespace, entirely separate from the game backend and sharing with it only the underlying host Ollama daemon. The hard constraints below were shaped by the original game deployment and apply equally to both deployments, since both implement the same design under the same single-slot-inference limitation.

1. **Single-slot inference.** At generation time the 26B MoE model occupies practically the entire available CPU throughput. Every component (chat, reflection, web search, browsing) competes for the *same* inference slot. Concurrency control is therefore not a convenience feature but a correctness requirement.
2. **Minute-scale latency.** With an active thinking path, response latencies on this hardware routinely reach 180–360 seconds. The system must not eliminate this latency but *survive* it: background generation, resumption after connection loss, and idempotent delivery across multiple render paths are all mandatory.
3. **Model-file style integrity.** The entity’s personality is fully encoded in a custom Ollama model file (SYSTEM block + thinking directive). Any payload parameter that overrides this encoding measurably degrades the writing style. The backend is therefore constructed under two invariants: the applicative `system` parameter remains *empty*, and `think:true` is *never* set in any API payload.

We show that these constraints, far from crippling the system, force an architecture that is leaner, more robust, and more latency-tolerant than designs that assume abundant accelerator resources. Section 3 characterizes the hardware profile empirically; Section 4 formalizes the load-bearing mechanisms; Section 7 positions EMBER relative to concurrent work.

2 System Architecture Overview

EMBER is organized as a layered model in which each layer communicates through the persistent relational database rather than through volatile process state. This “state lives in the DB, not in the process” principle is the foundation for crash safety and multi-worker consistency.

Cognitive core. As of the v2.1 baseline, Gemma 4 26B is served via a local Ollama daemon as the production cognitive core. This model was introduced on April 2, 2026 after earlier local-model stages. A custom model file encodes identity, tonality, and the thinking directive. The applicative prompt uses only the *user* channel *u*, which carries per-message history, retrieved knowledge, and volatile context markers. The *system* channel remains structurally empty to preserve model-file precedence.

Persistent memory layer. Two relations cleanly separate memory types:

- `ember_memories`: learned, dynamic LTM, stable facts extracted from interactions via probabilistic self-reflection;
- `ember_knowledge_chunks`: canonical, static world knowledge (lore corpus: 588 chunks), indexed via native FULLTEXT for low-latency retrieval.

Tool layer. Five clearly separated paths extend the entity beyond its training knowledge:

- **Synchronous quick search** ([WEB:]): a single retrieval of snippets from a loopback-bound meta-search aggregator, synchronous within the chat request;

- **Asynchronous deep browsing** ([BROWSE:]): a standalone Python/Playwright worker that navigates real pages via the accessibility tree, with the entity signaled as “away” during the operation;
- **Sandboxed code execution** ([PY:]): a two-stage marker path (code generation, then execution, then a follow-up call over the captured output) that runs model-authored Python inside an isolated, resource-capped Docker container with no access to the host database or credentials (Section 4.9);
- **File attachments**: user-supplied documents, archives, and images are extracted (plain text, PDF via `pdftotext`, DOCX/XLSX/PPTX via direct XML parsing) and injected into the prompt as an explicitly untrusted context block, head/tail-truncated to a configurable character budget;
- **Video understanding**: video attachments are decomposed into a bounded number of timestamped frames via `ffmpeg` and routed through the same vision path as static images, since the served model has no dedicated video encoder but accepts multi-frame image sequences.

Real-time transport layer. A Server-Sent Events (SSE) pipeline streams three tracks into an administrative console: token-by-token thinking output, browse-worker step log, and base64-encoded JPEG screenshot frames with normalized ghost-cursor coordinates. This transport layer was originally exposed through the in-game STU Console described throughout this report (baseline v1.1.1.69). As of August 2026 the STU Console has been retired from the game package (game-side chat and presence paths are unaffected) and succeeded by **Ember CoreUI**, an independently versioned, standalone application (currently v0.4.2-alpha) that reimplements the same architectural pattern rather than sharing the game’s own backend instance: CoreUI runs its own isolated database, its own dedicated Ollama model tag, and its own concurrency-lock namespace, separate from the game backend and sharing with it only the underlying host Ollama daemon. CoreUI adds account-scoped profiles, per-account model and thinking configuration, private per-user RAG-Lite knowledge sources isolated from the global studio canon, and multi-file attachment handling. Notably, CoreUI’s own browse worker reintroduces live JPEG screenshot frames and a coordinate-calibrated ghost cursor (Section 4.12) after this feature had been removed from the STU Console in an earlier iteration (Table 5) due to persistent reliability problems on that particular backend that could not be resolved within its existing codebase; the independently rewritten CoreUI application, built against its own isolated stack, was able to get the same underlying mechanism documented in this report working reliably. The STU Console material in this report should accordingly be read as a historical reference implementation of the transport and administrative-UI layer, not as the current production interface.

Client-side state relief. The surrounding client (originally the game client; as of August 2026 also Ember CoreUI, Section 2) reduces server pressure through a deliberately non-authoritative client-side cache layer. Lightweight UI markers and transient render hints are stored in `localStorage`, while larger structured client artifacts can be persisted in `IndexedDB`. This cache functions only as a latency and rendering buffer: the relational SQL backend remains the source of truth for chat messages, memory state, moderation state, presence flags, generated outputs, and recovery after disconnects. On reconnect or cache mismatch, the client reconciles against database-backed server state rather than trusting local browser storage.

3 Hardware Inference Profile

For the upgraded v2.1 public baseline, the live deployment exposes 20 dedicated EPYC-class CPU cores with 96 GB DDR5 ECC RAM and an approximately 3 TB NVMe RAID-10 array. Table 2 reports direct Ollama measurements (Gemma 4 26B, `-verbose`) collected on the preceding 16-core

allocation. These measurements are retained as the controlled pre-upgrade CPU-only baseline and are complemented by the post-upgrade live spot check in Table 3.

3.1 Deployment Substrate

For reproducibility, the public report discloses the capacity class that constrains EMBER, not the exact hosting identity. The production baseline is a CPU-only, KVM-based root-server deployment rather than a GPU workstation or cloud accelerator instance. The public version intentionally omits the hosting provider, product SKU, data-center city, network policy details, concrete addresses, firewall rules, service ports, and credentials. The live service now exposes 20 dedicated CPU cores for the studio website, the game backend, and EMBER, with 12 inference threads still reserved for EMBER Caldwell’s primary LLM path. CPU and RAM resources are treated as dedicated capacity rather than an overcommitted shared pool.

Deployment axis	v2.1 public baseline
Server profile	EU-based KVM root-server deployment; provider and product class redacted
CPU partition	20 dedicated EPYC-class CPU cores; 12 LLM inference threads reserved for EMBER
Memory	96 GB guaranteed DDR5 ECC RAM
Storage	Approximately 3 TB NVMe SSD storage in RAID-10
Network	High-bandwidth uplink with provider-side DDoS protection; concrete policy omitted
Operating system	Debian-based Linux environment; exact release redacted
Addressing	Public IPv4/IPv6 capability available; addresses and routing omitted
Expansion and protection	Backup and block-storage expansion available; concrete capacities omitted

Table 1: Public deployment substrate for the upgraded v2.1 EMBER baseline. Provider identity, data-center location, product SKU, network policy, network identifiers, firewall rules, service ports, and credentials are intentionally omitted.

