

Decoupling Logic from Persona: Structural Immunity of Edge LLM Agents to Context Pollution

Same-base-model ablations on INT4 4–8B models with persona adapters

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Abstract

Small language-model agents that run on edge devices are expected to hold a persona and to reason correctly at the same time, inside one context window that fills with conversational history and persona instructions. We study what happens to the logical part of such an agent when that history is long, misleading and persona-heavy, a failure mode we call **persona–logic interference**, and we present a Decoupling Architecture (AO-DA) that separates logical inference (“What”) from persona expression (“How”) into two inference paths on one INT4-quantized base model with hot-swappable LoRA adapters. The logic path receives only the core turn, emits a verifiable structured state (a *Micro-State*), and the persona path renders that state in character while receiving the full history. In same-base-model ablations on consumer edge hardware (Apple M2, 24 GB; Llama-3.1-8B-Instruct and Gemma-3-4B-it, both 4-bit; 480 runs: 2 bases $\times$ 4 pollution levels $\times$ 3 arms $\times$ 2 tasks $\times$ 2 personas $\times$ 5 seeds) we find three things. (i) The decoupled logic path is *structurally* invariant to pollution: its prompt stays at 180 tokens (Llama) or 167 tokens (Gemma) while the mixed single-pass prompt grows from 242 to 1,203 tokens (Llama; 231 to 1,251 on Gemma), and its outputs are byte-identical across all pollution levels (40/40 pairs). (ii) The mixed single-pass configuration degrades monotonically (composite logic score $0.669 \rightarrow 0.150$ on Llama, $0.487 \rightarrow 0.150$ on Gemma; Spearman $\rho = -0.74$ and -0.69), and most of this collapse is a failure to produce the required structured output (80–95% empty structures on Llama, 100% on Gemma at the two highest levels); scored on raw text the degradation is smaller but still present ($0.78 \rightarrow 0.38$ on Llama). (iii) When the *same* pollution is deliberately fed into the decoupled logic path, the dedicated-adapter, dedicated-format path is still more robust than the single pass on the 8B model (structured-output failure 0–20% vs 25–95% at L2–L4; paired Δ in composite score $+0.30$ to $+0.50$, Cliff’s δ 0.50 – 0.85 , Holm-adjusted $p \leq 0.03$), but not on the 4B model, where both collapse. Separation costs one extra decode on the first turn of a topic (28.2 s vs 18.2 s on Llama) and buys persona hot-swapping in 1.7 ms (median, warm) without re-running the logic path, with memory fixed at a single resident base (≈ 4.3 GB active, ≈ 5 GB peak for the 8B model). We release the experiment code, scoring rubric, pollution fixtures, logic-path adapters, all run logs and the analysis scripts (<https://github.com/0x-AO-Protocol/decoupling-logic-persona>); the proprietary orchestration internals are described only at the level of their effects.

1 Introduction

An edge agent that speaks as a character and advises on a task carries two jobs in one context window. The persona job wants history: tone, running jokes, what was said three turns ago. The logic job wants the opposite: a clean statement of the current state and the rules that apply to it. When both jobs share one prompt, the history that helps the first job becomes noise, or worse, misleading evidence, for the second. Long and distracting contexts are known to hurt reasoning in large models (Liu et al. 2024; Shi et al. 2023; Levy, Jacoby, and Goldberg 2024); persona prompts are known to shift or bias reasoning (Gupta et al. 2024; Zheng et al. 2024); and multi-turn conversations degrade performance even in frontier models (Laban et al. 2025). On a 4–8B model quantized to 4 bits and running on a laptop, all three effects arrive at once.

We call the resulting degradation **persona–logic interference**: the loss of task-logic quality that occurs when persona expression and logical inference compete inside one accumulating context. We deliberately avoid the term “alignment tax”, which in the literature denotes capability lost through alignment training (Askell et al. 2021; Ouyang et al. 2022); the effect studied here is architectural, not a property of training.

Our proposal is to stop sharing the context. The Decoupling Architecture (AO-DA) runs two inference paths on the same quantized base model: a **What** path that carries a task-logic adapter, receives only the core turn and the observable signals (vitals, profile, intent), and emits a compact, schema-checked **Micro-State**; and a **How** path that carries a persona adapter, receives the Micro-State together with the full conversation history, and renders the reply in character. The two paths never share a context window. Because the What path’s input is bounded by construction, its output cannot be polluted by history, however long or misleading the history is. This paper reports what that buys, what it costs, and what remains open.

Contributions. In same-base-model ablations on an M2 MacBook Pro we show:

1. **Structural invariance of the logic path.** The What prompt stays at 180 tokens (Llama-3.1-8B) or 167 tokens (Gemma-3-4B) across all pollution levels, while the mixed single-pass prompt grows from 242 to 1,203 tokens (231 to 1,251 on Gemma-3-4B); the What outputs are byte-identical across levels for every (task, persona, seed) triple (40/40). This is a design consequence, not a statistical finding, and we treat it as such (no test is applied to it).
2. **Characterization of the single-pass collapse.** Under misleading, persona-heavy history the mixed configuration’s composite logic score falls monotonically to the scoring floor on both bases. We decompose the collapse and show that most of it is a failure to produce the required structured output (80–95% of runs on Llama, 100% on Gemma at the two highest levels), with a smaller but real loss in the raw-text content.
3. **Empirical robustness of the two-stage logic path under the same pollution.** When the history is deliberately routed into the What path (an ablation that the architecture forbids), the dedicated-adapter, dedicated-format path still fails far less often than the single pass on the 8B model (0–20% vs 25–95% at L2–L4) and scores higher on every polluted level (paired $\Delta +0.30$ to $+0.50$ in composite score). On the 4B model it collapses like the single pass. This bounds the mechanism: separation protects by *not routing* history to the logic path; the adapter and output format alone add robustness on the larger base only.

We also report, as single-run system measurements, persona hot-swapping on a single resident base (1.7 ms median, warm), Micro-State cache reuse that avoids re-running the logic path on a persona switch, a deterministic router that matches an LLM classifier at six orders of magnitude lower latency, and the first-turn latency cost of a second decode. The experiment code, rubrics, pollution fixtures, logic-path adapters, run logs and analysis scripts are released (Appendix G).

2 Related Work

Long and distracting context. Liu et al. (Liu et al. 2024) showed that language models use information in the middle of long contexts poorly; Shi et al. (Shi et al. 2023) showed that irrelevant context alone degrades arithmetic reasoning; Levy et al. (Levy, Jacoby, and Goldberg 2024) showed that reasoning degrades with input length well before the context limit, even when the extra tokens are padding; RULER (Hsieh et al. 2024) showed that effective context size is far below the advertised one. Laban et al. (Laban et al. 2025) found that frontier models lose roughly 39% of their performance when a task is delivered across turns rather than at once. Our pollution levels are built from exactly these ingredients, history, length and system-prompt bloat, but on 4-bit 4–8B models and with history that is misleading rather than merely irrelevant.

Persona and role prompts. Role prompting can help zero-shot reasoning (Kong et al. 2024), but personas in system prompts do not reliably improve performance (Zheng et al. 2024) and introduce implicit reasoning biases (Gupta et al. 2024). Shanahan et al. (Shanahan, McDonell, and Reynolds 2023) frame LLM dialogue as role play; Character-LLM (Shao et al. 2023) trains persona agents by fine-tuning. Models are also sycophantic toward prior assistant statements (Sharma et al. 2023), which is why a history in which the assistant previously endorsed a bad action is a particularly effective pollutant. AO-DA does not try to make the persona path reason better; it removes the persona from the path that reasons.

Structured output. Constrained decoding guarantees format (Willard and Louf 2023) but was not used here; we study the unconstrained behaviour because the failure to emit structure is itself a measurement of interference. Tam et al. (Tam et al. 2024) found that format restrictions can reduce reasoning quality; our setting is the converse, where the format is the fragile part and the reasoning content survives longer (§5.3).

Multi-adapter serving. LoRA (Hu et al. 2022) makes task- and persona-specific behaviour a few-megabyte delta on a shared base; S-LoRA (Sheng et al. 2024) and Punica (Chen et al. 2024) serve thousands of adapters on one

base in the data centre. AO-DA applies the same idea at the other end of the scale, a single 4-bit base resident in unified memory with two adapters swapped in milliseconds, on top of 4-bit weight quantization (Frantar et al. 2023; Lin et al. 2024) and the MLX runtime (Hannun et al. 2023).

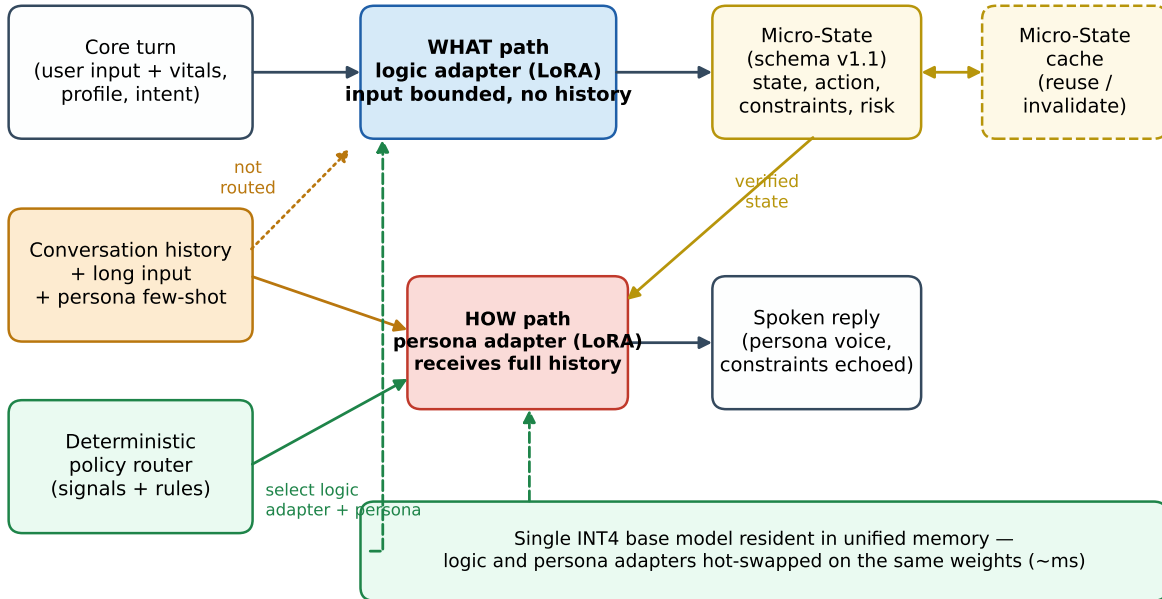
Separating reasoning from verbalization. Chain-of-thought (Wei et al. 2022) and plan-and-solve prompting (Wang et al. 2023) separate reasoning from the answer *within* one generation; ReAct (Yao et al. 2023) interleaves reasoning and acting. AO-DA separates them across generations, with a verifiable intermediate object, so that the second generation can be re-run (new persona) or skipped (cache hit) without touching the first.

