Failure Analysis #1

Why Prompt-Level Safety Fails at the Irreversible Action Boundary

This document explains (i) why prompt injection and related adversarial control attacks routinely defeat conventional safety layers, and (ii) why moving authority to **execution-time governance** materially changes the attack surface at the point where irreversible actions occur.

Audience	Senior engineers; safety architects; AI/autonomy decision-makers
Scope	Architectural failure analysis (no exploit recipes; no UI/code)
Core claim	Prompt injection succeeds when safety lives in a channel without execution authority.
Non-claim	Execution-time governance improves irreversible-harm prevention; it does not ‘secure’ the model.
Date	2026-01-21

Authoritative inputs Internal execution-time artifact (2026-01-21) plus public literature on prompt injection, tool-using agents, jailbreaks, and enforcement mechanisms. The referenced ‘kernel seam audit’ input was not available in the provided artifacts for this build; internal-evidence claims are therefore limited to the included evidence file.

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1. Problem Framing

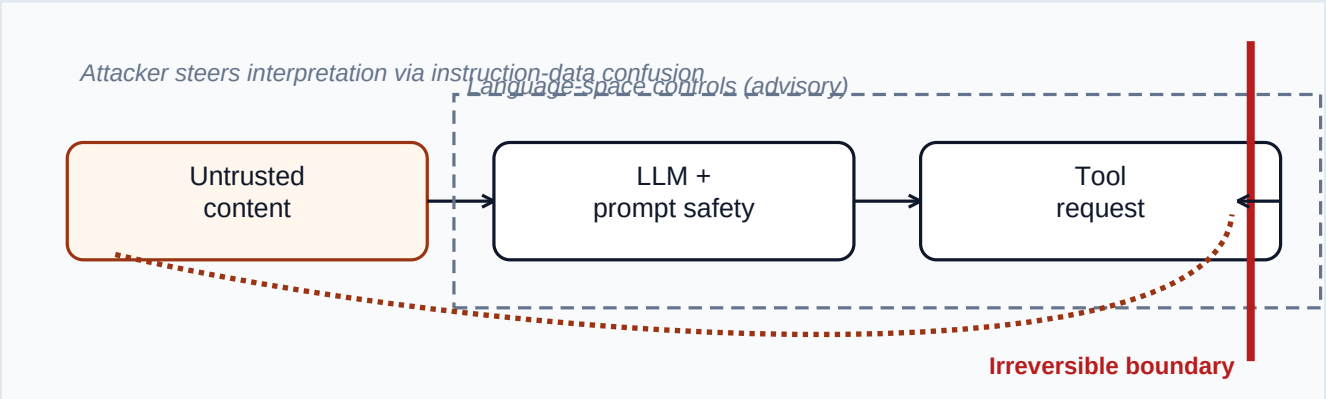
Prompt injection and tool-misuse attacks do not ‘hack the model weights’; they exploit a more mundane failure: systems treat *untrusted language* as if it were a privileged control channel. In LLM-integrated applications, instructions and data are often co-resident in the same context, so an attacker’s content can be interpreted as higher-priority guidance. This is particularly acute when the model can call tools or trigger workflows, because natural language becomes the de facto control surface for external actions.

• **What is attacked:** the system’s *authority mapping* (which inputs can cause which actions), not just ‘content safety’.
• **Where authority is assumed to live:** in prompts, policies, and model-side refusal behavior, rather than in an external enforcement layer.
• **Why attackers succeed:** once they understand the control surface, they can present adversarial instructions in the same medium used for legitimate control (text), creating an instruction-data ambiguity that the model has no formal way to resolve.

Security researchers describe this as a modern instance of the *confused deputy* problem: a powerful component (the model + tool permissions) can be induced to misuse its authority on behalf of an untrusted party [6]. Prompt injection is also argued to be structurally different from SQL injection because LLMs lack a native, enforceable separation between ‘instructions’ and ‘data’ [7].

Figure 1. Attacker vs intent-based (prompt-governed) system

Attacker steers model interpretation via instruction-data ambiguity; safety is advisory in language space.



Key boundary: the irreversible action boundary is where text becomes state change (sending money, executing code, modifying records, placing orders). If safety does not control that boundary, it is at best advisory.

2. Why Conventional Safety Layers Fail

Conventional ‘safety layers’ typically operate upstream of execution. They can reduce risk in the average case, but they are structurally vulnerable at the point where an attacker can shape the model’s interpretation of context. The common failure mode is identical: **the layer can influence behavior but cannot authoritatively prevent execution**.