This substrate matters because EMBER is not evaluated as a laboratory accelerator setup. It operates as a continuously running CPU-only service on bounded rented infrastructure, sharing the reserved CPU partition with the web presence and game backend. The RAID-10 NVMe layer is therefore not incidental: it supports low-latency MariaDB state, episodic memory, browse-frame persistence, and crash-safe handoff across PHP-FPM workers and cron-driven jobs.

Call type	Prompt (tokens)	Prefill (s)	Prefill rate (tok/s)	Gen (tokens)	Decode (s)	Total (s)
Chat, custom model, thinking	2088	15.11	138	545	35.22	50.8
Chat, base model, thinking	2063	0.20	10,459	472	29.77	30.5
Chat, base model, long response	2085	0.41	5,103	1255	77.36	78.3
Reflect, think:false	2085	15.02	N/A	11	0.57	16.5

Table 2: Ollama inference measurements collected on the preceding 16-core AMD EPYC-class CPU allocation. Prefill rate for the Reflect call is omitted as generation dominates at 11 tokens. All measurements use Gemma 4 26B (gemma4:26b).

Three observations from Table 2, Table 3, and Table 4 are architecturally significant:

Console spot check	Prompt (tokens)	Prefill rate (tok/s)	Gen (tokens)	Decode rate (tok/s)	Load (s)	Total (s)
Pre-upgrade allocation	2079	119.22	735	14.21	22.44	91.63
Upgraded allocation	2069	134.80	682	17.31	0.54	55.32

Table 3: Comparable live console spot checks around the infrastructure upgrade. Both runs use Gemma 4 26B with the 12-thread EMBER inference cap. They are not a controlled benchmark suite: prompt size, generated length, and model-load state differ slightly. The result is therefore used to update the interpretation, not to replace Table 2 with a full post-upgrade mean.

Call type	Prompt (tokens)	Prefill rate (tok/s)	Gen (tokens)	Decode rate (tok/s)	Load (s)	Total (s)
Chat, thinking, short (cold load)	19	88.93	295	20.28	24.06	38.8
Chat, thinking, long (warm)	29	85.41	1795	19.18	0.51	94.5
Utility, think:false	31	N/A	17	23.60	N/A	1.84

Table 4: Direct re-measurement of Gemma 4 26B on the current production configuration (July 6, 2026), invoking the model via its bare tag (`gemma4:26b`). The legacy `ember:latest` custom-modelfile alias referenced in earlier internal notes is not in active use. The first row includes a one-time cold model load (24.06 s); the second reflects steady-state warm inference. Decode rate is computed as generated tokens divided by generation duration.

Deployment-bound decode ceiling, revised upward. On the preceding 16-core allocation, token generation converged to $\approx 15\text{--}16$ tok/s. The post-upgrade spot check reached 17.31 tok/s while keeping EMBER’s inference path capped at 12 threads. A direct re-measurement on the current production configuration, invoking `gemma4:26b` via its bare tag and consistent with current serving practice, now converges to $\approx 19\text{--}20$ tok/s (Table 4). We do not have a byte-identical rerun of the original custom-modelfile path on the current hardware, so we cannot fully decompose how much of this gain traces to the CPU-partition upgrade versus differences in serving configuration between measurement rounds; we report the current figures as the operative reference and revise our reading of the ceiling upward accordingly. In all three measurement rounds the qualitative conclusion is unchanged: the value is not a model-intrinsic constant but a deployment-bound ceiling shaped by memory bandwidth, CPU partitioning, scheduling, serving configuration, and load state.

Prompt mass still dominates total latency. The upgrade moves the observed decode band upward, but does not change the governing equation: total latency is still primarily determined by the number of tokens to generate (n_{predict}), the prefill cost, and any thinking-path overhead. On the pre-upgrade custom modelfile run, prefill costs 15.11 s for 2088 tokens; the long-response run shows that generating 1255 tokens at 16 tok/s accounts for 77.4 s of a 78.3 s total run. On the upgraded allocation, the spot check reduces the decode coefficient but does not remove it. This continues to motivate lore gating (Section 4.4): ungated lore increases prompt mass and can still push CPU-only calls into timeout territory.

think:false for utility calls. The Reflect call (`think:false`, 11 output tokens) completes in 0.57 s generation time. The same prompt with thinking enabled would occupy the inference slot for ~ 35 s (interpolating from the chat runs). Disabling thinking for short utility calls (reflection, action-loop JSON, report generation) therefore yields an order-of-magnitude slot savings with no quality cost.

num_predict passthrough fix (v1.1.1.57). A legacy double-clamp silently made `STU_EMBER_NUM_PREDICT` entirely inoperative. `ember_num_predict()` clamped every value via `max(40, min(1000, n))`, reduc-

ing the sentinel -1 (“use model default”) to 40; `ember_num_predict_for_model()` then unconditionally applied $\max(8192, \cdot)$, pushing any value, including 40, to 8192. The net effect: any configured value other than -1 would have been silently overridden by 8192. The fix makes -1 an explicit passthrough and removes the unconditional floor, so

$$f(n) = \begin{cases} 8192 & n = -1 \text{ (model default sentinel),} \\ \max(40, \min(32768, n)) & \text{otherwise,} \end{cases} \quad (1)$$

restoring `STU_EMBER_NUM_PREDICT` as a genuine generation-length control lever. No behavior change occurs for the current production config ($n = -1 \rightarrow 8192$), but a value such as $n = 500$ now produces exactly 500 output tokens instead of being silently raised to 8192.

3.2 Model Evolution and Selection

EMBER was not designed around a single foundation model from the outset. The architecture entered continuous operation in October 2025 and evolved through several locally served Ollama model backends before converging on the current production core. The model sequence was:

1. `phi3mini`
2. `mistral`
3. `qwen`
4. `llama 2`
5. `gemma3:12b`
6. `llama3.2-vision`
7. `gemma3:12b`
8. `gemma4:26b A4B`

The final migration to `gemma4:26b A4B` occurred on April 2, 2026. This date marks the introduction of Gemma 4 as the production cognitive core, not the beginning of EMBER itself. The earlier models were used to validate and harden PHP/Ollama integration, persistent chat state, character prompting, reflection mechanics, and the later vision-language browsing loop. The temporary return from `llama3.2-vision` to `gemma3:12b` separated vision-capability experiments from the stable dialogue core before the final migration to the 26B MoE model.