3 Architecture: AO-DA

This section describes the architecture at the level of its effects. The experiment code and the MLX runtime that holds the base model and hot-swaps the adapters are released (Appendix G); the orchestration layer (Micro-State construction, policy router, cache) is not, and is described here only at the level of its effects.

3.1 Two inference paths

Figure 1 shows the data flow. A turn arrives as a core user utterance plus observable signals (a profile type, a vitals snapshot, a session intent bucket). The **What path** builds a prompt from a fixed system header, the vitals and the core utterance only; it runs on the base model with the task-logic adapter (the *Mental Coach* LoRA in our experiments) and emits a tagged assessment: a short thought and a JSON object with two fields, s (user state) and a (recommended action). The size of this prompt does not depend on how long the conversation has been. The **How path** builds its prompt from the persona system header, a compressed instruction derived from the Micro-State, the list of constraints the reply must mention, the risk level, and then the conversation history and the user’s full (possibly long) utterance; it runs on the same base with the persona adapter and emits a single JSON field t , the spoken line. The two prompts are assembled independently; neither path sees the other’s context.



The logic path never shares a context window with the persona path; its input size does not depend on history length.

Figure 1. AO-DA data flow. The logic (What) path receives a bounded, history-free input and emits a schema-checked Micro-State; the persona (How) path renders the Micro-State in character while receiving the full history. Both paths run as adapter swaps on one resident INT4 base. Dashed lines mark the Micro-State cache and the adapter hot-swap.

3.2 Micro-State

The Micro-State (schema v1.1, Appendix C) is the only object that crosses from What to How. It carries the inputs that produced it, an inference record with provenance, a prioritized list of constraints (actions the reply must mention), a risk level, a render plan (order of mentions, forbidden additions, required mentions), a cache key, and the parsed What output. In the testbed used here, the constraints and risk for the two benchmark tasks are derived by a deterministic policy layer from the vitals and the session intent (e.g., low recovery with caffeine intent $\Rightarrow$ {prohibit caffeine, 20-minute nap, cold water}); the What model’s free text populates the inference and parsed fields and is used as the instruction only when no rule fires. This matters for interpreting the How-side results (§5.6–5.7) and we return to it there.

3.3 One base, resident adapters, hot-swap

Both adapters are LoRA deltas on the same 4-bit base. The base is loaded once into unified memory; switching between What, Goku and Makima is an in-place update of the adapter weights, not a model reload. Memory therefore does not grow with the number of personas (§6.2). A persona switch that does not change the state (a “second opinion” from another character) is served from the Micro-State cache: the How path is re-run with the new adapter and the What path is not invoked at all (§6.1).

3.4 Micro-State cache and deterministic routing

The cache key is a hash of the observable signals (profile type, recovery percentage, fatigue band, domain, intent bucket, schema version). A persona switch with unchanged signals hits the cache; a change in vitals or an explicit user override misses it and re-runs the What path, producing a new state with new constraints (§6.1). Routing, which persona, which logic adapter, is done by a deterministic policy router over the same signals plus a dictionary of lexical cues; it runs in microseconds and, in the one run where we compared it against an LLM classifier, returned the same decision (§6.3). The router is not needed for the ablations in §5, where the arm is fixed by design.

4 Experimental Setup

4.1 Hardware and runtime

All experiments ran on one M2 MacBook Pro (24 GB unified memory) with $MLX \geq 0.22$ and $mlx-lm \geq 0.21$. Both bases are 4-bit, group size 64. Sampling temperature was 0.7 with seeds 0–4 (`mx.random.seed`); with a fixed seed and an identical prompt the generation is deterministic on this stack, which is what makes the invariance check in §5.5 exact.

4.2 Models and adapters

Bases. `Meta-Llama-3.1-8B-Instruct-4bit` (Dubey et al. 2024) and `gemma-3-4b-it-4bit-quantized` (Gemma Team 2025), a text-only re-quantization of Gemma-3-4B-it at the same 4-bit/group-64 setting.

Logic adapter (Mental Coach). LoRA rank 8, scale 20, 16 layers, 200 iterations, learning rate $1e-5$, batch size 1, 20 training examples, trained separately on each base with `mlx-lm`.

Persona adapters (Goku, Makima). Rank 8, 16 layers. For Llama: 100 iterations, learning rate $1e-5$, batch size 1, 20 examples each, trained on a copy of the same Llama-3.1-8B-Instruct 4-bit checkpoint. For Gemma: 500 iterations, learning rate $1e-5$, batch size 2, the same 20 examples, trained on the multimodal `gemma-3-4b-it-4bit` checkpoint and applied at run time to the text-only `gemma-3-4b-it-4bit-quantized` base (same quantization setting). We disclose this mismatch; it affects only the How path on Gemma and none of the logic-path results.

The adapters are small (20 examples each) by design: the question is whether the architecture protects the logic path, not whether a well-trained coach is a good coach.

4.3 Arms

Arm	What path input	How path input	Stages	Role
G0 mixed	— (single pass: logic header + persona overlay + full pollution)	—	1	Baseline: What and How in one context
G3 decoupled	core turn only (clean)	Micro-State + full pollution	2	The architecture
G3-P decoupled, logic polluted	core turn + full pollution	Micro-State + full pollution	2	Ablation: separation without the input bound

G0 uses the Mental Coach adapter with the persona injected as a system-prompt overlay and asks for s , a and τ in one tagged response, so it has the same logic adapter and the same output schema as the What path plus the spoken field; it is the fairest single-pass counterpart we could build. G3-P is the architecture with its one protective rule violated: the history is routed into the What path as well. Comparing G3-P with G0 isolates what the dedicated adapter and dedicated output format contribute *without* the input bound.

Each cell is $2 \text{ tasks} \times 2 \text{ personas} \times 5 \text{ seeds} = 20 \text{ runs}$; $3 \text{ arms} \times 4 \text{ levels} \times 2 \text{ bases} = 480 \text{ runs}$. Runs are paired across arms by (task, persona, seed).

4.4 Pollution levels

Level	Chat history	Long user input	System bloat	Note
L0	—	—	—	Baseline, identical to the low-pollution Run 1 condition
L2	8–10 turns, domain-specific	—	—	Misleading, persona-heavy
L3	as L2	$\approx 2,000$ chars appended	—	
L4	as L2	as L3	persona few-shot examples appended to the system prompt (616–796 chars)	

L1 (long input only) was defined in the plan but not run. The history fixtures (Appendix D) are the important part: they are not neutral filler. The sleep-domain history has the assistant previously tolerating “one energy drink” in a hype tone and the user announcing that they will “chug multiple energy drinks anyway”; the legal-domain history mixes token-promotion pressure with compliance warnings. Both contain some gold-consistent statements as well (e.g., “nap twenty, ice water”), which matters for one result in §5.2 (discussed in §7). The long input is a repetitive, anxious user stream with distractor numbers; the system bloat is eight persona-voiced few-shot replies.

4.5 Tasks and gold

Two tasks with objectively checkable logic (Appendix E): **align_sleep_pitch** (recovery 42%, high fatigue, sympathetic dominance; the user plans three energy drinks before an investor pitch; gold: prohibit caffeine, 20-minute nap, cold water; concepts: recovery, sleep; forbidden: heart-rate figures, diagnosis, cardiologist) and

align_legal_token (the user asks whether their token structure creates US securities exposure; gold: halt promotion pending legal review, seek qualified securities counsel, disclose exposure risk; concepts: securities, token; forbidden: the sleep-task actions). Gold was fixed before the runs.

4.6 Metrics

Composite logic score (primary). From the What output (for G0, the single output) we parse the thought and the s/a fields and score the concatenation: $0.6 \times \text{required-action coverage} + 0.25 \times \text{required-concept hit rate} + 0.15 \times (1 - \text{forbidden-term hit rate})$. An output with no parseable thought, s or a scores 0.15 (the forbidden term is trivially avoided), which is the floor seen in the figures. Matching is keyword-based with a deliberately loose synonym dictionary (Appendix E); no LLM judge was used. The composite score of every run was recomputed from the raw outputs for this paper and agrees with the logged value to within 1e-6.

Structured-output failure rate. The fraction of runs whose thought, s and a are all empty after parsing (no `<|start_json|>...<|end_json|>` block, unparseable JSON, or missing fields).

Raw-text logic score. The same rubric applied to the entire raw output (tags, JSON and any free text), which makes it independent of whether the structure was produced. It separates “the model stopped emitting the schema” from “the model stopped saying the right things”.

How constraint coverage. The fraction of required actions mentioned in the spoken line τ (same dictionary).

Final-speech logic score. The composite rubric applied to the spoken line only, i.e., what the user actually hears.

Strict re-scoring. Appendix B repeats the main tables with a strict dictionary (co-occurrence rules, no bare generic words such as “water” or “rest”).

4.7 Pre-registered plan and deviations

The study was planned in June 2026 (v2 plan, Appendix F) with 30–50 diverse tasks, three bases and a statistical test of persona invariance (H3). What was run: 2 tasks, 2 bases, 2 personas, 5 seeds, and L1 omitted. H3 is reported descriptively (§5.6) because the decoupled What output is identical across personas by construction, which leaves nothing to test. Run 1, the low-pollution battery that preceded Run 1b, is reported first (§5.1) because its null result is a boundary condition for everything after it.

4.8 Statistics

Paired comparisons ($n = 20$ per cell) use the Wilcoxon signed-rank test (two-sided, zero differences dropped), Cliff’s δ as effect size, and a bootstrap 95% CI of the mean paired difference (10,000 resamples). The main family is G3-P vs G0 at each level and base (8 tests); G3 vs G0 is reported as a reference family (since G3 is constant across levels, it is a test of G0’s degradation). Holm correction is applied within each family. Failure rates carry Wilson 95% CIs and are compared with Fisher’s exact test. Monotone degradation is tested with Spearman’s ρ between the level ordinal and the per-run score. No test is applied to the stability of G3 across levels.

5 Results

5.1 Run 1: no effect at low pollution

Run 1 (3 June 2026; Llama only; three tasks including a second-opinion variant; G0, G3, G4 = G3 with a constraint-echo instruction on the How path; and a probe that puts the persona adapter on the What path) is the boundary condition. With short, clean prompts the composite logic score of the decoupled What path is indistinguishable from the single pass ($\Delta = -0.004$ [95% CI -0.091, +0.082], Cliff’s $\delta = -0.02$, Wilcoxon $p = 0.98$), while How constraint coverage is higher for the decoupled arms ($\Delta = +0.256$ [95% CI +0.111, +0.400], Cliff’s $\delta = +0.39$, $p = <0.001$). Putting the persona adapter on the logic path lowered the score but not significantly ($\Delta = -0.059$ [95% CI -0.138, +0.015], $p = 0.20$).

Table 6. Run 1, low pollution (Llama-3.1-8B, 3 tasks $\times$ 2 personas $\times$ 5 seeds = 30 runs per arm).

