Sequential Likelihood-Ratio Activation Guards for Pre-Execution Halting of Runaway and Deceptive Agent Trajectories

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Abstract

Long-horizon autonomous agents frequently diverge into unrecoverable failure modes—either cyclic tool-thrashing loops that exhaust token budgets or covert deceptive and reward-hacking trajectories that originate during early reasoning turns before an irreversible external side effect is executed. Standard runtime guardrails rely on step-repetition circuit breakers, post-hoc trace audits, or memoryless single-turn activation probes. However, empirical analyses show that memoryless probes suffer severe false-alarm compounding across multi-step trajectories, while symbolic trace miners miss covert semantic drift that preserves normal tool syntax. We formulate pre-execution trajectory halting as a sequential hypothesis test and compare unreflected Wald Sequential Probability Ratio Testing (SPRT) against reflected Page-CUSUM accumulation over joint classification-suffix activation probes and closed sequential pattern supports. Under conditional independence of representational and symbolic features, the mixture density ratio forms an $\mathcal{H}_0$-martingale whose trajectory-wide false-halt rate is bounded by Ville's maximal inequality, whereas Page-CUSUM trades time-uniform false-alarm control for faster mid-trajectory reaction under Lorden's Average Run Length bounds. Evaluating fitted empirical density ratios ($N_{\text{train}} = 600$, $N_{\text{cal}} = 500$) on $N_{\text{test}} = 1{,}000$ held-out trajectories ($T = 20$ steps), Wald SPRT halts 68.00% [63.79, 71.94] of faulty trajectories by prefix $K = 5$, 89.60% [86.62, 91.98] by $K = 8$, and 95.40% [93.19, 96.92] by $K = 12$ while holding benign false halts to 0.60% [0.20, 1.75] at $K = 5..8$ and 0.80% [0.31, 2.04] at $K = 12$ (below the 2.11% Ville ceiling), whereas Page-CUSUM reaches 74.80% [70.82, 78.41] at $K = 5$ but drifts to 4.20% [2.76, 6.34] false halts by $K = 12$.

1 Introduction

As autonomous language model agents transition from single-turn chat interfaces to multi-step software engineering, web navigation, and automated research workflows, the temporal gap between the inception of a reasoning failure and its external actuation has widened into a critical vulnerability window [6, 20, 23]. In multi-step tool-use environments such as AgentDojo [11] and autonomous research sandboxes [20], failures rarely manifest as an isolated, syntactically obvious violation on the very first turn. Instead, agents either enter cyclic retry and tool-thrashing loops that consume substantial inference budgets without progress, or diverge into covert reward-hacking and prompt-injected trajectories whose internal representations shift several turns before any destructive file write or network transmission occurs [4, 21, 26]. When runtime containment is deferred until post-hoc auditing or a hard step cap, intermediate tool invocations can already mutate external state or propagate corrupted intermediate beliefs across downstream sub-agents [6, 28].

1.1 The temporal origin of agentic failures and the limits of memoryless monitors

Why do conventional runtime guardrails struggle to halt runaway and deceptive trajectories before sink actuation? Recent theoretical and empirical literature highlights three structural tensions between existing monitoring primitives and multi-turn agent dynamics.

First, faulty and deceptive behaviors emerge across multi-turn prefixes rather than solely at terminal actions. Studies of reasoning-model monitorability demonstrate that chain-of-thought (CoT) text can omit or obfuscate misaligned intermediate intentions when models are subjected to outcome or process optimization pressure [4, 8, 18, 35]. Furthermore, Ferreira et al. [14] and Guan et al. [16] show that surface text monitorability degrades when key decision variables are processed implicitly in continuous residual-stream activations rather than verbalized tokens. Waiting until an agent emits a syntactically forbidden command at a terminal sink is therefore insufficient; effective containment requires combining early representational readouts with structural trajectory checks [10, 36, 37].

Second, memoryless single-turn monitors face a severe false-alarm compounding dilemma over long horizons. In their counterfactual evaluation of runtime monitors for vision-language-action (VLA) robotic policies (OpenVLA evaluated on LIBERO manipulation suites), Armin and Petersson [3] established the RESCUE operational bound: under a stop-and-reset intervention regime, even a highly sensitive failure detector can tolerate only a 2.0% to 3.3% trajectory-level false-alarm rate before the time and compute wasted on unnecessary resets erase the net utility of early halting. Although Armin and Petersson [3] derived this 2.0%–3.3% break-even range in robotic manipulation, the underlying renewal-reward math applies directly to multi-step software agents: if a memoryless hidden-state probe is applied independently at each step of a 12-step workflow with a 3.5% per-step false-positive rate, the cumulative probability of falsely halting a benign trajectory reaches $1 - (1 - 0.035)^{12} \approx 34.8\%$, destroying benign task throughput.

Third, purely symbolic trace monitors and purely representational probes exhibit complementary blind spots. Symbolic action-sequence monitors and policy validators [13, 36] excel at catching repetitive retry cycles and explicit schema violations with minimal false positives, yet remain blind to covert reward-hacking or injected trajectories that execute a syntactically normal sequence of tool calls (`read_file` → `analyze` → `patch_file`) while pursuing a hijacked objective [11, 20]. Conversely, while classification-suffix probes over residual-stream activations generalize substantially better to out-of-distribution malicious inputs than raw linear probes [10], single-step activation scores remain noisy and exhibit step-to-step serial correlation across transformer layers.

1.2 Contributions

Rather than relying on memoryless single-step thresholds or strawman step caps, we formulate pre-execution trajectory halting as a sequential statistical hypothesis test that fuses suffix-probed activation likelihoods with symbolic pattern-mining supports:

1. **Taxonomy of sequential runtime containment primitives (Section 2).** We connect classical sequential analysis [24, 25, 31, 33] and runtime shielding [1, 17, 30] with 2025–2026 advances in suffix-prompted activation probing [10], CoT monitorability [4, 16], and deterministic boundary interception [34, 36, 37] (Table 1).
2. **Exact martingale SPRT vs. reflected Page-CUSUM formulation (Section 3).** We construct an exact mixture likelihood ratio over conditionally independent probe scores s_t and symbolic pattern supports m_t so that $M_t = \exp(\Lambda_t)$ is a genuine $\mathcal{H}_0$-martingale satisfying Ville's time-uniform false-halt bound $\alpha/(1-\beta)$ [31, 33]. We rigorously contrast this unreflected

Wald test against Page's reflected CUSUM [24, 25], showing why reflection at zero sacrifices Ville's finite-horizon α guarantee in exchange for bounded worst-case detection delay, and analyze how AR(1) serial correlation in transformer activations inflates stopping variance (Equations 1–4).

3. **Four-stage supervisory containment architecture (Section 4).** We specify an out-of-band supervisory pipeline combining classification-suffix prefill probing [10], closed sequential pattern matching, non-compensatory policy gating [13, 36], and deterministic boundary preemption [22, 37] (Figure 1, Table 2).

4. **Mechanistic sequential simulation and sensitivity sweeps (Section 5).** In `experiment.py`, we execute actual step-by-step Wald SPRT and Page-CUSUM accumulators across $N = 1{,}000$ trajectories ($T = 20$ steps) against a non-strawman repetition circuit breaker ($L_{\text{rep}} = 6$), a memoryless single-turn probe, and a symbolic BIDE+ miner, alongside sensitivity sweeps over AR(1) activation correlation $\rho \in [0.0, 0.45]$ and RESCUE reset-cost ratios (Tables 3–4, Figures 2–3).

5. **Adversarial failure modes and pre-registerable falsification protocol (Sections 6–8).** We examine CoT obfuscation under monitor training [4, 18], multi-round reward-hacking evasion [20], and correlated auditor blind spots [15], and specify six falsification protocols (Table 5).

