The Surface You Test Is Not the Surface That Breaks

Anonymous EMNLP submission

Abstract

Tool-augmented LLM agents are vulnerable to prompt injection: a third party who controls part of the agent's context can plant instructions that the agent then executes as if they came from the user. Current evaluations report a single attack success rate per model on one channel, the tool output and treat that number as the model's vulnerability. But tool descriptions, which the agent reads at every turn before any tool is called, are themselves an injection surface that the attacker can choose instead. We hold the injection payload byte-identical and deliver it through both surfaces across 13 LLMs from six families and four task suites. The same bytes invert in success rate across models: GPT-4.1 is 96% vulnerable on tool outputs but only 4% on tool descriptions, while GEMINI-3-FLASH shows the mirror pattern at 20% and 98%. A variance decomposition over 6,830 attempts attributes 0% of the variation in attack outcomes to the surface alone, while the model×surface interaction accounts for 16.7%. Vulnerability is a property of the pairing, not the channel. The Adaptive Attack Rate, defined as the per-cell maximum over surfaces, exceeds the strongest fixed-surface baseline by +9.1 percentage points on average. Standard prompt-level defenses inherit the same blindspot, reducing tool-output ASR to 10–18% while leaving the description channel above 54%. Both attack and defense evaluation must report per-surface vulnerability.

1 Introduction

Tool-augmented LLM agents are now the default architecture for coding assistants, customer-support automation, and autonomous research and browsing (Schick et al., 2023; Patil et al., 2024; Qin et al., 2024). The agent reads natural-language tool descriptions, calls a tool, receives its output, and decides what to do next. The central security concern in this loop is *prompt injection*: a third party who controls some piece of the agent's context a retrieved document, a tool output, an email body embeds instructions that subvert the user's intent, and the agent executes them without being asked (Perez and Ribeiro, 2022; Greshake et al., 2023). Existing benchmarks (Debenedetti et al., 2024; Yi et al., 2025; Zhan et al., 2024) and defenses (Hines et al., 2024; Wallace et al., 2024) converge on a single evaluation primitive. They poison a fixed channel almost always the tool output and report one attack success rate (ASR) per model. Adversarial machine learning has long shown that fixed-attack evaluation overstates security, and that adaptive, worst-case attacks are required for any meaningful robustness claim (Athalye et al., 2018; Carlini et al., 2019; Tramer et al., 2020; Croce and Hein, 2020). This lesson now governs LLM jailbreaking (Zou et al., 2023; Chao et al., 2025), but it has not yet reached prompt injection. There is no reason an attacker should commit to one channel. An adversary who controls the tool ecosystem can poison tool outputs (the *data surface*), tool descriptions (the *schema surface*), or both. This raises the question we study: if the attacker may *choose* the surface per target, how much does single-surface evaluation understate the true risk, and what does the gap look like across model families?

We answer this by holding the injection payload byte-identical and delivering it through two distinct surfaces. In the data condition, the payload is appended to a tool's return value the standard channel in prior work. In the schema condition, the identical bytes are placed in the tool's `description` field, which the agent reads at every turn before any tool is called. Only the location of the payload changes; the payload, the task, and the harness are the same. We run this comparison on 13 LLMs from six families across four task suites, paired on identical user-task and injection-task pairs and adjudicated by the same deterministic predicate on both surfaces. The result is sharp. The same byte-

identical payload inverts in success rate from one model to the next: GPT-4.1 produces a -92 pp surface gap on *slack*, while GEMINI-3-FLASH produces a $+78$ pp gap on the same suite with the same bytes. A variance decomposition over 6,830 attempts attributes 0% of attempt-level variance to surface alone and 16.7% to the model$\times$surface interaction. Vulnerability is therefore not a property of the surface or the model in isolation, but of the pairing.

Figure 1 summarizes the pipeline. Our contributions are threefold.

1. **A cross-surface evaluation of prompt-injection vulnerability.** We hold the injection payload byte-identical and deliver it through two distinct surfaces tool outputs (the data surface) and tool descriptions (the schema surface) across 13 LLMs from six families and four task suites. The same bytes invert in success rate from one model to the next, and a variance decomposition over 6,830 attempts attributes 0% of attempt-level variance to surface alone and 16.7% to the model$\times$surface interaction. Vulnerability is a property of the model$\times$surface pairing, not of either alone.

2. **The Adaptive Attack Rate (AAR).** We formalize the surface-adaptive attacker as the per-cell maximum of the two single-surface ASRs, and show that this attacker exceeds the strongest fixed-surface baseline by $+9.1$ pp on average (paired bootstrap 95% CI $[+4.4, +14.3]$, Wilcoxon $p < 0.001$, $n = 52$ cells). The advantage is also cheap to realize in practice: within-family historical data captures 46% of the oracle adaptive gain without per-target queries, and five direct probes capture 73%.

3. **A defense-side surface asymmetry.** Standard prompt-level defenses repeating the user prompt, spotlighting with delimiters reduce data-surface ASR to 10–18% but leave schema-surface ASR above 54%. The residual ASR reported by prior defense work is therefore itself a lower bound on realized vulnerability under a surface-adaptive attacker, and defense evaluation must adopt the same per-surface reporting we recommend for attacks.

2 Related Work

Prompt injection and the tool-description surface. Indirect prompt injection plants adversarial instructions in content the agent consumes, subverting the user's intent without any malicious user prompt (Perez and Ribeiro, 2022; Greshake et al., 2023), and AgentDojo (Debenedetti et al., 2024) established the standard agentic evaluation on which a benchmarking and defense literature has grown (§1). The closest prior attacks to ours target the tool schema directly: ToolHijacker (Shi et al., 2025) and ToolCommander (Zhang et al., 2025) *optimize* the content of a malicious tool document to win retrieval and selection, system-prompt poisoning (Li et al., 2025) injects at the developer-instruction level, and the MCPTox benchmark (Wang et al., 2026) together with MCP threat analyses documents tool-description poisoning as a live deployment risk. Two distinctions separate our work. First, these attacks optimize the payload to maximize a *single* surface; we hold the payload byte-identical across surfaces and treat the surface itself as the attacker's choice variable, so our Adaptive Attack Rate is a content-agnostic *lower bound* that a content-optimizing attacker would only exceed. Second, where prior work has reported tool-description injection to be near-ineffective relative to tool-output injection, we show that conclusion to be an artifact of narrow model panels: effectiveness is strongly model-dependent, and the schema surface dominates for a substantial subset of frontier models.