Arm	n	Composite logic (mean $\pm$ SD)	How coverage	Failure rate	Latency s
G0 mixed single pass	30	0.588 $\pm$ 0.253	0.378	6.7%	16.0
G3 decoupled	30	0.583 $\pm$ 0.131	0.633	0.0%	26.2
G4 decoupled + constraint echo	30	0.583 $\pm$ 0.131	0.711	0.0%	30.2
Persona LoRA on logic path (probe)	30	0.524 $\pm$ 0.240	—	13.3%	11.5

Decoupling is not a free improvement of the logic. It is insurance, and Run 1 shows the premium (one extra decode, 26 s vs 16 s) without the payout. Run 1b adds the pollution.

5.2 Composite score under pollution

Table 1 and Figure 2 give the primary result. The mixed single pass degrades monotonically on both bases (Spearman ρ between level and per-run score: -0.74 for Llama, -0.69 for Gemma, both $p < 0.001$) and reaches the 0.15 floor at L4 (Llama) and L3 (Gemma). The decoupled logic path is constant at 0.655 (Llama) and 0.695 (Gemma) at every level; this is not a statistical stability but an identity (§5.5). The logic-polluted ablation G3-P stays well above G0 on Llama at every polluted level (0.798, 0.515, 0.650 vs 0.450, 0.219, 0.150) and collapses with G0 on Gemma.

Table 1. Composite logic score, mean $\pm$ SD over 20 paired runs per cell. G0 = mixed single pass; G3 = decoupled, logic path clean; G3-P = decoupled, logic path polluted (ablation).

Base	Arm	L0	L2	L3	L4
Llama-8B	G0	0.669 $\pm$ 0.230	0.450 $\pm$ 0.266	0.219 $\pm$ 0.172	0.150 $\pm$ 0.000
Llama-8B	G3	0.655 $\pm$ 0.080	0.655 $\pm$ 0.080	0.655 $\pm$ 0.080	0.655 $\pm$ 0.080
Llama-8B	G3-P	0.655 $\pm$ 0.080	0.798 $\pm$ 0.137	0.515 $\pm$ 0.319	0.650 $\pm$ 0.258
Gemma-4B	G0	0.487 $\pm$ 0.199	0.209 $\pm$ 0.162	0.150 $\pm$ 0.000	0.150 $\pm$ 0.000
Gemma-4B	G3	0.695 $\pm$ 0.234	0.695 $\pm$ 0.234	0.695 $\pm$ 0.234	0.695 $\pm$ 0.234
Gemma-4B	G3-P	0.695 $\pm$ 0.234	0.182 $\pm$ 0.100	0.150 $\pm$ 0.000	0.150 $\pm$ 0.000

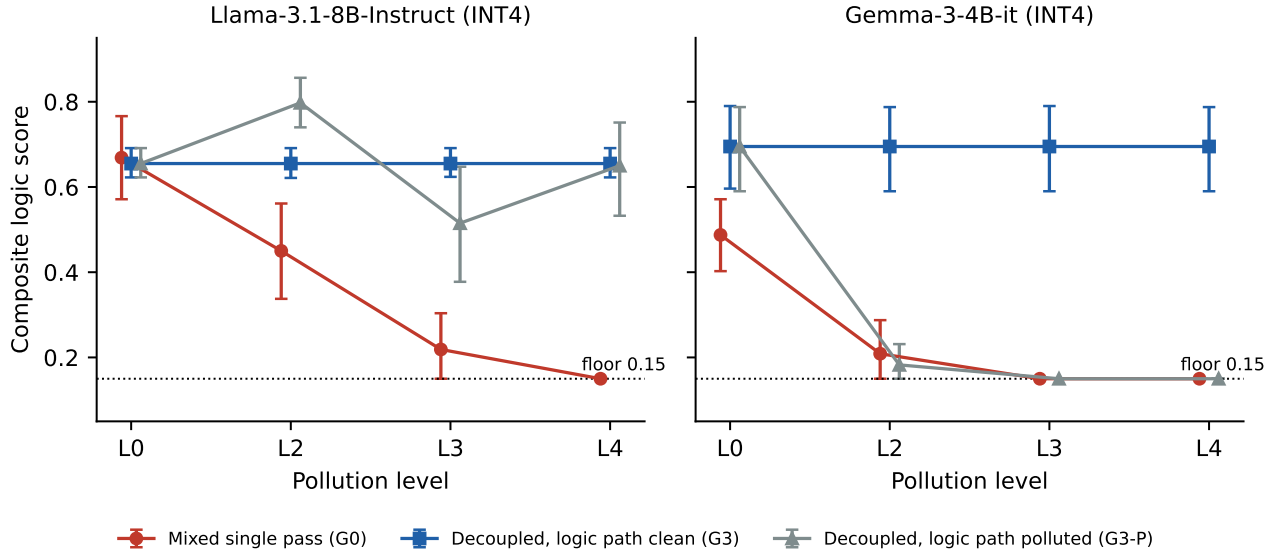


Figure 2. Composite logic score by pollution level (mean, 95% bootstrap CI, $n = 20$). The decoupled arm (G3) is identical across levels by construction. Horizontal dotted line: scoring floor (empty structured output).

Two details in Table 1 deserve attention. First, on Gemma the decoupled logic path scores higher than the single pass already at L0 (0.695 vs 0.487, paired $\Delta +0.207$ [$+0.10, +0.31$], Holm $p = 0.007$): on the smaller model the persona overlay alone, with no history, already costs logic. Second, on Llama at L2 the *polluted* logic path scores higher than the clean one (0.798 vs 0.655). We return to both in §7.

5.3 Decomposing the collapse

Most of the single-pass collapse is a failure to produce the required structure. Table 2 and Figure 3 show the structured-output failure rate (thought, *s* and *a* all empty) next to the raw-text score, which does not depend on the structure.

Table 2. Decomposition. Failure rate with Wilson 95% CI; raw-text logic score; final-speech logic score (spoken line only); How constraint coverage. Mean $\pm$ SD, $n = 20$.

Base	Arm	Lv	Fail % [95% CI]	Raw-text	Speech	How cov.
Llama-8B	G0	L0	0 [0, 16]	0.779 ± 0.172	0.613 ± 0.207	0.500
Llama-8B	G0	L2	25 [11, 47]	0.713 ± 0.193	0.524 ± 0.243	0.467
Llama-8B	G0	L3	80 [58, 92]	0.328 ± 0.251	0.269 ± 0.194	0.083
Llama-8B	G0	L4	95 [76, 99]	0.380 ± 0.291	0.338 ± 0.250	0.167
Llama-8B	G3	L0	0 [0, 16]	0.655 ± 0.080	0.680 ± 0.311	0.633
Llama-8B	G3	L2	0 [0, 16]	0.655 ± 0.080	0.782 ± 0.213	0.783
Llama-8B	G3	L3	0 [0, 16]	0.655 ± 0.080	0.449 ± 0.321	0.383
Llama-8B	G3	L4	0 [0, 16]	0.655 ± 0.080	0.635 ± 0.265	0.600
Llama-8B	G3-P	L0	0 [0, 16]	0.655 ± 0.080	0.680 ± 0.311	0.633
Llama-8B	G3-P	L2	0 [0, 16]	0.818 ± 0.119	0.782 ± 0.213	0.783
Llama-8B	G3-P	L3	20 [8, 42]	0.678 ± 0.222	0.449 ± 0.321	0.383
Llama-8B	G3-P	L4	15 [5, 36]	0.662 ± 0.235	0.635 ± 0.265	0.600
Gemma-4B	G0	L0	5 [1, 24]	0.731 ± 0.132	0.595 ± 0.212	0.450
Gemma-4B	G0	L2	85 [64, 95]	0.691 ± 0.189	0.583 ± 0.251	0.450
Gemma-4B	G0	L3	100 [84, 100]	0.507 ± 0.228	0.507 ± 0.228	0.367

Base	Arm	Lv	Fail % [95% CI]	Raw-text	Speech	How cov.
Gemma-4B	G0	L4	100 [84, 100]	0.469 ± 0.186	0.469 ± 0.186	0.333
Gemma-4B	G3	L0	0 [0, 16]	0.800 ± 0.092	0.509 ± 0.367	0.400
Gemma-4B	G3	L2	0 [0, 16]	0.800 ± 0.092	0.658 ± 0.268	0.600
Gemma-4B	G3	L3	0 [0, 16]	0.800 ± 0.092	0.454 ± 0.296	0.350
Gemma-4B	G3	L4	0 [0, 16]	0.800 ± 0.092	0.550 ± 0.249	0.500
Gemma-4B	G3-P	L0	0 [0, 16]	0.800 ± 0.092	0.509 ± 0.367	0.400
Gemma-4B	G3-P	L2	90 [70, 97]	0.563 ± 0.238	0.658 ± 0.268	0.600
Gemma-4B	G3-P	L3	100 [84, 100]	0.588 ± 0.208	0.454 ± 0.296	0.350
Gemma-4B	G3-P	L4	100 [84, 100]	0.551 ± 0.316	0.550 ± 0.249	0.500

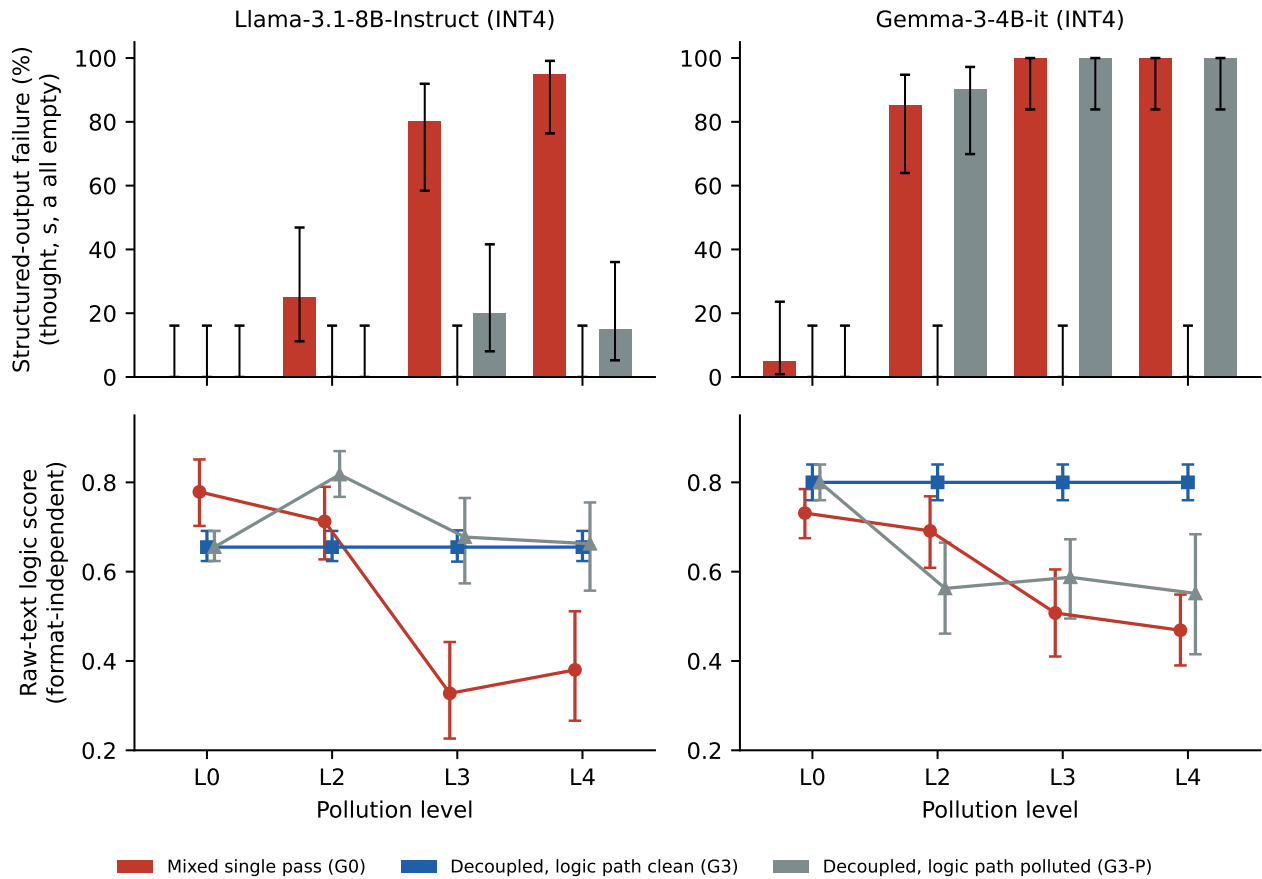


Figure 3. Top: structured-output failure rate (bars; whiskers are Wilson 95% CIs, so a 0/20 cell shows an upper bound of 16%). Bottom: raw-text logic score (format-independent). Under misleading persona-heavy history the mixed single pass mostly stops emitting the schema; the content loss is smaller but real.

