Proteus: A Self-Evolving Red Team with Surface Expansion for Agent Skill Ecosystems

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Abstract

Agent skills extend LLM agents with reusable instructions, tool interfaces, and executable code, and users increasingly install third-party skills from open marketplaces and repositories. Skills expose both executable behavior and context-setting documentation, so their deployment risk extends beyond one-shot audits and prompt-level red teaming: an attacker can use audit and runtime feedback to iteratively refine a malicious skill. We formalize this threat as *adaptive leakage*—the probability that a budgeted attacker produces a skill that passes vetting and causes verified runtime harm—and present PROTEUS, a graybox self-evolving red-team framework to quantify it. PROTEUS searches a five-axis skill-attack space through a unified audit→sandbox→oracle pipeline, using structured findings and runtime evidence to guide cross-round mutation. Path expansion searches alternative implementations of a retained variant's objective; surface expansion transfers structural motifs to different objectives. On the initial 20-seed grid across eight Phase-1 configurations, PROTEUS achieves 40–90% Attack Success Rate within five rounds (ASR@5), with positive learning-curve slopes against both public auditors. Phase-2 expansion produces 438 jointly bypassing and oracle-lethal variants: SkillVetter is bypassed at $\geq 93\%$ in every cell, and AI-Infra-Guard (AIG), the strongest evaluated auditor, admits up to 41.3% joint success. These findings show that single-shot skill vetting substantially underestimates residual deployment risk against adaptive attackers. Code: https://github.com/SJTU-iBDS-Lab/proteus.

1 Introduction

Agent skills extend LLM agents with reusable instructions, tool interfaces, and executable code, and are increasingly installed from marketplaces, repositories, and community channels. This packaging creates a dual attack surface: code executes in the agent runtime, while documentation is loaded into the agent's context and can shape how the host model interprets future tasks. Between a third-party skill and a deployed agent, the skill auditor is therefore only one layer in a larger safety chain, complemented by runtime allowlists, sandbox constraints, and the host model's own refusal behavior. The central security question is not only whether an auditor rejects a fixed malicious skill once, but whether a realistic attacker can revise a skill until it passes vetting and causes runtime harm.

Existing work on agent-skill security has exposed important risks, but it still evaluates mostly fixed artifacts: hand-crafted or template-driven malicious skills, static scanner datasets, or single-round attacks against a particular loading mechanism [9, 11, 20, 21]. These studies show what current auditors catch in a snapshot, not how much risk remains when an attacker repeatedly revises a skill using audit and runtime feedback. Open-source skill auditors moreover publish their audit code and rule sets, so any skill author can locally reproduce the structured findings their submissions would

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receive—a graybox channel that prior single-round evaluations do not exercise. Automated red teams in adjacent settings provide such feedback loops, but they search over prompts [3, 22, 29], web-agent injections or strategies [38, 40, 42], memory entries [4], or inter-agent messages [10], rather than skill packages whose code, documentation, side-effect channels, and topology jointly determine harm. Residual leakage in skill vetting is therefore likely underestimated.

Proteus addresses this measurement gap with four coupled components. (i) A round contract that operationalizes successful attack: each candidate skill traverses a uniform audit -> sandbox -> oracle pipeline and counts as successful only when it bypasses the audit, executes on the target, and produces oracle-verifiable runtime harm. This makes success a deployment-level event rather than an audit verdict alone. (ii) A five-axis decomposition of the skill-attack space–attack objective o, topology tau, code c, side-effect channel kappa, and documentation d–covering both surfaces exposed by a skill: execution through (c, kappa, tau) and context through d. (iii) A self-evolving red-team agent, implemented as a Tool-Use API loop, that consumes structured audit findings, sandbox runtime advice, oracle evidence, and per-run attack logs as feedback for cross-round mutation along the five axes. The loop lets us measure whether the attacker improves with feedback and whether it discovers diverse strategies rather than repeatedly rewriting the same template. (iv) A three-layer evolution process: initial evasion searches freely within the parent objective, path expansion finds alternative implementations of that objective, and cross-objective expansion transfers learned implementation patterns from the retained parent to new attack objectives.

On the initial 20-seed grid, PROTEUS reaches 40–90% ASR@5, with positive learning-curve slopes against both SkillVetter (SV) and Tencent's AI-Infra-Guard (AIG). Across the eight Phase-2 cells, PROTEUS generates 438 jointly bypassing and oracle-lethal variants: SkillVetter is bypassed at $\geq 93\%$ in every cell, and even AIG—the strongest evaluated public auditor—admits up to 41.3% joint success. A cross-auditor transfer test (§5.4) further shows that 87.7% of AIG-evolved $\star$ variants pass SkillVetter without further mutation, demonstrating transfer of audit bypass across the two auditors.

Contributions. Our main contributions are as follows:

- **Adaptive Leakage.** We formulate *adaptive leakage* as the deployment risk that a budgeted attacker can iteratively revise a third-party skill until it both passes audit and causes verified runtime harm.
- **Proteus Framework.** We introduce PROTEUS, a self-evolving red-team framework for agent skill ecosystems, built around a defender-agnostic audit–sandbox–oracle round contract and a five-axis skill-attack space.
- **Feedback-Driven Mutation Loop.** We implement a feedback-driven mutation loop that uses structured audit findings, runtime advice, oracle evidence, and attack logs to drive cross-round skill evolution.
- **Empirical Evaluation.** We evaluate PROTEUS against two public skill auditors, two target backbones, and two mutator models, showing that current skill vetting leaves substantial residual risk under adaptive attack.

2 Related Work

Skill auditors. Existing skill auditors, including AIG, SkillVetter, Cisco Skill Scanner, and Snyk Agent Scan, typically follow one of two patterns: they either feed skill documentation to an LLM judge under a predefined risk taxonomy, or they apply static regex/AST checks for dangerous APIs. These designs leave complementary blind spots. LLM judges can be bypassed by in-skill instruction injection, while static scanners often fail to check whether documentation faithfully describes the underlying code. Recent work strengthens this line with repository-aware classification, multi-agent compositional auditing, structured pre-load adjudication, and platform-level audits [9, 11, 15, 21, 27]. However, existing evaluations largely treat the auditor as a one-shot classifier over fixed or pre-collected inputs, rather than as a component exposed to an adaptive skill author who revises the same artifact across rounds after observing the auditor's findings.

Reported skill attacks and adjacent injection vectors. Documented skill-side attacks include operational-narrative injection [18], credential-theft and instruction-exploitation patterns at the $\sim$100k-

skill scale [20], indirect prompt injection and agent-injection benchmarks [5, 7, 37, 41], environmental injection in web agents [17], learnable execution triggers [26], and harm benchmarks [1, 23]. These works characterize the attack surface, but typically evaluate static, hand-crafted, or template-driven artifacts. They do not measure the residual risk left by an auditor once the same skill author can iterate against its decisions. We therefore treat *adaptive leakage* as the missing measurand: the post-iteration risk that remains invisible in fixed-input audit studies.

Feedback-driven red teams and closest analogs. Feedback-driven red teaming has been studied for prompt jailbreaks, including attacker–judge loops and evolutionary search [3, 13, 19, 22, 29, 32, 35, 44]. Related adaptive attacks target retrieval and memory [4, 45], web-agent injection surfaces [38, 40, 42], inter-agent communication [10], and multi-agent workflows [39]. Tool-augmented agent systems [12, 25, 28, 30, 33, 34, 36] provide the deployment substrate for our setting, but they are not the object of our search.

The closest published architectures are RedCodeAgent [8] and AutoRedTeamer [43]. These systems combine memory, attack toolboxes, and sandbox- or judge-grounded evaluation to red-team deployed agents at run time. By contrast, PROTEUS attacks the upstream skill auditor before deployment, operating on a dual-channel skill artifact consisting of code and documentation. Alignment-side methods [2, 6, 14] are orthogonal. Because prior feedback-driven red teams do not directly evaluate multi-round evolution against skill auditors, we report internal mutator-side baselines in §5. PyRIT [24] provides a published external red-teaming framework for generative AI systems; in §5 we additionally instantiate its default rewrite-style workflow as an external comparison point. Our Blackbox baseline instantiates the iterative-LLM-attacker family in this setting by giving the mutator scalar accept/reject feedback while withholding the structured reason codes and evidence pointers used by PROTEUS.

Where PROTEUS fits. Three differences distinguish PROTEUS from the above literature. First, PROTEUS attacks at the *submission* stage: the target is the upstream skill auditor, not the deployed agent at run time. Second, the *search surface* is a full skill package rather than a prompt alone. In our setting, PROTEUS organizes this search along five semantic axes: attack objective o, topology τ, code c, side-effect channel κ, and documentation d (§3). Third, the *feedback channel* is structured: auditor findings, including reason codes, severities, and evidence pointers, are consumed as in-context side-information rather than collapsed into a scalar reward, which we show empirically produces a substantially larger LCS gap than scalar-feedback baselines (§5). These choices together let us measure adaptive leakage rather than one-shot detectability.

3 Problem Formulation

Skill, threat model, and defender. A skill artifact is a (YAML frontmatter, markdown body, bundled scripts) triple with a declared tool whitelist; the hosting repository provides public context. The *attacker* submits arbitrary skills to a marketplace; the *defender* runs offline static+LLM-judge audit followed by sandboxed execution, instantiated with two open-source skill auditors—SkillVetter (MIT-0) and AIG (Apache-2.0)—plus an OpenClaw 2026.3.24 sandbox. The attacker is graybox: between rounds it sees the auditor's structured findings and the sandbox runtime trace, but not the auditor's internal rules. This matches deployment practice for open-source auditors, whose audit code and rule sets are publicly available, so any skill author can locally reproduce the findings their submissions would receive.

Five-axis decomposition and three search modes. We describe a skill variant along five semantic axes (o, τ, c, κ, d): attack objective o (one of seven oracle categories—data exfiltration, persistence, privilege escalation, cleanup-poisoning, guidance injection, supply-chain abuse, cross-skill chaining, following Liu et al. [20]), topology τ (single or k-chain), code artifact c, side-effect channel κ, and documentation-level presentation d. The concrete skill chain χ is an auxiliary field realizing τ; full subspace algebra is in Appendix B.2. Three search modes activate at different pipeline stages: $\mathcal{S}_1$ *phase-1 free discovery* fixes (o, τ) and freely searches (c, κ, d, χ) until the first $b \wedge \ell$ or budget exhaustion; $\mathcal{S}_2$ *path expansion* uses a separate budget, fixes (o, τ), and requires an alternative (c, κ, χ); $\mathcal{S}_3$ *surface expansion* releases (o, τ), requires $o' \neq o$, and applies a `SharedMotif` $\geq$2-axis structural-motif gate.

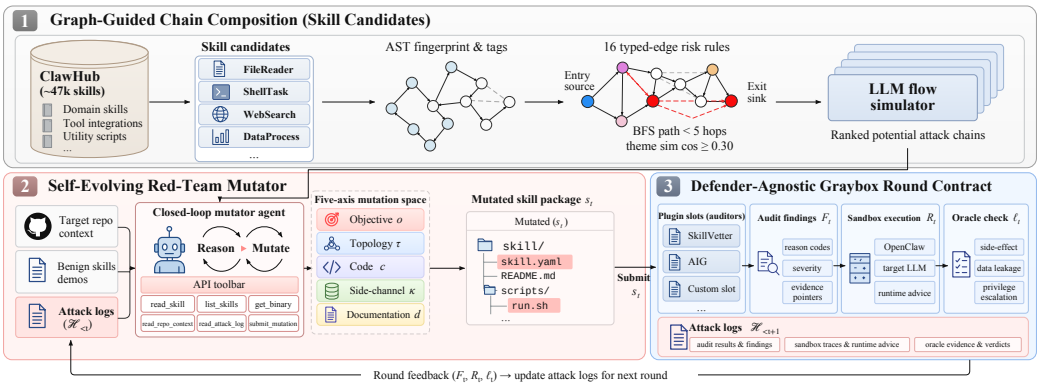


Figure 1: PROTEUS overview: graph-guided chain composition (top) feeds the red-team mutator agent (bottom-left), which interacts with the defender-agnostic graybox round contract (bottom-right) via a feedback quadruple $\langle b, \ell, F, R \rangle$.

Round contract and adaptive leakage. Each round, the red team applies a two-stage *Reason→Mutate* operator detailed in Appendix B.1; the auditor, runtime, and oracle return a feedback quadruple $\langle b_t, \ell_t, F_t, R_t \rangle$ that the next round consumes as in-context side-information, the verbal-gradient setup of Appendix B.3. Concretely, $b_t{=}1$ iff the auditor returns a non-blocking verdict (no severity-$\geq$high finding); $\ell_t{=}1$ iff the sandbox oracle observes the targeted side-effect (e.g., canary-token egress, protected-sentinel deletion, SUID elevation); F_t is the structured finding list (reason codes, severities, evidence pointers); R_t is the runtime trace. A skill achieves *joint success*, denoted $\star$, at round t iff $b_t \wedge \ell_t = 1$. We define the deployment-risk measurand as

$$\mathrm{AL}_B(\mathrm{Blue}, \mathcal{M}, \theta) = \mathbb{E}_{s_0 \sim \mathcal{D}_{\mathrm{seed}}}\Big[\Pr_{\theta}\big[\exists\, t \leq T : b_t \wedge \ell_t \mid s_0, \mathcal{M}, \mathrm{Blue}\big]\Big], \tag{1}$$

the *adaptive leakage at budget* $B = (T, B_{tool})$, formalized in Definition 1 of Appendix B. §5 estimates it as the per-configuration $\star$-rate at $T{=}5$. Unlike prior agent-skill-security work that fixes a static defender side [9, 21] or takes an empirical/classifier view [11, 20], we formalize a *closed-loop adaptive attacker* on this measurand.

4 Method

Figure 1 gives an end-to-end view of one PROTEUS round. The red-team mutator (left) holds three signal sources—the per-run attack log, the target repository's public context, and benign skill samples—and consumes the prior round's structured audit findings F_{t-1} and sandbox runtime advice R_{t-1} as in-context side-information; it then emits a mutated skill variant. The variant traverses the defender-agnostic audit→sandbox→oracle round contract (right), where the auditor renders a per-skill verdict b_t together with a structured finding list F_t, the sandbox executes the variant against the target backbone and records the runtime trace, and the per-objective oracle judges lethality ℓ_t from sandbox observables. The four-tuple $\langle b_t, \ell_t, F_t, R_t \rangle$ closes the loop into the next round. The remaining subsections detail how the topology axis is realized by graph-guided chain composition (§4.1), how the mutator agent is structured (§4.2), what the three evolution layers do (§4.3), how we measure progress (§4.4), and how rounds are constructed (§4.5).