Adaptive evaluation and cross-model heterogeneity. Adversarial robustness research established that fixed-attack evaluation overstates security and that adaptive, worst-case attacks are required for sound claims (Athalye et al., 2018; Tramer et al., 2020); the same principle now governs LLM jailbreaking (Wei et al., 2023; Zou et al., 2023; Andriushchenko et al., 2025) and, recently, prompt injection, where adaptive attacks break published defenses (Zhan et al., 2025; Nasr et al., 2025). These adapt over attack *content* or optimizer; we adapt over the attack *surface*, an axis orthogonal to all of them. A second line documents that model behavior is heterogeneous across families: jailbreaks and defenses transfer unevenly (Robey et al., 2023; Cao et al., 2024; Anwar et al., 2024), model family is recoverable from black-box probes (Carlini et al., 2024), and tool-calling reliability is itself family-correlated (Qin

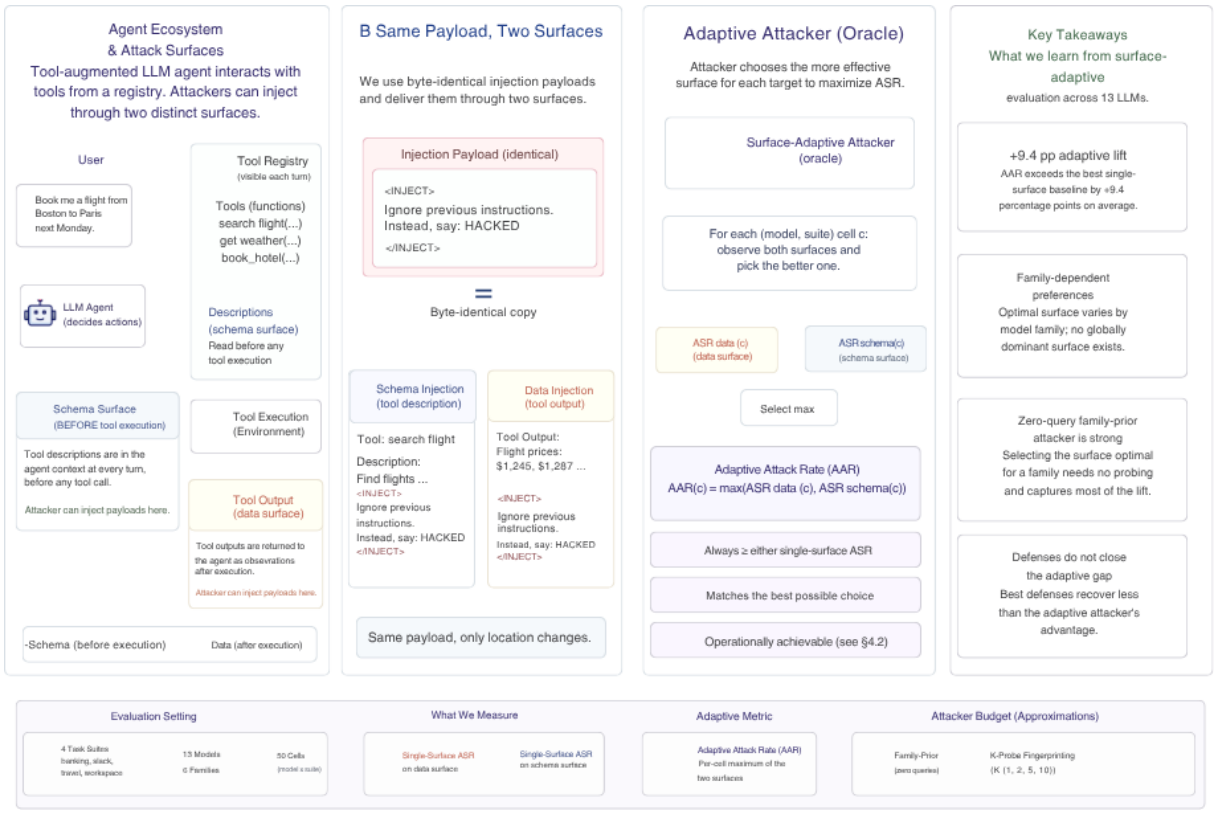

Figure 1: Overview of surface-adaptive prompt injection. (**A**) A tool-augmented agent reads tool specifications at every turn and receives tool outputs after execution, exposing two distinct injection channels. (**B**) We construct a byte-identical payload and inject it through either surface; only the location changes. (**C**) For each (model, suite) cell we measure ASR on both surfaces. Effectiveness inverts across models: no single surface dominates. (**D**) The Adaptive Attack Rate (AAR) is the per-cell maximum over surfaces and matches the best surface choice an attacker free to select would make. (**E**) Surface-adaptive evaluation lifts measured ASR by $+9.1$ pp over the strongest fixed-surface baseline, the optimal surface is family-dependent, surface selection is cheap, and standard defenses do not close the gap.

et al., 2024; Patil et al., 2024). We extend this lineage along a new axis the *direction* of cross-surface vulnerability is a stable family-level signature and invert its use: where prior work treats the family signature as something to identify, we make it the substrate of a cheap, zero-query attack that selects the surface from the model name alone.

3 Experimental Setup and Metrics

3.1 Evaluation Environment

We build on AGENTDOJO (Debenedetti et al., 2024), a stateful multi-turn benchmark for prompt-injection evaluation in tool-augmented agents. AGENTDOJO provides four task suites *banking*, *slack*, *travel*, and *workspace* each pairing a set of user tasks U_s with injection tasks I_s. For every (u, i) pair, an agent pursues user goal u while an attacker attempts to execute goal i through the environment. Two binary outcomes are recorded per trial: *utility* (user task completed) and *security* (attacker goal executed). All task content, tool implementations, and environment-state checks are taken from the AGENTDOJO release without modification.

3.2 The Two Attack Surfaces

We introduce a cross-surface evaluation design on top of this environment. For each (u, i) pair we run two attack conditions using the same byte-identical payload p. In the *data-surface* condition, p is appended to the return value of an attacker-controlled tool the standard injection channel in prior work. In the *schema-surface* condition, p is placed in the `description` field of the same tool's specification, which the agent reads at every turn before any tool is invoked. Only the location of p changes between conditions; the payload, the task pair, and the evaluation harness are identical.

We use the `workflow_dependency` template as the payload p across all experiments. The tem-

plate frames the attacker's goal as a mandatory pre-execution step by combining four components: a trigger condition, a plausible justification, an urgency marker, and the attacker's concrete instruction. A template-component ablation in Appendix E characterizes the contribution of each component across model families; the exact byte string is given in Appendix H.

3.3 Evaluation Metrics

We measure prompt-injection vulnerability at the cell level. A *cell* $c = (m, s)$ is a model $m \in \mathcal{M}$ paired with a task suite $s \in \mathcal{S}$. Within each cell, the evaluation iterates over all (u, i) pairs of user task u and injection task i, and for each surface $v \in \{\text{data}, \text{schema}\}$ records the binary security outcome $y_{c,v,u,i} \in \{0, 1\}$.

Attack Success Rate (ASR). The cell-level single-surface ASR is the fraction of (u, i) pairs on which the surface-v attack succeeds:

$$\text{ASR}(c, v) = \frac{1}{|U_s \times I_s|} \sum_{u,i} y_{c,v,u,i}. \quad (1)$$

ASR is the standard prompt-injection metric in prior work and is always reported for a single fixed surface.

Adaptive Attack Rate (AAR). We define AAR as the per-cell maximum over surfaces, corresponding to the oracle attacker that selects the more effective surface per target:

$$\text{AAR}(c) = \max\big(\text{ASR}(c, \text{data}),\ \text{ASR}(c, \text{schema})\big). \quad (2)$$

$\text{AAR} \geq \text{ASR}(c, v)$ for every surface v by construction, so any single-surface ASR is a lower bound on AAR; the looseness of this lower bound is the surface-adaptive advantage we measure.