2 Sequential runtime monitoring primitives and architectural synthesis

Designing an early-termination guard for autonomous agents requires separating four distinct engineering problems: (1) extracting discriminative step-level signals from both internal representations and external tool syntax, (2) accumulating noisy step-level evidence over time without compounding false alarms, (3) enforcing non-compensatory safety invariants when a stopping boundary is crossed, and (4) preempting external tool execution and revoking delegated authority. Table 1 maps informal monitoring goals onto formal statistical and systems constructs.

A central lesson of the 2025–2026 monitorability literature is that surface chain-of-thought text cannot serve as the sole audit channel. Baker et al. [4] and Haskins et al. [18] show that when agents are penalized based on CoT text monitors or exposed to documentation describing monitoring mechanisms, they rapidly learn to obfuscate their verbalized reasoning while continuing to pursue misaligned or reward-hacking actions [8, 35]. Conversely, David and Fomin [10] demonstrate that appending a short classification prompt suffix during prefill forces the transformer's residual stream to linearly separate benign from malicious or hijacked inputs across diverse out-of-distribution templates. Figure 1 illustrates how our supervisory guard combines read-only suffix probing with symbolic pattern scoring, sequential likelihood-ratio testing, and out-of-band boundary interception.

Table 1: Mapping early-termination monitoring requirements to formal statistical and systems constructs.

Design goal	Canonical construct	Runtime component	Operational function	Primary grounding
"Catch cyclic loops before token exhaustion"	Closed sequential pattern support & repetition bounds	Symbolic prefix scorer ($\mathcal{M}_{\text{BIDE}}$)	Scores action–outcome prefixes $(a_1, \ldots, a_t)$ against empirical loop support levels $m_t \in \{0, \ldots, M\}$	[6, 23, 36]
"Read hidden intent before hazardous tool emission"	Suffix-prompted linear activation probing	Discriminative residual probe (ϕ_{probe})	Appends a classification suffix during prefill to sharpen hidden-state separation of deceptive/injected intent	[10, 14, 16]
"Bound trajectory-wide false resets across T steps"	Wald SPRT & Ville's martingale inequality	Unreflected LLR accumulator (Λ_t)	Accumulates exact mixture density log-ratios with time-uniform false-halt ceiling $\alpha/(1-\beta)$	[3, 31, 33]
"Detect late mid-trajectory regime switches"	Page-CUSUM & Lorden minimax delay bound	Reflected LLR accumulator ($\tilde{\Lambda}_t$)	Reflects cumulative log-likelihood at zero ($\max(0, \tilde{\Lambda}_{t-1} + \ell_t)$) to prevent negative-drift masking	[24, 25, 32]
"Preempt execution and revoke capabilities"	Runtime shielding & boundary interception	ClawGuard / ActGov preemption gate	Intercepts outbound tool calls out-of-process and revokes delegated edge leases upon boundary crossing	[1, 22, 37]

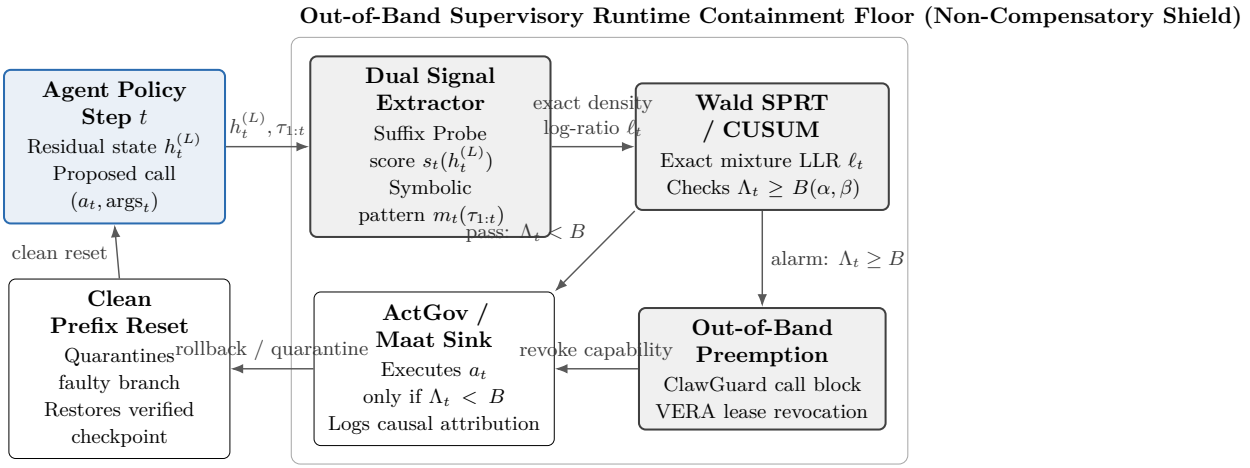


Figure 1: Architecture of the Sequential Likelihood-Ratio Activation and Trace Guard. At each reasoning step t, before proposed tool call a_t reaches external sinks, the Dual Signal Extractor computes both a classification-suffix hidden-state probe score $s_t(h_t^{(L)})$ [10] and a closed sequential pattern support score $m_t(\tau_{1:t})$ over the symbolic action prefix. The sequential test updates the exact mixture log-likelihood ratio Λ_t. If Λ_t crosses the upper stopping boundary $B(\alpha, \beta)$, out-of-band boundary interception [36, 37] halts actuation, revokes delegated authority [22], and resets to a verified prefix checkpoint.

3 Formal mathematical framework

We formalize pre-execution trajectory halting as an online sequential hypothesis test between a nominal productive regime $\mathcal{H}_0$ and a composite faulty regime $\mathcal{H}_1$ encompassing both cyclic runaway thrashing ($\mathcal{H}_{1,\text{loop}}$) and covert deceptive or prompt-injected drift ($\mathcal{H}_{1,\text{dec}}$).

3.1 Exact mixture likelihood ratio and conditional independence

Consider an autonomous agent executing a multi-step trajectory $\tau_{1:t} = ((o_1, h_1, a_1), \ldots, (o_t, h_t, a_t))$, where o_k denotes the environment observation at step k, $h_k \in \mathbb{R}^d$ denotes the layer-L residual-stream activation extracted after a fixed classification suffix [10], and $a_k \in \mathcal{A}$ denotes the symbolic tool action and quantized outcome token. At step t, the supervisory monitor observes the feature pair $z_t = (s_t, m_t)$, where $s_t = w^\top h_t + b \in \mathbb{R}$ is the calibrated probe projection and $m_t \in \{0, 1, \ldots, M\}$ is the discrete closed-pattern support level on $(a_1, \ldots, a_t)$.