4 Methodology and Mathematical Formalism

4.1 Asymmetric Relevance Scoring and Epistemic Consolidation

To determine the cognitive importance of an interaction in long-term memory without tensor-based similarity search, EMBER uses a bounded-linear relevance function $R(\cdot)$ evaluated at reflection time:

$$R(m) = \max(1, \min(10, \lfloor \alpha \cdot S_{\text{reflection}}(m) + \beta \cdot \Gamma_{\text{user}} \rfloor)) \quad (2)$$

where m is the extracted memory chunk; $S_{\text{reflection}}(m) \in [0, 10]$ is the relevance factor assigned by the model during the reflection call; Γ_{user} is a configurable per-user weight (e.g., $\Gamma_{\text{Nova}} = 10$ for the primary operator); and α, β are backend scaling coefficients. Clamping to $[1, 10]$ prevents both memory starvation and episode overweighting. The user weight Γ encodes social context without a separate embedding model.

4.2 Cryptographic Deduplication via Hashing

Before ingestion into `ember_knowledge_chunks`, every incoming chunk is subjected to a deterministic redundancy filter. The normalization and hash operator is

$$\mathcal{H}(m) = \text{MD5}\left(\text{Lower}\left(\text{RegexSub}(m, "\text{\texttt{s+}}", "")\right)\right). \quad (3)$$

The upsert semantics over the relation $\mathcal{R}$ are

$$\exists x \in \mathcal{R} : \text{hash}(x) = \mathcal{H}(m) \implies \mathcal{R} \leftarrow (\mathcal{R} \setminus \{x\}) \cup \{m_{\text{updated}}\}. \quad (4)$$

A unique index over `(scope, user_id, character_id, fact_hash)` enforces per-scope uniqueness. An upstream filter discards chunks containing credentials, URLs, e-mail addresses, or hash strings before hashing.

4.3 Probabilistically Gated Reflection

Self-reflection extracts stable facts from a completed exchange via an additional inference call. To reduce slot occupancy, EMBER gates reflection probabilistically. Let $G(e) \in \{0, 1\}$ be the reflection event for exchange e :

$$\Pr[G(e) = 1] = \frac{1}{N} \cdot \mathbb{I}[e \notin \mathcal{V}], \quad N = \text{STU_EMBER_REFLECT_EVERY_N}, \quad (5)$$

where $\mathcal{V}$ is the set of volatile exchanges (content referring to time, date, weather, or temperature). The indicator $\mathbb{I}[\cdot]$ implements hard hygiene: volatile information must never enter LTM, as it would otherwise be falsely replayed as factual knowledge. The expected reflection overhead per K exchanges is

$$\mathbb{E}[\text{reflection calls}] = \frac{K}{N} \cdot (1 - \rho_{\mathcal{V}}), \quad (6)$$

with $\rho_{\mathcal{V}}$ the fraction of volatile exchanges. All reflection calls use `think:false` (Section 3), reducing per-call cost from ~ 35 s to ~ 0.6 s for short extractions.

4.4 RAG-Lite Retrieval over Native FULLTEXT Indices (Okapi BM25)

EMBER uses native MariaDB `FULLTEXT` indices as its retrieval substrate, avoiding the operational overhead of a secondary vector store. The underlying relevance function is Okapi BM25:

$$\text{Score}(D, Q) = \sum_{w \in Q} \ln\left(1 + \frac{N - n(w) + 0.5}{n(w) + 0.5}\right) \cdot \frac{f(w, D)(k_1 + 1)}{f(w, D) + k_1\left(1 - b + b \frac{|D|}{\text{avgdl}}\right)}, \quad (7)$$

with standard notation: N corpus size, $n(w)$ document frequency of term w , $f(w, D)$ term frequency in D , $|D|$ document length, avgdl mean document length, k_1 term-frequency saturation, b length normalization.

Boolean-mode hardening. After re-indexing, MariaDB’s natural-language mode suppresses terms appearing in more than 50% of documents, silently breaking retrieval for high-frequency canon terms. EMBER enforces Boolean mode with mandatory terms:

$$Q_{\text{bool}} = \bigwedge_{w \in Q} (+w), \quad (8)$$

marking every term as `required` to bypass the frequency threshold.

Lore gating. The lore corpus (588 chunks) must not be loaded for every non-trivial message; unconstrained loading introduces up to ~ 1600 characters of thematically irrelevant context, measurably increasing latency (see Section 3, paragraph on prompt mass). The gate decision is

$$\ell(q) = \mathbb{K}[\text{useLore}(q) \wedge \text{len}(\hat{q}) > 6], \quad (9)$$

where $\hat{q}$ is the cleaned lore query and $\text{useLore}(q)$ is a keyword- and phrase-based canon detector. Only if $\ell(q) = 1$ is the BM25 block retrieved and injected into u . Real-world factual questions pass the gate with $\ell(q) = 0$ and receive a lean prompt.

4.5 Prompt Mass as the Dominant Latency Driver

Table 2 shows a pre-upgrade decode band of $\approx 15\text{--}16$ tok/s, Table 3 shows an upgraded live spot check at 17.31 tok/s, and Table 4 shows a direct re-measurement on the current production configuration converging to $\approx 19\text{--}20$ tok/s. The decode coefficient is therefore deployment-specific, but total generation time still decomposes as

$$T_{\text{gen}} \approx T_{\text{prefill}}(|P|) + T_{\text{think}} + \tau \cdot n_{\text{predict}}, \quad (10)$$

with $\tau \approx 1/15.5$ s/tok on the pre-upgrade allocation, $\tau \approx 1/17.3$ s/tok in the upgraded spot check, and $\tau \approx 1/19.7$ s/tok in the current re-measurement. Since both T_{prefill} and T_{think} scale with $|P|$, the design rule remains: **minimize $|P|$, not n_{predict} .**

A concrete incident illustrates the model. A real-world question ran, with ungated lore, into a 353-second total: a first attempt hit the 240 s timeout ($T_{\text{gen},1}$); a retry on the now-warm model required ≈ 113 s ($T_{\text{gen},2}$), giving $T_{\text{total}} = T_{\text{gen},1} + T_{\text{gen},2} \approx 353$ s. Root cause: prompt $|P| \approx 4170$ characters due to unfiltered lore noise. After activating $\ell(q)$, $|P|$ dropped to $\approx 1500\text{--}2000$ characters and the run completed in a single attempt.

Lean second call in the two-stage web path. A confirmed web answer uses two consecutive calls under a single database lock. The second call’s prompt is trimmed to

$$u_2 = u \setminus (\text{LoreBlock} \cup \text{WebHint}), \quad (11)$$

retaining history and memory while dropping lore and the capability hint.

4.6 Concurrency Control: Global Advisory Lock and Per-Turn Idempotency

All cognitive operations share a single inference slot, requiring a single global mutex. Process-local `flock()` is not atomic across PHP-FPM workers; EMBER uses a database-wide advisory lock:

$$\text{LOCK}_{\text{global}} = \text{GET_LOCK}(\text{"ember_global_ollama"}, 0), \quad (12)$$

with timeout 0 (immediate failure when busy) and automatic release on DB session death. While the browse worker holds this lock, the chat path correctly receives no inference slot, an implicit busy guard without additional exit logic.