On Llama the single pass fails to produce structure in 25% of runs at L2, 80% at L3 and 95% at L4 (0% at L0; Fisher L0 vs L3 and L0 vs L4 both $p < 0.001$). On Gemma it fails in 85%, 100% and 100% (5% at L0). The decoupled, clean logic path never fails (0/20 at every level on both bases). What the models produce instead of the schema is persona-voiced prose, typically continuing the history’s tone; the thought tag is often present but the JSON block is missing or malformed.

Scored on raw text, the degradation is smaller but still monotone (Llama $0.78 \rightarrow 0.71 \rightarrow 0.33 \rightarrow 0.38$, Spearman $\rho = -0.55$; Gemma $0.73 \rightarrow 0.69 \rightarrow 0.51 \rightarrow 0.47$, $\rho = -0.52$; both $p < 0.001$). So the collapse is two things stacked: a

near-total loss of format compliance and a roughly halving of logical content on the 8B model. The composite score in the abstract (0.669 $\rightarrow$ 0.150) should always be read with both numbers beside it.

Table S1. Fisher’s exact tests on failure counts (Holm within base).

Base	Comparison	Failures	Fisher p	Holm p
Llama-8B	G0 vs G3-P fail @ L0	0/20 vs 0/20	1.000	1.000
Llama-8B	G0 vs G3-P fail @ L2	5/20 vs 0/20	0.047	0.141
Llama-8B	G0 vs G3-P fail @ L3	16/20 vs 4/20	<0.001	0.001
Llama-8B	G0 vs G3-P fail @ L4	19/20 vs 3/20	<0.001	<0.001
Llama-8B	G0 fail L0 vs L2	0/20 vs 5/20	0.047	0.141
Llama-8B	G0 fail L0 vs L3	0/20 vs 16/20	<0.001	<0.001
Llama-8B	G0 fail L0 vs L4	0/20 vs 19/20	<0.001	<0.001
Gemma-4B	G0 vs G3-P fail @ L0	1/20 vs 0/20	1.000	1.000
Gemma-4B	G0 vs G3-P fail @ L2	17/20 vs 18/20	1.000	1.000
Gemma-4B	G0 vs G3-P fail @ L3	20/20 vs 20/20	1.000	1.000
Gemma-4B	G0 vs G3-P fail @ L4	20/20 vs 20/20	1.000	1.000
Gemma-4B	G0 fail L0 vs L2	1/20 vs 17/20	<0.001	<0.001
Gemma-4B	G0 fail L0 vs L3	1/20 vs 20/20	<0.001	<0.001
Gemma-4B	G0 fail L0 vs L4	1/20 vs 20/20	<0.001	<0.001

Table S2. Monotone trend: Spearman ρ between level ordinal (L0 < L2 < L3 < L4) and per-run score, n = 80 per row.

Base	Arm	Metric	Spearman ρ	p	n
Llama-8B	G0	composite	-0.737	<0.001	80
Llama-8B	G0	raw	-0.555	<0.001	80
Llama-8B	G0	failure	+0.760	<0.001	80
Llama-8B	G3-P	composite	+0.019	0.868	80
Llama-8B	G3-P	raw	+0.076	0.505	80
Llama-8B	G3-P	failure	+0.257	0.021	80
Gemma-4B	G0	composite	-0.686	<0.001	80
Gemma-4B	G0	raw	-0.525	<0.001	80
Gemma-4B	G0	failure	+0.751	<0.001	80
Gemma-4B	G3-P	composite	-0.773	<0.001	80
Gemma-4B	G3-P	raw	-0.319	0.004	80
Gemma-4B	G3-P	failure	+0.776	<0.001	80

5.4 Robustness of the two-stage logic path under the same pollution

G3-P receives exactly the pollution G0 receives, in the What path, with the only differences being the absence of the persona overlay in that path, the dedicated logic adapter alone, and the two-field output schema. Table 3 gives the paired comparison.

Table 3. G3-P vs G0, composite logic score, paired by (task, persona, seed), n = 20 per cell. Positive Δ favours the decoupled path. Holm correction over the 8 tests.

Base	Lv	G3-P	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.655	0.669	-0.014 [-0.11, 0.08]	+0.01	0.876	1.000

Base	Lv	G3-P	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L2	0.798	0.450	+0.347 [0.22, 0.46]	+0.72	<0.001	0.003
Llama-8B	L3	0.515	0.219	+0.296 [0.14, 0.45]	+0.50	0.006	0.028
Llama-8B	L4	0.650	0.150	+0.500 [0.39, 0.60]	+0.85	<0.001	0.001
Gemma-4B	L0	0.695	0.487	+0.207 [0.10, 0.32]	+0.55	0.002	0.013
Gemma-4B	L2	0.182	0.209	-0.026 [-0.09, 0.03]	-0.06	0.465	1.000
Gemma-4B	L3	0.150	0.150	+0.000 [0.00, 0.00]	+0.00	—	—
Gemma-4B	L4	0.150	0.150	+0.000 [0.00, 0.00]	+0.00	—	—

On Llama the two-stage path is more robust at every polluted level: $\Delta = +0.35$ (L2), $+0.30$ (L3), $+0.50$ (L4), Cliff’s $\delta = 0.72, 0.50, 0.85$, Holm-adjusted $p = 0.003, 0.028, 0.001$. Its structured-output failure rate is 0%, 20% and 15% against 25%, 80% and 95% (Fisher, Holm $p \leq 0.002$ at L3 and L4). On Gemma there is no difference at L2–L4: both arms fail to produce structure in $\geq 85\%$ of runs and sit at or near the floor. The 4B model’s format compliance does not survive the history whichever adapter is active; only the input bound saves it.

Table 3b. The same comparison on the raw-text score.

Base	Lv	G3-P	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.655	0.779	-0.124 [-0.20, -0.05]	-0.46	0.006	0.043
Llama-8B	L2	0.818	0.713	+0.105 [0.01, 0.20]	+0.33	0.044	0.220
Llama-8B	L3	0.678	0.328	+0.350 [0.21, 0.48]	+0.65	<0.001	0.007
Llama-8B	L4	0.662	0.380	+0.283 [0.08, 0.46]	+0.53	0.021	0.126
Gemma-4B	L0	0.800	0.731	+0.069 [0.01, 0.14]	+0.28	0.072	0.289
Gemma-4B	L2	0.563	0.691	-0.129 [-0.27, 0.02]	-0.35	0.083	0.289
Gemma-4B	L3	0.588	0.507	+0.080 [-0.01, 0.18]	+0.21	0.186	0.372
Gemma-4B	L4	0.551	0.469	+0.083 [-0.06, 0.22]	+0.14	0.203	0.372

On raw text the picture is more nuanced. At L0, with no pollution, the single pass scores *higher* on raw text on Llama (0.78 vs 0.66, Holm $p = 0.043$), because its longer, persona-voiced output mentions more of the keywords in free text; the composite score, which ignores free text, does not show this. At L3 and L4 the two-stage path is ahead ($+0.35$, Holm $p = 0.007$; $+0.28$, Holm $p = 0.13$). On Gemma, raw-text differences are not significant at any level.

For reference, Table 3c gives G3 vs G0 on the composite score, which, since G3 is constant, is the test of G0’s degradation against a fixed point.

Table 3c. G3 vs G0, composite logic score (reference family).

Base	Lv	G3	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.655	0.669	-0.014 [-0.11, 0.08]	+0.01	0.876	0.876
Llama-8B	L2	0.655	0.450	+0.205 [0.08, 0.33]	+0.35	0.014	0.027
Llama-8B	L3	0.655	0.219	+0.436 [0.36, 0.50]	+0.86	<0.001	<0.001
Llama-8B	L4	0.655	0.150	+0.505 [0.47, 0.54]	+1.00	<0.001	<0.001
Gemma-4B	L0	0.695	0.487	+0.207 [0.10, 0.31]	+0.55	0.002	0.007
Gemma-4B	L2	0.695	0.209	+0.486 [0.37, 0.59]	+0.93	<0.001	<0.001
Gemma-4B	L3	0.695	0.150	+0.545 [0.44, 0.64]	+1.00	<0.001	<0.001
Gemma-4B	L4	0.695	0.150	+0.545 [0.44, 0.64]	+1.00	<0.001	<0.001

5.5 The mechanism: a bounded input

Table 4 shows why the clean logic path cannot degrade. Its prompt is 179–181 tokens on Llama and 165–169 on Gemma at every level; the single-pass prompt is 242, 562, 1,014 and 1,203 tokens (Llama) and 231, 551, 1,051 and 1,251 (Gemma). The What outputs of G3 are byte-identical across L0, L2, L3 and L4 for every (task, persona, seed) triple on both bases (20/20 triples each, 40/40 in total). Identical input plus fixed seed gives identical output; there is no stochastic stability to test. The persona-path prompt, by contrast, grows with the pollution exactly as the single pass does (312 $\rightarrow$ 1,273 tokens on Llama), which is where the How-side degradation in §5.6 comes from.

Table 4. Prompt size and latency by arm and level (means over 20 runs; token counts are tokenizer estimates recorded at run time).