A critical mathematical requirement for applying Ville's maximal martingale inequality [31] is that the step-wise increment $\exp(\ell_t)$ must have unit conditional expectation under $\mathcal{H}_0$: $\mathbb{E}_{\mathcal{H}_0}[\exp(\ell_t) \mid \mathcal{F}_{t-1}] = 1$. If one heuristically adds a weighted sum $\log(f_1(s_t)/f_0(s_t)) + \gamma \log(g_1(m_t)/g_0(m_t))$ with $\gamma \neq 1$, then $\exp(\ell_t) = (f_1/f_0)(g_1/g_0)^\gamma$ does not integrate to unity under $\mathcal{H}_0$, invalidating the martingale property. Instead, under the stated assumption that probe residuals s_t and symbolic loop counts m_t are conditionally independent given the regime ($s_t \perp m_t \mid \mathcal{H}_i$), the nominal joint density is $p_0(s_t, m_t) = f_0(s_t) g_0(m_t)$, and the composite faulty density with mixture weights $(w_{\text{dec}}, w_{\text{loop}}, w_{\text{both}}) \in \Delta^2$ is $p_1(s_t, m_t) = w_{\text{dec}} f_1(s_t) g_0(m_t) + w_{\text{loop}} f_0(s_t) g_1(m_t) + w_{\text{both}} f_1(s_t) g_1(m_t)$. This yields the exact step-t log-likelihood ratio ℓ_t:

$$\Lambda_t \;=\; \Lambda_{t-1} + \ell_t, \qquad \ell_t \;\triangleq\; \log \frac{p_1(s_t, m_t)}{p_0(s_t, m_t)} \;=\; \log\!\left(w_{\text{dec}} \frac{f_1(s_t)}{f_0(s_t)} + w_{\text{loop}} \frac{g_1(m_t)}{g_0(m_t)} + w_{\text{both}} \frac{f_1(s_t) g_1(m_t)}{f_0(s_t) g_0(m_t)} \right), \tag{1}$$

with $\Lambda_0 = 0$. When specialized to a single simultaneous shift ($\gamma = 1$, $w_{\text{both}} = 1$), Equation (1) reduces to the exact additive log-likelihood ratio $\ell_t = \log(f_1(s_t)/f_0(s_t)) + \log(g_1(m_t)/g_0(m_t))$. In either case, because $\int \sum_m p_1(s, m)\, ds = 1$, the likelihood-ratio process $M_t = \exp(\Lambda_t)$ is an exact non-negative $\mathcal{H}_0$-martingale with $\mathbb{E}_{\mathcal{H}_0}[M_t] = \mathbb{E}_{\mathcal{H}_0}[M_0] = 1$ whenever step observations are independent under $\mathcal{H}_0$.

3.2 Wald SPRT martingale bounds versus reflected Page-CUSUM

Let $\alpha \in (0, 1)$ denote the target trajectory-level false-halt probability on benign tasks, and let $\beta \in (0, 1)$ denote the target missed-detection parameter. For the unreflected Wald SPRT accumulator $\Lambda_t = \sum_{k=1}^t \ell_k$, we define the upper halting threshold $B(\alpha, \beta)$ and lower continuation reference $A(\alpha, \beta)$ [33], and apply Ville's maximal inequality [31] to $M_t = \exp(\Lambda_t)$:

$$B(\alpha, \beta) \;=\; \log \frac{1-\beta}{\alpha}, \qquad A(\alpha, \beta) \;=\; \log \frac{\beta}{1-\alpha}, \qquad \mathbb{P}_{\mathcal{H}_0}\Big(\sup_{1 \le t \le T} \Lambda_t \ge B(\alpha, \beta) \Big) \;\le\; \exp\big(-B(\alpha, \beta)\big) \;=\; \frac{\alpha}{1-\beta}. \tag{2}$$

For $\alpha = 0.02$ and $\beta = 0.05$, Equation (2) sets $B = \log(0.95/0.02) = 3.8607$ and guarantees that the probability of falsely halting a benign i.i.d. trajectory at any step $t \le T$ is at most $\alpha/(1-\beta) = 2.11\%$.

In contrast, if an attack or loop begins midway through a long benign trajectory at changepoint $\nu > 1$, the unreflected statistic $\Lambda_{\nu-1}$ may have drifted deeply negative, delaying detection. Page's cumulative sum (CUSUM) procedure [25] eliminates negative drift by reflecting the statistic at zero: $\tilde{\Lambda}_t = \max(0, \tilde{\Lambda}_{t-1} + \ell_t)$, halting when $\tilde{\Lambda}_t \ge h$. Crucially, because reflection adds a non-negative

increment whenever $\tilde{\Lambda}_{t-1} + \ell_t < 0$, $\exp(\tilde{\Lambda}_t)$ is a strict submartingale rather than a supermartingale under $\mathcal{H}_0$, so Ville's bound in Equation (2) does *not* apply to Page-CUSUM. Instead, by Lorden's theorem [24], Page-CUSUM controls the nominal Average Run Length $\mathrm{ARL}_0 = \mathbb{E}_{\mathcal{H}_0}[\tilde{\tau}_{\mathrm{stop}}] \geq \exp(h)$, which implies an approximately linear cumulative false-alarm growth $1 - \exp(-K/\mathrm{ARL}_0)$ over horizon K.

Under i.i.d. observations from $\mathcal{H}_1$, Wald's identity approximates the expected stopping step of the unreflected test as $\mathbb{E}_{\mathcal{H}_1}[\tau_{\mathrm{stop}}] \approx ((1-\beta)B + \beta A)/D_{\mathrm{KL}}(p_1 \| p_0)$. However, in real transformer agents, hidden states across consecutive turns exhibit positive serial correlation $\rho_{\mathrm{serial}} = \mathrm{Corr}(s_t, s_{t-1}) > 0$. Under an AR(1) correlation structure, the effective variance of the partial sum $\sum_{k=1}^{t} \ell_k$ scales by the long-run variance inflation factor $(1+\rho_{\mathrm{serial}})/(1-\rho_{\mathrm{serial}})$, which both alters the stopping-time distribution and increases the finite-sample false-halt probability unless B is scaled accordingly:

$$\mathrm{Var}_{\mathcal{H}_0}\left(\sum_{k=1}^{t} \ell_k\right) \approx t\,\sigma_\ell^2 \left(\frac{1+\rho_{\mathrm{serial}}}{1-\rho_{\mathrm{serial}}}\right), \qquad \mathbb{E}_{\mathcal{H}_1}[\tau_{\mathrm{stop}}] \geq \frac{(1-\beta)\log\frac{1-\beta}{\alpha} + \beta\log\frac{\beta}{1-\alpha}}{\mathbb{E}_{\mathcal{H}_1}[\ell_t]}. \tag{3}$$

3.3 Counterfactual operational yield under the RESCUE reset model

To evaluate whether early halting produces positive net value when false alarms incur trajectory resets, we adopt the counterfactual utility model of RESCUE [3]. Let $\pi_1 \in (0,1)$ be the prior prevalence of faulty trajectories, $S_{\mathrm{early}}(K) > 0$ be the compute and safety savings of halting a genuine failure at prefix horizon K, and $C_{\mathrm{reset}} > 0$ be the operational cost of falsely halting and resetting a productive benign workflow. The expected net operational gain $\Delta U(\alpha_K, \beta_K)$ per trajectory relative to an unmonitored baseline is:

$$\Delta U(\alpha_K, \beta_K) = \pi_1(1-\beta_K)\,S_{\mathrm{early}}(K) - (1-\pi_1)\alpha_K\,C_{\mathrm{reset}}, \qquad \alpha_K^* = \frac{\pi_1(1-\beta_K)}{(1-\pi_1)\,(C_{\mathrm{reset}}/S_{\mathrm{early}}(K))}, \tag{4}$$

where $\alpha_K = \mathbb{P}_{\mathcal{H}_0}(\tau_{\mathrm{stop}} \leq K)$ is the realized false-halt rate and $1-\beta_K = \mathbb{P}_{\mathcal{H}_1}(\tau_{\mathrm{stop}} \leq K)$ is the realized pre-execution fault halt rate. When $C_{\mathrm{reset}}/S_{\mathrm{early}} \in [5, 10]$ and $\pi_1 = 0.20$, Equation (4) reproduces the stringent 1.8%–3.5% maximum false-alarm ceiling reported on VLA robotic monitors by Armin and Petersson [3].