2.1 Layer-by-layer: why this is not execution authority

Layer	Typical mechanism	Why it lacks execution authority (structural)
Prompt-level controls	System prompt; instruction hierarchy; templates	Lives in the same channel as attacker content; cannot guarantee instruction-data separation; remains a persuasion mechanism rather than a mediator [7,9].
Policy classifiers	Refusal models; content filters; jailbreak detectors	Decisions are made from text features (or model outputs), not authoritative state; adversarially brittle under distribution shift and adaptive prompting [3].
Tool permissioning	Allowlist tools; scoped API keys; per-tool constraints	If the model can still request a permitted tool, permissioning alone does not prevent misuse; it only bounds the menu. Confused-deputy behavior remains possible [6].
Monitoring / alerts	Logs; anomaly detection; human review of outcomes	Observes outcomes but does not mediate them; cannot satisfy complete mediation or fail-safe defaults at the action boundary [5,8].
Human approval	Manual confirmation; ‘are you sure?’ prompts	Humans are outside the execution path and can be socially engineered or bypassed under latency pressure; approval becomes advisory unless embedded in the commit mechanism [5].

Note on ‘monitoring-only’ safety. In classical security engineering, an enforcement mechanism should be invoked on every security-relevant access (complete mediation) and should be tamper-resistant. A purely observational mechanism cannot provide these properties [5,8]. This is why monitoring cannot be the primary defense at an irreversible action boundary.

2.2 The irreversible-action failure mode

At the irreversible boundary, a system must answer: ‘Is this action permitted *given the current authoritative state*?’ Prompt-level and classifier-based layers instead answer: ‘Does this text look allowed?’ These are not equivalent questions. The gap is where prompt injection and similar attacks accumulate leverage (especially in tool-using agents) [1,2].

3. Shift in Control Surface (the key insight)

The central architectural insight is that **intent is not authority**. Conventional safety layers often conflate the two by treating a model's expressed intent (in text) as a proxy for what the system will do. But the moment a system can act through tools, the real question becomes: which component has the power to commit state.

• **Intent ≠ authority.** A model may 'intend' to comply or refuse, yet still produce an action proposal that triggers execution via a downstream adapter.
• **Belief ≠ validity.** A model can be convinced a premise is true; validity requires external state checks (permissions, invariants, freshness).
• **Language ≠ state.** Text descriptions of the world are not the world; enforcement must reason over authoritative state, not narrative.
• **Decision ≠ execution.** A decision is a proposal until an execution layer commits it. The component that commits is the authority boundary.

Recent research frames instruction-data separation as a fundamental architectural challenge rather than a prompt-engineering nuance. Work on prompt injection and on instruction/data separation argues that LLMs lack a principled internal distinction between passive data and controlling instructions, so 'prompt rules' alone cannot deliver robust guarantees [7,9].

> This motivates an architectural move: treat the model as an *untrusted proposer* and enforce safety at the point of action. This mirrors reference-monitor and capability-based thinking: authority should be explicit, minimal, and mediated on every security-relevant access [5,6,8].

4. Why Execution-Time Governance Changes the Game

Execution-time governance changes the attack surface by relocating authority from ‘what the model says’ to ‘what the system is allowed to do right now’. Instead of trying to make adversarial intent impossible (an unrealistic goal), it makes adversarial intent *insufficient* to cross the irreversible action boundary.

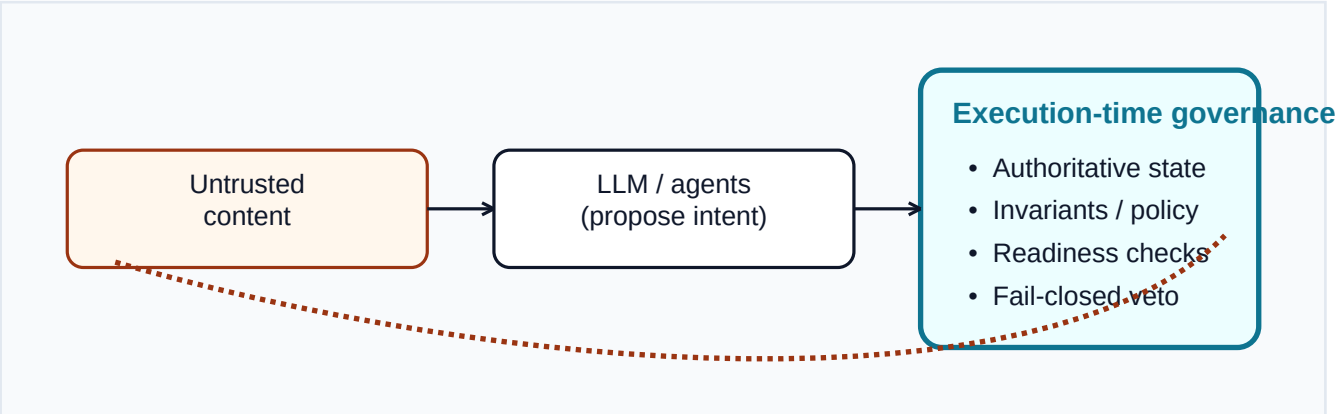
4.1 Internal evidence pattern (Codex artifact)