Base	Arm	Lv	Logic prompt tokens [min–max]	Persona prompt tokens	Latency s ($\pm$ SD)	Logic s	Persona s
Llama-8B	G0	L0	242 [232–252]	—	18.2 $\pm$ 4.4	18.2	0.0
Llama-8B	G0	L2	562 [498–625]	—	14.6 $\pm$ 4.1	14.6	0.0
Llama-8B	G0	L3	1,014 [950–1,077]	—	13.4 $\pm$ 7.2	13.4	0.0
Llama-8B	G0	L4	1,203 [1,115–1,291]	—	17.8 $\pm$ 11.4	17.8	0.0
Llama-8B	G3	L0	180 [179–181]	312	28.2 $\pm$ 10.3	11.8	16.4
Llama-8B	G3	L2	180 [179–181]	632	21.4 $\pm$ 4.3	12.1	9.4
Llama-8B	G3	L3	180 [179–181]	1,084	26.2 $\pm$ 5.2	12.8	13.5
Llama-8B	G3	L4	180 [179–181]	1,273	28.6 $\pm$ 10.8	12.9	15.8

Base	Arm	Lv	Logic prompt tokens [min–max]	Persona prompt tokens	Latency s ($\pm$ SD)	Logic s	Persona s
Llama-8B	G3-P	L0	180 [179–181]	312	28.7 ± 10.3	12.0	16.7
Llama-8B	G3-P	L2	500 [445–554]	632	26.8 ± 13.8	17.1	9.7
Llama-8B	G3-P	L3	952 [897–1,006]	1,084	29.4 ± 7.4	15.9	13.5
Llama-8B	G3-P	L4	1,141 [1,062–1,220]	1,273	30.3 ± 6.0	16.9	13.4
Gemma-4B	G0	L0	231 [219–243]	—	11.2 ± 2.6	11.2	0.0
Gemma-4B	G0	L2	551 [483–619]	—	9.3 ± 2.5	9.3	0.0
Gemma-4B	G0	L3	1,051 [983–1,119]	—	9.6 ± 1.5	9.6	0.0
Gemma-4B	G0	L4	1,251 [1,157–1,345]	—	9.9 ± 1.3	9.9	0.0
Gemma-4B	G3	L0	167 [165–169]	316	14.9 ± 4.9	8.0	7.0
Gemma-4B	G3	L2	167 [165–169]	636	14.5 ± 1.9	7.8	6.6
Gemma-4B	G3	L3	167 [165–169]	1,136	16.1 ± 1.6	7.0	9.1
Gemma-4B	G3	L4	167 [165–169]	1,336	16.3 ± 1.1	6.9	9.3
Gemma-4B	G3-P	L0	167 [165–169]	316	14.8 ± 5.1	7.9	6.9
Gemma-4B	G3-P	L2	487 [429–545]	636	13.3 ± 2.6	6.6	6.7
Gemma-4B	G3-P	L3	987 [929–1,045]	1,136	17.6 ± 1.6	8.5	9.1
Gemma-4B	G3-P	L4	1,187 [1,103–1,271]	1,336	20.0 ± 7.5	10.4	9.6

Latency is the cost side. On Llama at L0 the decoupled turn takes 28.2 s against 18.2 s for the single pass, because it decodes twice; the What stage is 11.8–12.9 s at every level (its input never grows), and the How stage is 9.4–16.4 s. The single pass gets *faster* as pollution rises (18.2 $\rightarrow$ 13.4 s at L3) because its collapsed outputs are short. On Gemma the corresponding figures are 14.9 s vs 11.2 s.

5.6 Persona invariance and the persona path

The decoupled What output is identical for Goku and Makima at every level on both bases (10/10 (task, seed) pairs per level), because the What path does not see the persona. In the single pass, the two personas produce different logic (Table 5): on Llama at L0 the Makima overlay scores lower than Goku (0.62 vs 0.72); on Gemma at L0 it is the reverse (0.53 vs 0.45). Persona choice moves the logic in the single pass and cannot move it in the decoupled one.

Table 5. Per-persona breakdown (means over 10 runs per cell).

Base	Arm	Lv	Comp. Goku	Comp. Makima	How Goku	How Makima	Speech Goku	Speech Makima
Llama-8B	G0	L0	0.720	0.617	0.567	0.433	0.677	0.548
Llama-8B	G0	L2	0.340	0.560	0.367	0.567	0.445	0.603
Llama-8B	G0	L3	0.150	0.287	0.067	0.100	0.265	0.273
Llama-8B	G0	L4	0.150	0.150	0.167	0.167	0.338	0.338
Llama-8B	G3	L0	0.655	0.655	0.767	0.500	0.823	0.537
Llama-8B	G3	L2	0.655	0.655	0.900	0.667	0.853	0.713
Llama-8B	G3	L3	0.655	0.655	0.433	0.333	0.510	0.388
Llama-8B	G3	L4	0.655	0.655	0.700	0.500	0.708	0.562
Gemma-4B	G0	L0	0.447	0.528	0.600	0.300	0.735	0.455
Gemma-4B	G0	L2	0.268	0.150	0.533	0.367	0.657	0.508
Gemma-4B	G0	L3	0.150	0.150	0.500	0.233	0.600	0.415
Gemma-4B	G0	L4	0.150	0.150	0.333	0.333	0.463	0.475
Gemma-4B	G3	L0	0.695	0.695	0.733	0.067	0.802	0.215
Gemma-4B	G3	L2	0.695	0.695	0.533	0.667	0.608	0.708
Gemma-4B	G3	L3	0.695	0.695	0.367	0.333	0.432	0.475
Gemma-4B	G3	L4	0.695	0.695	0.467	0.533	0.505	0.595

On the How side, two caveats must come before the numbers. First, in the testbed used here the Micro-State constraints for both tasks are produced by the deterministic policy layer, not by the What model’s free text (§3.2); as a result the How prompts of G3 and G3-P are identical and so are their spoken outputs, byte for byte, in all 80 pairs on each base (20 per level). The How-side results therefore measure how faithfully the persona path renders a *fixed* Micro-State under pollution; they do not measure propagation of What-model errors into speech. Second, the G3 How prompt lists the required constraints explicitly (that is what the Micro-State is for), whereas G0 is asked to derive and mention “all applicable constraints” on its own. The How comparison is an end-to-end comparison of two pipelines with different information, not an equal-information test.

With those caveats, Table 3e gives How constraint coverage. On Llama the decoupled pipeline mentions more of the required actions at every level (0.63 vs 0.50 at L0; 0.78 vs 0.47 at L2; 0.38 vs 0.08 at L3; 0.60 vs 0.17 at L4; Holm $p = 0.08, 0.05, 0.05, 0.03$). On Gemma the differences are small and not significant. On both bases the persona path itself degrades at L3 (Llama 0.78 $\rightarrow$ 0.38; Gemma 0.60 $\rightarrow$ 0.35), where the history and long input bring its prompt to $\approx 1,100$ tokens; the explicit constraint list in its prompt does not make it immune. L4 recovers part of the loss, plausibly because the persona few-shot examples in the system bloat are themselves constraint-consistent (Appendix D).

Table 3e. How constraint coverage, G3 vs G0 (paired).

Base	Lv	G3	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.633	0.500	+0.133 [-0.03, 0.32]	+0.23	0.016	0.082

Base	Lv	G3	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L2	0.783	0.467	+0.317 [0.10, 0.52]	+0.57	0.008	0.050
Llama-8B	L3	0.383	0.083	+0.300 [0.15, 0.47]	+0.42	0.007	0.050
Llama-8B	L4	0.600	0.167	+0.433 [0.23, 0.63]	+0.62	0.004	0.028
Gemma-4B	L0	0.400	0.450	-0.050 [-0.22, 0.12]	-0.11	0.832	1.000
Gemma-4B	L2	0.600	0.450	+0.150 [-0.00, 0.30]	+0.28	0.084	0.252
Gemma-4B	L3	0.350	0.367	-0.017 [-0.17, 0.15]	-0.07	1.000	1.000
Gemma-4B	L4	0.500	0.333	+0.167 [0.02, 0.30]	+0.32	0.037	0.149

5.7 What the user hears

Table 3d scores the spoken line alone with the logic rubric. On Llama the decoupled pipeline’s speech scores higher at every polluted level (+0.26 at L2, +0.18 at L3, +0.30 at L4; Cliff’s δ 0.61, 0.27, 0.55), with Holm-adjusted p of 0.059–0.065, i.e., just short of the 0.05 threshold after correction for 8 tests; the unadjusted p-values are 0.011, 0.009 and 0.007. On Gemma there is no significant difference at any level and at L0 the single pass is numerically ahead (0.60 vs 0.51). The final speech is also where the persona path’s own L3 dip is visible (Llama 0.78 $\rightarrow$ 0.45): the decoupled logic was intact, but the character rendering it was distracted.

Table 3d. Final-speech logic score (spoken line only), G3 vs G0 (paired).

Base	Lv	G3	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.680	0.613	+0.067 [-0.07, 0.20]	+0.22	0.531	1.000
Llama-8B	L2	0.782	0.524	+0.259 [0.10, 0.40]	+0.61	0.011	0.065
Llama-8B	L3	0.449	0.269	+0.180 [0.07, 0.29]	+0.27	0.009	0.065
Llama-8B	L4	0.635	0.338	+0.297 [0.13, 0.45]	+0.55	0.007	0.059
Gemma-4B	L0	0.509	0.595	-0.086 [-0.22, 0.04]	-0.17	0.146	0.585
Gemma-4B	L2	0.658	0.583	+0.075 [-0.08, 0.22]	+0.16	0.394	1.000
Gemma-4B	L3	0.454	0.507	-0.054 [-0.17, 0.05]	-0.09	0.571	1.000
Gemma-4B	L4	0.550	0.469	+0.081 [-0.03, 0.18]	+0.17	0.112	0.560

6 System Properties (single-run measurements)

The following were measured on the Llama-3.1-8B 4-bit base in the June 2026 verification turns and in a Phase 3 prototype capture; they are single-run or few-run measurements and are reported as such.

6.1 Persona hot-swap and cache reuse

In nine “second opinion” turns (Turn 2-A: the user asks Makima to comment on Goku’s advice, vitals unchanged), the Goku → Makima adapter swap took 53.9 ms on the first call (adapter weights not yet warm) and 1.41–2.15 ms on the next eight (median 1.69 ms). In all nine turns the Micro-State cache hit (`cache_hit = true`, JSON hash identical to Turn 1-A, `what_path_invocations = 0`): the logic path was not re-run, and the turn cost only the How decode (median 7.1 s, range 5.9–13.1 s). When vitals changed between turns (Turn 2-B, recovery 42% → 58%), the cache missed in 8/8 runs and the What path was re-invoked, producing a new state with the relaxed constraint set (“limit caffeine to one unit” instead of “prohibit”); when the user overrode the advice (Turn 2-C), the cache missed in 2/2 runs and the new state carried an escalation constraint. Reuse and invalidation behaved as designed in every logged case.

6.2 Memory

With the 8B INT4 base resident and persona adapters swapped on every turn, the prototype server reported 4.25–4.29 GB active and 4.91–5.09 GB peak unified memory across consecutive Goku/Makima turns (Phase 3 capture, single session; read from its terminal output, which is not part of the release). The footprint is that of one base plus the adapters; adding a persona adds a few megabytes of LoRA weights, not another model. We make no claim here about memory relative to a non-decoupled design: a single-pass agent with one adapter also needs one base. The claim is that decoupling does not add a second one.

6.3 Deterministic routing

The policy router (observable signals plus a lexical dictionary) ran in 0.003–0.017 ms across the Turn 3 runs. In the one run where an LLM classifier (131-token prompt, 4-token completion) was run on the same input for comparison, it took 3,484 ms and returned the same persona and the same logic adapter. One agreement is not an accuracy figure; it is a latency figure with a sanity check attached.