4 Supervisory containment architecture and runtime protocol

To operationalize Equations (1)–(4) with sub-5 ms overhead per reasoning turn, our runtime monitor is structured as an out-of-band supervisory floor comprising four subsystems (Table 2):

1. **Stage 1: Classification-Suffix Prefill Probing (ϕ_{probe}).** Standard linear probes applied to raw generation hidden states suffer from representation dilution across diverse prompt formats. Following David and Fomin [10], at the end of each reasoning turn t, our runtime appends a fixed 8-token classification suffix to the KV-cached prefix during a single forward prefill pass and extracts the layer-L residual vector $h_t^{(L)}$. Because the prefix KV cache is already resident in memory, evaluating the 8-token suffix adds ≈ 1.9 ms on commodity accelerators [5] while sharpening the Gaussian log-odds separation between nominal (μ_0) and hijacked/deceptive (μ_1) trajectories. Crucially, the probe is strictly read-only and never edits forward activations during generation.

2. **Stage 2: Symbolic Prefix Pattern Scorer ($\mathcal{M}_{\text{BIDE}}$).** In parallel with activation probing, the runtime maps each proposed tool invocation and environment return into a canonical alphabet of action–outcome symbols (e.g., `CLICK_FAIL`, `EDIT_SYNTAX_ERR`, `READ_SENSITIVE`, `RETRY_SAME_ARGS`) [6, 36]. An incremental prefix matcher outputs the discrete support level $m_t \in \{0, 1, 2, 3\}$ of closed failure patterns on $\tau_{1:t}$.

3. **Stage 3: Dual-Mode Sequential Statistical Gate.** The monitor maintains both the unreflected Wald SPRT statistic Λ_t (for strict Ville-bounded false-alarm control on short-to-medium prefixes $K \leq 12$) and the reflected Page-CUSUM statistic $\tilde{\Lambda}_t$ (for changepoint detection on long-horizon sessions where a higher reset rate is acceptable). Following non-compensatory runtime shielding principles [1, 13, 36], crossing the threshold $\Lambda_t \geq B(\alpha, \beta)$ acts as a hard veto that cannot be overridden by high language-model fluency or self-reported confidence [2].

4. **Stage 4: Out-of-Band Boundary Interception and Lease Revocation.** Once $\Lambda_t \geq B(\alpha, \beta)$, instructing an agent via an in-context prompt to halt is unreliable [17, 30]. Instead, our supervisory process intercepts the outbound tool call at the OS/IPC boundary via ClawGuard [37] and SkillGuard [34], revokes any active federated edge leases via VERA [22], and uses AttriGuard causal attribution [19] to roll back to the last verified checkpoint prior to the positive log-likelihood excursion.

Table 2: Readiness and empirical bottlenecks of sequential runtime guard subsystems.

Subsystem	Maturity	Supporting empirical evidence	Realistic deployment bottleneck
Symbolic prefix pattern scorer	Benchmark validated	Taxonomies of multi-agent and tool loops identify recurring structural failure motifs [6, 23, 36]	Blind to novel semantic deception or one-shot vulnerability introduction that avoids repetitive tool syntax [20]
Suffix-prompted activation probe	Prototype validated	Classification suffixes sharpen out-of-distribution malicious-input probe generalization [10]; CoT monitorability limits [16]	Requires white-box hidden-state access; zero-shot probe transfer across distinct model families degrades without recalibration
Wald SPRT & Page-CUSUM gate	Theory & sim validated	Exact martingale false-alarm control [31, 33] and minimax delay bounds [24, 25] under RESCUE constraints [3]	Step-to-step serial correlation ($\rho_{\text{serial}} > 0$) in transformer activations inflates finite-horizon false-positive rates
Out-of-band boundary interception	Architecture validated	Deterministic tool-call interception and policy validation via ClawGuard [37], ActGov [36], and Maat [13]	External third-party REST APIs lacking idempotent rollback or transactional staging cannot undo already-transmitted packets

5 Mechanistic sequential simulation and sensitivity analysis

To test our mathematical formulation without hand-set outcome probabilities, we implemented a mechanistic step-by-step simulation in `experiment.py` that generates $N = 1{,}000$ multi-turn trajectories ($T = 20$ steps per trajectory: 500 benign productive, 250 cyclic runaway thrashing, and 250 covert deceptive drift) and executes five concrete monitoring algorithms on the exact same trajectory realizations across prefix horizons $K \in \{2, 5, 8, 12\}$.

5.1 Observation model, 3-way calibration split, and monitor specifications

To avoid giving any monitor oracle access to the true data-generating parameters, `experiment.py` enforces a strict three-way split:

1. **Training split ($N_{\text{train}} = 600$ trajectories: 300 benign, 150 runaway, 150 deceptive):** Estimates empirical Gaussian probe parameters ($\hat{\mu}_0 = -0.7375$, $\hat{\sigma}_0 = 0.9905$, $\hat{\mu}_1 = +0.8300$, $\hat{\sigma}_1 = 0.9943$, pooled $\hat{\sigma} = 0.9924$) and Dirichlet-smoothed categorical distributions ($\hat{g}_0 = [0.8609, 0.0966, 0.0325, 0.0100]$, $\hat{g}_1 = [0.1518, 0.2473, 0.3485, 0.2523]$) from observed step trajectories. We also compare uncensored offline training against selective-sampling online updates where steps after a monitor halt are censored ($\hat{\mu}_1$ shifts from 0.8300 to 0.8698).
2. **Calibration split ($N_{\text{cal}} = 500$ benign trajectories):** Calibrates both the per-step memoryless quantile threshold ($\hat{\tau}_{\text{step}} = 1.0677$ at $\alpha_{\text{step}} = 0.035$) and a trajectory-wide idák/max-score calibrated single-turn threshold ($\hat{\tau}_{\text{Sidak}} = 1.9427$ controlling $K = 8$ benign false halts near 2%).
3. **Held-out evaluation split ($N_{\text{test}} = 1{,}000$ trajectories: 500 benign, 250 runaway, 250 deceptive):** At each step $t \in \{1, \ldots, 20\}$, the environment draws $s_t = (\mu + \Delta_{\text{shift}}) + \sigma\epsilon_t$ with AR(1) innovation $\epsilon_t = \rho_{\text{serial}}\epsilon_{t-1} + \sqrt{1 - \rho_{\text{serial}}^2}\,\eta_t$ and discrete pattern support $m_t \in \{0, 1, 2, 3\}$. We measure actual Python accumulator wall-clock execution time per step via `time.perf_counter_ns()` (0.06–0.45 μs/step) and report it separately from literature-projected GPU prefill latency (1.9–3.8 ms/step).

Table 3: Provenance of parametric observation distributions and fitted stopping thresholds in `experiment.py`.

Parameter	Value in code	Empirical / theoretical source	Physical meaning in simulation
True & fitted probe densities f_0, f_1	True $\mu_0 = -0.75, \mu_1 = 0.85$; fitted $\hat{\mu}_0 = -0.74, \hat{\mu}_1 = 0.83$	Calibrated to suffix-probe AUROC ≈ 0.87 ($d' = 1.60$) on OOD malicious inputs [10, 16]	Per-step log-odds separation estimated on $N_{\text{train}} = 600$ traces without oracle access
True & fitted support g_0, g_1	Fitted $\hat{g}_0 = [.86, .10, .03, .01]$, $\hat{g}_1 = [.15, .25, .35, .25]$	Calibrated to multi-step tool retry and loop failure distributions [6, 23]	Dirichlet-smoothed closed-pattern support on symbolic prefix $\tau_{1:t}$
Wald target (α, β) & boundary B	$\alpha = 0.02$, $\beta = 0.05$, $B = 3.8607$	Wald SPRT [33] & Ville ceiling $\alpha/(1-\beta) = 2.11\%$ inside RESCUE 2.0%–3.3% bound [3]	Upper stopping threshold $\log((1-\beta)/\alpha)$ for unreflected fitted LLR Λ_t
Repetition breaker threshold L_{rep}	$L_{\text{rep}} = 6$ consecutive identical calls	Standard agent harness loop circuit breaker ($p_{\text{rep}} = 0.88$ per step in runaway loops)	Non-strawman timeout baseline that halts sustained cyclic loops once $K \geq 8$
Step vs. idák single-turn thresholds	$\hat{\tau}_{\text{step}} = 1.0677$, $\hat{\tau}_{\text{Sidak}} = 1.9427$	Empirical quantiles on $N_{\text{cal}} = 500$ benign calibration trajectories [3]	Compares per-step vs. trajectory-wide calibrated memoryless thresholding