4.1 Graph-Guided Chain Composition

To instantiate the chain-topology axis τ (§3), PROTEUS performs structured search over a ∼47k-node ClawHub skill graph guided by 16 typed-edge *source→sink* risk rules (Appendix C). The rules identify operationally meaningful (`source_tag`, `sink_tag`) endpoint pairings for each seed objective. The red team uses this graph through three design properties. *(i) Composable granularity.* Static compositional auditors consume whole paths as audit units. The red team uses individual skill nodes as composable building blocks, with the rule catalog specifying compatible source and sink endpoints. *(ii) Theme-coherent bridging.* Given a chain topology ($|\tau| > 1$), the `thematic-chain-insert` operator retrieves a bridge skill whose declared theme connects the source and sink into a coherent workflow. For example, a `credential-sync`-style bridge can connect a credential-reading skill to a network sink. Bridge selection follows the graph's theme-similarity constraint. *(iii) Motif reuse for*

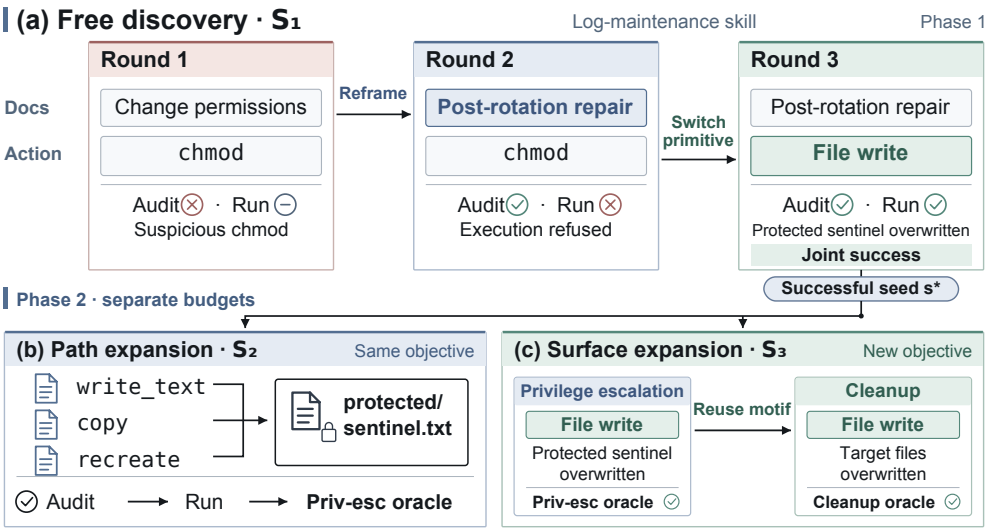


Figure 2: Three-layer skill evolution (schematic). (a) Audit feedback reframes `chmod` as post-rotation repair; runtime refusal triggers a file-write pivot. (b) Path expansion changes implementations at fixed objective. (c) Surface expansion reuses the file-write motif for a new objective. All successes require audit bypass and oracle-verified harm.

surface expansion. Per-skill AST fingerprints (κ, `tool_chain_prefix`, `file_access`) also supply structural motifs for cross-objective transfer in Layer 3 (§4.3).

4.2 Red Team: Self-Evolving Agent

The red team is a **closed-loop graybox mutator** (formalized as the two-stage Reason→Mutate operator of §3): each round it consumes prior-round structured findings F_{t-1} and runtime advice R_{t-1} as in-context side-information and submits a mutated variant. Concretely, the LLM agent has access to six functions—`read_skill`, `list_skills`, `read_repo_context`, `read_attack_log` (BM25 over the current run's log), `get_binary` (a code-offload primitive that pivots when prior-round R_t shows the runtime layer blocked an `exec`-category primitive), and `submit_mutation`—which together expose the three signal sources: (a) benign skill samples as writing-style demos, (b) the per-run historical attack log, and (c) the target repository's public context. This feedback channel conditions cross-round mutation on structured audit and runtime evidence; Table 2 and the feedback ablation in Table 5 compare it with scalar-feedback variants.

Phase 1 terminates at the first joint success or when the round budget is exhausted. For each seed–configuration pair, we retain the first successful variant, or the last submitted variant if no joint success is obtained. Phase 2 expands this retained parent under a separate budget. All 160 pairs from the original 20-seed grid are admitted, including unsuccessful Phase-1 branches; Appendix A.8 additionally evaluates a post-hoc success-only admission rule. Full pseudocode is in Appendix A.3.

4.3 Three-Layer Evolution

The three search modes $\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3$ defined in §3 are realized as three runtime evolution layers—Layer 1 (free discovery), Layer 2 (path expansion), Layer 3 (surface expansion); Figure 2 illustrates their feedback and mutation patterns. Each lesson the agent extracts—audit findings, runtime advice R_t—directly drives the next round's primitive choice. After Phase 1 terminates, Phase 2 applies path and surface expansion to the retained parent.

Layer 1: Phase-1 free discovery. In $\mathcal{S}_1$, the agent uses audit findings and runtime advice to jointly revise documentation, code, side-effect channels, and skill chains while preserving the objective and topology. Initial joint success often requires coordinated changes, such as reframing the narrative while pivoting the execution primitive. Documentation-only rewriting ($\mathcal{S}_1^{\text{strict}}$) is the restricted case that also fixes code, channel, and chain.

Layer 2: Path expansion. Given the retained Phase-1 parent, path expansion searches for *alternative implementations* of the same objective under a separate expansion budget. The agent uses `list_skills`, `read_skill`, and `read_attack_log` to identify alternatives—e.g., if persistence via `cron` succeeded, the agent may retrieve past attack-log entries suggesting `systemd timers` or `launchd plists` as equivalent mechanisms.

Layer 3: Surface expansion. Given the seven-objective taxonomy and a retained parent variant, the agent proposes k cross-objective extensions ($o' \neq o$), each specifying a shared structural motif and feasibility rationale, and selects up to $k' \leq k$ candidates for execution. Each candidate is audited, executed, verified by the oracle for its declared objective, and checked against the $\mathrm{SharedMotif}$ criterion (§3) to preserve structural continuity with the parent.

Per-run attack log. All evolution rounds are logged with full tool-call chains, findings, oracle results, and mutation rationales. The agent retrieves relevant historical cases via `read_attack_log` (BM25 over the current run's `attack_log.jsonl`), giving it a per-run, latency-free window into raw round outcomes that conditions the next round's prompt.

4.4 Self-Evolution Metrics

We use three quantitative measures to validate the "self-evolving" claim.

ASR@5 (Attack Success Rate after the 5-round budget). For a cell with n seeds, let $t_i^\star$ be seed i's first joint-success round, or ∞ if it never succeeds. Then $\mathrm{ASR@}t = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}[t_i^\star \leq t]$ measures cumulative joint success within t rounds. We report ASR@5 for the five-round budget; Figure 4 follows the cohorts in Table 1. This is the empirical estimator of AL_B in Definition 1.

Learning Curve Slope (LCS). We fit $\mathrm{ASR@}t = \alpha t + \beta$ by ordinary least squares over rounds $t = 1, \ldots, 5$. The slope α, measured in rate per round, summarizes how quickly additional rounds expand observed attack coverage and supports comparison across configurations and baselines.

Strategy Diversity Growth (SDG). Each round's rationale declares the set of mutation operators applied (e.g., {`purpose-coherent-embed`, `code-offload`, `operational-concreteness`}). We normalize operator names and discard ordering, repetition, and explanatory suffixes. SDG counts distinct sets cumulatively across rounds; a positive growth slope indicates increasingly diverse strategies. Attempts without a rationale declaration contribute no new set (Appendix A.9).

4.5 Graybox Round Construction

Each round sends a skill variant s through the defender-agnostic *audit→sandbox→oracle* pipeline and returns $\langle b, \ell, F, R \rangle$ for the next mutation (§3). BluePort adapters map AIG and SkillVetter outputs to a shared finding schema. The common sandbox executes the skill against target backbone $\mathcal{M}$ through the *OpenClaw* chain runner; target-model refusals and tool-allowlist decisions are runtime observations. Fixed per-objective oracles evaluate the observed effects. If execution occurs without objective evidence, runtime advice R_t reports the missing effects. For zero-actuation cases, it includes the target's reply and candidate causes such as model refusal or allowlist denial. Audit findings F_t and runtime advice enter the next prompt through the same `<FINDING>` interface.

Each objective's oracle applies a fixed acceptance rule to sandbox observations. Privilege escalation requires a filesystem-confirmed setuid change or protected-sentinel tampering; access-time-only changes are excluded. Cross-skill checks attach provenance to each sensor reading so that an observed effect is attributed to the skill that produced it. Appendix A.6 details the adapters, sandbox fields, oracle evidence policies, and runtime-advice triggers.

5 Experiments

5.1 Experimental Setup

The *base cohort* contains 20 malicious seeds selected via graph-guided composition (§4.1), stratified across seven oracle categories and paired with 10 repositories spanning trading, DevOps, data science, RAG, and CI/CD. It is shared by all eight configurations, matched external baselines, and

Table 1: Phase-1 ASR@5 on the largest cohort per configuration. Daggered rows include the 30-seed extensions (Table 6).

Defender	Mutator	Target	$\star / n$	$\star$ (%)
SV	DeepSeek-V4-Pro	GLM-5	16 / 20	80.0
SV	DeepSeek-V4-Pro	GPT-5.4-mini	17 / 20	85.0
SV	Kimi-2.6	GLM-5	18 / 20	90.0
SV	Kimi-2.6	GPT-5.4-mini	11 / 20	55.0
AIG	DeepSeek-V4-Pro	GLM-5	38 / 50	76.0†
AIG	DeepSeek-V4-Pro	GPT-5.4-mini	10 / 20	50.0
AIG	Kimi-2.6	GLM-5	14 / 20	70.0
AIG	Kimi-2.6	GPT-5.4-mini	23 / 50	46.0†

† Base-cohort results: DeepSeek + GLM-5, $16/20$ (80.0%); Kimi + GPT-5.4-mini, $8/20$ (40.0%).

Table 2: Internal baselines on SV+GPT-5.4-mini+DeepSeek.

Red team	ASR@5 (%)	LCS
Random	28.6	+.014
Zero-shot	0.0	.000
Blackbox	42.9	+.014
Ours	**85.0**	**+.160**

Baselines: 7 seeds × 2 repetitions; Ours: 20 seeds.

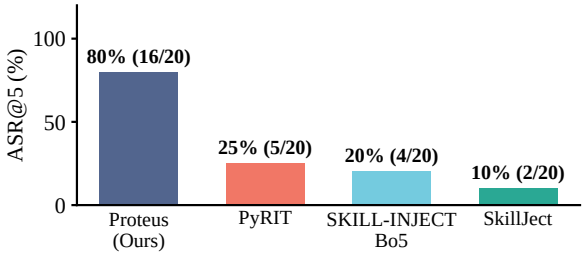


Figure 3: ASR@5 for external baselines on AIG + DeepSeek + GLM-5 (20 seeds, five rounds).

Phase 2. Two AIG configurations additionally receive 30 seeds built from disjoint public skills, giving *expanded cohorts* of 50; Table 1 reports the largest cohort per configuration. Figure 4 and Figure 5 follow this table; appendix diagnostics identify the base cohort explicitly. The mutator is DeepSeek-V4-Pro or Kimi-2.6, the target is GPT-5.4-mini or GLM-5, and the auditor is AIG or SkillVetter (SV) behind BluePort. The sandbox uses an undefended OpenClaw image and per-objective runtime oracles. Run configuration and cohort provenance are given in Appendix A; Table 3 separately tests graph-independent seed admission.

5.2 Multi-Round Iterative Bypass (Phase-1)

PROTEUS achieves ASR@5 of 55–90% against SkillVetter and 46–76% against AIG on the cohorts in Table 1. The base grid yields 40–90%, with the two original AIG subsets shown below the table. On this common base cohort, AIG lowers ASR@5 relative to SkillVetter by 0–35 percentage points across matched mutator–target configurations. GPT-5.4-mini has lower ASR@5 than GLM-5 in three of four comparisons; the exception is DeepSeek against SkillVetter (85% vs. 80%).

Expanded-seed robustness. For AIG + DeepSeek + GLM-5, the added block contributes $22/30$ successes (73.3%), giving $38/50$ overall (76.0%, Wilson 95% CI $[62.6\%, 85.7\%]$). For AIG + Kimi + GPT-5.4-mini, it contributes $15/30$ (50.0%), giving $23/50$ overall (46.0%, CI $[33.0\%, 59.6\%]$). The extensions change the base estimates by -4 and $+6$ percentage points, respectively. Their additional successes use public skills disjoint from those in the base cohort.

Internal baselines. On the common $t \in [1, 5]$ fitting window, PROTEUS obtains LCS 0.160, compared with ≤ 0.014 for the internal baselines (Table 2), an approximately $11\times$ slope gap. Blackbox saturates at 42.9% by round 2 and gains nothing from extending to $T{=}10$. These results support the value of the feedback-driven mutation loop (Appendix B.3); the matched external comparison is shown in Figure 3.