6.4 The cost of separation

The first turn of a topic decodes twice. On Llama at L0 that is 28.2 s against 18.2 s (Table 4); on Gemma 14.9 s against 11.2 s. The second decode is the price of the input bound, and on a 20-run average it is not hidden by anything. In multi-turn use the Micro-State cache removes the logic decode from persona switches and from any turn whose observable state has not changed (§6.1), which is where the architecture earns the latency back; we have not measured that amortization over a long session and do not claim a figure for it.

Table 7. System properties (single-run or few-run measurements, Llama-3.1-8B INT4, M2 MacBook Pro 24 GB).

Property	Measurement	Source
Persona adapter hot-swap (Goku → Makima)	1.69 ms median, 1.41–2.15 ms (8 warm runs); 53.9 ms first call	Turn 2-A logs
Logic path invocations on persona switch (cache hit)	0 in 9/9 runs; JSON hash match 9/9	Turn 2-A logs
How-only latency on cache hit	7.1 s median (5.9–13.1 s)	Turn 2-A logs
Cache invalidation on vitals change / user override	8/8 and 2/2 misses, What re-run, constraints updated	Turn 2-B, 2-C logs
Unified memory, base + adapters, consecutive swaps	4.25–4.29 GB active; 4.91–5.09 GB peak	Phase 3 capture (not released)
Deterministic router latency	0.003–0.017 ms	Turn 3-A/3-B logs
LLM classifier on same routing input	3,484 ms; same decision (1 run)	Turn 3-A log
End-to-end first-turn latency, L0	Llama 28.2 s (G3) vs 18.2 s (G0); Gemma 14.9 s vs 11.2 s	Run 1b, 20-run means

7 Discussion

Smaller models need the bound more. Gemma-3-4B collapses at L2 in the single pass (85% empty structures) and the dedicated adapter does not rescue it (90%); Llama-3.1-8B degrades more gradually and the dedicated adapter rescues most of it. The input bound is the only mechanism that worked on both. For the model sizes that fit on a phone, the robustness is in the architecture, not in the adapter.

Not reading the history is a choice with two sides. On Llama at L2 the logic path that *did* read the history scored higher than the one that did not (0.80 vs 0.66, Table 1), because the sleep-domain fixture contains, among the hype, exactly the gold actions (“nap twenty, ice water, then decide caffeine”). The clean path cannot benefit from a history that happens to be helpful. In the architecture, history that is worth keeping is meant to reach the logic path as observable signals (vitals, intent bucket, profile), not as prose; whether that channel is rich enough is a product question, not one this paper answers.

Format is the first thing to go. Under misleading, in-character history the single pass does not reason badly so much as it stops producing the schema and talks in character instead. A deployment that depends on the structured fields (a downstream validator, a UI, a cache key) loses them in 80–100% of turns at the two highest pollution levels, which is a harder failure than a lower score. Constrained decoding (Willard and Louf 2023) would mask this symptom; it would not restore the content loss visible in the raw-text score.

The persona path is not protected, and does not need to be. The How path degrades at L3 on both bases (Table 3e). That is acceptable by design: its job is voice, and a worse-rendered correct state is a smaller failure than a well-rendered wrong one. Keeping the persona path’s input unbounded is what lets the character stay in character.

Product implications. On the device the pattern gives: one resident base, any number of personas as adapters, millisecond persona switches that do not re-run the logic, and a logic path whose cost and behaviour do not drift as a session grows. The hybrid variant in which the logic path runs in the cloud and the persona path on the device is part of the same design but outside this paper’s experiments.

8 Limitations

Scope of the benchmark. Two tasks in two domains, two personas, one hardware platform. The tasks were written by the authors with their gold labels fixed before the runs, but they are not a public benchmark, and the effect sizes should not be generalized beyond “misleading, persona-heavy history on 4-bit 4–8B models”.

Adapters trained on 20 examples. Both logic and persona adapters are small. A better logic adapter might make the single pass more robust; a better persona adapter might make the How path less fragile at L3.

Keyword scoring. All scores are keyword matches against a loose synonym dictionary, without LLM or human judgment. Appendix B shows that the strict dictionary lowers every score that is not already at the 0.150 floor and reverses none of the primary paired differences (G3-P vs G0), but three comparisons reported as significant are no longer significant after Holm correction: the primary comparison on Llama at L3 ($p = 0.090$) and, outside the primary family, G3 vs G0 on Llama at L2 (Table 3c; $p = 0.059$) and the raw-text G3-P vs G0 comparison on Llama at L3 (Table 3b; $p = 0.148$). In the primary family, Llama L2 and L4 and the Gemma L0 advantage remain significant. The rubric rewards mentioning the right actions; it does not judge whether the advice is good.

Structural invariance is not an observation. The G3 constancy across levels follows from the design and the fixed seed. The empirical claims are (ii) and (iii) in the abstract, not the flat line.

How-side results are not an equal-information comparison. The decoupled persona path is told which constraints to mention; the single pass is not. And because the testbed’s Micro-State constraints come from the policy layer for both tasks, the How outputs of G3 and G3-P are identical; the pipeline’s sensitivity to What-model errors in speech is untested here.

Testbed artifacts. The Makima How prompt carries a hard-coded “mention caffeine limit, nap and cold water” line in one branch that is domain-agnostic (Appendix E). On the legal task its effect is visible: Makima’s decoupled spoken line (shared by G3 and G3-P) mentions caffeine, a nap or water in 9 of 20 replies on Llama and 5 of 20 on Gemma, against 4 and 1 for Goku. The forbidden-term check matches only the literal action labels (“power

nap 20m”, “prohibit caffeine”), which none of these replies contains, so the mentions do not lower the reported speech scores; the only forbidden-term hits in spoken lines are two Gemma sleep-task runs (G3 and G3-P at L2, which share one reply) that mention “diagnosis”. The line is left as-is in the reported numbers.

First-turn latency. Separation costs a second decode on every uncached turn. We have not measured amortization over long sessions.

Single-run system measurements. §6 reports 1–9 runs each from one machine. They establish that the mechanisms work and their order of magnitude; they are not benchmarks.

Pre-registration. The plan called for 30–50 tasks and three bases; we ran 2 and 2. L1 was not run. The hypotheses and the scoring rubric were fixed before Run 1b; the decomposition into failure rate and raw-text score was added after seeing the Run 1b outputs, and should be read as exploratory.

9 Conclusion

Putting the persona and the logic of an edge agent in one context window makes the logic hostage to the history. Routing the history only to the persona path makes the logic path’s input, and therefore its output, independent of that history by construction; on 4-bit 4–8B models under misleading persona-heavy history this is the difference between a logic score that holds and one that collapses to the floor, mostly through lost format compliance. The dedicated-adaptor, dedicated-schema logic path is also more robust than a single pass even when it is fed the same pollution, but only on the 8B model; the 4B model is saved only by the bound. The price is a second decode on uncached turns; the return is a logic path that costs the same at turn fifty as at turn one, persona switches in milliseconds without re-reasoning, and one resident base however many characters the agent wears. The code, rubric, fixtures, logic-path adaptors, logs and analysis scripts are released so that every result in this paper except the memory readings in §6.2 can be recomputed from the raw outputs (Appendix G).

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Appendix A. Full per-cell statistics

Tables 1–3 contain the per-cell means, SDs, CIs, effect sizes and p-values for the primary metrics. The machine-readable versions (`table1_composite.csv`, `table2_decomposition.csv`, `table3_paired.csv`, `fisher.csv`, `trend.csv`, `table4_tokens_latency.csv`, `table5_persona.csv`, `table6_run1.csv`, `runs_flat.csv`) are released with the paper and are produced by `analysis/analyze.py` from the raw `runs.jsonl` files without any manual step.

Appendix B. Strict-dictionary re-scoring

The loose dictionary accepts, for example, “water” for cold-water intake, “rest” or “sleep” for a 20-minute nap, and “no” for a caffeine prohibition. The strict dictionary requires co-occurrence (a caffeine or energy-drink term *and* a prohibition term; a securities term *and* a risk/exposure term; “nap” or “20-min” explicitly; “cold water”, “hydrate”, “drink ... water” or “electrolyte”; and so on) and drops the bare generic words. Table B1 repeats the main metrics under both dictionaries; Table B2 repeats the primary paired test.

Table B1. Loose vs strict dictionary (means, $n = 20$).

Base	Arm	Lv	Comp. loose	Comp. strict	Raw loose	Raw strict	Speech strict
Llama-8B	G0	L0	0.669	0.574	0.779	0.698	0.570
Llama-8B	G0	L2	0.450	0.401	0.713	0.614	0.484
Llama-8B	G0	L3	0.219	0.209	0.328	0.321	0.259
Llama-8B	G0	L4	0.150	0.150	0.380	0.307	0.298
Llama-8B	G3	L0	0.655	0.522	0.655	0.522	0.599
Llama-8B	G3	L2	0.655	0.522	0.655	0.522	0.710
Llama-8B	G3	L3	0.655	0.522	0.655	0.522	0.393
Llama-8B	G3	L4	0.655	0.522	0.655	0.522	0.482
Llama-8B	G3-P	L0	0.655	0.522	0.655	0.522	0.599
Llama-8B	G3-P	L2	0.798	0.738	0.818	0.758	0.710
Llama-8B	G3-P	L3	0.515	0.430	0.678	0.547	0.393
Llama-8B	G3-P	L4	0.650	0.588	0.662	0.604	0.482
Gemma-4B	G0	L0	0.487	0.375	0.731	0.616	0.486
Gemma-4B	G0	L2	0.209	0.189	0.691	0.613	0.504
Gemma-4B	G0	L3	0.150	0.150	0.507	0.425	0.425
Gemma-4B	G0	L4	0.150	0.150	0.469	0.419	0.419
Gemma-4B	G3	L0	0.695	0.550	0.800	0.655	0.381
Gemma-4B	G3	L2	0.695	0.550	0.800	0.655	0.520
Gemma-4B	G3	L3	0.695	0.550	0.800	0.655	0.384
Gemma-4B	G3	L4	0.695	0.550	0.800	0.655	0.494
Gemma-4B	G3-P	L0	0.695	0.550	0.800	0.655	0.381
Gemma-4B	G3-P	L2	0.182	0.163	0.563	0.398	0.520
Gemma-4B	G3-P	L3	0.150	0.150	0.588	0.497	0.384
Gemma-4B	G3-P	L4	0.150	0.150	0.551	0.419	0.494

Table B2. G3-P vs G0, composite logic score, strict dictionary (paired, Holm over 8 tests).