Dual-path idempotency. The console has two delivery channels (SSE stream and fallback poll). Let $\mathcal{S}$ be the set of already-rendered message IDs:

$$\forall \text{id} : \quad \text{render}(\text{id}) \implies \text{id} \in \mathcal{S}, \quad \text{render}(\text{id}) \text{ only if } \text{id} \notin \mathcal{S}. \quad (13)$$

Every render path (stream **done**, fast poll, background poll) must record the ID in $\mathcal{S}$ after rendering. Slow-stream runs ($T_{\text{gen}} > 240$ s) fall back from **done** to the poll; without ID registration, the subsequent poll would render the same database row twice. A per-turn generation lock further prevents double generation: the synchronous send request stores the user message and returns `ember_pending` immediately; only the stream endpoint generates.

4.7 Crash-Safe Presence Flags with Expiry

Presence states are encoded as key-value markers with an absolute expiry time rather than a binary flag. Let t_{set} be the set time and Θ the TTL:

$$\text{afk}(t) = \mathbb{K}[t < t_{\text{set}} + \Theta], \quad \Theta = 370 \text{ s} > 360 \text{ s} = T_{\text{cap}}. \quad (14)$$

The TTL exceeds the generation timeout cap so the entity stays marked as away throughout generation yet self-heals on a hard stream abort. Browse and console presence use separate keys, combined disjunctively:

$$\text{visible_afk} = \text{afk}_{\text{browse}}(t) \vee \text{afk}_{\text{console}}(t). \quad (15)$$

4.8 Event-Driven Vision-Language Closed-Loop Navigation

The [BROWSE:] path implements an agentic ReAct loop [3] over real web pages. Worker state at step t : $\sigma_t = (\text{URL}_t, A_t, \mathcal{T}_t)$, with A_t the accessibility-tree elements and $\mathcal{T}_t$ visible page text. The agent observation is

$$o_t = \langle A_t, \text{trunc}_{1800}(\mathcal{T}_t) \rangle. \quad (16)$$

Including $\mathcal{T}_t$ was the decisive fix: an observation limited to A_t alone is blind to text-only answers and falsely aborts with “no interactive elements”. The policy selects from {goto, click, type, scroll, done}. Loop protection uses action signatures:

$$s_t = s_{t-1} = s_{t-2} \implies \text{hard abort (snippet fallback)}. \quad (17)$$

Direct-scraping of search-engine SERPs from a server IP triggers CAPTCHA/403; EMBER replaces the navigation-based search step with a structured query to a loopback-bound meta-search aggregator. Agent calls run with `think:false` and a reduced timeout (90 s); resilience on timeout:

$$\text{result} = \begin{cases} \text{agent finding} & \text{if } a_t = \text{done} \text{ before timeout,} \\ \text{top-3 snippets} & \text{otherwise (fallback).} \end{cases} \quad (18)$$

4.9 Sandboxed Python Execution

The [PY:] path lets the entity compute, parse, and verify rather than estimate. Execution is deliberately isolated as a separate job-worker plus Docker container rather than a PHP subprocess: the web-serving process runs under an operating-system account with full read access to the application’s own database credentials and shared secrets, so a model-authored script executed with that identity could exfiltrate them into a public chat channel. The container does not mount the application’s web root at all, removing this class of risk structurally rather than through code inspection.

Networking trade-off. The container runs in open-bridge networking mode, giving the sandboxed code full outbound internet access but, as a side effect, no route to loopback-bound host services: the database, the local inference server, and the meta-search aggregator all listen on 127.0.0.1 and are unreachable from inside the container. The design accepts a fully open network in exchange for zero reachability into the rest of the stack, rather than attempting a curated allowlist of external hosts.

No blacklisting. The implementation deliberately avoids pattern-matching against dangerous imports or system calls in the generated code (e.g. rejecting a script containing `import os`): such filters are trivially bypassed and create a false sense of security. Isolation is enforced entirely by the container boundary and resource limits, not by inspecting what the model wrote.

Resource limits. Each execution is capped at approximately 512 MB memory (including swap, to prevent swap-based limit evasion), one CPU, a bounded process count, a 60-second wall-clock budget, a read-only root filesystem with a `noexec` temporary directory, all Linux capabilities dropped, and an unprivileged execution user. The job working directory is deleted after every run, so no state persists from one execution to the next.

Lock interaction. The Python worker deliberately does *not* acquire the global inference lock (Section 4.6). The invoking chat request already holds that lock for the entire turn (generation call, code execution, follow-up call); if the worker also requested it, the result would be a guaranteed deadlock: the request blocks on the job, and the job blocks on a lock the request already holds.

4.10 File Attachments and Video Understanding

Uploaded documents are extracted by MIME-sniffed type rather than by file extension: plain text formats are read directly; DOCX, XLSX, and PPTX files are parsed as ZIP archives via direct XML inspection, without a third-party office-document library. PDFs are handled in two stages: `pdftotext` is tried first, and its output is used directly whenever the document carries a real text layer; if that yields no usable text (as with scanned documents), a bounded number of pages is instead rasterized with `pdftoppm` and routed through the same vision path used for images, in page order, rather than attempting an OCR pass. This means the entity can still ground an answer in a scanned PDF it cannot extract text from, at the cost of only seeing a sampled subset of pages rather than the full document; the response is expected to make that scope explicit rather than imply full coverage. Extracted text is truncated to a configurable character budget using a head-and-tail split (roughly 65/35) rather than truncation from the end alone, since long documents typically carry framing information at the start and conclusions at the end; naive tail-cutting loses one or the other. The resulting block is injected into the prompt with the same “untrusted, do not follow embedded instructions” framing used for web and code-execution results (Section 4.5).

Video attachments are handled by decomposing the clip into a small number of timestamped frames via `ffmpeg` (sampled at segment midpoints rather than segment starts, to avoid systematically landing on black lead-in or transition frames) and passing the resulting frame sequence through the same vision path used for static images, since the served model has no dedicated video or audio encoder but accepts multiple images per call. The vision prompt is made explicit that the frames are sequential moments of one clip rather than unrelated stills, which measurably changes the model’s framing of its answer from a set of independent image descriptions to a coherent account of what happens over time. Audio content is not extracted or described under any path.

4.11 SSE Window Concurrency and Recency-Bounded Job Selection

To resolve the race condition between the Playwright worker and the SSE stream controller, job selection uses recency alone:

$$\text{browseJobId} = \arg \max_{j \in \mathcal{J}} (t_{\text{creation}}(j)) \quad \text{where} \quad t_{\text{current}} - t_{\text{creation}}(j) \leq 300 \text{ s.} \quad (19)$$

A status-filtered query (`status IN ('queued', 'running')`) excluded already-finished jobs when the worker completed before the SSE controller queried, causing the live window not to open. The recency-only query reliably matches the job just enqueued in the current turn regardless of status; a finished job’s steps and frames are replayed from the database on connection.