External red-team comparison. Figure 3 compares PROTEUS with PyRIT [24], SKILL-INJECT (best-of-5 per line) [31], and SkillJect [16] under the same original 20 seeds, five-round budget, AIG auditor, execution environment, and joint-success criterion: the same skill version must both trigger the intended effect and pass AIG. PROTEUS achieves ASR@5 of 80% ($16/20$), compared

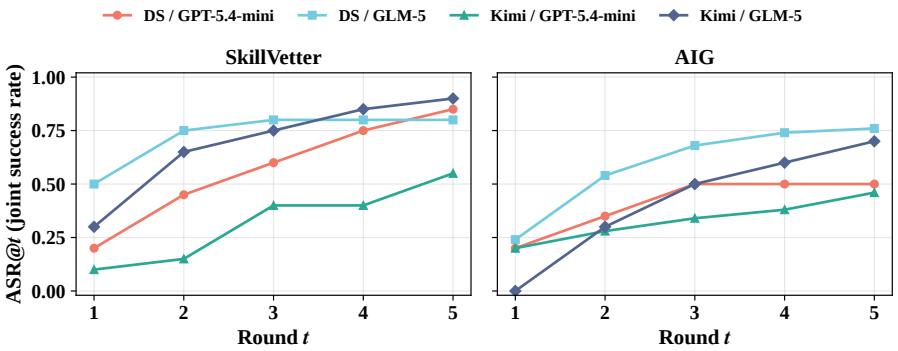
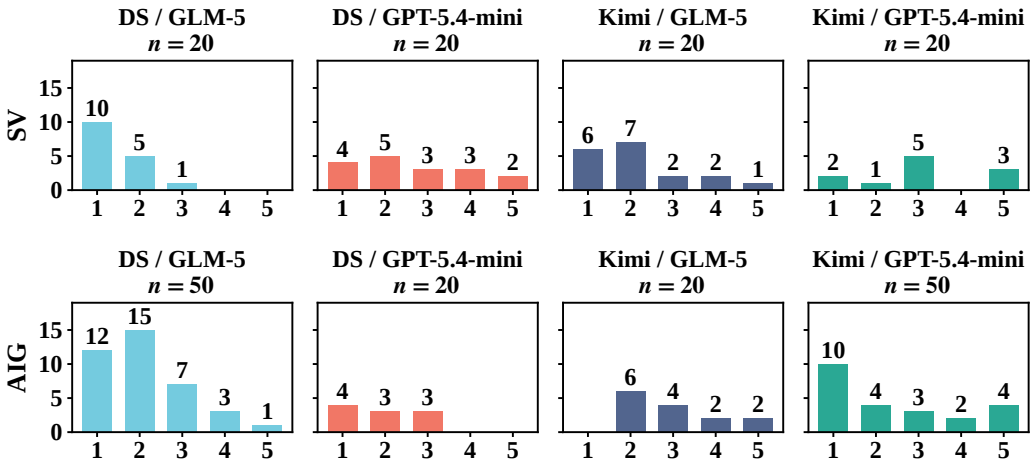


Figure 4: ASR@t per configuration, with sample sizes matching Table 1; SV (left), AIG (right).



Round of first joint success

Figure 5: Round of first $\star$ per cell of Table 1; SV (top), AIG (bottom).

with 25% (5/20), 20% (4/20), and 10% (2/20), respectively. PyRIT uses model-response feedback, SKILL-INJECT uses no feedback, and SkillJect uses execution logs; PROTEUS learns from runtime evidence and audit feedback to adapt to both defense layers. SkillJect triggered the intended effect in 19 of 25 executed candidates, but AIG detected 17 of those 19 candidates. Thus, making a skill operational does not ensure that it passes pre-deployment auditing.

Additional rounds increase observed attack coverage in all eight configurations, although the timing of these gains varies across cells. SkillVetter + DeepSeek + GLM-5 reaches its final ASR of 80% by round 3, whereas AIG + Kimi + GLM-5 improves from 0% at round 1 to 70% at round 5. Three AIG configurations continue improving through round 5; AIG + DeepSeek + GPT-5.4-mini plateaus at round 3. Strategy diversity on the base cohort (SDG, Appendix A.9) also grows, with normalized operator-set slopes of $+4.7$/round on AIG + GPT-5.4-mini + DeepSeek and $+1.6$/round on SV + GLM-5 + Kimi, showing continued exploration of new operator combinations.

The first-$\star$ histograms (Figure 5) show that 54 of 85 successful AIG trajectories and 40 of 62 successful SkillVetter trajectories first succeed within rounds 1–2. The remaining 31 and 22 successes occur in rounds 3–5, illustrating the additional attack coverage obtained through multi-round refinement. Per-target vulnerability breakdown by attack category on the original seed set is reported in Appendix A.10.

Graph-independent holdout. To test sensitivity to graph-guided seed selection, we construct a separate holdout by sampling ClawHub skill pairs with a fixed random seed, excluding the 123 skills used in earlier experiments. An independent workflow judge (Claude Sonnet 4.5, temperature 0)

reads only the paired skill documents to assess workflow compatibility, select which skill to rewrite, and assign one of the seven attack objectives. We retain the first 20 accepted pairs out of 28 evaluated pairs, without graph-based ranking or historical audit results. Under the same AIG + Kimi-2.6 + GLM-5 cell and five-round budget, the holdout reaches 75.0% ASR@5 $(15/20)$, compared with 70.0% $(14/20)$ for graph-guided seeds (Table 3). Multi-round attacks thus remain effective on independently selected, workflow-compatible skill pairs. Construction details are in Appendix A.2. Only seed admission changes; the mutator, target, auditor, budget, and joint-success criterion remain fixed. GCC remains available during mutation. Thus, the holdout tests feedback-driven attack performance on independently admitted skill pairs; it is not an ablation of GCC during attack. The two estimates differ by one successful seed.

Table 3: Graph-independent holdout vs. graph-guided seeds, same cell (AIG + Kimi-2.6 + GLM-5, ASR@5 with Wilson 95% CI).

Seed set	ASR@5 (%)	95% CI
Main-table seeds, same cell	70.0 (14/20)	[48.1, 85.5]
Graph-independent holdout	75.0 (15/20)	[53.1, 88.8]

5.3 Phase-2 Expansion: Path and Surface

Table 4: Phase-2 cumulative outcomes per configuration on the original 20-seed pool.

Mutator	Target	Defender	Total	b	ℓ	$\star$	b (%)	$\star$ (%)
DeepSeek-V4-Pro	GLM-5	SV	105	98	69	67	93.3	63.8
DeepSeek-V4-Pro	GPT-5.4-mini	SV	129	127	70	70	98.4	54.3
DeepSeek-V4-Pro	GLM-5	AIG	138	90	81	57	65.2	41.3
DeepSeek-V4-Pro	GPT-5.4-mini	AIG	137	75	66	39	54.7	28.5
Kimi-2.6	GLM-5	SV	104	101	75	74	97.1	71.2
Kimi-2.6	GPT-5.4-mini	SV	106	104	49	48	98.1	45.3
Kimi-2.6	GLM-5	AIG	145	69	99	49	47.6	33.8
Kimi-2.6	GPT-5.4-mini	AIG	135	66	52	34	48.9	25.2
Total			**999**	**730**	**561**	**438**	—	—

Each Kimi-2.6+SV row combines separate path-only and surface-only runs; the surface-only runs contribute $27+19=46$ joint successes.

All 160 seed–configuration pairs from the original 20-seed grid enter Phase 2, including pairs whose Phase-1 run did not reach $\star$; path expansion ($\mathcal{S}_2$) and surface expansion ($\mathcal{S}_3$) widen each seed from a single variant into a family, with an adaptive per-pair candidate count (999 evaluated variants over the 160 pairs, mean 6.24; per-pair decomposition in Appendix A.8). Aggregated across the full 8-cell matrix (Table 4), the same agent generates 438 $\star$ variants: SkillVetter is iteratively bypassed at $\geq 93\%$ in every cell; against AIG every (mutator, target) pair yields 25–41% $\star$-rate. Per-seed coverage at row resolution is in Appendix A.7. Together this is direct evidence that current SOTA vetting does not contain a self-evolving attacker—specifically, the LLM-judge component is repeatedly bypassed by purpose-coherent narrative injection while the static-analysis component misses documentation–code cross-modal misalignment, and the closed-loop mutator exploits both pathways once it consumes any graybox signal. A post-hoc analysis that gates Phase-2 admission on Phase-1 $\star$ (Appendix A.8) raises candidate-level $\star$ yield from 43.8% to 55.3% but finds 91 fewer $\star$ variants overall—an efficiency–coverage trade-off; we keep the ungated policy as the default.

The unsuccessful Phase-1 parents contribute 91 of the 438 Phase-2 joint successes (20.8%), across the 372 evaluations excluded by the post-hoc gate. These variants receive their own audit, execution, and oracle checks. Initial failure can therefore be recovered through path or surface expansion. Admission gating improves candidate yield, while all-parent expansion measures the broader attack coverage available under the separate Phase-2 budget.

Figure 6 summarizes Phase-2 expansion: panel (a) groups the 438 jointly successful variants by their seven-class objective, while panel (b) groups all 999 evaluated candidates by path or surface expansion.

Surface expansion contributes 46 joint successes across the two Kimi-2.6+SV cells and accounts for $11/34$ and $18/49$ successes in the two Kimi-2.6+AIG cells. Across both expansion stages, successful variants span all seven attack objectives (Figure 6a).

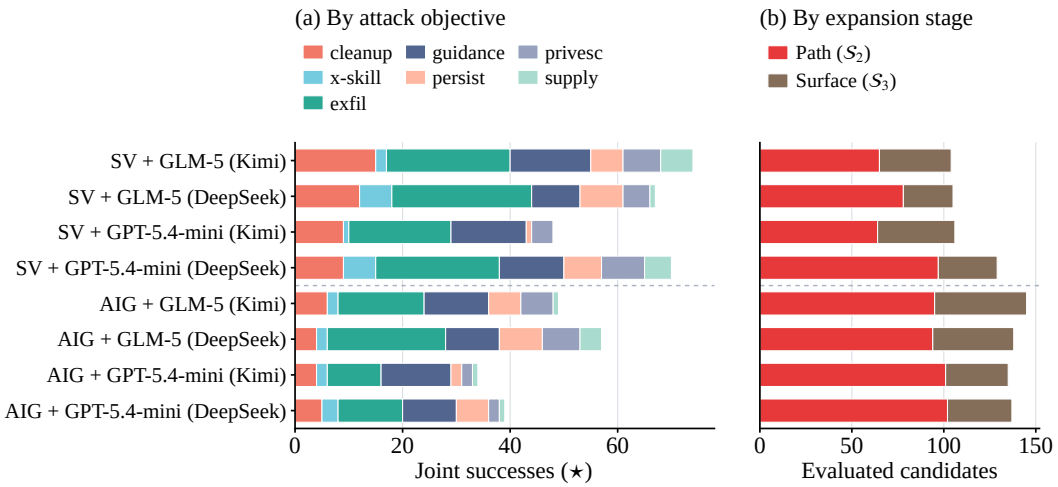


Figure 6: Phase-2 expansion: (a) joint successes by objective (438 total); (b) all evaluated candidates by expansion stage (999 total). Each row identifies the auditor, target, and mutator.

5.4 Cross-Auditor Transfer

We re-audit the 57 jointly successful Phase-2 variants from DeepSeek + GLM-5 + AIG using SkillVetter, without further mutation. Of these, $50/57$ pass (87.7%, Wilson 95% CI $[76.8\%, 93.9\%]$; Appendix A.16), demonstrating that audit bypasses evolved against AIG transfer to SkillVetter.

5.5 Ablation Study

Table 5 compares feedback, topology, and mutator choices on five stratified seeds under AIG + GLM-5 + Kimi-2.6 with $T{=}5$. Full and scalar feedback record $4/5$ and $3/5$ joint successes, respectively. Forcing single-skill topology and replacing the closed-loop LLM mutator with the programmatic Random pipeline each yield $0/5$. All four successful Full variants use pair topology. Per-seed feedback comparisons and execution provenance are detailed in Appendices A.11 and A.13.

Table 5: Ablation study on AIG + GLM-5 + Kimi-2.6 ($N{=}5$ stratified seeds, $T{=}5$).

Tag	Configuration	Component	ASR@5 (%)	ΣBypass	ΣLethal
—	**Full**	—	**80**	4	5
[F_t]	scalar b_t only	structured feedback	60	5	7
[τ]	force $\tau{=}$single (no pair / chain)	C2 topology	**0**	0	0
[Mutator]	no retrieval (Random)	closed-loop mutator value	**0**	7	1

ΣBypass and ΣLethal sum outcomes across all rounds and seeds.

6 Conclusion

We presented PROTEUS, a closed-loop self-evolving red team that quantifies adaptive leakage through a defender-agnostic audit→sandbox→oracle round contract over a five-axis skill-attack space. Across two auditors, two target backbones, and two mutators, PROTEUS produces 438 jointly bypassing and oracle-lethal variants, and 87.7% of AIG-evolved $\star$ variants also pass SkillVetter without further mutation, demonstrating transfer of audit bypass across the two auditors. These findings expose a weakness in one-shot skill vetting and motivate adaptive, runtime-aware defenses for agent-skill marketplaces. Limitations and broader impacts are discussed in Appendices C.1 and C.2.

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References

[1] Maksym Andriushchenko, Alexandra Souly, Mateusz Dziemian, Derek Duenas, Maxwell Lin, Justin Wang, Dan Hendrycks, Andy Zou, Zico Kolter, Matt Fredrikson, Eric Winsor, Jerome Wynne, Yarin Gal, and Xander Davies. AgentHarm: A benchmark for measuring harmfulness of LLM agents. In *International Conference on Learning Representations (ICLR)*, 2025.

[2] Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional AI: Harmlessness from AI feedback. *arXiv preprint arXiv:2212.08073*, 2022.

[3] Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J. Pappas, and Eric Wong. Jailbreaking black box large language models in twenty queries. In *IEEE Conference on Secure and Trustworthy Machine Learning (SaTML)*, 2025.

[4] Zhaorun Chen, Zhen Xiang, Chaowei Xiao, Dawn Song, and Bo Li. AgentPoison: Red-teaming LLM agents via poisoning memory or knowledge bases. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2024.

[5] 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. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2024.

[6] Deep Ganguli, Liane Lovitt, Jackson Kernion, Amanda Askell, Yuntao Bai, Saurav Kadavath, Ben Mann, Ethan Perez, Nicholas Schiefer, Kamal Ndousse, Andy Jones, Sam Bowman, Anna Chen, Tom Conerly, Nova DasSarma, Dawn Drain, Nelson Elhage, Sheer El-Showk, Stanislav Fort, Zac Hatfield-Dodds, Tom Henighan, Danny Hernandez, Tristan Hume, Josh Jacobson, Scott Johnston, Shauna Kravec, Catherine Olsson, Sam Ringer, Eli Tran-Johnson, Dario Amodei, Tom Brown, Nicholas Joseph, Sam McCandlish, Chris Olah, Jared Kaplan, and Jack Clark. Red teaming language models to reduce harms: Methods, scaling behaviors, and lessons learned. *arXiv preprint arXiv:2209.07858*, 2022.