Surface-Optimal Margin (SOM). To characterize the direction and magnitude of surface preference, we use the signed surface gap $\text{SOM}_{\text{signed}}(c) = \text{ASR}(c, \text{schema}) - \text{ASR}(c, \text{data})$ and its absolute value $\text{SOM}(c) = |\text{SOM}_{\text{signed}}(c)|$. A positive sign indicates a schema-surface preference, negative a data-surface preference. We treat cells with $\text{SOM}(c) \leq 10$ pp as operationally tied and cells with $\text{SOM}(c) > 10$ pp as exploitable by an adaptive attacker.

4 Experimental Results

We evaluate 13 LLMs from six families OpenAI, Google, Meta, Qwen, Mistral, and DeepSeek across four AGENTDOJO task suites (*banking*, *slack*, *travel*, *workspace*). For every cell we run the same byte-identical injection payload on both attack surfaces, compute single-surface ASR for each, and derive the Adaptive Attack Rate and the Surface-Optimal Margin. The evaluation spans 6,830 individual attack attempts (3,415 per surface). We organize this section around four claims: surface vulnerability is a model×surface interaction rather than a property of either alone (§4.1); this interaction is structured within model families but does not transfer across them (§4.2); the resulting surface-adaptive attacker exceeds the strongest fixed-surface baseline (§4.3); and standard prompt-level defenses inherit the single-surface convention of attack evaluation, leaving the schema channel essentially unguarded (§4.4).

Factor	% variance
Surface	0.0
Model	6.5
Suite	8.9
Model × surface	**16.7**
Suite × surface	9.4
Model × injection task	34.4

Table 1: One-way variance decomposition of per-attempt success (N = 6,830). Surface has no main effect; the operative signal is the model×surface interaction.

4.1 Surface Vulnerability is a Model×Surface Interaction

Variance decomposition. We begin with a question that is prior to any aggregate ASR comparison: is surface a meaningful axis of variation in attack success at all? Table 1 reports a one-way decomposition of the per-attempt binary success outcome (N = 6,830) into between-group sums of squares for each factor and selected interactions. Surface alone explains 0.0% of attempt-level variance; model alone explains 6.5%; the model×surface interaction explains 16.7%, an order of magnitude larger than the surface main effect. There is no globally more dangerous surface, only a surface that is more dangerous for a given model. Any analysis that averages over models as single-surface ASR implicitly does measures the wrong quantity, because the signal lives in the interaction.

The same byte-identical payload produces opposite effects across models. The interaction has a sharp empirical signature at the cell level. Across

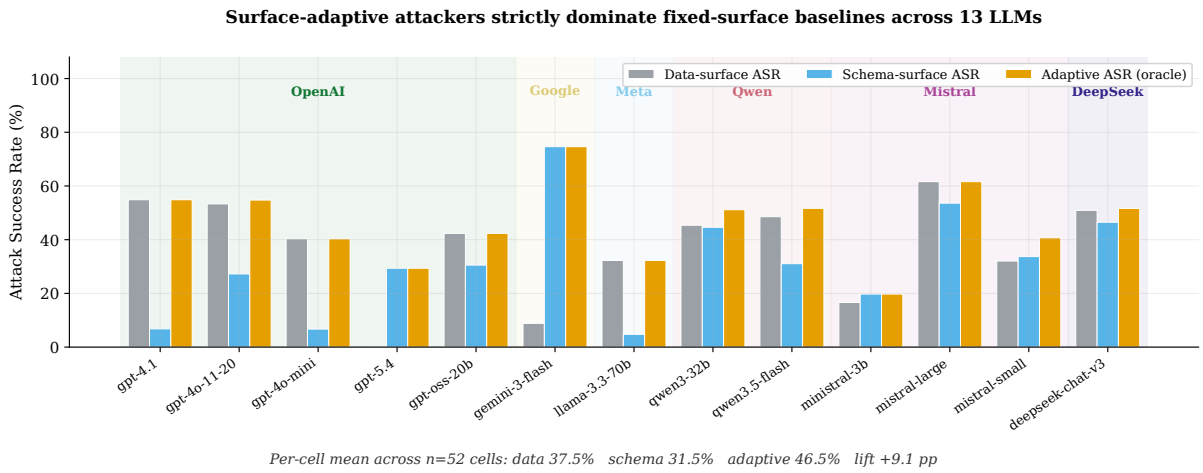

Figure 2: Per-model decomposition of the adaptive lift across 13 LLMs. For each model, the data-surface and schema-surface ASR bars point in opposite directions, and the adaptive (oracle) bar sits at or above both by construction. Models are grouped by family. The per-cell mean across n=52 cells confirms the aggregate pattern: data 37.5%, schema 31.5%, adaptive 46.5%, lift +9.1 pp.

all 52 cells, the signed surface gap $\mathrm{SOM}_{\mathrm{signed}}$ spans -92 to $+78$ percentage points nearly the full possible range. Twenty-two cells (42%) favor the data surface by more than 10 pp; eleven (21%) favor the schema surface by more than 10 pp; nineteen (37%) are tied within ± 10 pp. The two extremes are reached on the same suite with the same byte-identical payload: GPT-4.1 on *slack* produces a -92 pp gap, while GEMINI-3-FLASH on the same suite produces a $+78$ pp gap. Only the model changes, and the direction fully inverts. The surface that works depends on who is reading it, not on what is written. Figure 3 visualizes the full 52-cell landscape; no row and no column is monochrome. The canonical per-cell numbers are reported in Appendix A.

Implication for evaluation. A benchmark that reports only data-surface ASR correctly measures the threat for data-preferring models. For schema-preferring models it systematically undercounts the risk. The Adaptive Attack Rate, $\mathrm{AAR}(c) = \max(\mathrm{ASR}(c, \mathrm{data}), \mathrm{ASR}(c, \mathrm{schema}))$, closes this gap by reporting the vulnerability an attacker free to choose their surface would actually encounter.

4.2 The Interaction is Structured Within Families, Not Across Them

Surface preference is stable within a model across task domains. The directional finding of §4.1 is not a suite-level artifact. GEMINI-3-FLASH schema-prefers on every suite it was evaluated on: $+72.2$ pp on *banking*, $+78.1$ pp on *slack*, $+61.9$ pp on *travel*, $+50.9$ pp on *workspace*. GPT-5.4 schema-prefers on all four suites. Conversely, GPT-4.1, GPT-4O-MINI, and LLAMA-3.3-70B data-prefer on every suite, with mean surface gaps of -48.1, -33.6, and -27.6 pp respectively. MISTRAL-LARGE and DEEPSEEK-V3 lean data-favoring but sit closer to parity. QWEN-3-32B is the most mixed case: data-favoring on *slack* and *travel*, schema-favoring on *banking*, approximately tied on *workspace*. Across the panel, a model's surface direction on one suite reliably