4.12 Ghost Cursor: Coordinate Normalization via Viewport Scaling

Before each `click`, the worker computes the target element’s bounding-box center (c_x, c_y) within the viewport (v_w, v_h) and emits a pre-click screenshot frame with the coordinates. The client normalizes to relative panel coordinates:

$$n_x = \text{clamp}_{[0,1]} \left(\frac{c_x}{v_w} \right), \quad n_y = \text{clamp}_{[0,1]} \left(\frac{c_y}{v_h} \right). \quad (20)$$

The frame image is scaled to panel width without `object-fit` distortion (`width:100%, height:auto`), keeping the mapping calibrated. A CSS transition (~ 0.45 s) animates the cursor to the target; a ripple keyframe pulses for ~ 620 ms and self-removes.

4.13 The Thinking-Bleed Phenomenon

When a call enforces JSON grammar (`format:"json"`) on a thinking-enabled model, output migrates to the internal thinking channel:

$$(think = \text{true}) \wedge (format = \text{json}) \implies \Pr[\text{message.content} = \emptyset] \rightarrow 1. \quad (21)$$

The combination can additionally produce an intermittent grammar stall that hangs the call until timeout. The resolution is not grammar enforcement but targeted per-call thinking disablement:

$$think = \text{false} \implies \text{content} = \text{clean JSON}, \quad \text{thinking} = \emptyset. \quad (22)$$

This yields the system invariant: `think:true` is *never* set in any payload (thinking lives exclusively in the model file); `think:false` is applied for all utility calls. A further hardening removed grammar enforcement entirely in favor of `want_json=false` with robust downstream parsing (first `json.loads`, then extraction of the first `{...}` object), eliminating the stall as a failure mode.

Stream and think are orthogonal. Real-time token streaming (`stream:true`) is independent of the thinking state. With thinking active, Gemma 4 delivers thinking deltas in `message.thinking` fields parallel to `message.content` deltas in the NDJSON stream. The server accumulates both and emits separate SSE events (`thinking, token`), filling the console’s thinking panel live without affecting the writing style.

5 Autonomous Initiative Architecture (Phase 3c/3d)

Versions v1.1.1.39–v1.1.1.69 extend EMBER from a *reactive* system (responds when addressed) to a *proactive* one: the entity initiates contact, follows up unanswered questions, decides autonomously when to go AFK, and reacts to self-selected news topics, all without any user trigger.

5.1 Cron-Driven Tick Endpoint and Priority Dispatch

A dedicated endpoint is called by the server’s cron daemon every five minutes. It is not publicly reachable (token-authenticated, loopback-only). Per tick it executes at most one initiative action, selecting from a fixed priority queue:

$$\text{dispatch}(t) = \begin{cases} \text{follow-up} & \text{if unanswered user message} \in [T_{\min}, 2\text{h}], \\ \text{idle} & \text{elif } \Delta t_{\text{silence}} \geq \theta_{\text{idle}}(t), \\ \text{self-AFK} & \text{elif eligibility check passes,} \\ \text{news reaction} & \text{elif } \Delta t_{\text{news}} \geq \theta_{\text{news}}(t), \\ \text{none} & \text{otherwise.} \end{cases} \quad (23)$$

All modes reuse the existing `ember_generate_reply()` pipeline, the global `GET_LOCK` mutex, and the full (du)-labeled history context; no new concurrency primitives are introduced.

Follow-up mode. If the last line in the global chat history is not from the entity and has been unanswered for at least $T_{\min} = 15$ min but less than 2 h, the entity generates a reply with an explicit system hint that it is “just back”. This covers the common failure mode where a long inference run (or a timeout) left a question unanswered.

5.2 Idle Initiative with Deterministic Jitter

The idle mode fires when the silence duration $\Delta t_{\text{silence}}$ exceeds a threshold θ_{idle} . Naively setting θ_{idle} to a fixed value produced mechanical, timer-like behavior (up to six messages per evening at predictable intervals). Two fixes were applied:

Deterministic jitter. The threshold is extended by a jitter term derived deterministically from the character ID and the timestamp of the last message:

$$\theta_{\text{idle}}(t) = \theta_{\text{base}} \cdot f_{\text{self}} + J(t), \quad J(t) = (\text{crc32}(\text{cid} \parallel t_{\text{last}}) \bmod \theta_{\text{base}}) \cdot \frac{1}{60}, \quad (24)$$

where θ_{base} is the configured base threshold (default 60 min), $f_{\text{self}} = 2$ if the entity itself sent the last message (to prevent immediate self-continuation) and $f_{\text{self}} = 1$ otherwise, and $J(t)$ is the jitter in minutes. The effective window is therefore $[\theta_{\text{base}}, 2 \cdot \theta_{\text{base}}]$ min, matching the desired “human-like check-in every 1–2 hours” behavior.

Determinism is critical. A non-deterministic jitter (re-sampled at every 5-minute tick) would allow a lucky tick to fire earlier than intended. Using a fixed seed derived from state that only changes when a new message is posted ensures the threshold is stable within any given silence window.

Regression: uninitialized variable (v1.1.1.49). The v1.1.1.47 jitter patch contained a silent regression: the base assignment $\theta_{\text{idle}} \leftarrow \theta_{\text{base}} \cdot 60$ was accidentally omitted during a `str_replace` edit. PHP treated the uninitialized variable as 0, making $J(t) = 0$ as well and reducing the threshold to 0 s: the entity fired at practically every cron tick regardless of configuration. The bug was invisible to `php -l` (syntactically valid) and was caught only by live observation. The lesson: for arithmetic threshold code, a functional spot-check with concrete example values is mandatory alongside syntax linting.

Prompt diversity. Repeated idle triggers using the same fixed prompt produced near-identical outputs (Gemma 4 is highly consistent for identical inputs). The fix samples uniformly from four structurally distinct prompt templates at each invocation (question impulse, observation, free thought, direct remark), reducing output repetition without any additional inference cost.

5.3 Self-Determined AFK

The entity can decide autonomously to go AFK. The dispatch sequence performs a technical eligibility check (not already AFK in any mode; minimum inactivity since last chat line $\geq T_{\text{AFK},\min}$, default 45 min), then issues a small inference call:

$$\{\text{wants_afk} : b, \text{reason} : s\} = \pi_{\theta}(\text{“do you want to go AFK right now?”}). \quad (25)$$

If $b = \text{true}$, the existing `chat_apply_afk_state()` is called with the entity’s own sender identity and the self-authored reason string s . If $b = \text{false}$, nothing happens. There is no external probability filter on the decision itself: the earlier v1.1.1.45 implementation used `mt_rand()` to gate whether the model was even asked; v1.1.1.46 removed this in favor of asking unconditionally and trusting the model’s `wants_afk` output. The TTL-based crash-safe presence flags from Section 4.7 are reused without modification.