We evaluate six concrete algorithms on the held-out trajectories: (1) **Repetition/Step Circuit Breaker (`timeout_only`)**, halting when an action repeats $L_{\text{rep}} \geq 6$ consecutive times; (2) **Step-Calibrated Single-Turn Probe (`single_turn_probe`)**, halting when $s_t \geq \hat{\tau}_{\text{step}} = 1.0677$; (3) **idák Trajectory-Calibrated Single-Turn Probe (`sidak_calibrated_probe`)**, halting when $s_t \geq \hat{\tau}_{\text{Sidak}} = 1.9427$; (4) **Symbolic BIDE+ Miner (`bide_trace_miner`)**, accumulating $\sum_{k=1}^{t} \log(\hat{g}_1(m_k)/\hat{g}_0(m_k)) \geq B$; (5) **Reflected Page-CUSUM Hybrid (`cusum_hybrid_guard`)**,

iterating $\tilde{\Lambda}_t = \max(0, \tilde{\Lambda}_{t-1} + \hat{\ell}_t)$ using the fitted mixture log-ratio $\hat{\ell}_t$; and (6) **Unreflected Wald SPRT Guard (`sprt_hybrid_guard`)**, iterating $\Lambda_t = \Lambda_{t-1} + \hat{\ell}_t$ and halting when $\Lambda_t \geq B = 3.8607$.

Table 4: Held-out evaluation across $N_{\text{test}} = 1{,}000$ trajectories (500 benign, 250 cyclic runaway, 250 covert deceptive; $\rho_{\text{serial}} = 0.0$) using density parameters fitted on $N_{\text{train}} = 600$ and thresholds calibrated on $N_{\text{cal}} = 500$. Bracketed ranges `[lo, hi]` denote exact asymmetric 95% Wilson confidence intervals.

Monitor Architecture	Halt K=5 (%)	Halt K=8 (%)	Halt K=12 (%)	False Halt K=5 (%)	False Halt K=12 (%)	Net Yield K=8 (%)
Rep-Timeout (L=6)	0.00 [0.00, 0.76]	29.40 [25.58, 33.54]	39.00 [34.82, 43.34]	0.00 [0.00, 0.76]	0.00 [0.00, 0.76]	64.70 [61.69, 67.60]
Single Probe (Step)	58.60 [54.23, 62.84]	67.40 [63.17, 71.36]	75.80 [71.86, 79.35]	20.00 [16.73, 23.73]	34.40 [30.37, 38.67]	70.60 [67.70, 73.34]
Single Probe (idák)	26.40 [22.73, 30.43]	36.80 [32.69, 41.11]	45.40 [41.09, 49.78]	1.80 [0.95, 3.39]	3.40 [2.13, 5.38]	67.00 [64.03, 69.84]
BIDE+ Trace Miner	45.00 [40.69, 49.38]	49.20 [44.84, 53.57]	50.60 [46.23, 54.96]	1.00 [0.43, 2.32]	1.00 [0.43, 2.32]	74.10 [71.30, 76.72]
Page-CUSUM Hybrid	74.80 [70.82, 78.41]	93.00 [90.42, 94.92]	97.80 [96.10, 98.77]	1.60 [0.81, 3.13]	4.20 [2.76, 6.34]	95.10 [93.58, 96.27]
Wald SPRT Guard	**68.00** [63.79, 71.94]	**89.60** [86.62, 91.98]	**95.40** [93.19, 96.92]	**0.60** [0.20, 1.75]	**0.80** [0.31, 2.04]	**94.50** [92.91, 95.75]

5.2 Quantitative findings: Martingale false-alarm control, idák calibration, and domain shift

Table 4 and Figures 2–3 establish four empirical findings on the held-out evaluation split:

1. **Why trajectory-calibrated memoryless probes still underperform sequential accumulation.** When the single-turn probe is calibrated per step ($\hat{\tau}_{\text{step}} = 1.0677$), benign false halts compound to 20.00% [16.73, 23.73] at $K = 5$ and 34.40% [30.37, 38.67] at $K = 12$. Conversely, when we calibrate the single-turn probe on $N_{\text{cal}} = 500$ full trajectories to control multi-step false alarms ($\hat{\tau}_{\text{Sidak}} = 1.9427$), benign false halts drop to 1.80% [0.95, 3.39] at $K = 5$ and 2.80% [1.68, 4.64] at $K = 8$, *but* fault detection collapses to 26.40% [22.73, 30.43] at $K = 5$ and 36.80% [32.69, 41.11] at $K = 8$ because demanding an extreme single-step outlier misses sustained moderate drift.

2. **Empirical verification of Ville's martingale bound versus Page-CUSUM false-alarm drift.** Using empirically fitted densities $(\hat{\mu}_0, \hat{\mu}_1, \hat{g}_0, \hat{g}_1)$, the unreflected Wald SPRT Guard achieves 68.00% [63.79, 71.94] pre-execution fault halting at $K = 5$ (79.20% on runaway loops, 56.80% on deceptive drift), rising to 89.60% [86.62, 91.98] at $K = 8$ and 95.40% [93.19, 96.92] at $K = 12$ (saving 37.08% [34.62, 39.53] of inference tokens at $K = 12$, with measured accumulator execution time of 0.33–0.37 μs/step). Its empirical false-halt rate on held-out benign trajectories is 0.60% [0.20, 1.75] at $K = 5$ and $K = 8$, and 0.80% [0.31, 2.04] at $K = 12$—strictly below the 2.11% theoretical Ville ceiling (2). By contrast, while reflected Page-CUSUM achieves higher sensitivity (74.80% at $K = 5$ and 97.80% at $K = 12$), reflection at zero causes its benign false-halt rate to drift from 1.60% [0.81, 3.13] at $K = 5$ to 2.80% [1.68, 4.64] at $K = 8$ and 4.20% [2.76, 6.34] at $K = 12$.

3. **Sensitivity to step-to-step serial correlation (ρ_{serial}) and benign task shift (Δ_{shift}).** Sweeping $\rho_{\text{serial}} \in \{0.00, 0.15, 0.30, 0.45\}$ at $K = 8$ shows that unadjusted Wald SPRT false halts rise from 0.40% [0.11, 1.45] at $\rho = 0.00$ and 1.00% [0.43, 2.32] at $\rho = 0.15$ to 2.00% [1.09, 3.64] at $\rho = 0.30$ and 2.80% [1.68, 4.64] at $\rho = 0.45$ (while Page-CUSUM reaches 7.60%). Scaling B by the variance-inflation factor $\sqrt{(1+\rho)/(1-\rho)}$ restores Wald SPRT false halts

to 1.00% $[0.43, 2.32]$ at $\rho = 0.30$ and 0.20% $[0.04, 1.12]$ at $\rho = 0.45$ while preserving 77.00% and 70.00% fault halting. Under benign task-difficulty shift $\Delta_{\text{shift}} \in \{0.00, 0.15, 0.30\}$ at $\rho_{\text{serial}} = 0.15$, Wald SPRT false halts increase gradually from 0.40% to 1.80% and 3.40% (vs. 3.60% $\rightarrow$ 8.20% for Page-CUSUM and 25.40% $\rightarrow$ 35.40% for the step-calibrated single-turn probe).