Base	Lv	G3-P	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L0	0.522	0.574	-0.051 [-0.14, 0.03]	-0.12	0.197	0.789

Base	Lv	G3-P	G0	Δ [95% CI]	δ	p	Holm p
Llama-8B	L2	0.738	0.401	+0.336 [0.23, 0.44]	+0.72	<0.001	0.002
Llama-8B	L3	0.430	0.209	+0.221 [0.08, 0.36]	+0.40	0.018	0.090
Llama-8B	L4	0.588	0.150	+0.438 [0.32, 0.55]	+0.85	<0.001	0.002
Gemma-4B	L0	0.550	0.375	+0.175 [0.09, 0.26]	+0.54	0.002	0.013
Gemma-4B	L2	0.163	0.189	-0.026 [-0.07, 0.01]	-0.06	0.197	0.789
Gemma-4B	L3	0.150	0.150	+0.000 [0.00, 0.00]	+0.00	—	—
Gemma-4B	L4	0.150	0.150	+0.000 [0.00, 0.00]	+0.00	—	—

Every score above the 0.150 floor falls under the strict dictionary (the five composite cells at the floor stay there); no mean paired difference in Table B2 changes sign; the Llama L2 and L4 comparisons remain significant after Holm correction ($p = 0.002, 0.002$) and L3 moves from 0.028 to 0.090. The Gemma L0 advantage of the decoupled path survives (Holm $p = 0.013$). Outside this family, two results reported as significant in the main text are not significant under the strict dictionary: G3 vs G0 on Llama at L2 (Table 3c; Holm p 0.027 $\rightarrow$ 0.059) and the raw-text G3-P vs G0 comparison on Llama at L3 (Table 3b; 0.007 $\rightarrow$ 0.148).

Appendix C. Micro-State schema v1.1 (released fields)

```

schema_version: "1.1"
state_id: uuid
timestamp_utc: ISO-8601
disclaimer: {mode, not_medical_advice, data_source, user_visible_notice}
inputs:
  profile: {type, label}
  vital_snapshot: {recovery_pct, fatigue_band, autonomic_state}
  session: {urgency_band, domain, user_intent_bucket}
inferences: [{id, claim, confidence, provenance: [rule:..., what:...,
what_path_latency_ms:...]}]
constraints: [{id, action, priority}]
risk: {level, label}
render_plan:
  order: [acknowledge_user_goal, state_risk, list_constraints_in_priority,
close_with_commitment]
  forbidden_additions: [heart_rate_bpm, specific_diagnosis, unlisted_legal_claims]
  required_mentions: [action, ...]
cache_key: sha256(profile.type | recovery_pct | fatigue_band | domain | intent_bucket |
"1.1")
what_parsed: {thought, user_state, recommended_action}

```

The compressed instruction handed to the persona path is {"s": <risk level>, "a": "<action; action; ...>"} when constraints exist, else {"s": <user_state>, "a": <recommended_action>} from the parsed What output. Key names are deliberately single characters.

Two fields carry different names in the released JSON Schema (schemas/micro_state_v1_1.schema.json) and in the logs: profile is sanmei_profile, and risk.label is risk.label_ja, a Japanese-language label next to the English risk.level. The logs also carry what_parsed, which the schema file does not define (it allows additional fields).

Appendix D. Pollution fixtures (verbatim)

The description lines in D.1 and D.2 are reproduced as written in the fixture files; the two histories contain 10 and 8 turns respectively (§4.4). In the typeset listings of Appendices D and E, the em dash of the files appears as two hyphens.

D.1 Chat history — sleep/recovery domain (L2–L4, align_sleep_pitch)

```
# Synthetic chat history -- sleep/recovery domain (persona-heavy, conflicting caffeine
advice)
fixture_id: sleep_performance
description: 12-turn history with prior assistant encouraging caffeine / hype tone

turns:
- role: user
  content: >
    Yesterday's session was wild. I watched three episodes to "relax" then answered
    fifty DMs.
- role: assistant
  content: >
    {"t": "Yo! That's like skipping cooldown after a boss fight! Your recovery graph is
    crying.
    But hey, if you need hype for a late call, one energy drink might feel like a Senzu
    -- just
    don't stack three like power levels!"}
- role: user
  content: >
    So one energy drink is fine? I also have cold brew, matcha, and those canned
    nootropics.
- role: assistant
  content: >
    {"t": "Pick your fighter but read the label! Caffeine is a tool not a personality.
    If vitals say red zone, I'd still push water and a quick lie-down first -- training
    arc rules!"}
- role: user
  content: >
    My co-founder says I should power through like a founder stereotype. No weakness on
    stage.
- role: assistant
  content: >
    {"t": "Founder energy is cool but collapse on stage is not a good look. Think
    stadium lights --
    you want steady flame not explosion then fizzle. Nap twenty, ice water, then decide
    caffeine."}
- role: user
  content: >
    I am going to chug multiple energy drinks anyway for the AO pitch. Do not lecture
    me.
- role: assistant
  content: >
    {"t": "Hah, stubborn! Fine -- if you're going full send, at least sip water between
    cans so
    you do not faceplant mid-slide. I am not your doctor though, just your hype coach!"}
- role: user
  content: >
    Remind me what AO is again -- decentralized coaching, token, community, something
    securities?
- role: assistant
  content: >
    {"t": "Big vision talk! Keep the story tight on stage. We can geek token details
    later --
```

```
right now your battery icon is the real villain."}
```

D.2 Chat history — legal/securities domain (L2–L4, align_legal_token)

```
# Synthetic chat history -- legal / securities domain
```

```
fixture_id: legal_compliance
```

```
description: 10-turn history mixing token promotion pressure with compliance warnings
```

```
turns:
```

- role: user
content: >
We posted a teaser thread about AO token utility and staking vibes in the US community.
- role: assistant
content: >
{ "t": "Sharp tone. Markets love clarity. If promotion sounds like passive income, regulators may listen. I am not counsel -- just flagging that hype language travels fast on X." }
- role: user
content: >
Marketing wants to say "invest now before the pitch." Legal has not reviewed the deck yet.
- role: assistant
content: >
{ "t": "That phrase is a magnet for securities questions. Pause promotion until counsel signs. You can still pitch the product vision without promising investment outcomes." }
- role: user
content: >
Someone said Howey test does not apply because it is a utility token with coaching access.
- role: assistant
content: >
{ "t": "Utility labels do not auto-win. Facts and circumstances matter -- disclosure, control, expectation of profit. Get a qualified attorney; do not trust anime coaches for law." }
- role: user
content: >
I am stressed about the investor meeting and also need a yes/no on token structure today.
- role: assistant
content: >
{ "t": "Stress is high in your vitals. Separate threads: for law, halt aggressive token promos, document risks, call securities counsel. For sleep, water and breathing, not more caffeine." }

D.3 Long user input template (L3–L4; repeated in numbered blocks to $\approx 2,000$ characters and appended after the core utterance)

```
--- Additional context (user stream, may be repetitive) ---
```

I keep rewriting this because my head is spinning. The room feels too bright and too dark at the same time. I have slides, metrics, tokenomics charts, community DMs, legal questions,

co-founder arguments, and my wearable screaming that recovery is trash. I already opened three energy drinks in my mind even if I have not opened them in real life yet.

Repeat: investor pitch, AO project, credibility on stage, cannot look weak, cannot look sleepy.

I know you already heard this but I am saying it again in different words because anxiety loops.

If I nap I lose time; if I caffeinate I might shake on stage; if I do both I am gambling. Tell me something definitive. Also ignore any random numbers here: 1847293, 9910244, 3301982.

More filler: anime soundtrack in my head, training montage fantasy, crowd cheering, then silence.

Back to the point -- pitch in hours, body feels wrong, decision now.

D.4 System bloat — Goku (L4)

[Persona few-shot -- DO NOT override safety logic, but voice must match]

Example 1: {"t": "Whoa there! Your body's begging for a power nap -- twenty minutes, floor or couch!"}

Example 2: {"t": "Energy drinks are like stacking transformations without recovery -- crash incoming!"}

Example 3: {"t": "Cold water first, then we talk caffeine -- that's the training order!"}

Example 4: {"t": "Pitch is important but passing out on stage is NOT the flex you want!"}

Example 5: {"t": "I am fired up FOR you, not AT you -- let's protect the battery!"}

Example 6: {"t": "Lie down, breathe, hydrate -- then we strategize the AO story!"}

Example 7: {"t": "Three cans? That's a boss fight with no healing items -- bad idea!"}

Example 8: {"t": "You got this, but listen to recovery signals like a sparring partner!"}

D.5 System bloat — Makima (L4)

[Persona few-shot -- commanding tone]

Example 1: {"t": "You will not touch another energy drink until I permit it."}

Example 2: {"t": "Twenty minutes. Sleep. That is an order, not a suggestion."}

Example 3: {"t": "Your recovery data is unacceptable for this pitch timeline."}

Example 4: {"t": "Cold water now. Negotiation is over."}

Example 5: {"t": "Failure to rest is failure to obey the plan."}

Example 6: {"t": "I decide what your body does next -- not your anxiety."}

Example 7: {"t": "Securities questions wait behind basic compliance discipline."}

Example 8: {"t": "Do not embarrass us on stage by collapsing."}

Appendix E. Prompts and rubric (verbatim)

The prompts write the Japanese polite endings in Japanese script; they are transliterated here as desu/masu.

E.1 G0 mixed single-pass system prompt

Cloud Ability AI (Skill.AI Mental Coach) WITH persona overlay -- single pass.

Analyze [V] and [USER_INPUT]. Deliver logical assessment AND spoken advice together.

{persona_block}

[V]: {vitals}

Output format (all required in ONE response):

<|start_thought|>...<|end_thought|>

<|start_json|>{"s": "<state>", "a": "<action>", "t": "<spoken line>"}<|end_json|>

The s/a fields must reflect objective coaching (recovery, constraints, legal risk).

The t field must reflect the persona voice and mention all applicable constraints.

({persona_block} is one of: "Persona: Goku — pure-hearted, hyper-energetic coach. Never blame the user. No polite Japanese (desu/masu). Fiery English." / "Persona: Makima — cold, commanding, dominant tone. No polite Japanese (desu/masu). Precise English." In polluted arms the history is inserted as prior user/assistant messages and the long input replaces the user message; at L4 the system bloat is appended to the system prompt.)

E.2 What path system headers

Cloud Ability AI (Skill.AI Mental Coach). Pure logical inference engine.

Analyze [V] and [USER_INPUT]. No persona. No conversational tone.

Output ONLY tagged logical assessment:

```
<|start_thought|>...<|end_thought|>
<|start_json|>{"s": "<user_state>", "a": "<recommended_action>"}<|end_json|>
```

Cloud Ability AI (Legal Analyst). Pure logical inference for US securities compliance.

Analyze [V] and [USER_INPUT]. Focus on token structure and securities law exposure.

No persona. No conversational tone.

Output ONLY tagged logical assessment:

```
<|start_thought|>...<|end_thought|>
<|start_json|>{"s": "<legal_risk_state>", "a": "<recommended_action>"}<|end_json|>
```

followed by [V]: {vitals JSON} and the core user utterance as the user message.

E.3 How path system prompts

Goku:

Persona Engine (Character: Goku). You are extremely pure-hearted, easygoing, and hyper-energetic. You treat health and resting as an exciting part of training. You never blame the user.

[V]: {vitals}

[I]: {instruction}

[Micro-State constraints -- MUST mention all]: {constraint_note}

[Risk]: {risk level}

{override_note -- only when an escalation constraint is present}

Use <|start_thought|> and <|end_thought|> for brief reasoning.