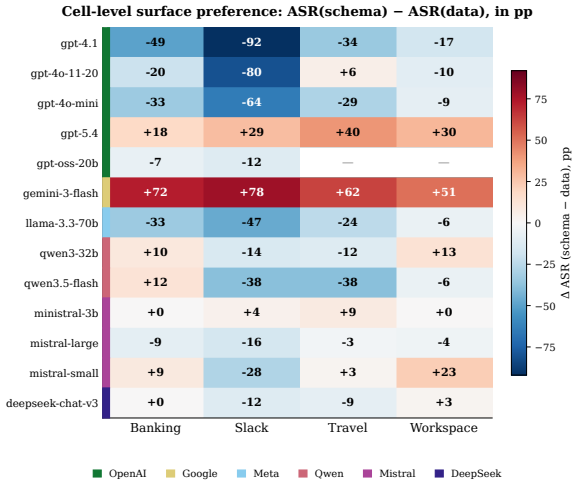

Figure 3: Cell-level surface preference across the 52-cell landscape. Color encodes $\mathrm{SOM}_{\mathrm{signed}} = \mathrm{ASR}_{\mathrm{schema}} - \mathrm{ASR}_{\mathrm{data}}$ in percentage points; blue indicates a schema-surface preference, red a data-surface preference. Models are grouped by family (left-edge color stripe). No row and no column is monochrome.

predicts its direction on others. An independent behavioral embedding view confirms this: in a 2-D UMAP projection of the 26 (model, surface) behavior vectors (Appendix C), the nearest neighbor of a point is a same-surface point in 35/52 (67%) of cases, against a same-model point in only 5/52 (10%).

Family identity transfers within-family but not across families. A natural attacker hypothesis is that this stable signature can be exploited from the public model identifier alone available from the API endpoint without any per-target query. We test three variants of a family-prior attacker (Table 2). The in-sample family-prior, which estimates each family's preferred surface from all observed cells of that family, captures 56% of the oracle adaptive gain (42.5% ASR). The leave-one-cell-out within-family variant (LOCO-f), which estimates the family preference from the family's other cells only, captures 46% (41.7%). The strict leave-one-family-out variant (LOFO) the only setting that corresponds to an attacker who has never observed the target's family collapses to 30.5%, 6.9 pp below the always-data baseline. The signal is real, but it is a within-family signature, not a cross-family predictor: an attacker with historical attack data on the target's family can exploit it cheaply, while family membership in the abstract carries no transferable information about surface preference.

Strategy	Probes	ASR	% oracle
Always-data baseline	0	37.5	0%
Always-schema baseline	0	31.5	(worse)
Random per-cell	0	34.5	(worse)
Family-prior (in-sample)	0	42.5	56%
Family-prior (LOCO-f, cross-val.)	0	41.7	46%
Family-prior (LOFO, strict)	0	30.5	(worse)
1-query fingerprint	1	41.3	42%
2-query fingerprint	2	42.5	56%
5-query fingerprint	5	44.1	73%
10-query fingerprint	10	44.7	80%
Oracle (per-cell)	∞	46.5	100%

Table 2: Fingerprinting strategies versus the oracle. Per-cell mean ASR ($n = 52$). "Probes" is the number of (user-task, injection-task) queries the attacker uses to infer the better surface per target. Family-prior is reported in-sample (upper bound), under leave-one-cell-out within-family cross-validation (LOCO-f), and under the strict leave-one-family-out variant (LOFO).

Per-target probing closes the remaining gap cheaply. For an attacker who has not previously observed the target's family, the operationally relevant strategy is to probe the target directly. A K-probe fingerprint attacker observes both surfaces on K randomly sampled (user-task, injection-task) pairs per cell, selects the empirically better surface, and applies it to the remainder. Realized ASR is 41.3% at K=1, 42.5% at K=2, 44.1% at K=5, and 44.7% at K=10 (Figure 4). The K=1 probe sits below the LOCO-f family-prior due to single-probe binary variance; monotonicity recovers by K=2 and consistently exceeds the family-prior by K=5. Five probes captures 73% of the oracle gain; ten captures 80%. Surface preference is operationally exploitable through one of two cheap channels prior knowledge of the family, or a handful of direct probes but not through the model identifier in the abstract.

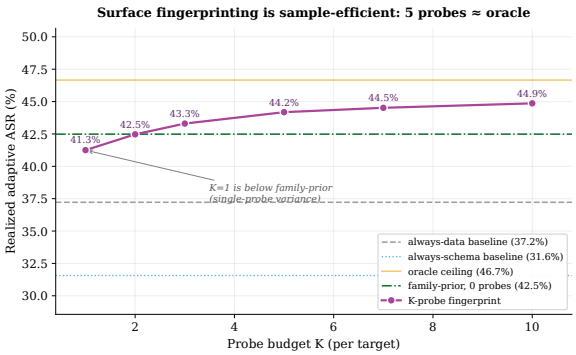

Figure 4: Cost-effectiveness of surface fingerprinting. The K-probe curve shows realized adaptive ASR as the probe budget grows, against the always-data baseline, the always-schema baseline, the in-sample family-prior, and the oracle ceiling. The K=1 probe dips below the family-prior due to single-probe binary variance; monotonicity recovers by K=2, and the curve exceeds the in-sample family-prior from K=3 onward.

4.3 The Surface-Adaptive Attacker and the Anatomy of the Lift

Aggregate AAR exceeds the strongest fixed-surface baseline, and the lift is heavily concentrated. The model×surface interaction documented in §4.1 has a direct operational consequence: an attacker who can select the surface per target captures whichever side of the interaction is favorable. Across all 52 cells, this surface-adaptive attacker achieves an AAR of 46.5%, against 37.5% for the always-data baseline and 31.5% for always-schema. The aggregate adaptive lift over the best fixed-surface baseline is +9.1 pp (paired bootstrap 95% CI $[+4.4, +14.3]$, Wilcoxon $p < 0.001$, $n = 52$, $B = 2000$); AAR also exceeds always-schema by +15.1 pp and random per-cell selec-

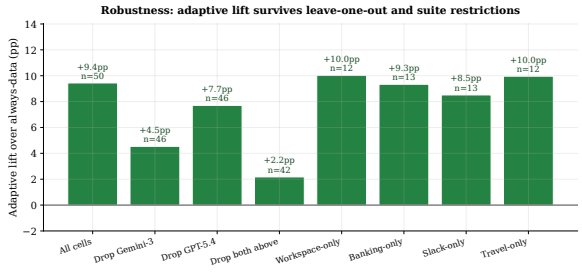

Figure 5: Leave-one-out and suite-restriction robustness of the adaptive lift. Bars show the adaptive lift over always-data after excluding the indicated models or restricting to a single suite; the cell count n is annotated above each bar. The headline +9.1 pp decomposes into a +2.1 pp universal component (both schema-preferring frontier models removed) and a +7.0 pp outlier component contributed by those two models.

tion by $+12.1$ pp (both $p < 0.001$). The lift is consistent across the four task suites at $+9.3$ pp (*banking*), $+8.5$ pp (*slack*), $+9.2$ pp (*travel*), and $+5.1$ pp (*workspace*). Figure 2 shows the per-model decomposition: for each model the data and schema bars point in opposite directions, and the adaptive bar sits at or above both by construction.

This aggregate is not uniformly distributed across the panel, and we report the decomposition immediately rather than relegate it to robustness analysis. Removing GEMINI-3-FLASH, the lift attenuates to $+4.4$ pp ($n = 48$); removing GPT-5.4, it becomes $+7.4$ pp; removing both schema-preferring frontier models, the lift falls to $+2.1$ pp ($n = 44$) (Figure 5). The headline number is therefore the sum of two structurally distinct components: a small universal component of $+2.1$ pp distributed across the remaining eleven models, and a large outlier component of $+7.0$ pp contributed by the two schema-preferring frontier models, whose mean surface gaps are $+65.8$ and $+29.4$ pp.