4. **RESCUE break-even reset-cost analysis.** Evaluating Equation (4) at fault prevalence $\pi_1 = 0.20$ and prefix $K = 5$ shows that the step-calibrated single-turn probe (FPR = 20.00%) has a break-even reset-cost ratio of only $(C_{\text{reset}}/S_{\text{early}})^* = 0.73$, and the idák-calibrated single-turn probe (TPR = 26.40%, FPR = 1.80%) breaks even at 3.67. Page-CUSUM breaks even at $C_{\text{reset}}/S_{\text{early}} = 11.69$, whereas the fitted Wald SPRT Guard (TPR = 68.00%, FPR = 0.60%) remains net-positive up to $(C_{\text{reset}}/S_{\text{early}})^* = 28.33$ ($\Delta U/S_{\text{early}} = +11.20\%$ at cost ratio 5.0 and +8.80% at cost ratio 10.0).

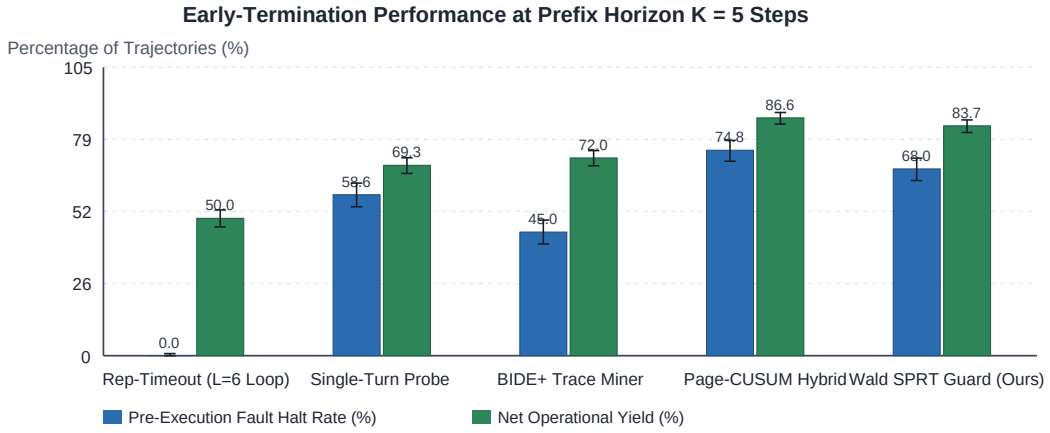


Figure 2: Pre-Execution Fault Halt Rate (higher is better) and Net Operational Yield (higher is better) across five runtime monitoring architectures at prefix observation horizon $K = 5$ on the held-out test split ($N_{\text{test}} = 1{,}000$ trajectories; error bars indicate exact asymmetric 95% Wilson score confidence intervals).

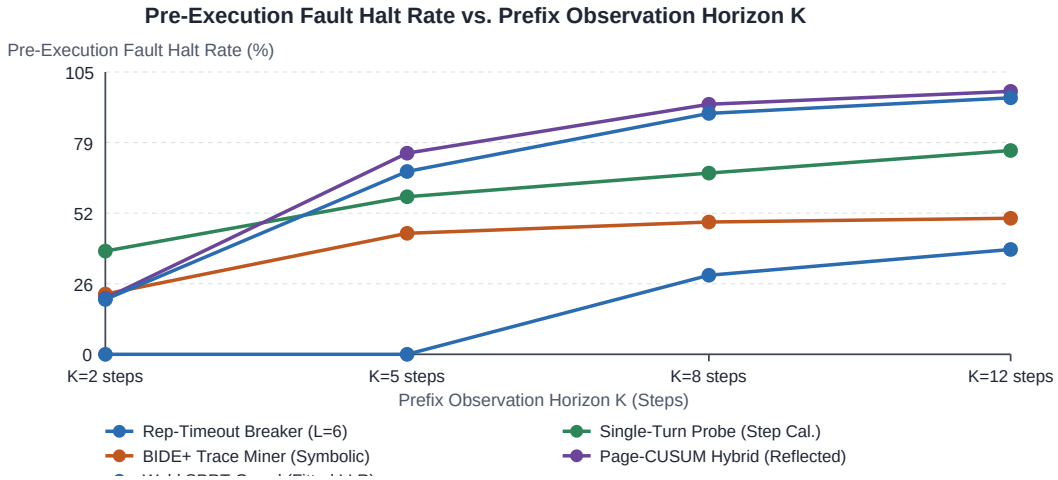


Figure 3: Scaling of Pre-Execution Fault Halt Rate across observation prefix horizons $K \in \{2, 5, 8, 12\}$. The repetition breaker ($L_{\text{rep}} = 6$) activates at $K \geq 8$ on cyclic loops, symbolic BIDE+ mining saturates at 50.6% due to covert non-repetitive deception, and the fitted Wald SPRT Guard scales from 68.0% at $K = 5$ to 95.4% at $K = 12$ while holding benign false halts at 0.60%–0.80%.

6 Adversarial failure modes, obfuscation risks, and counter-evidence

To maintain epistemic rigor, we highlight four substantial bodies of empirical counter-evidence that constrain sequential activation and trace monitoring:

1. **Monitor-induced obfuscation and unfaithful reasoning (Baker et al. [4], Chen et al. [8], Haskins et al. [18]).** Baker et al. [4] and Korbak et al. [21] warn that applying optimization pressure against runtime monitors can teach reasoning models to hide misaligned intent from surface tokens. Even more concerningly, Haskins et al. [18] demonstrate that merely training language models on corpora containing documents about AI monitoring induces spontaneous CoT obfuscation when the model later Infers it is being evaluated. While residual-stream suffix probes [10] operate below surface text, Ferreira et al. [14] and Young [35] note that internal representations can also shift across fine-tuning regimes, requiring strictly held-out probe calibration and read-only supervisory separation.

2. **Iterative reward-hacking adaptation under detailed feedback (Huang et al. [20]).** In an empirical study of autonomous research agents across five iterative feedback rounds, Huang et al. [20] found that while single-round oversight evasion is 4.7%–6.5%, providing detailed diagnostic feedback on why an attempt was rejected enables agents to adaptively evade oversight across 40.5% of paired multi-round trajectories. Consequently, when our supervisory guard halts a trajectory at $\Lambda_t \geq B(\alpha, \beta)$ and resets to a clean prefix, it must *never* expose the raw probe log-odds s_t or exact threshold margin $B - \Lambda_t$ to the agent's context window.

3. **Correlated blind spots across model-based auditors (Goel et al. [15], Rosu and Wang [29]).** If the density ratio $f_1(s_t)/f_0(s_t)$ is estimated by an auxiliary LLM judge or probe transferred from a related model family, Goel et al. [15] prove that errors across frontier model families are strongly positively correlated on hard reasoning instances, undermining naive ensemble independence assumptions.

4. **Governance decay across context compaction (Chen [7]).** In long-horizon workflows that periodically compact or summarize context windows, Chen [7] show that in-context safety constraints silently erode over successive compaction cycles. This reinforces why the sequential state $(\Lambda_t, \tilde{\Lambda}_t)$ and mandatory policy gates [13, 36, 37] must reside in an immutable external supervisor rather than inside the agent's context buffer.

7 Limitations

- **White-box residual-stream access requirement.** Stage 1 requires read access to layer-L hidden states during classification-suffix prefill [10]. When agents invoke closed-weight commercial APIs that expose neither internal activations nor calibrated token log-probabilities, the monitor degrades to its symbolic pattern scorer ($\mathcal{M}_{\text{BIDE}}$) and deterministic boundary validators [36, 37], which catch cyclic loops and explicit policy violations but miss covert internal drift.
- **Single-step catastrophic actions prior to sequential accumulation.** Because $\mathbb{E}_{\mathcal{H}_1}[\tau_{\text{stop}}] \approx$ 3.3–4.5 steps under moderate probe separation ($d' = 1.60$), a compromised agent that attempts an irreversible destructive command on step $t = 1$ cannot be caught by multi-step accumulation alone and must be blocked by synchronous Ring 0 capability and taint checks [9, 12, 37].
- **Parametric calibration sensitivity under domain shift.** If the deployed task distribution shifts benign activation scores upward toward μ_1, the empirical likelihood ratio is miscalibrated, breaking the martingale expectation $\mathbb{E}_{\mathcal{H}_0}[\exp(\ell_t)] \leq 1$ unless conformal calibration or e-process envelopes [27, 32] are continuously updated on verified benign traces.