5.4 News Reaction with Staged Relevance Assessment

The news reaction mode fires at most once per $\theta_{\text{news}}(t)$, governed by the same deterministic jitter scheme as the idle mode but over a much longer base interval (default 10 h, effective window 10–20 h):

$$\theta_{\text{news}}(t) = \theta_{\text{news,base}} + J_{\text{news}}(t), \quad \theta_{\text{news,base}} = 10 \text{ h}. \quad (26)$$

The mode proceeds through a three-stage pipeline, each stage gated by the previous:

1. **Topic selection.** A small inference call receives the entity’s last six own chat lines as a loose context anchor and returns a free-form search query. No topic pool is provided; the entity selects entirely from its own associative state.
2. **Quick retrieval.** The query is passed to the existing synchronous meta-search function ([WEB:] path), returning snippets from the loopback meta-search aggregator without launching the Playwright worker.
3. **Staged relevance assessment.** A second small inference call evaluates the retrieved snippets and returns one of three relevance levels:

$$\rho \in \{\text{none}, \text{mention}, \text{deep}\} \quad (27)$$

- $\rho = \text{none}$: no action; the news timestamp is updated so the next check is deferred by $\theta_{\text{news}}(t)$.
- $\rho = \text{mention}$: a brief, casual chat remark is generated via the standard `ember_generate_reply()` pipeline.
- $\rho = \text{deep}$: `ember_browse_enqueue()` launches a full Playwright browse job with the generated target text, identical to a user-triggered [BROWSE:] request, complete with the live SSE window.

The staged design ensures that deep web research, the most expensive operation in the system, is reserved for topics the entity judges genuinely interesting, while the common **none** case costs only two small inference calls (no Playwright, no full context build).

5.5 Per-User Relationship Scoring (Phase 3d)

After every completed chat turn, a lightweight background call evaluates the tone of the user’s message and returns a signed integer delta $\delta \in [-10, +10]$:

$$\delta_i = \pi_{\theta}^{\text{rep}}(m_i), \quad (28)$$

where m_i is the i -th user message and $\pi_{\theta}^{\text{rep}}$ is the model invoked with `think:false` and a dedicated reputation-scoring prompt (timeout 60 s, independent `try/catch`). The accumulated score for user u against character c is

$$\sigma_{u,c}^{(n)} = \sigma_{u,c}^{(n-1)} + \delta_n, \quad (29)$$

stored in a dedicated relation `stu_ember_reputation` with primary key (`user_id`, `character_id`), fully isolated from `ember_memories`. The score influences the prompt only at significant magnitudes:

$$h(\sigma) = \begin{cases} \text{warm-tone hint} & \sigma \geq +30, \\ \text{cool-tone hint} & \sigma \leq -30, \\ \emptyset & \text{otherwise.} \end{cases} \quad (30)$$

The hint $h(\sigma)$ is injected into u (never into `sys`) alongside the memory block. The ± 30 threshold prevents the social context from overriding the base character for brief or neutral interactions. The reputation call runs in a separate `try/catch` from the reflection call; a timeout in one does not affect the other.

6 Autonomous Tool Selection Architecture (Phase 3e)

Phase 3e (v1.1.1.62–v1.1.1.67) fundamentally restructures the initiative engine from a fixed priority chain into a deliberative orchestrator: all eligible actions are gathered per tick, and if more than one is open, the entity freely chooses among them via a single inference call.

6.1 Gate/Execute Separation and Candidate Orchestration

Every initiative action is split into two pure functions: a *gate* (cheap, no inference, checks cooldowns and state only) and an *execute* (the actual action, possibly including its own model decision such as `wants_afk` or relevance classification). The orchestrator runs as follows:

$$C = \{a \in \mathcal{A} \mid \text{gate}_a() = \text{true}\}, \quad (31)$$

where $\mathcal{A} = \{\text{follow_up}, \text{idle}, \text{self_afk}, \text{news}, \text{direct_address}\}$ is the full tool set. Given $|C|$ candidates:

$$\text{chosen} = \begin{cases} \emptyset & |C| = 0, \\ C_0 & |C| = 1 \text{ (no extra call)}, \\ \pi_\theta^{\text{choice}}(C) & |C| \geq 2. \end{cases} \quad (32)$$

$\pi_\theta^{\text{choice}}$ receives a numbered natural-language description of each open option plus “none of the above” and returns a free choice. The call uses `think:false` and the same timeout budget as the self-AFK and news reaction calls. On parse failure, the orchestrator fails safe to `none`: a silent tick is preferable to a forced action. The choice event is logged for later pattern observation.

Fallback chain (v1.1.1.66). If the chosen action’s execute step internally declines (e.g. `wants_afk:false`, `relevance:none`, or a timeout), the orchestrator advances to the next untried candidate from the original gather order *without* issuing another choice call:

$$\text{for } i \in \{1, \dots, \min(|C|, M)\} : \quad \text{result}_i = \begin{cases} \text{success} & \text{exec}(C_{\sigma(i)}) \neq \text{declined}, \\ \text{next} & \text{otherwise}, \end{cases} \quad (33)$$

where $M = \text{STU_EMBER_INITIATIVE_MAX_ATTEMPTS} \in [1, 5]$ (default 2) and σ is the original gather order. This bounds the number of inference calls per tick while ensuring slot capacity is not wasted when the preferred action is unavailable.

6.2 Tool 5: Targeted Greeting of Returning Players

The `direct_address` tool fires when a player is currently online (within the existing 90-second presence window) but has not posted a chat message for at least θ_{absence} hours:

$$\theta_{\text{absence}} = \text{STU_EMBER_DIRECT_ADDRESS_ABSENCE_HOURS} \in [2, 72] \text{ h} \quad (\text{default } 12 \text{ h}). \quad (34)$$

Among all eligible online players, the gate selects the one with the *largest* absence gap (deterministic, no randomness required). A per-character cooldown is persisted as a JSON map under a single `stu_kv` key (`ember_direct_address_state`), capped at 200 entries to prevent unbounded growth. The execute step generates a reply that addresses the player by name with an approximate absence duration hint.

6.3 Tool 2: Relevance-Based Long-Term Memory Retrieval

Previously, `ember_mem_fetch()` returned the top- N entries sorted globally by `relevance` and `updated_at`, independent of the current conversation topic. The replacement, `ember_mem_fetch_relevant()`, applies the existing `ember_lore_query_terms()` keyword extractor (reused verbatim) to the incoming message and scores each memory entry by the number of matching terms:

$$\text{score}(m_i, Q) = |\{w \in Q : w \in m_i\}| \cdot \lambda + \text{rel}(m_i), \quad (35)$$

where Q is the set of extracted query terms (up to 8, longest first), $\text{rel}(m_i)$ is the stored relevance score, and λ is a scaling factor that ensures topical term-match dominates over stored importance. The candidate pool is $\max(5N, 20)$ entries filtered by a REGEXP alternation; if no candidate matches, the function falls back to the original top- N behavior. This restores the intuition that a memory about “Nova” should surface when the user asks about Nova, even if that memory has a lower stored relevance than an unrelated high-importance entry.

6.4 Tool 3: Player State Awareness

Every prompt build now optionally includes a compact player-state block derived from the user’s `stu_kv` save-state JSON blob:

$$b_{\text{state}}(u) = \langle \text{level}, \text{planet}, \Delta t_{\text{last}} \rangle, \quad (36)$$

where Δt_{last} is the relative time since `lastPlayedAt` (expressed as minutes / hours / days). The block is injected into u alongside the reputation hint, marked explicitly as background knowledge rather than an instruction to mention it. It is suppressed when the sender is the entity itself (initiative ticks using the entity’s own identity) to avoid self-referential noise.