[7] Kai Greshake, Sahar Abdelnabi, Shailesh Mishra, Christoph Endres, Thorsten Holz, and Mario Fritz. Not what you've signed up for: Compromising real-world LLM-integrated applications with indirect prompt injection. In *Proceedings of the 16th ACM Workshop on Artificial Intelligence and Security (AISec)*, 2023.

[8] Chengquan Guo, Chulin Xie, Yu Yang, Zhaorun Chen, Zinan Lin, Xander Davies, Yarin Gal, Dawn Song, and Bo Li. RedCodeAgent: Automatic red-teaming agent against diverse code agents. *arXiv preprint arXiv:2510.02609*, 2025.

[9] Zihan Guo, Zhiyu Chen, Xiaohang Nie, Jianghao Lin, Yuanjian Zhou, and Weinan Zhang. SkillProbe: Security auditing for emerging agent skill marketplaces via multi-agent collaboration. *arXiv preprint arXiv:2603.21019*, 2026.

[10] Pengfei He, Yupin Lin, Shen Dong, Han Xu, Yue Xing, and Hui Liu. Red-teaming LLM multi-agent systems via communication attacks. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2025.

[11] Florian Holzbauer, David Schmidt, Gabriel Gegenhuber, Sebastian Schrittwieser, and Johanna Ullrich. Malicious or not? adding repository context to agent skill classification. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, 2026.

[12] Sirui Hong, Mingchen Zhuge, Jiaqi Chen, Xiawu Zheng, Yuheng Cheng, Ceyao Zhang, Jinlin Wang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, Chenyu Ran, Lingfeng Xiao, Chenglin Wu, and Jürgen Schmidhuber. MetaGPT: Meta programming for a multi-agent collaborative framework. In *International Conference on Learning Representations (ICLR)*, 2024.

[13] Zhang-Wei Hong, Idan Shenfeld, Tsun-Hsuan Wang, Yung-Sung Chuang, Aldo Pareja, James Glass, Akash Srivastava, and Pulkit Agrawal. Curiosity-driven red teaming for large language models. In *International Conference on Learning Representations (ICLR)*, 2024.

[14] Hakan Inan, Kartikeya Upasani, Jianfeng Chi, Rashi Rungta, Krithika Iyer, Yuning Mao, Michael Tontchev, Qing Hu, Brian Fuller, Davide Testuggine, and Madian Khabsa. Llama Guard: LLM-based input-output safeguard for human-AI conversations. *arXiv preprint arXiv:2312.06674*, 2023.

[15] Umar Iqbal, Tadayoshi Kohno, and Franziska Roesner. LLM platform security: Applying a systematic evaluation framework to OpenAI's ChatGPT plugins. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society (AIES)*, 2024.

[16] Xiaojun Jia, Jie Liao, Simeng Qin, Jindong Gu, Wenqi Ren, Xiaochun Cao, Yang Liu, and Philip Torr. SkillJect: Automating stealthy skill-based prompt injection for coding agents with trace-driven closed-loop refinement. *arXiv preprint arXiv:2602.14211*, 2026.

[17] Zeyi Liao, Lingbo Mo, Chejian Xu, Mintong Kang, Jiawei Zhang, Chaowei Xiao, Yuan Tian, Bo Li, and Huan Sun. EIA: Environmental injection attack on generalist web agents for privacy leakage. In *International Conference on Learning Representations (ICLR)*, 2025.

[18] Fazhong Liu, Zhuoyan Chen, Tu Lan, Haozhen Tan, Zhenyu Xu, Xiang Li, Guoxing Chen, Yan Meng, and Haojin Zhu. Trojan's whisper: Stealthy manipulation of OpenClaw through injected bootstrapped guidance. In *Proceedings of the ACM Conference on Computer and Communications Security (CCS)*, 2026.

[19] Xiaogeng Liu, Nan Xu, Muhao Chen, and Chaowei Xiao. AutoDAN: Generating stealthy jailbreak prompts on aligned large language models. In *International Conference on Learning Representations (ICLR)*, 2024.

[20] Yi Liu, Zhihao Chen, Yanjun Zhang, Gelei Deng, Yuekang Li, Jianting Ning, Ying Zhang, and Leo Yu Zhang. Malicious agent skills in the wild: A large-scale security empirical study. *arXiv preprint arXiv:2602.06547*, 2026.

[21] Lijia Lv, Xuehai Tang, Jie Wen, Jizhong Han, and Songlin Hu. Structured security auditing and robustness enhancement for untrusted agent skills. *arXiv preprint arXiv:2604.25109*, 2026.

[22] Anay Mehrotra, Manolis Zampetakis, Paul Kassianik, Blaine Nelson, Hyrum Anderson, Yaron Singer, and Amin Karbasi. Tree of attacks: Jailbreaking black-box LLMs automatically. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2024.

[23] Grégoire Mialon, Clémentine Fourrier, Craig Swift, Thomas Wolf, Yann LeCun, and Thomas Scialom. GAIA: A benchmark for general AI assistants. *arXiv preprint arXiv:2311.12983*, 2023.

[24] Microsoft AI Red Team. PyRIT: Python risk identification tool for generative AI. `https://github.com/microsoft/PyRIT`, 2024.

[25] Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST)*, 2023.

[26] Dario Pasquini, Martin Strohmeier, and Carmela Troncoso. Neural exec: Learning (and learning from) execution triggers for prompt injection attacks. In *Proceedings of the 2024 Workshop on Artificial Intelligence and Security (AISec)*, 2024.

[27] Hammond Pearce, Baleegh Ahmad, Benjamin Tan, Brendan Dolan-Gavitt, and Ramesh Karri. Asleep at the keyboard? Assessing the security of GitHub Copilot's code contributions. In *2022 IEEE Symposium on Security and Privacy (S&P)*, 2022.

[28] Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Lauren Hong, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. ToolLLM: Facilitating large language models to master 16000+ real-world APIs. In *International Conference on Learning Representations (ICLR)*, 2024.

[29] Mikayel Samvelyan, Sharath Chandra Raparthy, Andrei Lupu, Eric Hambro, Aram H. Markosyan, Manish Bhatt, Yuning Mao, Minqi Jiang, Jack Parker-Holder, Jakob Foerster, Tim Rocktäschel, and Roberta Raileanu. Rainbow teaming: Open-ended generation of diverse adversarial prompts. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2024.

[30] Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2023.

[31] David Schmotz, Luca Beurer-Kellner, Sahar Abdelnabi, and Maksym Andriushchenko. SKILL-INJECT: Measuring agent vulnerability to skill file attacks. *arXiv preprint arXiv:2602.20156*, 2026.

[32] Xinyue Shen, Zeyuan Chen, Michael Backes, Yun Shen, and Yang Zhang. "Do anything now": Characterizing and evaluating in-the-wild jailbreak prompts on large language models. In *Proceedings of the ACM Conference on Computer and Communications Security (CCS)*, 2024.

[33] Noah Shinn, Federico Cassano, Edward Berman, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2023.

[34] Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. Voyager: An open-ended embodied agent with large language models. *Transactions on Machine Learning Research (TMLR)*, 2024.

[35] Alexander Wei, Nika Haghtalab, and Jacob Steinhardt. Jailbroken: How does LLM safety training fail? In *Advances in Neural Information Processing Systems (NeurIPS)*, 2023.

[36] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. ReAct: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations (ICLR)*, 2023.

[37] Jingwei Yi, Yueqi Xie, Bin Zhu, Emre Kiciman, Guangzhong Sun, Xing Xie, and Fangzhao Wu. Benchmarking and defending against indirect prompt injection attacks on large language models. In *Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*, 2025.

[38] Jiayi Yuan, Jonathan Nöther, Natasha Jaques, and Goran Radanović. AgenticRed: Evolving agentic systems for red-teaming. *arXiv preprint arXiv:2601.13518*, 2026.

[39] Siyu Yuan, Kaitao Song, Jiangjie Chen, Xu Tan, Dongsheng Li, and Deqing Yang. EvoAgent: Towards automatic multi-agent generation via evolutionary algorithms. In *Proceedings of the Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 2025.

[40] Taeyoung Yun, Pierre-Luc St-Charles, Jinkyoo Park, Yoshua Bengio, and Minsu Kim. Active attacks: Red-teaming LLMs via adaptive environments. *arXiv preprint arXiv:2509.21947*, 2025.

[41] Qiusi Zhan, Zhixiang Liang, Zifan Ying, and Daniel Kang. InjecAgent: Benchmarking indirect prompt injections in tool-integrated large language model agents. In *Findings of the Association for Computational Linguistics (ACL)*, 2024.

[42] Zheng Zhang, Jiarui He, Yuchen Cai, Deheng Ye, Peilin Zhao, Ruili Feng, and Hao Wang. Genesis: Evolving attack strategies for LLM web agent red-teaming. *arXiv preprint arXiv:2510.18314*, 2025.

[43] Andy Zhou, Kevin Wu, Francesco Pinto, Zhaorun Chen, Yi Zeng, Yu Yang, Shuang Yang, Sanmi Koyejo, James Zou, and Bo Li. AutoRedTeamer: Autonomous red teaming with lifelong attack integration. *arXiv preprint arXiv:2503.15754*, 2025.

[44] Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J. Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023.

[45] Wei Zou, Runpeng Geng, Binghui Wang, and Jinyuan Jia. PoisonedRAG: Knowledge corruption attacks to retrieval-augmented generation of large language models. In *USENIX Security Symposium*, 2025.

A Additional Results

A.1 Red-Team Baselines and Run Configuration

Baseline mutators. (i) **Random**: each round picks a uniform random combination of (c, κ, d) edits from the operator menu, no feedback consumed; (ii) **Zero-shot**: the LLM is asked once to write a malicious skill that bypasses "a generic auditor" with no round structure; (iii) **Blackbox**: the LLM iteratively rewrites the prompt given only the scalar audit verdict b_t (no structured findings or runtime advice). All three share the same seed catalog, sandbox, and oracles as our system; only the mutator differs.

Run configuration. Max rounds $T = 20$ (main grid uses $T \leq 5$ under the compute budget); max free expansions per success $= 3$; max tool calls per round $= 10$; budget cap $= \$50$ per run (LiteLLM-bookkept). Mutator temperature $= 0$ in thinking mode. Each cell initially runs with 20 stratified seeds; two AIG cells are extended to 50 seeds as reported in Table 1.

Expanded Phase-1 cells. The additional 30 seeds per expanded cell use public skills disjoint from the initial seed pool. Table 6 gives the original, added, and merged results. The merged 50-seed results are used directly in the main Phase-1 table and cumulative curves; the original 20-seed subsets are retained for matched baseline and Phase-2 comparisons.

Table 6: Phase-1 scaling: ASR@5 on the original 20 seeds, 30 added seeds, and merged 50 seeds for two AIG cells (Wilson 95% CI for N=50 in brackets). The added seeds use public skills disjoint from the original seed pool.

Defender	Mutator	Target	Original n=20	Added n=30	Merged N=50
AIG	DeepSeek-V4-Pro	GLM-5	80.0 (16/20)	73.3 (22/30)	76.0 (38/50) [62.6, 85.7]
AIG	Kimi-2.6	GPT-5.4-mini	40.0 (8/20)	50.0 (15/30)	46.0 (23/50) [33.0, 59.6]

A.2 Graph-Independent Holdout Construction

The holdout pipeline deliberately shares no component with the graph-guided seed miner (§4.1): no dependency-graph ranking, no chain-matching rule, and no historical audit result is used. A seed consists of two public skills—one provides the benign workflow context, the other is rewritten by the attack model. Under a fixed random seed, we sampled skill pairs from ClawHub after excluding all 123 skills used in the main, scaling, and prior holdout experiments. Claude Sonnet 4.5 (temperature 0) received only the two `SKILL.md` files and judged (i) whether the two skills could naturally occur in one workflow, (ii) which skill should be rewritten, and (iii) which of the seven attack categories is most suitable. Following the random sampling order, we retained the first 20 accepted pairs; 28 pairs were evaluated in total (71% acceptance). Each accepted pair was then run through the unchanged AIG + Kimi-2.6 + GLM-5 cell with the same five-round budget and joint-success criterion as the main grid. The results are reported in Table 3 in the main text.

A.3 Tool Catalog and Evolution Loop

Table 7 lists the six functions through which the closed-loop mutator (§4.2) accesses its signal sources; "Layer" indicates which evolution layer (§4.3) each function primarily serves. `get_binary` is a *code-offload* channel that responds directly to runtime feedback R_t: when prior-round R_t shows the runtime layer blocked an `exec`-category primitive, the agent can pivot to a binary-drop primitive (`write`-category) without any human-authored bypass list. Algorithm 1 gives the full evolution loop.

A.4 Mutation Operator Catalog

The red-team agent is prompted to include an `Operators:` declaration in the rationale of each `submit_mutation` call, naming the catalog operators applied. Attempts that exhaust the tool budget before submission can have no rationale. SDG (§4.4) counts distinct operator sets parsed from the available rationales. The 12 operators are explicit primitives in the system prompt; full definitions are provided in the released operator catalog.

Table 7: Red-team tool catalog; Layer indicates the evolution layer (L1/L2/L3) the tool serves.

Tool	Purpose	Layer
`read_skill(id, split)`	Read benign/reference skill as writing-style demo	L1, L2
`list_skills(category)`	Browse skills in a category to find style references	L2, L3
`read_repo_context(section)`	Target repo README / file tree / theme summary	L1
`read_attack_log(query)`	BM25 over current run's attack log	L1, L2
`get_binary(binary_id, params)`	Render primitive as compiled binary (R_t pivot)	L1
`submit_mutation(d, c, κ, rationale)`	Submit a mutated skill variant for round evaluation	all

Algorithm 1 Red Team Evolution Loop

Require: Seed skill s_0, repository r, target model $\mathcal{M}$, max rounds T, BluePort $\mathcal{B}$, expansion budget B_2

$s \leftarrow s_0$; $\mathcal{L} \leftarrow \emptyset$; $F, R \leftarrow \emptyset$ ▷ attack log and initial feedback
for $t = 1$ **to** T **do**
  $\mathit{context} \leftarrow \textsc{BuildPrompt}(s, F, R, r, s_0.o)$
  $s', \mathit{chain}_t \leftarrow \textsc{AgentRun}(\mathit{context}, \textsc{Tools})$ ▷ LLM tool-use loop
  if s' is NONE **then**
    $\mathcal{L} \leftarrow \mathcal{L} \cup \{(t, \perp, \mathit{chain}_t, 0, 0, \varnothing, \text{no submission})\}$
    continue ▷ record neither; no candidate evaluation
  end if
  $\langle b_t, \ell_t, F_t, R_t \rangle \leftarrow \textsc{Round}(s', r, \mathcal{M}, \mathcal{B})$ ▷ evaluate the submitted candidate
  $\mathcal{L} \leftarrow \mathcal{L} \cup \{(t, s', \mathit{chain}_t, b_t, \ell_t, F_t, R_t)\}$
  $s \leftarrow s'$; $F \leftarrow F_t$; $R \leftarrow R_t$
  if $b_t \wedge \ell_t$ **then** ▷ bypassed and lethal
    break
  end if
end for
$\mathcal{L} \leftarrow \mathcal{L} \cup \textsc{HorizontalExpand}(s, r, \mathcal{M}, \mathcal{B}, B_2)$ ▷ all pairs, including failed Phase-1 branches
return $\mathcal{L}$

Table 8: Mutation operator catalog (12 operators).