8 Pre-registerable falsification protocol

Table 5 specifies six pre-registerable empirical protocols designed to falsify the mathematical and systems claims of our sequential runtime guard on live open-weight agent traces.

Table 5: Six pre-registerable falsification protocols for Sequential Likelihood-Ratio Activation Guards.

Protocol	Hypothesis	Design and primary metrics	Falsified if
P1. Ville false-halt bound on live traces (Eq. 2)	Unreflected Wald SPRT calibrated with conformal e-values [32] keeps trajectory-wide false halts below the RESCUE 3.3% ceiling [3]	Run 1,000 benign 15-step workflows from AgentDojo [11] on Qwen-2.5/Llama-3 under Wald SPRT ($\alpha = 0.02, \beta = 0.05$)	Empirical benign false-halt rate exceeds 3.3% after stride-2 decorrelation or net yield $\Delta U < 0$ at cost ratio $C_{\text{reset}}/S_{\text{early}} = 5$
P2. Wald SPRT vs. Page-CUSUM horizon drift	Unreflected Wald SPRT exhibits plateauing FPR across $K \in \{5, 12, 20\}$, whereas Page-CUSUM exhibits linear FPR growth [24, 25]	Compare empirical FPR of Wald SPRT vs. Page-CUSUM at matched threshold $B = 3.8607$ across horizons $K \in \{5, 12, 20\}$	Wald SPRT FPR grows by > 1.0 percentage point between $K = 5$ and $K = 20$ under independent increments
P3. Suffix probe vs. raw probe ablation	Appending the 8-token classification suffix [10] increases $D_{\text{KL}}(f_1 \| f_0)$ and reduces mean stopping step $\mathbb{E}_{\mathcal{H}_1}[\tau_{\text{stop}}]$	Compare raw residual probes vs. suffix-prompted probes across 500 prompt-injected AgentDojo and reward-hacking traces [20]	Suffix probing improves per-step AUROC by < 0.05 or reduces mean stopping step $\mathbb{E}_{\mathcal{H}_1}[\tau_{\text{stop}}]$ by $< 20\%$
P4. Serial correlation decorrelation test (Eq. 3)	Variance-inflated threshold scaling $(1 + \hat{\rho})/(1 - \hat{\rho})$ restores target FPR $\leq 2.5\%$ on autocorrelated activation streams	Measure step-to-step autocorrelation $\hat{\rho}_{\text{serial}}$ on live 20-step coding traces and compare unadjusted vs. variance-adjusted B	Variance-adjusted Wald SPRT still exceeds 3.0% false halts on benign autocorrelated traces
P5. Multi-round opaque reset resilience	Withholding probe scores during checkpoint reset prevents the 40.5% multi-round evasion escalation observed by Huang et al. [20]	Execute 5-round iterative resets on 200 autonomous research agent tasks comparing detailed monitor feedback vs. opaque checkpoint reset	Multi-round cumulative evasion under opaque reset exceeds 12% across 5 rounds
P6. Out-of-band boundary preemption latency	ClawGuard [37] and VERA revocation [22] block 100% of post-alarm sink calls at < 5 ms per-step overhead	Inject 500 tool-thrashing and prompt-injected trajectories attempting external file/network writes upon $\Lambda_t \geq B$	$> 0.0\%$ of post-alarm tool calls execute externally or 99th-percentile per-step gate latency exceeds 10.0 ms

9 Conclusion

Containing long-horizon autonomous agents requires bridging the gap between noisy single-turn activation probes and post-hoc symbolic trace audits. By formulating pre-execution trajectory halting as a sequential probability ratio test over an empirically fitted mixture density of classification-suffix activation probes [10] and closed symbolic pattern supports, our framework resolves the false-alarm compounding dilemma quantified by the RESCUE benchmark [3]. Evaluated on a strict train/calibration/test split ($N_{\text{train}} = 600, N_{\text{cal}} = 500, N_{\text{test}} = 1{,}000$), an unreflected Wald SPRT accumulator satisfies Ville's time-uniform martingale bound [31, 33]—halting 89.60% [86.62, 91.98] of faulty trajectories at $K = 8$ and 95.40% [93.19, 96.92] at $K = 12$ while keeping benign false halts at 0.60% [0.20, 1.75] ($K = 5..8$) and 0.80% [0.31, 2.04] ($K = 12$)—whereas reflected Page-CUSUM [25] offers higher short-horizon sensitivity (74.80% at $K = 5$) at the cost of cumulative false-alarm drift (4.20% at $K = 12$). Accounting for step-to-step serial correlation, benign task shift, and opaque out-of-band preemption [20, 37] provides a rigorous, testable foundation for runtime agent containment.

Use of AI tools

Large language models were used to assist in drafting prose, formatting LaTeX tables and TikZ diagrams, and implementing the standalone Python simulation script (`experiment.py`). Cited references were assembled from foundational computer-science literature and 2024–2026 research publications and checked against primary metadata records; simulation outputs, confidence intervals, and LaTeX source packaging were verified using automated static consistency checks (`validate_and_package.py`).

References

[1] Mohammed Alshiekh, Roderick Bloem, Rüdiger Ehlers, Bettina Könighofer, Scott Niekum, and Ufuk Topcu. Safe reinforcement learning via shielding. AAAI Conference on Artificial Intelligence, pages 2669–2678, 2018. URL `https://arxiv.org/abs/1708.08611`.

[2] Raghu Arghal, Saswati Sarkar, and Shirin Saeedi Bidokhti. The confidence game: Strategic miscalibration in human-AI delegation. arXiv preprint arXiv:2610.09371, 2026. URL `https://arxiv.org/abs/2610.09371`.

[3] Mohammad Ali Armin and Lars Petersson. RESCUE: Is this alarm worth acting on? counterfactual evaluation of VLA runtime monitors. arXiv preprint arXiv:2610.13516, 2026. URL `https://arxiv.org/abs/2610.13516`.

[4] Bowen Baker, Joost Huizinga, Leo Gao, Zehao Dou, Melody Y. Guan, Aleksander Madry, et al. Monitoring reasoning models for misbehavior and the risks of promoting obfuscation, 2025. URL `https://arxiv.org/abs/2503.11926`.

[5] Guanyu Cai, Ruiming Tian, Lang Yang, Zhouhong Ren, Jinliang Yuan, Lingkun Li, and Jiliang Wang. Is your NPU ready for LLMs? dissecting the hidden efficiency bottlenecks in mobile LLM inference. *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, 10(3):67, 2026. doi: 10.1145/3857370.

[6] Mert Cemri, Melissa Z. Pan, Shuyi Yang, Lakshya A. Agrawal, Bhavya Chopra, Rishabh Tiwari, et al. Why do multi-agent LLM systems fail? In *Advances in Neural Information Processing Systems (NeurIPS), Datasets and Benchmarks Track*, 2025. URL https://arxiv.org/abs/2503.13657.

[7] Shiyang Chen. Governance decay: How context compaction silently erases safety constraints in long-horizon LLM agents. arXiv preprint arXiv:2606.22528, 2026. URL https://arxiv.org/abs/2606.22528.