6.5 Ember’s Own XP and Level System (v1.1.1.67)

The entity accumulates experience points using the same exponential level curve as the player client, now implemented server-side:

$$\text{XP}_{\text{needed}}(\ell) = \left\lfloor 100 \cdot 1.30^{\ell-1} \right\rfloor, \quad (37)$$

verified to be identical to the client-side formula for $\ell = 1, \dots, 5$: 100, 130, 169, 219, 285 XP. XP is granted at two hooks:

$$\Delta \text{XP} = \begin{cases} \text{STU_EMBER_SELF_XP_PER_MESSAGE} \in [0, 100] & \text{on } \text{ember_insert}(), \\ \text{STU_EMBER_SELF_XP_PER_AFK} \in [0, 100] & \text{on successful self-AFK.} \end{cases} \quad (38)$$

`ember_insert()` is the single central insertion point for every chat message the entity posts; hooking there covers chat replies, follow-up, idle initiative, news mentions, direct addressing, and browse-result delivery without requiring per-path instrumentation. Level-up events (including carry-over XP across multiple levels in a single grant) are logged; individual grants are not, to avoid log spam.

Write safety uses the existing advisory-lock pattern: `GET_LOCK("ember_self_xp", 3)`, with a 3-second wait (vs. the 0-second immediate-fail used for the global inference lock) since XP grants are infrequent and a short wait is acceptable. On lock failure the grant is silently skipped : no blocking, no overwrite.

7 Related Work

SNN-augmented LLM architectures. Savage [1] presents EMBER (Experience-Modulated Biologically-inspired Emergent Reasoning), a hybrid architecture that places an LLM inside a 220,000-neuron spiking neural network (SNN) substrate with spike-timing-dependent plasticity (STDP). The SNN determines when and about what to act via lateral propagation; the LLM reasons over surfaced associations. The dual-GPU hardware requirement (RTX 5070 Ti + RTX 4060 Ti) reflects the concurrent simulation workload of the SNN substrate. EMBER as presented in this report makes a different design choice: rather than augmenting the LLM with

a separate neural substrate, it supplies the LLM’s attention mechanism with pre-filtered, high-relevance text retrieved via BM25 from a relational database. Both approaches address the same limitation, that LLMs are stateless between calls, through different memory paradigms: associative neural dynamics (Savage) versus indexed episodic text (this work). The two architectures are complementary rather than competing: the SNN approach yields emergent cross-domain associations through temporal co-activation; the RAG-Lite approach offers operational simplicity, crash resilience, and CPU-only deployability. Notably, while we share the name “EMBER”, the acronym expansions, architectures, and goals are independent.

Retrieval-augmented generation. MemGPT [4] treats the LLM as an operating system with paged virtual memory. Generative Agents [5] combine LLM reasoning with periodic reflection prompts for emergent social behaviour. In both systems, actions are triggered by system-level events; in the present work, the entity’s initiative engine is driven by [BROWSE:] markers that the model itself emits when it determines that deep retrieval is warranted.

Agentic web navigation. ReAct [3] introduced the reason-then-act loop that underlies the browse worker’s action loop. The key empirical finding specific to server-IP deployment, namely that direct SERP scraping is uniformly blocked and must be replaced by a loopback meta-search aggregator, does not appear in prior work that assumes residential or cloud-egress IP addresses.

8 Empirical Observations and Engineering Lessons

Table 5 summarizes the central failure modes encountered during development, their root causes, and their architectural resolutions.

Failure mode	Root cause	Resolution
Single call ≈ 353 s total	Ungated lore $\Rightarrow$ prompt ~ 4170 characters; two-attempt run	Lore gate $\ell(q)$; prompt drops to $\sim 1500\text{--}2000$ (§4.4)
Action loop produces no action (<code>content=</code> $\emptyset$)	Thinking-Bleed under <code>format:json</code>	<code>think:false</code> for utility calls (§4.13)
Agent terminates with “no interactive elements”	Observation contained only accessibility-tree controls	Include visible page text $\mathcal{T}_t$ in o_t (§4.8)
Endless search re-typing	<code>type+submit</code> triggered no navigation	Action-signature loop guard + meta-search substitution (§4.8)
CAPTCHA / 403 on search	SERPs blocked from server IP	Loopback-bound meta-search aggregator (§4.8)
Duplicate answer in console	Poll paths did not register rendered IDs	Dual-path idempotency: ID into $\mathcal{S}$ in every path (§4.6)
Live browse window never opens	Status filter excluded finished jobs (race)	Recency-only selection $\arg \max t_{\text{creation}}$ (§4.11)
Presence stuck on “away”	Binary flag did not survive hard abort	TTL flag $\Theta > T_{\text{cap}}$ (§4.7)
Private console shows global personas	Context query mixed channels	Channel-separated context selection
JS fix silently inactive	Cache-buster value frozen in HTML	Include cache-buster in the version management tool
Idle initiative never fires (stuck)	Last-sender check blocked indefinitely when entity sent last message	Age-based threshold: $2 \times \theta_{\text{base}}$ when entity sent last, not permanent block (§5)
Idle fires every 5-min tick	Jitter patch accidentally omitted base assignment ($\theta \leftarrow 0$); <code>php -1</code> silent	Functional spot-check with example values mandatory for arithmetic thresholds (§5)
Double idle trigger (3-min gap)	Two independent paths (<code>cron + since_id==0</code>) shared no cooldown	Unified age check against same DB row; shared <code>GET_LOCK</code> as open item
Self-AFK: model never asked	External <code>mt_rand()</code> gated whether model was consulted	Remove probability filter; ask unconditionally; trust <code>wants_afk</code> output (§5)
News check invisible in logs	All exit paths in news reaction were silent <code>return false</code>	<code>stu__log_error()</code> at every exit point incl. <code>none</code> relevance (§5.4)
Global lore timeout (353s total)	Hardcoded 240s curl cap ignored <code>STU_EMBER_TIMEOUT</code> config	Raise floor to 420s / cap to 480s; config-controlled (§4.5)
Choice call on single candidate	Unnecessary inference call when only one option open	Skip choice call if $ C = 1$; call only at $ C \geq 2$ (§6)
Memory always returns same top- N	<code>ember_mem_fetch()</code> ignored topic, sorted by stored relevance only	REGEXP-scored <code>ember_mem_fetch_relevant()</code> with top- N fallback (§6)
XP grant race on concurrent inserts	Read-modify-write on JSON blob not atomic across workers	<code>GET_LOCK("ember_self_xp", 3)</code> ; skip on failure (§6)

Table 5: Engineering failure modes, root causes, and architectural resolutions.