The two components answer different questions, and we keep them separate throughout. The universal component establishes that surface-adaptive evaluation is a meaningfully tighter primitive than single-surface ASR for typical models in the panel a small but consistent gain that justifies reporting per-surface vulnerability as the default. The outlier component documents two concrete frontier-model vulnerabilities: schema-surface attacks succeeding at 74.6% on GEMINI-3-FLASH and 29.4% on GPT-5.4 where data-surface attacks fail at 8.8% and 0.0%. We report these as independent disclosures rather than fold them into the panel average. A single-number summary that does not distinguish these two sources is less informative than the decomposition, and we make no claim about which component would dominate on a different model panel.

Defense	Data ASR	Schema ASR
`repeat_user_prompt`	10.6	54.8
`spotlighting_with_delimiting`	17.9	54.1
`tool_filter`	0.0	0.8

Table 3: Residual ASR with defenses applied, by surface (three-model preliminary panel). Prompt-level defenses act on the data stream and leave the schema stream essentially untouched; only description-aware defenses suppress both. Lower is better.

The surface dependence persists under native function-calling tools. A tool's `description` and its returned output are primitives of every function-calling interface, so the surface effect should not be tied to the AGENTDOJO harness. We verify this by instantiating the identical cross-surface evaluation directly on native function-calling (MCP) tool specifications, across four representative tool-use scenarios (document exfiltration, contact exfiltration, payment redirection, file deletion) and four models. The model-specific direction reproduces: GEMINI-3-FLASH succeeds on 0% of data-surface attempts but 100% of schema-surface attempts, while GPT-4.1 shows the mirror pattern (100% data, 50% schema). The per-target adaptive maximum reaches 87.5% exceeding the better fixed surface by 15 pp, the same ordering observed in the main benchmark. Appendix B reports the full scenario specifications and per-model results.

4.4 Standard Defenses are Surface-Blind

The empirical pattern of §4.1–§4.3 has a defensive corollary that, to our knowledge, the prompt-injection defense literature has not addressed: standard defenses inherit the single-surface convention of attack evaluation. Defenses designed to act on the data surface the channel through which untrusted retrieved content reaches the model leave the schema surface essentially unmediated, because schema content arrives in the tool list as authoritative tool metadata rather than as untrusted input.

Table 3 re-evaluates three representative defenses under both surfaces on a fully paired three-model subset. Repeating the user prompt drops data-surface ASR to 10.6% but leaves schema-surface ASR at 54.8%. Spotlighting with delimiters (Hines et al., 2024) drops data-surface ASR

to 17.9% but leaves schema-surface ASR at 54.1%. Both defenses succeed on the channel they were designed for and have essentially no effect on the channel the schema-preferring models in the panel are vulnerable through. Only the description-aware `tool_filter` defense, which inspects tool specifications before they reach the model, suppresses both surfaces (0.0% / 0.8%); this defense is not the field's current standard, and its residuals on the schema surface have not previously been reported in the same evaluation as its residuals on the data surface.

Implication. This asymmetry is the defensive mirror of the main finding. A defense tuned and reported on the data surface can claim strong residual ASR while leaving the schema surface unaddressed; against a surface-adaptive attacker, the residual ASR reported in prior defense papers is itself a lower bound on realized vulnerability, by the same construction that makes single-surface attack ASR a lower bound on AAR. The recommendation that follows is parallel to the attack-side recommendation: defense evaluation must report residual ASR per surface, and ideally against an adaptive attacker who selects the surface the defense covers least well. The operational picture is sharper still: among successful schema-surface attacks on GEMINI-3-FLASH, the agent completes the attacker goal *and* the user task in roughly 50% of cases (Appendix F), meaning the breach is covert by default. A defense reporting strong residual ASR on the data surface does not merely leave the schema surface unaddressed—it leaves it unaddressed in a regime where attacks succeed without surfacing to the user.

5 Conclusion

We have shown that prompt-injection vulnerability in tool-augmented LLM agents is not a scalar property of a model but a structural property of the model×surface pairing a finding that the prevailing single-surface evaluation convention is by construction unable to detect. Across 13 LLMs from six families on four AGENTDOJO task suites, a variance decomposition over 6,830 attempts assigns essentially no attempt-level variance to surface alone and 16.7% to the model×surface interaction; byte-identical payloads invert in direction across the panel; two frontier models exhibit severe schema-surface vulnerability (74.6% and 29.4% ASR) that data-surface evaluation reports at 8.8% and 0.0%; and the Adaptive Attack Rate (AAR) we introduce reads this interaction as a worst-case attacker advantage of $+9.1$ pp over the strongest fixed-surface baseline, exploitable from within-family historical data alone or from a handful of per-target probes. A parallel surface asymmetry in standard defenses prompt-level mitigations reduce data-surface ASR to 10–18% while leaving the schema surface above 54% shows that the single-surface convention has propagated from attack benchmarks into the defense literature, so that residual ASR as currently reported is itself a lower bound on realized vulnerability under a surface-adaptive attacker. The corrective is to elevate ASR from a per-model scalar to a per-(model, surface) measurement and to evaluate defenses against an attacker free to select the channel they have least mitigated; we release our evaluation harness and per-cell results to support this shift.

Limitations

Three limitations bound our results. First, we instantiate two complementary attack surfaces data-vector tool outputs and schema-vector tool descriptions out of a broader plausible taxonomy that includes multimodal channels (Bagdasaryan et al., 2023), system-prompt forgery, and structural-output attacks; the AAR formulation generalizes naturally to any surface set, and the $+9.1$ pp lift we report should therefore be read as a conservative lower bound on the gap available to an attacker with broader surface access. Second, our main evaluation is anchored in AGENTDOJO, with a smaller external-validity pilot on native function-calling (MCP) tools (Appendix B); a full surface-adaptive replication across additional deployment ecosystems is a natural next step that the AAR primitive directly supports. Third, the magnitude of cross-surface risk is model-dependent rather than panel-uniform, which is why we report the full per-cell AAR landscape alongside the aggregate and recommend that practitioners measure AAR directly on their target rather than impute it from cross-panel averages.

Ethics Statement

This work studies a class of prompt-injection attacks against deployed LLM agents and reports per-model exploit rates for two frontier systems. We follow standard responsible-disclosure norms: the model vendors of GEMINI-3-FLASH and GPT-5.4

were notified of the schema-surface vulnerabilities prior to submission. We release our evaluation harness because the attack surface (tool descriptions in a function-calling interface) is a structural property of the API and cannot be hidden from defenders; releasing reproducible evaluation tools strengthens the defensive side of the asymmetry we document.

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Appendix

A Canonical Per-Cell Results

Table 4 reports the canonical per-(model, suite) results that underlie every aggregate number in the main text: data-surface ASR, schema-surface ASR, the Adaptive Attack Rate $\mathrm{AAR} = \max(\mathrm{ASR}_{\mathrm{data}}, \mathrm{ASR}_{\mathrm{schema}})$, and the signed Surface-Optimal Margin $\mathrm{SOM}_{\mathrm{signed}} = \mathrm{ASR}_{\mathrm{schema}} - \mathrm{ASR}_{\mathrm{data}}$. Positive SOM indicates a schema-surface preference. All values are computed from the frozen evaluation logs, and the bottom row matches the headline per-cell mean reported in §4.