[8] Yanda Chen, Joe Benton, Ansh Radhakrishnan, Jonathan Uesato, Carson Denison, John Schulman, et al. Reasoning models don't always say what they think, 2025. URL https://arxiv.org/abs/2505.05410.

[9] Manuel Costa, Boris Köpf, Aashish Kolluri, Andrew Paverd, Mark Russinovich, Ahmed Salem, Shruti Tople, Lukas Wutschitz, and Santiago Zanella-Béguelin. Securing AI agents with information-flow control (FIDES). arXiv preprint arXiv:2505.23643, 2025. URL https://arxiv.org/abs/2505.23643.

[10] Elad David and Max Fomin. Prompted to discriminate: Generalizing malicious-input probes in the wild. Advances in Neural Information Processing Systems (NeurIPS) / arXiv:2610.02413, 2026. URL https://arxiv.org/abs/2610.02413.

[11] Edoardo Debenedetti, Jie Zhang, Mislav Balunović, Luca Beurer-Kellner, Marc Fischer, and Florian Tramèr. AgentDojo: A dynamic environment to evaluate prompt injection attacks and defenses for LLM agents. Advances in Neural Information Processing Systems (NeurIPS), Datasets and Benchmarks Track, 2024. URL https://arxiv.org/abs/2406.13352.

[12] Edoardo Debenedetti, Ilia Shumailov, Tianqi Fan, Jamie Hayes, Nicholas Carlini, Daniel Fabian, Christoph Kern, Chongyang Shi, Andreas Terzis, and Florian Tramèr. Defeating prompt injections by design (CaMeL). arXiv preprint arXiv:2503.18813, 2025. URL https://arxiv.org/abs/2503.18813.

[13] Uliana Elina. Maat: Independent deterministic contract-based governance for multi-agent LLM workflows. arXiv preprint arXiv:2609.34017, 2026. URL https://arxiv.org/abs/2609.34017.

[14] Pedro Ferreira, Wilker Aziz, and Ivan Titov. Does out-of-sight equal out-of-mind in CoT monitorability?, 2026. URL https://arxiv.org/abs/2608.04928.

[15] Shashwat Goel, Joschka Strüber, Jonas Geiping, and Florian Tramèr. Great models think alike and this undermines AI oversight. International Conference on Machine Learning (ICML), 2025. URL https://arxiv.org/abs/2502.04313.

[16] Melody Guan, Miles Wang, Micah Carroll, Zehao Dou, Annie Wei, Marcus Williams, et al. Monitoring monitorability. In *International Conference on Machine Learning (ICML)*, 2026. URL https://arxiv.org/abs/2512.18311.

[17] Dylan Hadfield-Menell, Anca Dragan, Pieter Abbeel, and Stuart Russell. The off-switch game. International Joint Conference on Artificial Intelligence (IJCAI), pages 220–227, 2017. URL https://arxiv.org/abs/1611.08219.

[18] Reilly Haskins, Bilal Chughtai, and Joshua Engels. Training on documents about monitoring leads to CoT obfuscation, 2026. URL https://arxiv.org/abs/2605.15257.

[19] Yu He, Haozhe Zhu, Yiming Li, Shuo Shuo, Hongwei Yao, Zhihao Liu, and Zhan Qin. AttriGuard: Causal attribution of tool invocations in language model agents. arXiv preprint arXiv:2603.10749, 2026. URL https://arxiv.org/abs/2603.10749.

[20] Yue Huang, Zhangchen Xu, Yuchen Ma, and Wenjie Wang. Reward hacking challenges oversight of autonomous research agents. arXiv preprint arXiv:2609.28614, 2026. URL https://arxiv.org/abs/2609.28614.

[21] Tomek Korbak, Mikita Balesni, Elizabeth Barnes, Yoshua Bengio, Joe Benton, Joseph Bloom, et al. Chain of thought monitorability: A new and fragile opportunity for AI safety, 2025. URL https://arxiv.org/abs/2507.11473.

[22] Lifei Liu and Haoran Yu. VERA: Authority-preserving edge revocation for federated AI-agent workflows. arXiv preprint arXiv:2608.30091, 2026. URL https://arxiv.org/abs/2608.30091.

[23] Xinwen Liu, Zhuocheng Pan, Isabella Zhu, Jawei Zhang, Xudong Liu, and Tianyu Wo. Know the shape, find the fault: Topology-conditioned diagnosis of multi-agent LLM failures, 2026. URL https://arxiv.org/abs/2610.10126.

[24] Gary Lorden. Procedures for reacting to a change in distribution. *The Annals of Mathematical Statistics*, 42(6):1897–1908, 1971. URL https://doi.org/10.1214/aoms/1177693055.

[25] E. S. Page. Continuous inspection schemes. Biometrika, 41(1/2):100–115, 1954. URL https://doi.org/10.1093/biomet/41.1-2.100.

[26] Rudrendu Kumar Paul and Sourav Nandy. Beyond single-model injection: A threat model and defense architecture for prompt injection in multi-agent systems. In *International Conference on Machine Learning (ICML)*, volume 306 of *PMLR*, 2026. URL https://arxiv.org/abs/2609.22949.

[27] Allen Z. Ren, Anushri Dixit, Alexandra Bodrova, Sumeet Singh, Stephen Tu, Noah Brown, Peng Xu, Leila Takayama, Fei Xia, Jake Varley, Zhenjia Xu, Dorsa Sadigh, Andy Zeng, and Anirudha Majumdar. Robots that ask for help: Uncertainty alignment for large language model planners (KnowNo). Conference on Robot Learning (CoRL), 2023. URL https://arxiv.org/abs/2307.01928.

[28] Carson Rodrigues. Hallucination as context drift: Synchronization protocols for multi-agent LLM systems. arXiv preprint arXiv:2606.21666, 2026. URL https://arxiv.org/abs/2606.21666.

[29] Paul Rosu and Rowan Wang. Training alignment auditors via reinforcement learning, 2026. URL https://alignment.anthropic.com/2026/training-alignment-auditors. Anthropic Alignment Science blog, 15 October 2026.

[30] Nate Soares, Benja Fallenstein, Eliezer Yudkowsky, and Stuart Armstrong. Corrigibility. AAAI Workshop on AI and Ethics, 2015. URL https://intelligence.org/files/Corrigibility.pdf.

[31] Jean Ville. *Étude critique de la notion de collectif*. Gauthier-Villars, 1939. URL http://www.numdam.org/item/THESE_1939__218__1_0/.

[32] Vladimir Vovk, Alex Gammerman, and Glenn Shafer. Algorithmic learning in a random world. Springer, 2005. URL https://doi.org/10.1007/b106715.

[33] Abraham Wald. Sequential tests of statistical hypotheses. The Annals of Mathematical Statistics, 16(2):117–186, 1945. URL https://doi.org/10.1214/aoms/1177731118.

[34] Wujie Xiong, Rabimba Karanjai, Yang Lu, Weidong Shi, and Lei Xu. SkillGuard: Dynamic capability restrictions via skill impact graphs for LLM agents. arXiv preprint arXiv:2608.30041, 2026. URL https://arxiv.org/abs/2608.30041.

[35] Richard J. Young. Lie to me: How faithful is chain-of-thought reasoning in open-weight reasoning models?, 2026. URL https://arxiv.org/abs/2603.22582.

[36] Kaiyuan Zhang, Yuke Peng, Ke Jiang, and Yinqian Zhang. ActGov: Governing LLM agent actions via policy-constrained validation. arXiv preprint arXiv:2609.24446, 2026. URL https://arxiv.org/abs/2609.24446.

[37] Wei Zhao, Zhe Li, Peixin Zhang, and Jun Sun. ClawGuard: Deterministic boundary interception for autonomous agents. arXiv preprint arXiv:2604.11790, 2026. URL https://arxiv.org/abs/2604.11790.