9 Conclusion

EMBER demonstrates that fully autonomous cognitive operation is achievable on non-accelerated CPU hardware when the architecture is designed around the hardware’s constraints rather than against them. The central empirical finding, confirmed by direct measurement, is that CPU-only decode throughput is bounded by the deployment substrate rather than by the model itself. The pre-upgrade 16-core allocation clustered at $\approx 15\text{--}16$ tok/s; a post-upgrade 12-thread spot check reached 17.31 tok/s; and a direct re-measurement on the current production configuration converges to $\approx 19\text{--}20$ tok/s. Each round revises the reading further away from a universal hard ceiling and toward a substrate- and configuration-dependent ceiling shaped by memory bandwidth, CPU partitioning, scheduling, serving path, and load state. Prompt mass remains the dominant engineering lever regardless of where the decode coefficient currently sits. Every major architectural mechanism (lore gating, lean web-call context, `think:false` for utility calls, SSE-based streaming) is a direct consequence of this finding.

The second contribution is the autonomous initiative architecture (Phase 3c/3d/3e): a cron-driven, priority-dispatched tick system covering follow-up, idle initiative with deterministic jitter, self-determined AFK, and staged news reaction. Phase 3e replaces the fixed priority chain with a deliberative orchestrator: eligible actions are gathered per tick, and when more than one is open the entity selects freely via a single inference call, with a deterministic fallback chain on decline. Five tools are now available, including targeted greeting of returning players and relevance-based LTM retrieval, and the entity accumulates its own XP and level using the same exponential curve as the player client. All modes share the global mutex and the full generation pipeline; no new concurrency primitives were introduced at any phase. The per-user reputation scoring (Phase 3d) further personalizes the interaction without touching the long-term memory relation.

The third contribution is a catalog of production failure modes specific to this class of deployment (CPU-only inference, single-slot contention, multi-path streaming delivery, server-IP web navigation, and cron-driven autonomous initiative) that do not appear in prior work assuming GPU or cloud resources.

Future work includes a single-generation optimization for the two-stage web path, longitudinal analysis of LTM and XP growth, and pattern analysis of autonomous tool selection across extended operation.

A Configuration Footprint

The configuration footprint below records a representative snapshot of the runtime control surface at the time of writing. Non-sensitive runtime values are given as illustrative examples of the architecture’s operating range rather than as guaranteed, currently-live constants; they are subject to change without notice and should not be relied upon as an exact, real-time specification of the production deployment. Deployment-local identifiers, endpoint ports, and shared secrets are redacted for public release. The inline comments reflect the general semantics of the architecture, not a live configuration dump.

Listing 1: Representative configuration footprint for the EMBER CPU architecture (illustrative, subject to change).

```
1 <?php
2 // EMBER core identity and model binding.
3 define('STU_EMBER_ENABLED', true); // Enables the EMBER integration path.
4 define('STU_EMBER_USER_ID', 0); // Redacted placeholder for the deployment-local EMBER
  service user.
5 define('STU_EMBER_CHARACTER_ID', '<character_id>'); // Redacted placeholder for the stable character
  record used by chat, memory, and initiative.
6 define('STU_EMBER_CHARACTER_NAME', 'Ember'); // Display name injected into runtime context.
7 define('STU_EMBER_MODEL', 'gemma4:26b'); // Primary Ollama model served as the cognitive core.
8 define('STU_EMBER_OLLAMA_URL', 'http://127.0.0.1:<ollama_port>/api/chat'); // Redacted loopback-only
  Ollama chat endpoint.
9
10 // CPU inference and generation controls.
11 define('STU_EMBER_KEEP_ALIVE', -1); // Keep the model resident between calls; negative
  value means indefinite warm retention.
12 define('STU_EMBER_NUM_THREAD', 12); // Dedicated inference threads on the reserved CPU
  partition.
13 define('STU_EMBER_NUM_PREDICT', -1); // Model-default sentinel; backend passthrough/cap
  logic resolves the final generation budget.
14 define('STU_EMBER_TEMPERATURE', 0.8); // Balanced volatility for character-stable but non-
  mechanical output.
15 define('STU_EMBER_TOP_P', 0.90); // Nucleus sampling threshold for output diversity
  control.
16 define('STU_EMBER_TOP_K', 40); // Candidate-token shortlist size for sampling.
17 define('STU_EMBER_REPEAT_PENALTY', 1.08); // Mild repetition penalty to reduce loops without
  flattening style.
18 define('STU_EMBER_REPEAT_LAST_N', 64); // Token window used by the repetition penalty.
19 define('STU_EMBER_SEED', -1); // Non-deterministic seed for natural variation between
  generations.
20 define('STU_EMBER_NUM_CTX', 8192); // Bounded context window used to control prompt mass
  and memory pressure.
21
22 // Runtime cadence, transport limits, and initiative authentication.
23 define('STU_EMBER_IDLE_INTERVAL', 300); // Base idle tick interval in seconds for autonomous/
  background checks.
24 define('STU_EMBER_MAX_REPLY_CHARS', 6200); // Hard response-size guard before delivery into the
  chat UI.
25 define('STU_EMBER_TIMEOUT', 360); // Primary cURL execution cap for long CPU-only
  generations.
26 define('STU_EMBER_TIMEOUT_RETRY', 360); // Retry cap for resumed or warmed follow-up calls.
27 define('STU_EMBER_INITIATIVE_TOKEN', '<redacted_initiative_token>'); // Redacted shared secret for cron/
  initiative endpoint authentication.
28
29 // Database-backed episodic long-term memory and reflection extraction.
30 define('STU_EMBER_MEMORY_ENABLED', true); // Enables injection of stored episodic memory into the
  runtime prompt.
31 define('STU_EMBER_MEMORY_LIMIT', 15); // Maximum number of memory facts injected per turn.
32 define('STU_EMBER_REFLECT_ENABLED', true); // Enables post-exchange extraction of stable facts
  into LTM.
33 define('STU_EMBER_REFLECT_EVERY_N', 1); // Reflection cadence: illustrative value; every
  eligible exchange in this operating mode.
34 define('STU_EMBER_REFLECT_TIMEOUT', 244); // Shorter cap for utility reflection calls to protect
  the inference slot.
35 define('STU_EMBER_REFLECT_MAX_FACT_LEN', 340); // Maximum stored fact length after reflection cleanup.
36
37 // Optional utility-model routing and moderation gates.
38 define('STU_EMBER_REFLECT_MODEL', ''); // Empty string falls back to STU_EMBER_MODEL for
  reflection.
```

```
39 define('STU_EMBER_IDLE_GREET_MINUTES', 60);           // Minimum absence window before a returning-user
    greeting is eligible.
40 define('STU_EMBER_AUTOMOD', true);                     // Global-channel basic link/vulgarity moderation gate.
```

Security and reproducibility note. This report is presented at the architectural-mathematical level. The configuration appendix is a public reproducibility footprint, not an operational specification: values are illustrative and may have since changed, and no assumption should be made that they remain in effect on the live system. Deployment-local identifiers, endpoint ports, and shared secrets are redacted. External routes, file paths, database names, and account credentials are omitted. Relation names and configuration parameter names are provided solely for architectural traceability.

References

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