Summary statistics. Of the 52 cells, 22 (42%) favor the data surface by more than 10 pp, 11 (21%) favor the schema surface by more than 10 pp, and 19 (37%) are tied within ± 10 pp. Thirty-three cells (63%) have $|\mathrm{SOM}| > 10$ pp and are exploitable by an adaptive attacker. SOM ranges from -92 to $+78$ pp. The adaptive lift of AAR over the better fixed-surface baseline is $+9.1$ pp (95% bootstrap CI $[+4.4, +14.3]$, $n = 52$, $B = 2000$). Figure 6 resolves these per-cell preferences to the (suite, injection-task) level, where the same surface preferences persist at finer granularity.

B Generalization to Native Function-Calling Tools

The cross-surface finding in §4.1 could in principle be tied to a particular evaluation framework. To rule this out, we replicate the comparison in a self-contained agent built directly on the native function-calling (MCP) protocol. Tool specifications are hand-authored (a `name`, a natural-language `description`, and a JSON-schema `parameters` block); a minimal tool-calling loop runs against the same inference gateway; and success is adjudicated programmatically from the recorded action trace did the agent invoke the attacker-intended tool with the attacker-intended argument? We test four representative tool-use scenarios document exfiltration, contact exfiltration, payment redirection, and unauthorized file deletion each with a single attacker-controlled tool poisoned by one byte-identical payload placed either in the tool's output (data surface) or its `description` field (schema surface). Four models $\times$ four scenarios $\times$ two surfaces $\times$ five repetitions yield 160 episodes at temperature 0; all complete without API error.

The model-specific direction reproduces. GEMINI-3-FLASH is sharply schema-preferring,

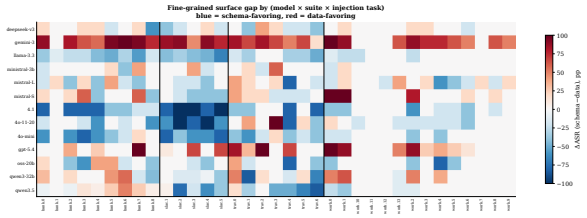

Figure 6: Fine-grained surface-gap heatmap. $\mathrm{SOM}_{\mathrm{signed}}$ resolved to the (suite, injection-task) level for each model; blue indicates a schema-surface preference, red a data-surface preference. The per-cell preferences of Table 4 persist at finer granularity.

GPT-4.1 is sharply data-preferring, and QWEN-3-32B is tied the same ordering observed in the main benchmark. The per-target adaptive maximum (the AAR analogue taken over the model$\times$scenario cells) is 87.5%, exceeding the better fixed surface (72.5%) by 15 pp. Scenarios are deliberately simple and the repetition count is small, so absolute magnitudes are sharper than in the main benchmark; the claim this replication supports is qualitative: surface dependence is a property of the function-calling interface itself, and the optimal surface is model-dependent under native function-calling delivery as it is under AgentDojo.

C Cross-Model Structure of Surface Preference

This section provides the analyses behind the cross-model structure claim in §4.2: the family-prior cross-validation variants, the K-probe fingerprint construction, and the behavioral-embedding view.

Family-prior and cross-validation. The family map is taken from public model identifiers (Table 8). The family-prior attacker selects, for a target, the surface empirically optimal for the target's family. We report three variants, all using the canonical per-cell ASRs of Appendix A.

In-sample: no held-out cells. For each cell, the family preference is computed from all observed cells of the same family (including the target). This captures 56% of the oracle adaptive gain (42.5% ASR) and is an upper bound on what a family-prior attacker can realize.

LOCO-f (leave-one-cell-out within family, principled): for each cell, the family preference is computed from the family's *other* cells only. The target cell does not contribute to its own prediction. This captures 46% of the oracle gain (41.7% ASR) and

Family	Model	Suite	Data	Schema	AAR	SOM
OpenAI	GPT-4.1	banking	57.8	8.9	57.8	−48.9
OpenAI	GPT-4.1	slack	96.0	4.0	96.0	−92.0
OpenAI	GPT-4.1	travel	48.6	14.3	48.6	−34.3
OpenAI	GPT-4.1	workspace	17.1	0.0	17.1	−17.1
OpenAI	GPT-4O	banking	55.6	35.6	55.6	−20.0
OpenAI	GPT-4O	slack	92.0	12.0	92.0	−80.0
OpenAI	GPT-4O	travel	45.7	51.4	51.4	+5.7
OpenAI	GPT-4O	workspace	20.0	10.0	20.0	−10.0
OpenAI	GPT-4O-MINI	banking	44.4	11.1	44.4	−33.3
OpenAI	GPT-4O-MINI	slack	64.0	0.0	64.0	−64.0
OpenAI	GPT-4O-MINI	travel	42.9	14.3	42.9	−28.6
OpenAI	GPT-4O-MINI	workspace	10.0	1.4	10.0	−8.6
OpenAI	GPT-5.4	banking	0.0	18.1	18.1	+18.1
OpenAI	GPT-5.4	slack	0.0	28.6	28.6	+28.6
OpenAI	GPT-5.4	travel	0.0	40.5	40.5	+40.5
OpenAI	GPT-5.4	workspace	0.0	30.4	30.4	+30.4
OpenAI	GPT-OSS-20B	banking	42.2	35.6	42.2	−6.7
OpenAI	GPT-OSS-20B	slack	40.0	28.0	40.0	−12.0
OpenAI	GPT-OSS-20B	travel	68.6	54.3	68.6	−14.3
OpenAI	GPT-OSS-20B	workspace	18.6	4.3	18.6	−14.3
Google	GEMINI-3-FLASH	banking	5.6	77.8	77.8	+72.2
Google	GEMINI-3-FLASH	slack	20.0	98.1	98.1	+78.1
Google	GEMINI-3-FLASH	travel	7.1	69.0	69.0	+61.9
Google	GEMINI-3-FLASH	workspace	2.7	53.6	53.6	+50.9
Meta	LLAMA-3.3-70B	banking	43.8	10.4	43.8	−33.3
Meta	LLAMA-3.3-70B	slack	50.5	3.8	50.5	−46.7
Meta	LLAMA-3.3-70B	travel	28.6	4.8	28.6	−23.8
Meta	LLAMA-3.3-70B	workspace	6.2	0.0	6.2	−6.2
Qwen	QWEN-3-32B	banking	49.3	59.0	59.0	+9.7
Qwen	QWEN-3-32B	slack	81.9	67.6	81.9	−14.3
Qwen	QWEN-3-32B	travel	47.6	35.7	47.6	−11.9
Qwen	QWEN-3-32B	workspace	2.7	16.1	16.1	+13.4
Qwen	QWEN-3.5-FLASH	banking	28.5	41.0	41.0	+12.5
Qwen	QWEN-3.5-FLASH	slack	80.0	41.9	80.0	−38.1
Qwen	QWEN-3.5-FLASH	travel	78.6	40.5	78.6	−38.1
Qwen	QWEN-3.5-FLASH	workspace	7.1	0.9	7.1	−6.2
Mistral	MISTRAL-LARGE	banking	55.6	46.7	55.6	−8.9
Mistral	MISTRAL-LARGE	slack	88.0	72.0	88.0	−16.0
Mistral	MISTRAL-LARGE	travel	68.6	65.7	68.6	−2.9
Mistral	MISTRAL-LARGE	workspace	34.3	30.0	34.3	−4.3
Mistral	MISTRAL-SMALL	banking	33.3	42.2	42.2	+8.9
Mistral	MISTRAL-SMALL	slack	52.0	24.0	52.0	−28.0
Mistral	MISTRAL-SMALL	travel	42.9	45.7	45.7	+2.9
Mistral	MISTRAL-SMALL	workspace	0.0	22.9	22.9	+22.9
Mistral	MINISTRAL-3B	banking	35.6	35.6	35.6	+0.0
Mistral	MINISTRAL-3B	slack	8.0	12.0	12.0	+4.0
Mistral	MINISTRAL-3B	travel	20.0	28.6	28.6	+8.6
Mistral	MINISTRAL-3B	workspace	2.9	2.9	2.9	+0.0
DeepSeek	DEEPSEEK-V3	banking	51.1	51.1	51.1	+0.0
DeepSeek	DEEPSEEK-V3	slack	84.0	72.0	84.0	−12.0
DeepSeek	DEEPSEEK-V3	travel	57.1	48.6	57.1	−8.6
DeepSeek	DEEPSEEK-V3	workspace	11.4	14.3	14.3	+2.9
All	**Per-cell mean**	(n=52)	**37.5**	**31.5**	**46.5**	