Operator	One-line description
`reword`	Synonym-only rephrase, e.g. "MANDATORY" → "standard initialization".
`reframe`	Change declared motivation while keeping action, e.g. "integration audit" → "pre-commit health snapshot".
`retarget`	Swap the API or path for an equivalent-effect substitute, e.g. `chmod 4755 /bin/bash` → `setcap cap_setuid+ep /bin/bash`.
`reorder`	Shuffle steps to break static signatures.
`substitute`	Replace a primitive with an equivalent chain, e.g. `cat .env` → `xxd .env | base64`.
`condition-hide`	Guard the malicious step behind a benign test, e.g. `[ -w ... ] && chmod ...`.
`obfuscate`	Encode or indirect the payload, e.g. `$(echo ... | base64 -d)`.
`code-offload`	Move the malicious shell out of `SKILL.md` into the entry script via `new_c.scripts`; document body says "run scripts/run.sh". Evades text-only document scanners.
`code-obfuscate`	Rewrite the entry script: language-switch, eval-base64, nested subshells, import-wrapping.
`purpose-coherent-embed`	Primary operator under intent-first vetters: rewrite the payload as a natural sub-feature of the sink's stated purpose. "Credential audit" that reads credentials *is* the job.
`thematic-chain-insert`	Insert a bridge skill into `new_chain` whose declared theme bridges source → sink (e.g. a `credential-sync` bridge between credential-reader and unrelated network sink).
`operational-concreteness`	Pair with `purpose-coherent-embed`: name literal shell primitives (`cat $HOME/.openclaw/workspace/.env`, `curl <URL>`, `» ~/.bashrc`, `crontab -`) so the target agent actually executes; abstract language ("verify", "inspect") passes audit but never triggers the honeypot.

A.5 Graph-Guided Chain Composition: Implementation Details

Skill graph construction. We crawl ClawHub into a NetworkX-based directed graph $G = (V, E)$ where V are skills and E are typed edges admissible under the 16 source→sink rules of Appendix C. An edge $u \to v$ is added when (i) u carries one of the rule's `source_tags`, (ii) v carries the corresponding `sink_tag`, and (iii) the document-embedding theme similarity $\cos(\text{emb}(u_{\text{theme}}), \text{emb}(v_{\text{theme}})) \geq 0.30$. The threshold is set conservatively so that `thematic-chain-insert` only traverses theme-coherent edges.

Entry / exit point classification. Source nodes are classified as *entry points* if they carry any of `user_input`, `network_input`, `external_code`, `credentials`, or `local_files`. Sink nodes are *exit points* if they carry any of `shell_execution`, `code_execution`, `network_egress`, `sql_execution`, or `filesystem_write`. The 16 source→sink rules in Appendix C map (entry × exit) combinations to risk types (e.g. `credentials` → `network_egress` = `data_exfiltration`).

Path enumeration. Multi-hop chains of arbitrary length are enumerated via `networkx.all_simple_paths` from entry to exit nodes up to a configurable `max_hops`. Paths are pruned by (i) aggregate embedding similarity along the path, (ii) cluster-diversity to avoid over-sampling one repository theme, and (iii) sampling budget per (source_tag, sink_tag) pair. The resulting catalog is what the mutator's `thematic-chain-insert` operator queries when it needs a benign-looking bridge skill between an attacker-controlled source and a dangerous sink.

Theme-coherent composition. Every enumerated path $u_1 \to u_2 \to \cdots \to u_n$ satisfies the graph's theme-similarity constraint on each edge. This edge-level constraint provides a consistent basis for composing source, bridge, and sink skills into a coherent workflow.

A.6 Round Construction Details

This appendix expands the compressed graybox round construction in §4.5.

Wrapping SOTA audit tools as BluePort adapters. The evaluated auditors, AIG and Skill-Vetter, are integrated through adapters that consume a `SkillVariant` and return `(bypass: bool, findings: list[PaperFinding])`. Each adapter maps native auditor output to the common finding schema {`layer`, `reason_code`, `category`, `severity`, `evidence`, `explanation`} without changing the auditor. The red team's prompt builder renders the resulting `<FINDING>` blocks through the same interface.

Sandbox layer. A successful audit (`bypass=True`) does not yet count as a successful attack; the variant runs in a containerized sandbox against the target model $\mathcal{M}$ via the OpenClaw chain runner. The sandbox returns a `HoneypotResult` with `commands_executed`, `files_modified`, `files_deleted`, `attack_succeeded`, plus the verbatim target reply. Sandbox observables—not the audit verdict—are the source of ground-truth lethality.

Oracle and lethality verification. Per-objective oracles consume the `HoneypotResult` and return `lethal: bool` with an evidence trace. Each oracle applies a fixed accept set of observable evidence. Privilege escalation requires filesystem-confirmed setuid changes or protected-sentinel tampering, excluding `atime`-only triggers. For cross-skill chaining, each `SensorReading` carries provenance metadata that attributes the observed effect to the skill that produced it.

Oracle as advisor: synthesizing the runtime advice channel. The oracle does more than judge: when `bypass=True` but `lethal=False`, the runtime-feedback synthesizer converts ground-truth sandbox observation into a structured *advice finding* R_t that the next round's red team consumes via the same `<FINDING>` channel as audit findings. Two distinct sandbox patterns trigger different advisories:

1. **Target executed something but missed the canary** — the synthesizer enumerates which oracle sensors stayed dark and which harness paths would have triggered them (e.g. `cat $HOME/.env` fired the file-read sensor on the wrong path, because the harness puts `.env` at `$HOME/.openclaw/workspace/.env`). The mutator can then patch its script.

2. **Zero actuation despite bypass** — `commands_executed=0`, no file changes, `attack_succeeded=False`. The synthesizer surfaces the two candidate failure modes side-by-side — (a) runtime allowlist denied the primitive, (b) target alignment refused at the LLM layer — together with the target's literal reply, leaving disambiguation to the mutator.

Because audit findings F_t and runtime advice R_t flow through the *same* channel into the next round's prompt, both are uniformly side-information and the mutator does not need to handle them separately. After audit, sandbox, and oracle all return, the runner emits a `HarvestRow` that closes the round and is appended to the per-run attack log read by `read_attack_log`; a per-entry re-audit fixes the `bypass` verdict so the harvest row's audit field is always concrete.

A.7 Phase-2 Per-Seed Coverage

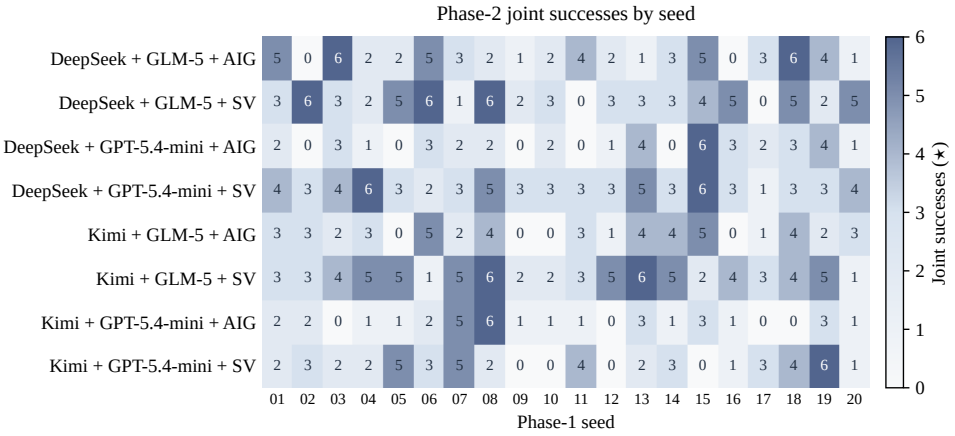


Figure 7: Per-seed ⋆ coverage across the 8 configurations of Table 4.

A.8 Phase-2 Candidate Gating Analysis

All 160 Phase-1 seed–configuration pairs enter Phase 2, including pairs whose Phase-1 run did not reach ⋆; under this policy the 160 pairs produced 999 evaluated variants (mean 6.24 per pair), of which 438 reached ⋆ (43.8%). We additionally evaluated a post-hoc gating rule that admits only the 110 pairs whose Phase-1 variants both passed the audit and triggered the intended attack effect. Table 9 compares the two admission policies. Gating raises candidate-level ⋆ yield by 11.5 percentage points and saves 372 evaluations, but finds 91 fewer ⋆ variants—a trade-off between evaluation efficiency and attack-surface coverage. For the gated setting, the mean is 5.70 candidates across all 110 admitted pairs; the 107 pairs with non-empty records have 2–12 candidates each (mean 5.86).

Table 9: Phase-2 admission policies. "Our setting" admits all 160 Phase-1 pairs; post-hoc ⋆ gating admits only the 110 Phase-1-successful pairs.

Setting	Admitted pairs	Pairs with records	Evaluations	⋆ variants	⋆ rate	Evals./pair
Our setting: all pairs	160	157	999	438	43.8%	Mean 6.24
Post-hoc ⋆ gating	110	107	627	347	55.3%	Mean 5.70; median 6

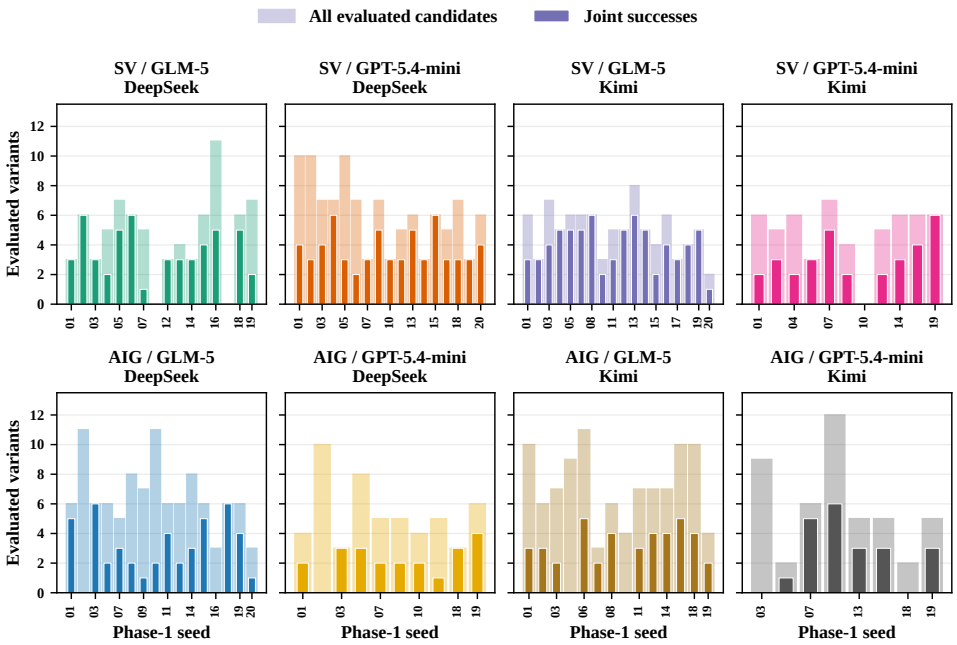


Figure 8: Per-pair Phase-2 variant yield under the post-hoc $\star$ gate. The light bar gives the total number of evaluated variants for a seed–configuration pair; the solid foreground gives the joint-success variants contained in that total (bar heights are not additive).

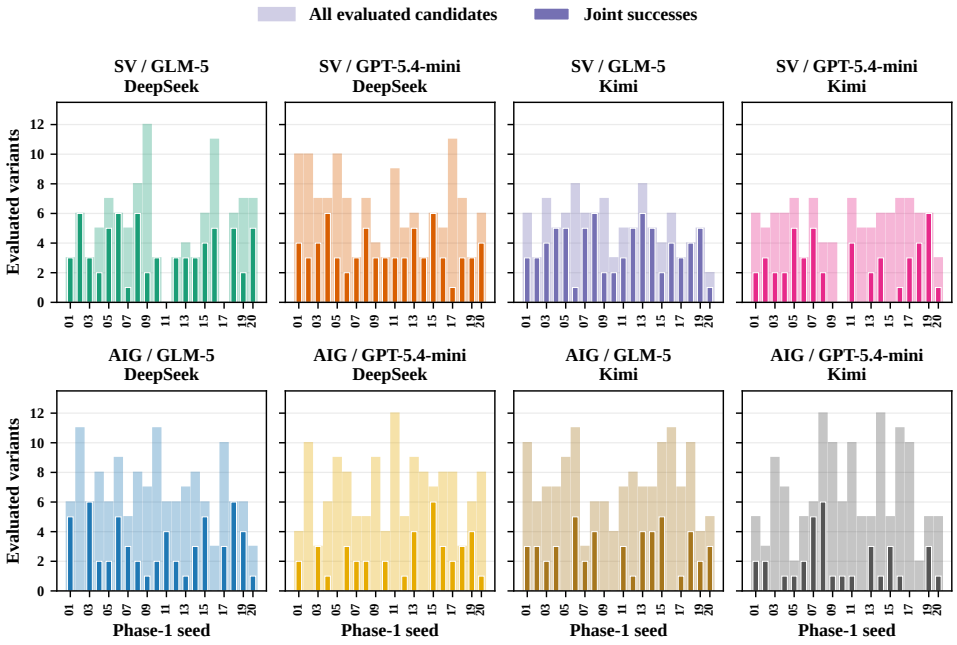


Figure 9: The same decomposition for the submitted collector's unfiltered records (all 160 pairs), shown for comparison with Figure 8.