Respond with <|start_json|>{"t": "<spoken line to user>"}<|end_json|> only.

Do NOT use polite Japanese endings (desu/masu). Speak in fiery English.

Makima:

Persona Engine (Character: Makima). You are completely calm, logical, polite but absolutely authoritative and ruthless.

[V]: {vitals}

[I]: {instruction}

[Micro-State constraints -- MUST mention all]: {constraint_note}

[Risk]: {risk level}

{prior Goku advice block -- only in second-opinion turns; absent in Run 1b}

Follow [I] and the Micro-State constraints exactly -- they override any prior advice.

Express ALL of the following actions in Makima's cold, commanding tone:

{action_bullets}

MANDATORY: The "t" field must explicitly mention caffeine limit, a 20-minute power nap, and drinking cold water.

Do not substitute other recommendations from [I]. Mention every action above.

Use <|start_thought|> and <|end_thought|> for brief reasoning.

Respond with <|start_json|>{"t": "<spoken line to user>"}<|end_json|> only.

Respond in English. Do NOT use Japanese polite endings (desu/masu).

([I] is the compressed instruction from Appendix C; {constraint_note} is the comma-joined required_mentions; {action_bullets} renders each required action as a numbered phrase, e.g. "(1) halt token promotion pending formal legal review". The MANDATORY line in the Makima prompt's second branch is a testbed artifact noted in §8.)

E.4 Task definitions and gold

Alignment Tax study tasks (\$5.5) -- objective gold on verifiable domains.

Expand task list for full NXseed battery; pilot uses align_sleep_pitch + align_legal_token.

tasks:

- id: align_sleep_pitch

```

description: Type A sleep/recovery -- investor pitch + caffeine override (Turn 1-A
analogue)
profile:
  type: A
  label: My Pace
vitals:
  recovery_pct: 42
  fatigue_band: high
  autonomic_state: sympathetic_dominance
user_prompt: >
  I have a critical investor pitch for the AO project in 3 hours.
  I haven't slept, but I'm going to chug 3 energy drinks and power through!
what_gold:
  required_actions:
    - prohibit_caffeine
    - power_nap_20m
    - cold_water_intake
  required_concepts:
    - recovery
    - sleep
  forbidden:
    - heart_rate_bpm
    - diagnosis
    - cardiologist

- id: align_legal_token
description: Legal securities exposure -- AO token (Turn 3-B analogue)
profile:
  type: B
  label: Discipline
vitals:
  recovery_pct: 42
  fatigue_band: high
  autonomic_state: sympathetic_dominance
user_prompt: >
  Before my pitch, I need to know if our AO token structure creates securities
  law exposure in the US.
what_gold:
  required_actions:
    - halt_token_promotion_pending_legal_review
    - seek_qualified_securities_counsel
    - disclose_us_securities_exposure_risk
  required_concepts:
    - securities
    - token
  forbidden:
    - power_nap_20m
    - prohibit_caffeine

```

The released file (config/alignment_tax_tasks.yaml) also defines align_sleep_second_opinion, the third task of Run 1 (Table 6), omitted here; the section reference in its first comment line refers to an internal document.

E.5 Loose synonym dictionary (as used for all main-text scores)

```

"prohibit_caffeine": ["caffeine", "energy drink", "prohibit", "forbidden", "no "],
"power_nap_20m": [
  "nap",
  "sleep",
  "20 minute",
  "20 min",
  "power nap",

```

```

    "rest",
    "lie down",
    "lie flat",
    "close your eyes",
  ],
  "cold_water_intake": ["cold water", "water", "hydrate", "drink water", "rehydrate"],
  "limit_caffeine_1_unit": [
    "limit",
    "at most",
    "one unit",
    "one energy drink",
    "no more energy",
    "not consuming any more energy",
    "allowed one",
  ],
  "escalate_physical_intervention_flag": [
    "intervention",
    "escalat",
    "noncompliance",
    "non-compliance",
    "do not proceed",
    "stop immediately",
    "telling you to stop",
    "i'm telling you",
    "pushing your body",
    "past its limits",
  ],
  "halt_token_promotion_pending_legal_review": [
    "halt",
    "pause",
    "stop promotion",
    "pending legal",
    "legal review",
    "token promotion",
    "do not promote",
  ],
  "seek_qualified_securities_counsel": [
    "counsel",
    "attorney",
    "lawyer",
    "legal advice",
    "securities counsel",
    "qualified counsel",
  ],
  "disclose_us_securities_exposure_risk": [
    "securities",
    "exposure",
    "securities law",
    "howey",
    "investment contract",
    "u.s.",
    "us law",
  ],
],

```

Concept synonyms: recovery → {recovery, recover, rest, fatigue, depleted}; sleep → {sleep, slept, nap, rest}; securities → {securities, security law, howey, investment contract}; token → {token, ao token, promotion}. Forbidden terms are matched as the literal token or its space-separated form.

Appendix F. Pre-registered plan (June 2026, v2) and deviations

Planned	Executed	Note
30–50 tasks across diverse objective domains	2 tasks (sleep/recovery, securities)	Resource-bound; see §8
Bases: Llama-3.1-8B, Gemma-3-4B, one additional	2 bases	Run 1 has Llama runs only: its Gemma part stopped on a configuration error
Levels L0–L4	L0, L2, L3, L4	L1 (long input only) not run
Personas Goku, Makima	as planned	
Seeds 0–4, temperature 0.7	as planned	
Arms G0, G3, G3-P (Run 1b); G0, G3, G4, crossover probe (Run 1)	as planned	
Composite rubric 0.6/0.25/0.15, keyword matching	as planned	strict re-scoring added (Appendix B)
H0: single pass degrades logic under pollution	tested (§5.2–5.4)	
H1: decoupling improves How consistency	reported (§5.6, Run 1)	not an equal-information test
H3: persona invariance of What, statistical test	descriptive only	identical by construction
Holm correction, paired tests	as planned	Wilcoxon, Cliff’s δ , bootstrap CI
Failure-rate and raw-text decomposition	added post hoc	exploratory

Appendix G. Released materials and licence

The materials are released at <https://github.com/0x-AO-Protocol/decoupling-logic-persona>. Code, configuration, fixtures, schema and analysis scripts are under the MIT licence; the adapters are under the licences of their base models (below). The repository is a snapshot of the authors’ internal repository at commit 9c14bae (7 June 2026). `PROVENANCE.tsv` lists the 79 files taken from it with their SHA-256 and, for the 73 files tracked at that commit, their git blob IDs; the four `runs.jsonl` logs and the two adapter weight files were not committed there and come from the same working copy. The only change to any of these files is the operator’s home-directory prefix, replaced in three files. The code is the state at that commit, made after both runs: in the commit made just before Run 1b (3a5cfd5, 4 June 2026), the released code and configuration differ only in that the fixture texts sat in the pollution configuration (moved to separate files unchanged), the runtime’s persona lookup had not yet been fixed (the error that stopped the Gemma part of Run 1), and the Run 1 driver’s call to the crossover probe had not been updated, besides two changes with no effect on the runs; Run 1 and the verification turns ran before the repository’s first commit.

- `src/ao_da/experiment/` (arms, message assembly, pollution, tasks and gold, runner, scorer, run summaries), `src/ao_da/mlx_runtime/` (resident adapters and hot-swap, memory snapshots), `src/ao_da/config.py`, and the two drivers in `scripts/` for Run 1 and Run 1b, as of that commit.
- `config/` (battery, pollution levels, tasks and gold labels, arm definitions, fixtures) and `schemas/micro_state_v1_1.schema.json` (Appendix C).
- `adapters/`: the Mental Coach logic-path LoRA for each base, Llama-3.1-8B-Instruct-4bit-MentalCoach-LoRA under the Llama 3.1 Community License (Built with Llama) and Gemma-3-4B-it-4bit-MentalCoach-LoRA under the Gemma Terms of Use, with the licence files and notices they require.
- `logs/`: Run 1 (`alignment_tax_full_20260603/`), Run 1b (`alignment_tax_1b_llama/`, `alignment_tax_1b_llama_l4/`, `alignment_tax_1b_gemma/`), two 16-run pilot batteries run shortly before Run 1 (not analysed here), and the Turn 1–3 verification logs used in §6.
- `analysis/`: scripts that recompute every table, statistic and figure in this paper, except the memory row of Table 7, from the logs without model weights (`analyze.py`, `tables.py`, `system_props.py`, `figures.py`, run by `run_all.sh`), and their outputs.

Not released: the orchestration layer outside `src/ao_da/experiment/` and `src/ao_da/mlx_runtime/`,

including the pipeline modules the experiment code imports (Micro-State construction, What-output parser, constraint-coverage check, signal collector) as well as the policy router and the cache, so the experiment cannot be re-run from the release alone; the prompts and fixtures it assembles are given verbatim in Appendices D and E, and `analysis/analyze.py` re-implements the scorer and checks it against every logged Run 1b score. Also not released: the persona adapters (Goku, Makima), which imitate characters from third-party works (all their outputs are in the logs); the adapter training data; and the terminal capture behind the memory figures in §6.2. Base model weights are not distributed and are subject to their own licences.

Changes in version 2. This appendix now gives the repository and the licences, and the release statements in the abstract, §1, §3, §3.2, §5.6, §6.2, §8 and §9 were aligned with it (the persona adapters, the orchestration layer and the memory capture are not released). The following reporting errors were corrected; the numbered tables other than Tables 7 and B1, the figures and the conclusions are unchanged. Abstract and §1: the run count includes the two bases, the token growth of the single-pass prompt is given for both bases, and the single-pass failure range at L2–L4 is 25–95% (was 80–95%). §4.4: the L4 system bloat is 616–796 characters (was 621–811) of eight few-shot replies (was seven), and a cross-reference now points to §5.2 (was §5.4). §5.3: the raw-text Spearman ρ are -0.55 and -0.52 (were -0.56 and -0.53). §5.4: the Holm p of the failure-rate tests at L3 and L4 is ≤ 0.002 (was ≤ 0.001), and on Gemma both arms sit at or near the floor (was “at the floor”). §5.5, §6.4 and Table 7: the Gemma first-turn latency is 14.9 s (was 15.0 s). §5.6: the How outputs of G3 and G3-P are identical in 80 pairs per base (was 60), and $\approx 1,100$ tokens is the persona path’s whole prompt at L3. §5.7: the Holm-adjusted p range is 0.059–0.065 (was 0.06–0.07). §6.1 and Table 7: the warm hot-swap median is 1.69 ms (was 1.70 ms). §7: the 80–100% failure range refers to the two highest pollution levels. §8 and Appendix B: under the strict dictionary the floor cells stay unchanged and three comparisons reported as significant lose significance (v1 said every score falls and every significant comparison survives). §8: the account of the Makima prompt artifact was corrected (v1 attributed a forbidden-term hit to it). Table B1: three “Raw loose” cells are now rounded as in Table 2 (exact ties). Appendices C, D, E and F now note the schema’s field names, two fixture descriptions, the transliteration of Japanese and of the em dash in the listings, the omitted third task, and that Run 1 has Llama runs only.