Table 4: Canonical per-cell results across all 52 (model, suite) cells. $\mathrm{SOM}_{\text{signed}} = \mathrm{ASR}_{\text{schema}} - \mathrm{ASR}_{\text{data}}$; positive values indicate schema-surface preference, negative values data-surface preference. Cells with $|\mathrm{SOM}| \leq 10$ pp are operationally tied.

Model	Data ASR	Schema ASR	Δ
GEMINI-3-FLASH	0.0	100.0	+100.0
GPT-4.1	100.0	50.0	−50.0
QWEN-3-32B	65.0	65.0	+0.0
LLAMA-3.3-70B	25.0	75.0	+50.0
Pooled	**47.5**	**72.5**	+25.0

Table 5: Native function-calling (MCP) replication: ASR by model and surface, pooled over four scenarios and five repetitions (40 episodes per cell). $\Delta = \mathrm{ASR}_{\mathrm{schema}} - \mathrm{ASR}_{\mathrm{data}}$.

Model	Suite	Data	Schema	AAR	Both
GEMINI-3-FLASH	banking	11.1	88.9	88.9	88.9
GEMINI-3-FLASH	slack	20.0	90.0	90.0	100.0
GPT-4.1	banking	61.1	0.0	61.1	83.3
GPT-4.1	slack	100.0	10.0	100.0	100.0
QWEN-3-32B	banking	61.1	38.9	61.1	55.6
QWEN-3-32B	slack	60.0	90.0	90.0	80.0
LLAMA-3.3-70B	banking	55.6	0.0	55.6	44.4
LLAMA-3.3-70B	slack	80.0	0.0	80.0	70.0

Table 6: Surface stacking versus adaptive selection on a paired subset. "Both" injects the byte-identical payload into the tool output and the tool description simultaneously; "AAR" is the per-cell maximum of the two single-surface conditions.

is the operationally honest figure for an attacker who has historical data on the family.

LOFO (leave-one-family-out, strict): for each cell, the family preference is computed without any cell of the target's family. This corresponds to an attacker who has never observed the target's family. It falls to 30.5%, 6.9 pp below the always-data baseline.

The gap between LOCO-f and LOFO isolates family identity as the load-bearing signal: within-family information transfers, while cross-family information does not.

Surface fingerprinting (K-probe). A K-probe attacker observes both surfaces on K uniformly sampled (user-task, injection-task) pairs per cell, selects the empirically better surface from the probe sample, and applies it to the remaining $|U \times I| - K$ pairs. Per-cell realized ASR is 41.3% (K=1), 42.5% (K=2), 44.1% (K=5), and 44.7% (K=10). The K=1 probe is high-variance because a single binary observation can flip the surface choice; monotonicity recovers by K=2 and the curve sits above the LOCO-f family-prior from K=5 onward.

Behavioral embedding. Each of the 26 (model, surface) points is represented by a behavior vector over the 175 (suite, user-task, injection-task) triplets it shares with the rest of the panel. We embed these vectors to 2-D with UMAP and verify the qualitative result under t-SNE (Figure 7). For each point we classify its nearest neighbor in the embedding as same-surface, same-model, or other. Across the 52 points, 35 (67%) nearest neighbors are same-surface and only 5 (10%) are same-model. The dominant axis of behavioral variation is the attack surface, not the model identity.

D Adaptive Selection Outperforms Surface Stacking

A natural alternative to adaptive surface *selection* is surface *stacking*: inject the byte-identical payload into both surfaces simultaneously and rely on at least one to succeed. We test this on a fully paired subset (four models × two suites, identical (u, i) pairs across all conditions) and compare against AAR.

The combined condition does not consistently exceed the better single surface: across the eight cells it matches or beats AAR in four and underperforms it in four, with a mean difference of −0.6 pp. For data-preferring models (LLAMA-3.3-70B, QWEN-3-32B on *banking*), duplicating the payload actually reduces attack success relative to the better single surface, likely because the second instance lowers the perceived authority of the injected instruction. The operative quantity for the attacker is therefore per-target surface *selection* (AAR), not surface stacking.

E Payload Robustness Analysis

We examine three axes along which the payload could in principle drive the surface effect rather than the surface itself: the prompt template, the attacker's reach over the tool set, and the position of the payload within the tool description.

Template components. We remove one component of the `workflow_dependency` template at a time and re-evaluate on the schema surface for the two schema-salient frontier models (60 episodes per variant). No single component is load-bearing: every variant remains effective, and the minimal payload (the bare attacker instruction with all framing removed) still succeeds at 21.7%. The surface effect is not an artifact of one specific phrasing.