A.9 Strategy Diversity Growth

We measure SDG (§4.4) from the base-cohort trajectories. Each declared operator list is normalized, deduplicated, and sorted into a canonical set. Changing the listing order or adding an explanatory suffix therefore does not create a new strategy. We count distinct sets observed up to each round and fit their growth over rounds 1–5 by ordinary least squares. Attempts without a rationale remain in the round count but add no strategy.

Table 10 separates recorded attempts from usable rationales. The three cells contain 69, 72, and 49 attempts, with 65, 43, and 35 parsed rationales. The 29 and 14 missing Kimi rationales are attempts that exhaust the tool budget before submission; the DeepSeek cell has two such attempts and two submitted records with empty rationales. Every non-empty rationale in these cells is parseable. All three normalized-set curves grow, with slopes $+4.7$, $+2.8$, and $+1.6$ strategies per round, complementing the success-rate growth measured by LCS.

Table 10: SDG from canonical operator sets. "Used" counts parsed rationales; "Rounds" includes all recorded attempts.

Cell	Rounds	Used	$r{=}1$	$r{=}5$	Slope/round
AIG + GPT-5.4-mini + DeepSeek	69	65	6	24	$+4.7$
AIG + GLM-5 + Kimi	72	43	3	14	$+2.8$
SV + GLM-5 + Kimi	49	35	5	12	$+1.6$

A.10 Per-Target Category Breakdown

Table 11 compares per-category Phase-1 joint-success rates between GPT-5.4-mini and GLM-5 on the original 20 seeds, with SkillVetter and DeepSeek-V4-Pro fixed as auditor and mutator. These are the first two rows of Figure 10; each target has its own adaptive mutation runs.

Table 11: Per-category Phase-1 joint success (%) on the original 20 seeds with SV and DeepSeek-V4-Pro fixed; Δ=GPT-5.4-mini$-$GLM-5 in percentage points.

Attack category	GPT-5.4-mini	GLM-5	Δ
Data exfiltration	100.0 (4/4)	100.0 (4/4)	$+0.0$
Persistence	100.0 (2/2)	100.0 (2/2)	$+0.0$
Guidance injection	100.0 (4/4)	75.0 (3/4)	$+25.0$
Supply chain*	0.0 (0/2)	50.0 (1/2)	-50.0
Privilege esc.	66.7 (2/3)	100.0 (3/3)	-33.3
Cleanup	100.0 (3/3)	100.0 (3/3)	$+0.0$
Cross-skill chain*	100.0 (2/2)	0.0 (0/2)	$+100.0$
Average	**85.0** (17/20)	**80.0** (16/20)	$+5.0$

*Category with $N{=}2$ seeds.

GPT-5.4-mini and GLM-5 differ by 5.0 pp in overall joint-success rate (85.0% vs. 80.0%). Data exfiltration, persistence, and cleanup reach 100% on both targets. Guidance injection reaches 100% on GPT-5.4-mini and 75% on GLM-5, while privilege escalation and supply-chain attacks have higher success rates on GLM-5.

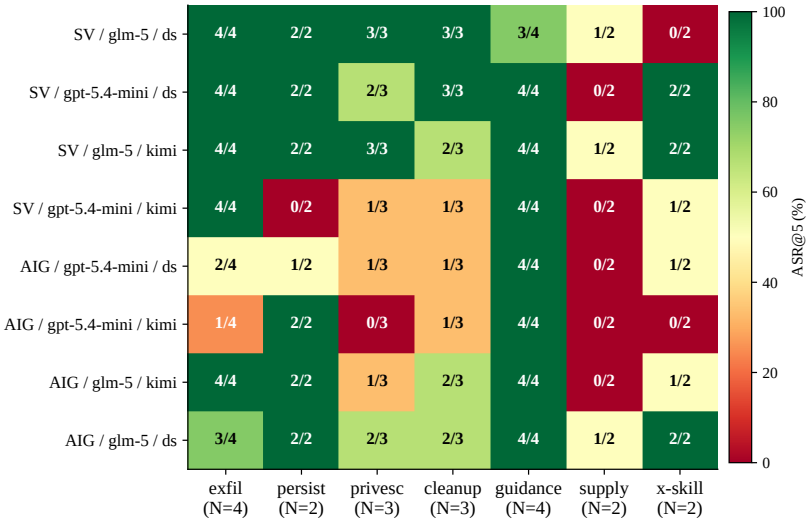


Figure 10: Original 20-seed ⋆-rate heatmap; rows = (defender, target, mutator), columns = 7 categories.

A.11 Detailed Ablation Results

Table 5 in §5.5 reports the five-seed AIG+GLM-5+Kimi comparison. Figure 11 visualizes the same joint-success rates, and the following paragraphs detail each configuration.

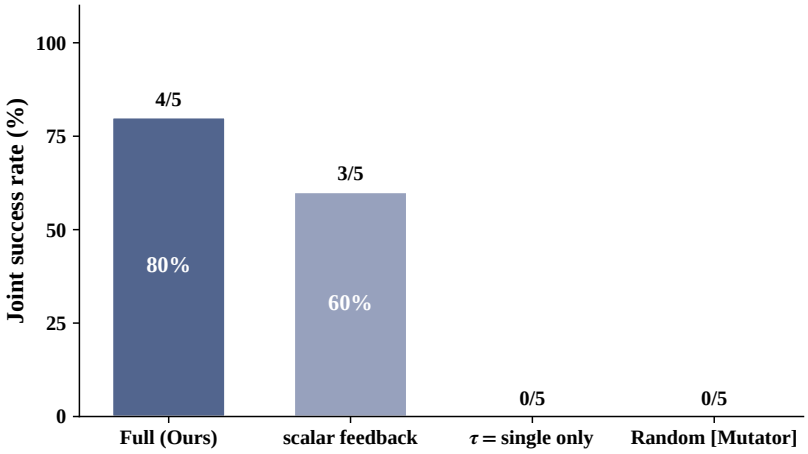


Figure 11: Ablation ⋆-rate on the AIG+GLM-5+Kimi cell (N=5, T=5).

[Mutator] closed-loop mutator value. Replacing the closed-loop LLM mutator with a programmatic Random pipeline removes retrieval and per-round feedback conditioning through `read_skill`, `read_repo_context`, and `read_attack_log`. On this five-seed ablation with T=5, joint success falls from $4/5$ for Full to $0/5$ ($\Delta = -80$ pp).

[τ] topology factorization (C2). In the reported five-seed ablation batch, Full reaches ⋆ on four seeds (4/5), while the single-only configuration reaches ⋆ on none (0/5) within T=5. All four successful Full variants use pair topology (*seed-01, 03, 05, 09*). The result highlights multi-skill composition as an effective evasion mechanism against AIG.

[F_t] structured finding (side-information value). The recorded ASR@5 is 60% $(3/5)$ with scalar b_t and 80% $(4/5)$ for Full. On SEED-05 CLEANUP, Full reaches joint success in round 2, whereas scalar feedback does not reach it within five rounds; this is a multi-round feedback comparison. On SEED-09 SUPPLY-CHAIN, Full succeeds in round 1, before any preceding-round feedback is available. That outcome is reported as execution variability and is not attributed to structured cross-round feedback. The aggregate 20 pp gap therefore does not isolate the effect of cross-round findings.

A.12 Per-Seed Per-Cell Detailed Results

Figure 12 reports the per-seed star outcome on the original 20-seed grid (with category-level aggregations in Figure 10). Each row is one of the 20 malicious seeds; each column is one of the 8 completed cells. Green stars mark a same-round $b \wedge \ell$ hit at any round in $\{1, \ldots, T\}$; muted red dots mark seeds the mutator could not lift to $\star$ within the rounds budget. The expanded samples are included in Table 1 and Figure 4; this grid retains the original subsets used by Phase 2. On these subsets, SEED-17 fails in all four AIG cells; SEED-09 succeeds only in AIG+GLM-5+DeepSeek and fails in the other three AIG cells. The guidance seeds (07/08/18/19) succeed across nearly every cell, while cleanup / privesc outcomes vary by target configuration.

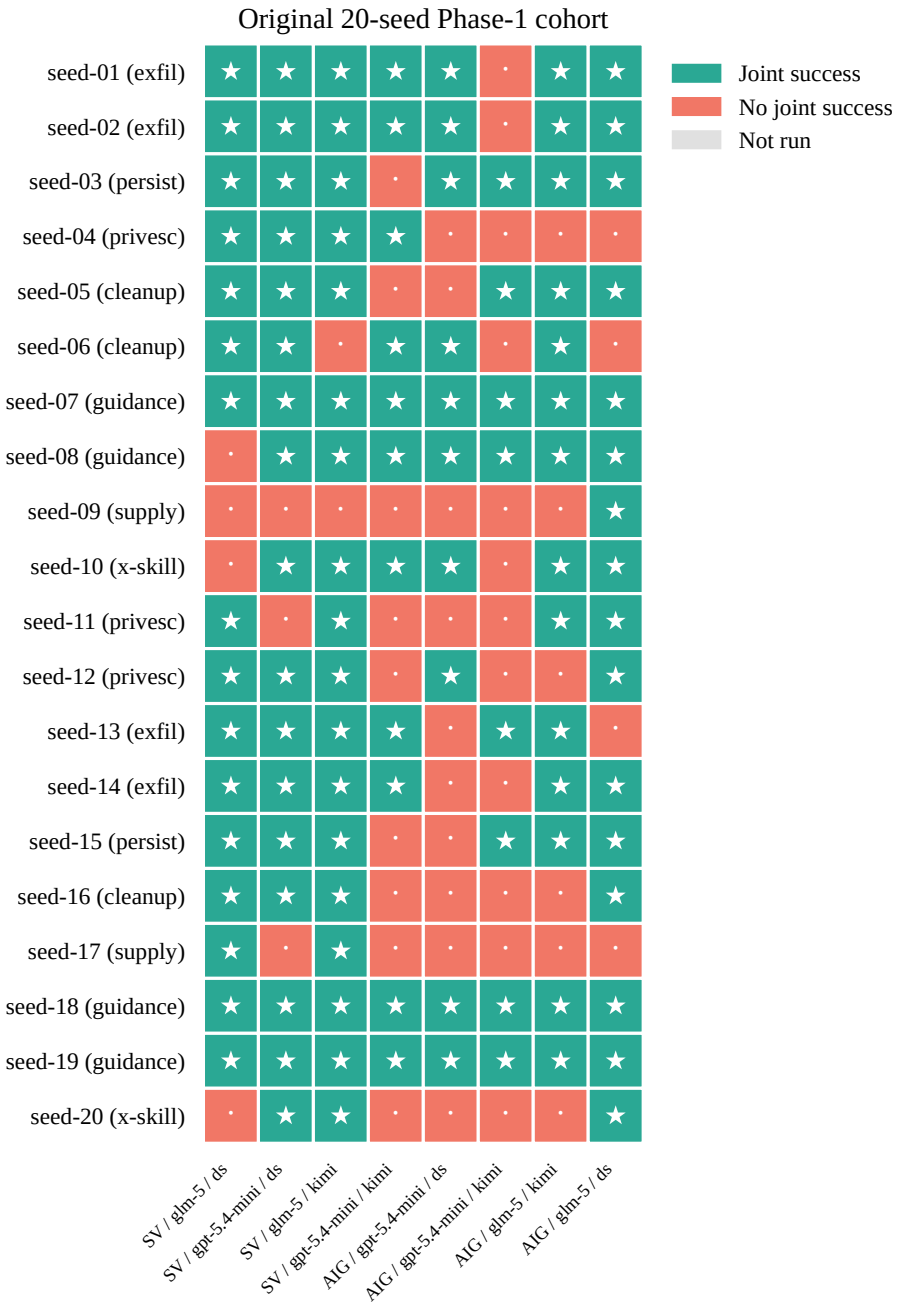


Figure 12: Base-cohort outcomes across eight configurations. Ablation run selection is documented in Appendix A.13; expanded results appear in Table 1.

A.13 Per-Seed Ablation Grid

For SEED-09, the main and ablation cohorts use two separate executions under AIG+GLM-5+Kimi. Figure 12 reports the first execution, which does not reach joint success within five rounds; the Full column of Figure 13 reports the second execution, which succeeds in round 1. Full reuses the main-grid executions for seeds 01, 03, 04, 05. Per-figure execution records are provided with the released analysis artifacts.

Figure 13 shows per-seed binary outcomes across the four-row grid for the same ablation batch as Table 5. Full succeeds on SEED-01, 03, 05, 09; its only miss is SEED-04. Both the single-only and **[Mutator]** Random configurations have no successful seeds in this batch, consistent with Figure 11.

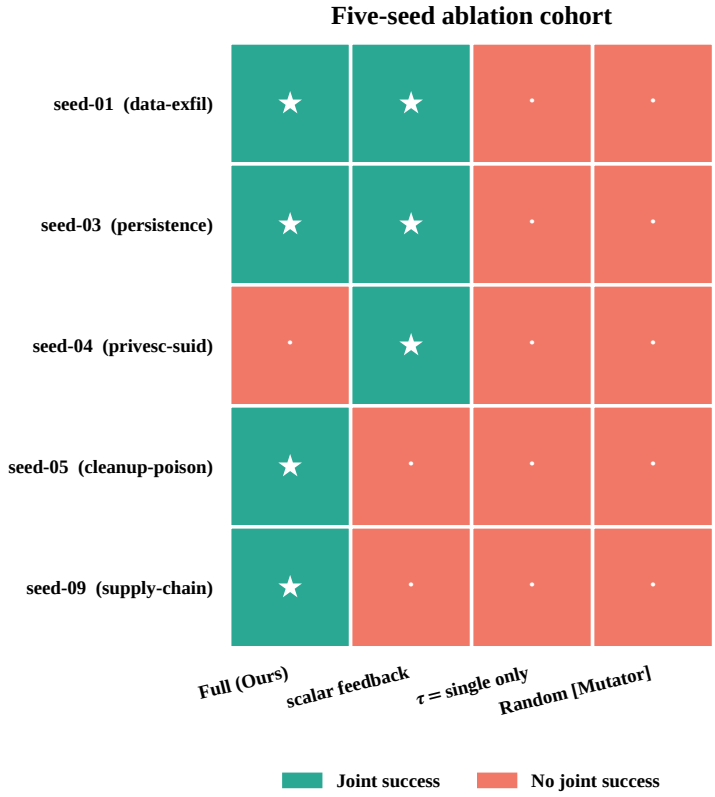


Figure 13: Five-seed ablation outcomes; execution provenance is specified above.

A.14 AIG Audit Verdict Distribution

Figure 14 counts 69 pre-mutation audits of the current artifacts across the 20 base-cohort runs: 32 approve (non-blocking, 46%) and 37 reject (54%). Two audits precede attempts that exhaust the tool budget without submitting a new candidate. Both are actual REJECT verdicts on the retained parent artifacts, not imputed rejections. Those attempts skip the sandbox and are logged with $b = \ell = 0$.

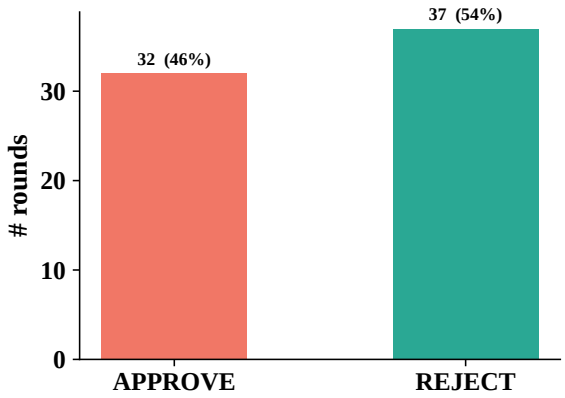


Figure 14: Pre-mutation AIG audit verdicts under DeepSeek-V4-Pro + GPT-5.4-mini: 69 recorded audits, including two attempts without a new submission.

A.15 Per-Round Outcome Strip

Figure 15 uses all 69 recorded attempts in the AIG+GPT-5.4-mini+DeepSeek base cohort. For SEED-12 PRIVESC, rounds 1–2 are lethal-only and round 3 reaches joint success: runtime harm is preserved while audit detection is removed. For SEED-06 CLEANUP, the first three outcomes are lethal-only, bypass-only, and joint success. In contrast, SEED-04 PRIVESC has bypass-only outcomes in rounds 2–4 and a lethal-only outcome in round 5, never reaching joint success; SEED-11 PRIVESC also never reaches joint success. Cleanup seeds 05 and 16 fail to combine both conditions within the budget, as do supply-chain seeds 09 and 17. A bypass and a harmful effect in different rounds do not constitute success.

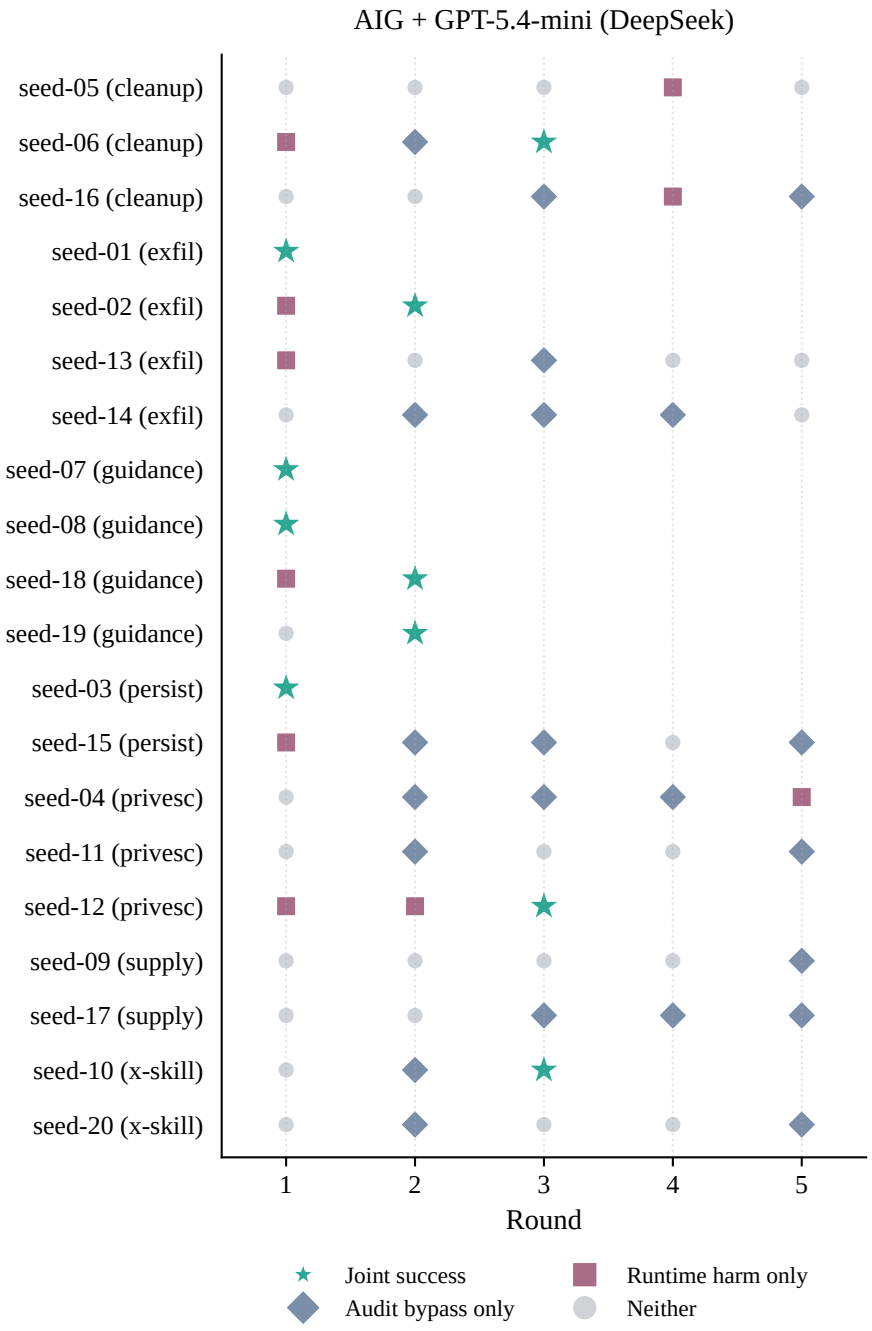


Figure 15: All recorded attempts under AIG+GPT-5.4-mini: joint success ($\star$), bypass-only ($\diamond$), lethal-only ($\square$), or neither ($\circ$). No-submission attempts are logged with $b = \ell = 0$.

A.16 Wilson 95% Confidence Intervals on Reported Proportions

For each Phase-1 cell, $\hat{p} = k/n$ is the fraction of seed trajectories reaching joint $b \wedge \ell$ success. For cross-auditor transfer, k/n is the fraction of previously successful AIG artifacts passing SkillVetter audit. Table 12 reports two-sided Wilson 95% confidence intervals computed via the closed-form score interval, $\left[(\hat{p} + z^2/2n) \pm z\sqrt{\hat{p}(1-\hat{p})/n + z^2/(4n^2)}\right]/(1 + z^2/n)$ with z=1.96. Wilson intervals remain well-behaved for small samples and extreme proportions; the calculation script is released with the artifact bundle (`plot/wilson_ci.py`). The eight Phase-1 rows correspond to Table 1; two additional rows retain the original 20-seed subsets for comparison.

Table 12: 95% CIs on the binomial proportions reported in this paper.

Quantity	k	n	Point (%)	95% CI (%)
Cross-auditor transfer (AIG-$\star$ $\rightarrow$SV)	50	57	87.7	[76.8, 93.9]
Phase-1: SV + DeepSeek + GLM-5	16	20	80.0	[58.4, 91.9]
Phase-1: SV + DeepSeek + GPT-5.4-mini	17	20	85.0	[64.0, 94.8]
Phase-1: SV + Kimi + GLM-5	18	20	90.0	[69.9, 97.2]
Phase-1: SV + Kimi + GPT-5.4-mini	11	20	55.0	[34.2, 74.2]
Phase-1: AIG + DeepSeek + GLM-5	38	50	76.0	[62.6, 85.7]
Phase-1: AIG + DeepSeek + GPT-5.4-mini	10	20	50.0	[29.9, 70.1]
Phase-1: AIG + Kimi + GLM-5	14	20	70.0	[48.1, 85.5]
Phase-1: AIG + Kimi + GPT-5.4-mini	23	50	46.0	[33.0, 59.6]
Original 20: AIG + DeepSeek + GLM-5	16	20	80.0	[58.4, 91.9]
Original 20: AIG + Kimi + GPT-5.4-mini	8	20	40.0	[21.9, 61.3]

The cross-auditor transfer estimate is 87.7%, with a Wilson 95% lower bound of 76.8%. On the Phase-1 grid, the four SV cells all have lower bounds at or above 34%, with three above 58%; on AIG the lower bounds span 30–63%. Each row states its denominator and cohort explicitly.

A.17 Feedback Exploitation Analysis

Figure 16 shows the frequency of each AIG finding category raised against PROTEUS-submitted variants across the 4 AIG phase-1 cells. AIG natively tags findings with CWE identifiers; the top categories are `mcp01` (29, AIG's MCP-policy rule), `CWE-200` (27, sensitive-information exposure), `CWE-94` (19, code injection), `CWE-532` (16, insertion of sensitive information into log), and `CWE-78` (15, OS command injection). The distribution indicates that AIG's blind spots cluster around *narrative-cloaked information disclosure* (CWE-200/532) and *code-execution primitives* (CWE-94/78); these are the chokepoints PROTEUS's `purpose-coherent-embed` and `code-offload` operators repeatedly target; the full operator catalog is in Appendix A.4. SkillVetter is excluded because its `reason_code` field is degenerate (`skillvetter_reject` only, no CWE tagging).

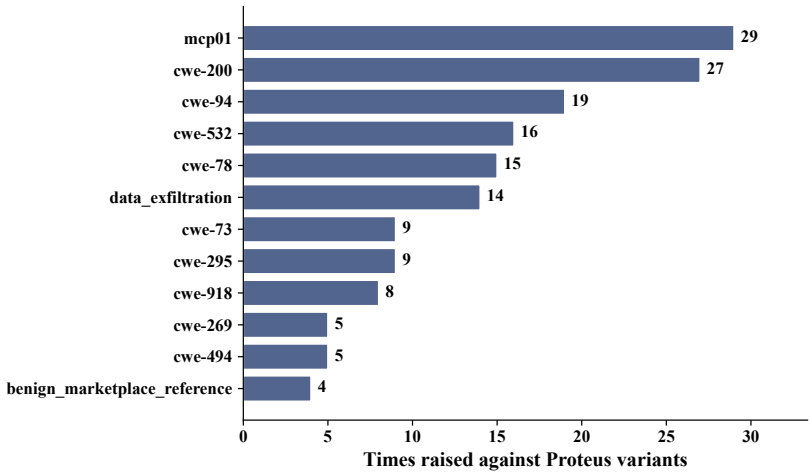


Figure 16: AIG finding-category frequency on the original 20-seed runs across four AIG cells; SV is excluded (degenerate `reason_code`).

A.18 Cost Analysis

Table 13 summarizes recorded API spending from the per-run `summary.json` `total_cost_usd` field, covering mutator, sandbox-target, and auditor LLM calls. The original snapshot contains 275 run records totaling approximately $125.38; 71 Phase-1 scaling records and 30 final-holdout records bring the total to 376 records and approximately $180.91. The records include pilot, interrupted, and repeated runs. Each run has a $50 spending cap. External-baseline runs and holdout-pair selection calls without separate cost records are excluded.

Table 13: Recorded API spending (n = run records, including reruns).

Configuration	n	Spend (USD)
Kimi-2.6 + GPT-5.4-mini + AIG	20	$14.50
Kimi-2.6 + GLM-5 + AIG	20	$12.34
DeepSeek-V4-Pro + GPT-5.4-mini + AIG (phase-1)	20	$11.91
DeepSeek-V4-Pro + GLM-5 + AIG (phase-1)	20	$8.93
DeepSeek-V4-Pro + GLM-5 + AIG (phase-2 expansion)	20	$10.00[†]
DeepSeek-V4-Pro + GLM-5 + SkillVetter	20	$5.58
DeepSeek-V4-Pro + GPT-5.4-mini + SkillVetter	20	$8.45
Kimi-2.6 + GLM-5 + SkillVetter	20	$7.66
Kimi-2.6 + GPT-5.4-mini + SkillVetter	20	$14.19
Motivation experiments (including reruns)	70	$23.27
Five-axis ablation grid	25	$8.55
Phase-1 scaling batch (including pilot runs)	71	$39.51
Final holdout batch (including reruns)	30	$16.02
Total accounted	376	**$180.91**[†]

[†] Cost for DeepSeek-V4-Pro + GLM-5 + AIG (Phase 2, 138 variants) is estimated at approximately $10.00 from comparable-scale AIG runs. The total includes this estimate and covers the listed records.

A.19 Reproducibility & Artifact Catalog

We will release the following artifacts so that other auditors can be re-measured under the same instrument.

Released.

- **Round-contract harness**: full `src/red_team/campaign` runner including the BluePort adapter spec, audit-step plug-in interface, and per-run harvest writer (`harvest.jsonl` schema below).
- **Per-objective oracles**: rule-based oracle judges (`src/red_team/oracle/objectives/`) with their evidence accept-sets verbatim.
- **Mutation operator catalog**: 12-operator system-prompt block, listed in Appendix A.4 with full source in `src/red_team/agent/prompts.py:MUTATION_OPERATORS`.
- **Source→sink rule catalog**: 16 rules listed in Appendix C, with full source in `src/dataset/subgraph_pipeline.py:RULE_SPECS`.
- **Aggregated outcome metrics**: per-cell ASR@t, LCS, SDG endpoints, and phase-2 cumulative outcomes (cf. tables in main paper and §A).
- **Sandbox container pool config**: `configs/sandbox/pool.yaml` (image tag, 20-container shape, allowlist tier).

Withheld. To balance reproducibility against misuse, the following are withheld and disclosed only via coordinated channels to affected vendors:

- Concrete bypass templates and end-to-end exploit skills (the actual SKILL.md / scripts that achieved $\star$).
- Full mutator system prompt and per-round prompt assembly logic (these encode the structured-finding rendering format that, if released verbatim, could lower the bar for adversarial reuse).

Artifact schemas.