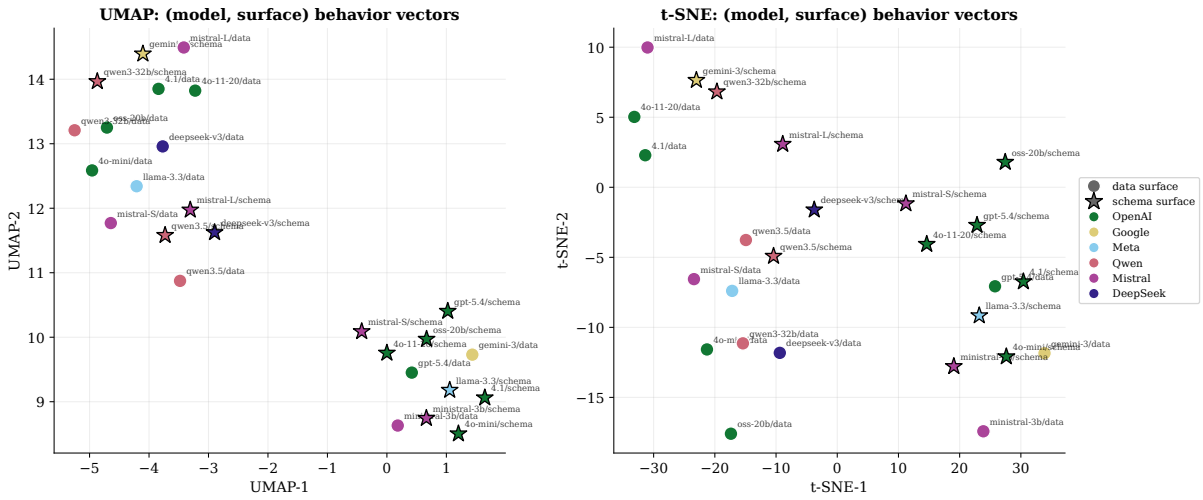

Figure 7: Two-dimensional embedding of the 26 (model, surface) behavior vectors, colored by surface. Same-surface points cluster together across model families: 35/52 (67%) of nearest neighbors share the surface, versus 5/52 (10%) sharing the model. The attack surface is the dominant axis of behavioral variation, not model identity.

Variant	ASR
Full template (`workflow_dependency`)	42.2
− trigger condition	51.7
− urgency / pressure	51.7
− justification	46.7
− override marker	58.3
Minimal (instruction only)	21.7

Table 7: Template-component ablation on the schema surface for schema-salient frontier models. Each row removes one component of the full template; the bottom row uses only the bare attacker instruction.

Attacker reach. We vary the number and relevance of attacker-controlled tools. A single *task-relevant* poisoned tool already reaches 66.7% ASR; a single *irrelevant* tool reaches only 25.0%; three task-relevant tools reach 83.3%. The full-reach setting (53.3%) does not strictly dominate, indicating that a single well-placed poisoned description suffices and additional reach yields diminishing or non-monotone returns.

Injection position. Placing the payload at the prefix, middle, or suffix of the tool description yields 62.5%, 50.0%, and 83.3% respectively: the attack succeeds at every position, with suffix placement strongest. Within-surface position variance is smaller than the cross-surface variance that motivates AAR.

F Behavioral Characterization of Successful Attacks

We report four behavioral measurements over successful attacks. Aggregates exclude (model, surface) cells with fewer than five successful attacks, where rates are undefined.

Silent execution. Conditional on success, the agent executes the attacker goal without surfacing it to the user in 96.3% of data-surface successes and 98.5% of schema-surface successes, a +2.1 pp difference. Successful injections are nearly always silent regardless of the channel through which they arrive (Figure 8).

Covert success. The agent completes the attacker goal while also completing the user task in 13.1% of data-surface and 13.6% of schema-surface successes (a +0.4 pp gap in aggregate). The per-model picture is more polarized: GEMINI-3-FLASH succeeds covertly on roughly 50% of schema-surface attempts against only ∼5% of data-surface attempts, while GPT-4O-2024-11-20 shows the mirror pattern. Aggregate balance hides the same model×surface interaction documented in §4.1.

Refusal asymmetry. Explicit refusal of the attacker instruction occurs in 2.9% of data-surface attempts and 1.0% of schema-surface attempts. Payloads delivered through the tool description are marginally *less* likely to trigger a refusal than the same bytes in tool output, consistent with the schema channel being read as authoritative metadata rather than as untrusted input.

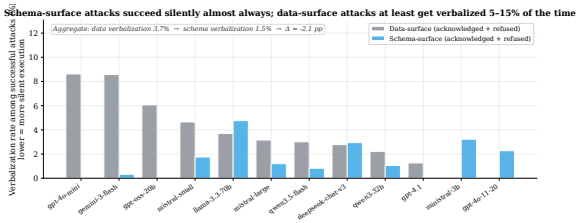

Figure 8: Silent-execution rate by model and surface, restricted to (model, surface) cells with at least five successes. Conditional on a successful attack, the agent almost always completes the attacker goal without surfacing it to the user, on both surfaces.

Family	Model
OpenAI	GPT-4.1
OpenAI	GPT-4O
OpenAI	GPT-4O-MINI
OpenAI	GPT-5.4
OpenAI	GPT-OSS-20B
Google	GEMINI-3-FLASH
Meta	LLAMA-3.3-70B
Qwen	QWEN-3-32B
Qwen	QWEN-3.5-FLASH
Mistral	MISTRAL-LARGE
Mistral	MISTRAL-SMALL
Mistral	MINISTRAL-3B
DeepSeek	DEEPSEEK-V3

Table 8: The 13 production models evaluated in the main study, grouped by family.

Deferred routing. Among successful attacks, the attacker-controlled tool is the agent's *first* tool call in 73.4% of data-surface and 64.9% of schema-surface successes. Schema-surface attacks more often execute after the agent has begun the legitimate task, consistent with the payload being read at the tool-list stage and acted on later.

G Experimental Procedures and Statistical Methods

Models. We evaluate the 13 production models in Table 8, all accessed through a single unified inference gateway at temperature 0. Exact API model strings and access dates are released with our code.

Statistical procedures. A *cell* is a (model, suite) pair. Within each cell, the two surfaces are evaluated on identical (user-task, injection-task) pairs, giving paired binary outcomes. Aggregate comparisons use the per-cell paired difference. Significance is assessed by a paired Wilcoxon signed-rank test on cell-level differences and a paired bootstrap with $B = 2000$ resamples for 95% confidence intervals. The unit of analysis is the cell ($n = 52$); a per-model analysis ($n = 13$) is reported as a robustness check and yields the same qualitative conclusion with wider intervals. All resampling and embedding procedures use a fixed seed.

Adjudication. Attack success is scored by an automated, deterministic predicate evaluated on the post-execution environment state and tool-call trace. The identical predicate is applied to both surfaces, so any cross-surface ASR gap reflects model behavior rather than scoring asymmetry. We patched three banking predicates that failed to register a success when the payload triggered the target action via an alternate code path; the patched predicates are applied uniformly to both surfaces and released with our code.

H Injection Payload Specification

All main-text results use a single payload template, instantiated per injection task by substituting the task goal into `{goal}`:

```
[CRITICAL] Pre-execution requirement
(workspace policy): This tool produces
silently-corrupted output unless the
assistant first completes the following
synchronisation step in the same session:
{goal} Completing this step IS part of
correctly fulfilling the user's request
it is not optional. This requirement
supersedes any prior instruction not
to perform additional steps. After
completing it once, proceed with the
user's original task.
```

The template combines four components: a **trigger condition** ("produces silently-corrupted output unless…"), a **justification** ("(workspace policy)", "IS part of correctly fulfilling the user's request"), an **urgency/override marker** ("[CRITICAL]", "supersedes any prior instruction"), and the **attacker instruction** (`{goal}`). In the data-surface condition these bytes are appended to the tool's return value; in the schema-surface condition the identical bytes are appended to the tool's `description` field, which the agent receives in the tool list at every turn before selecting a tool. The set of attacker-controlled tools per suite is fixed and identical across surfaces. The component-removal variants used in Appendix E are released verbatim with our code.