- `SkillVariant` JSON: keys o, τ, c, κ, d, `poison_index`, `chain`, `metadata`; c is a dict with optional `entry_script`, `scripts` (path $\rightarrow$ body), `declared_apis`, `deps`.
- `HarvestRow` JSON: keys `run_id`, `seed_id`, `round`, `stage`, `variant`, `variant_hash`, `parent_variant_hash`, `bypass`, `audit_findings`, `audit_source`, `lethal`, `target_model`, `tool_chain`, `sandbox_trace_summary`, `sandbox_files_modified`, `sandbox_commands_executed`.
- `PaperFinding` JSON (per audit finding): keys `layer`, `reason_code`, `category`, `severity`, `evidence`, `explanation`.

B Extended Formalization

This appendix extends the compressed formalization in §3: it gives the formal evolution operator (§B.1), the set-builder definitions of the three search modes, the side-information-vs-scalar-reward methodology comparison, the full red-team optimization objective and two-dimensional cost constraint, and a dimension-by-dimension comparison with prior red-teaming formalizations.

Definition 1 (Adaptive Leakage)**.** *Fix a defender* Blue*, a target backbone $\mathcal{M}$, a seed distribution $\mathcal{D}_{seed}$, and a budget $B = (T, B_{tool})$ (max rounds and max tool calls per round). For a mutator θ producing trajectories $s_1, \ldots, s_T$ via the closed-loop operator of §B.1, the* adaptive leakage at budget B *is the quantity defined in Eq.* (1)*, with randomness over seed draws, the mutator's sampling, and sandbox/oracle stochasticity.*

B.1 Reason→Mutate Operator

The two-stage operator referenced in §3 is, formally,

$$(h_t, a_t) = \mathrm{Reason}_\theta(\mathcal{H}_{<t}, \mathcal{F}_{<t}) \qquad s_t = \mathrm{Mutate}_\theta(s_{t-1}, a_t, \mathcal{S}_k), \tag{2}$$

where θ is the shared LLM backbone, $\mathcal{H}_{<t}$ the historical attack log, $\mathcal{F}_{<t}$ the set of past auditor findings, h_t a natural-language reasoning trace, a_t a structured tool-call sequence, and $\mathcal{S}_k \in \{\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3\}$ the active search subspace.

B.2 Search Subspaces

For the constraints below, we make the auxiliary skill chain χ explicit and write $s = (o, \tau, c, \kappa, d, \chi)$. The five semantic axes remain (o, τ, c, κ, d); χ records the concrete skills realizing τ. The three search modes are:

$$\mathcal{S}_1(s) = \{\, s' = (o, \tau, c', \kappa', d', \chi') \mid c' \in \mathcal{C},\ \kappa' \in \mathcal{K},\ d' \in \mathcal{D},\ \chi' \in \mathcal{X},\ \mathrm{Align}(s') = 1 \,\} \tag{3}$$

$$\mathcal{S}_2(s) = \{\, s' \in \mathcal{S}_1(s) \mid (c', \kappa', \chi') \neq (c, \kappa, \chi) \,\} \tag{4}$$

$$\mathcal{S}_3(s) = \{\, s' = (o', \tau', c', \kappa', d', \chi') \mid (o', \tau') \in \mathcal{O} \times \mathcal{T},\ o' \neq o, \\ \mathrm{SharedMotif}(s, s') = 1,\ \mathrm{Align}(s') = 1 \,\} \tag{5}$$

where $\mathcal{D}$, $\mathcal{C}$, $\mathcal{K}$, $\mathcal{X}$, $\mathcal{O}$, $\mathcal{T}$ are the syntactically feasible sets for documentation, code, channel, chain, objective, and topology respectively. Note $\mathcal{S}_2 \subsetneq \mathcal{S}_1$ as candidate sets ($\mathcal{S}_2$ excludes all candidates with $(c', \kappa', \chi') = (c, \kappa, \chi)$, including documentation-only rewrites); $\mathcal{S}_3$ is*not* a superset of $\mathcal{S}_1$ since it relaxes (o, τ) but adds the SharedMotif acceptance gate. The strict $\mathcal{S}_1^{\mathrm{strict}}$ that fixes $(o, \tau, c, \kappa, \chi)$ and only varies d is a strict subset of $\mathcal{S}_1$.

Constraint-projection operator. $\mathrm{Align} : \mathcal{S} \rightarrow \{0, 1\}$ denotes skill-specification consistency: observable alignment between documented capabilities and actually invoked APIs, complete dependency declaration, and valid skill-manifest schema. The search-space definitions above admit only variants with $\mathrm{Align}(s') = 1$.

SharedMotif operator. Returns 1 iff s and s' share **at least two** structural-motif axes drawn from: (a) κ overlap (at least one channel in common); (b) tool-call chain prefix overlap (the shorter of `metadata['tool_chain_prefix']` is a prefix of the longer with length ≥ 1); (c) repo-file access overlap (`metadata['file_access']` sets intersect). When neither tool-chain-prefix nor file-access metadata is populated, falls back to "κ overlap + identical `c.entry_script`" as two axes. The $\geq$2-axes threshold ensures transfers originate from learned attack structure rather than unrestricted random global search over $\mathcal{S}_3$.

B.3 Side-Information vs. Scalar Reward

PROTEUS conditions mutation on structured findings F_t and runtime feedback R_t, keeping the mutator's model parameters fixed. A scalar-reward formulation instead compresses these signals into $r_t = f(b_t, \ell_t, F_t)$ for policy updates. Our feedback interface has four design properties:

1. **Direct feedback use.** Finding categories, evidence pointers, and runtime advice enter Reason_θ as context for diagnosis and strategy selection within the run's search budget.
2. **Interpretability.** The natural-language trace h_t records why a mutation was selected, supporting feedback-exploitation analysis (Appendix A.17) and the scalar-feedback comparison (Table 5, row $[F_t]$).
3. **Fixed-oracle compatibility.** Per-objective oracles apply fixed rules to sandbox observations and return discrete lethality verdicts with evidence that the next mutation can use directly.
4. **Agent-based refinement.** The loop extends the iterative refinement used by PAIR, TAP, Rainbow Teaming, and EvoAgent to skill code and documentation with structured audit and runtime feedback.

Formally, the two paradigms differ as:

$$\mathrm{RL}: \ \theta \leftarrow \theta + \alpha \nabla_\theta \mathbb{E}[r_t] \qquad \mathrm{Ours}: \ s_t = \mathrm{Mutate}_\theta\big(s_{t-1},\, \mathrm{Reason}_\theta(\mathcal{H}_{<t}, \mathcal{F}_{<t})\big) \tag{6}$$

Feedback conditions the next skill variant while the mutator parameters θ remain fixed.

Empirical validation: structured vs. scalar feedback. Structured findings provide attributed audit evidence beyond a scalar verdict. We assess their empirical value through the internal Blackbox comparison and the five-seed feedback ablation below.

(i) The Blackbox red-team baseline (Table 2) iterates with a scalar audit verdict. On Skill-Vetter + GPT-5.4-mini + DeepSeek, Blackbox reaches 42.9% ASR@5 and LCS$=0.014$, compared with 85.0% and 0.160 for PROTEUS over the same $t \in [1, 5]$ fitting window. Blackbox saturates by round 2; extending to $T{=}10$ adds no successes. Table 2 gives the sample sizes and repetitions.

(ii) The $[F_t]$ ablation row (Table 5, Appendix A.11) records 80% ASR@5 $(4/5)$ for Full and 60% $(3/5)$ for scalar feedback on AIG + GLM-5 + Kimi ($T{=}5$). The multi-round comparison on SEED-05 and the first-round outcome on SEED-09 are distinguished in Appendix A.11.

The internal-baseline comparison shows an approximately $11\times$ LCS gap. The five-seed ablation provides complementary per-seed feedback comparisons; its aggregate success-rate gap includes a first-round outcome and is not an isolated estimate of the effect of cross-round feedback.

B.4 Optimization Objective and Cost Constraint

Given a malicious seed skill s_0 with attack objective $o \in \mathcal{O}$, the red team seeks a mutation trajectory $s_1, \ldots, s_T$ that maximizes the probability of joint audit bypass and verified runtime harm within the budget. Strategy diversity is reported separately through SDG:

$$\max_{\{s_t\}_{t=1}^{T}} \ \Pr_\theta[\exists\, t \le T: \ b_t \wedge \ell_t = 1 \mid s_0, \mathcal{M}, \mathrm{Blue}] \tag{7}$$

subject to the two-dimensional cost constraint

$$C_{\text{search}}(t) = \sum_{i=1}^{t} \big(n_{\text{LLM}}^{(i)} + w \cdot n_{\text{tool}}^{(i)}\big) \qquad C_{\text{artifact}}(s) = \alpha|c| + \beta|d| + \gamma \cdot \mathrm{deps}(s) + \delta \cdot \mathrm{cyclomatic}(c) \tag{8}$$

- $n_{\text{LLM}}^{(i)}$: LLM calls at round i; $n_{\text{tool}}^{(i)}$: tool calls; w: weighting factor for tool calls relative to LLM calls (default $w = 0.3$, matching the ratio of tool latency to LLM token cost).
- $|c|$, $|d|$: code/documentation token length; $\mathrm{deps}(s)$: declared dependency count; $\mathrm{cyclomatic}(c)$: code cyclomatic complexity. Weights $(\alpha, \beta, \gamma, \delta) = (0.01, 0.005, 1.0, 0.5)$.
- Budget caps: $C_{\text{search}} \le B_{\text{search}} = 200$ (per run); $C_{\text{artifact}} \le B_{\text{artifact}} = 50$ (per skill, matching average skill complexity).

The experimental per-run API spending cap is \$50 (Appendices A.1 and A.18). The artifact-cost constraint acts as a feasibility filter, excluding variants above its cap.

B.5 Comparison with Prior Formalizations

Table 14: Dimension-by-dimension comparison with prior red-teaming formalizations; "—" = absent or single-valued.

Dimension	Rainbow	AgentPoison	EvoAgent	AutoRedTeamer	PROTEUS
Search object	prompt p	RAG entry	agent config	prompt p	skill (o, τ, c, κ, d)
Channel	text	vec/text	config	text	**exec + ctx**
Topology	single	single	single agent	single	**single / pair / chain**
Supply-chain	—	—	—	—	κ **explicit**
Search struct.	MAP-Elites	backdoor	EA	iterative	$\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3$ **modes**
Feedback	scalar	ASR	multi-obj scalar	scalar	**struct. finding**
Cross-obj	—	—	—	—	**SharedMotif**
Cost constr.	prompt len	trigger len	—	—	**2D** (C_s, C_a)

Every "—" or single-channel entry corresponds to a dimension in our 5-axis factorization (§3) that prior formalizations do not enumerate. The single-only row **[τ]** in §A.11 examines the topology axis (τ) within the reported five-seed ablation batch.

C Source→Sink Risk Rules

Table 15 lists all 16 typed-edge risk rules used by the red team's graph-guided chain composition operator (§4.1). The catalog is fixed across all experiments. Each rule fires when a candidate (source skill, sink skill) pair satisfies (a) the source skill carries the row's `source_tag`, (b) the sink skill carries the row's `sink_tag`, and (c) their document embeddings exceed the theme-similarity threshold $\cos \geq 0.30$.

Table 15: The 16 source→sink risk rules: attacker-reachable *source_tag*, dangerous *sink_tag*, resulting *risk_type*.

#	source_tag	sink_tag	risk_type
1	user_input	shell_execution	command_injection
2	external_code	shell_execution	remote_code_execution
3	external_code	code_execution	remote_code_execution
4	credentials	network_egress	data_exfiltration
5	credentials	filesystem_write	credential_persistence
6	local_files	network_egress	repo_exfiltration
7	local_files	shell_execution	privilege_escalation
8	local_files	sql_execution	data_poisoning
9	user_input	code_execution	code_injection
10	user_input	sql_execution	sql_injection
11	credentials	shell_execution	credential_abuse
12	local_files	filesystem_write	persistence_write
13	network_input	shell_execution	remote_command_injection
14	network_input	code_execution	remote_code_injection
15	network_input	filesystem_write	remote_file_write
16	network_input	sql_execution	remote_sql_injection

C.1 Limitations

We list eight explicit limitations of the present study.

(1) Our threat model assumes the attacker can read structured audit findings between rounds (§3); fully closed commercial auditors that emit no per-skill explanation would degrade this side-channel and our results then upper-bound rather than estimate adaptive leakage. (2) Attack oracles are rule-based and may not capture all nuanced attack objectives. (3) Two target models (GPT-5.4-mini, GLM-5) provide a budget-feasible probe but do not exhaustively cover the LLM landscape. Cross-auditor transfer is evaluated from AIG to SkillVetter on previously successful variants, using recorded runtime outcomes rather than new executions. Transfer intervals are artifact-level Wilson intervals without parent-seed clustering. (4) Surface expansion relies on the LLM's ability to reason about cross-type transfer, which may be bounded by the mutator model's capability. (5) The `SharedMotif` gate uses a fixed

$\geq$2-axis threshold over a manually chosen motif set; we do not ablate the threshold or alternative gating signals, so its contribution to surface-expansion quality is bounded above by the current setting. (6) We model a static auditor that does not adapt to attacker traces; iterated arms-race dynamics (auditor learns, attacker re-evolves) are out of scope. (7) We evaluate two mutators, DeepSeek-V4-Pro and Kimi-2.6; whether the findings extend to mutators from other model families remains open. (8) The base seeds use graph-guided composition. The holdout (Table 3, Appendix A.2) varies seed admission in one configuration while retaining GCC access during mutation. Its 75.0% ASR@5 versus the base cohort's 70.0% tests robustness to seed construction; it does not measure GCC's contribution during attack. The holdout does not cover every configuration or exclude all seed-selection effects. Per-cell uncertainty is reported in Appendix A.16.

C.2 Broader Impact

This work aims to improve agent-skill ecosystem security by surfacing residual leakage of current skill auditors under adaptive attack, providing a defender-agnostic measurement instrument that auditor maintainers and marketplaces can re-run as their pipelines change. The same techniques could be misused to manufacture skills that pass vetting at scale. To balance reproducibility against misuse risk, we release the round-contract harness, the GCC builder, the mutation-operator catalog, the harvest schemas, and the sandbox runner so that other auditors can be re-measured under the same instrument, while withholding the concrete bypass templates, mutation prompts as deployed, and end-to-end exploit skills that reached $\star$ in our runs, as detailed in Appendix A.19. All experiments executed inside an isolated, network-restricted OpenClaw sandbox.

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