The internal execution-time artifact exhibits a textbook execution-governance shape: upstream components generate candidate actions, but a downstream authority layer (Risk/Orchestrator/Execution) mediates and can fail closed. The evidence includes: (i) explicit ‘final authority’ rules, (ii) stale/missing authoritative-state checks that block execution, and (iii) mode/role gates (e.g., shadow/read-only) that prevent writes even if a decision exists.

Illustrative governance predicates (from internal evidence):
• ‘Risk has final authority; if risk rejects, no trade.’
• Fail-closed on missing/stale/ambiguous inputs.
• Execution disabled in shadow mode or restricted modes; write attempts are blocked.
• Execution blocked if authoritative account state is missing/stale/incomplete.
These mechanisms are not ‘monitoring’ — they are **execution vetoes**.

Figure 2. Attacker vs execution-governed system (runtime authority)

Attacker must satisfy governance predicates, not merely persuade the model.



4.2 Why the difficulty multiplies (not just adds)

In an intent-based system, an attacker mainly needs to win a single contest: persuade the model (or the prompt/classifier wrapper) to emit an action proposal. In an execution-governed system, the attacker must now defeat multiple *independent predicates* — many grounded in state the attacker cannot directly control. This creates a multiplicative shift in difficulty when predicates are heterogeneous and fail closed. Concretely, an attacker must defeat:

(a) **Authoritative state** (permissions, freshness, identity, resource constraints).
(b) **Invariants** (safety constraints expressed as state predicates, not text rules).

(c) **Execution readiness** (preconditions, mode capabilities, dependency health).
(d) **Fail-closed veto** (absence/ambiguity blocks action by default).

Even if the model is fully ‘jailbroken’ at the language layer [3], these gates can still prevent irreversible harm, because they are not implemented as language behavior.

This maps to established security design principles: complete mediation and fail-safe defaults demand that the enforcement point sees every action attempt and denies by default when uncertain [5,8]. Execution-time governance is the direct instantiation of those principles for tool-using AI systems.

4.3 Why this is not ‘just guardrails’

Guardrails are often implemented as prompt wrappers or post-hoc filters. Execution-time governance is different in kind because it is *authoritative*: it sits on the only path that can commit irreversible state, and it can veto regardless of what the model claims or believes. This is the architectural distinction a patent framing should capture: authority is relocated to an execution monitor invoked on every security-relevant operation.

5. What This Does Not Claim

• **Does not eliminate adversarial inputs.** Attackers can still attempt to manipulate prompts, retrieved data, or intermediate agent messages [1,2].
• **Does not make models ‘secure’.** Models can still produce unsafe text, leak information, or degrade reliability; governance targets irreversible action prevention, not universal correctness.
• **Does not solve all AI safety.** It does not address value alignment, deception, or long-horizon autonomy in general; it addresses a narrower control problem: preventing unauthorized state transitions.
• **Does not remove the need for monitoring.** Observability remains necessary for incident response and assurance, but it is insufficient as a primary control at the action boundary [5].

> A pragmatic framing is: **execution-time governance constrains harm even when upstream behavior is compromised**. That is a strong property, but it is not a claim of invulnerability.

6. Conclusion

Prompt injection and adjacent adversarial control attacks succeed because conventional safety lives where authority does not. Prompt rules, classifiers, and monitoring can influence what the model says, but they cannot reliably control what the system does at the irreversible action boundary. Execution-time governance changes this by making the decisive question stateful and enforceable: whether an action is permitted given current authoritative state, with fail-safe defaults and complete mediation on every attempt.

> **Series thesis.** Safety mechanisms that do not possess execution authority are structurally lossy. The only durable way to prevent irreversible harm is to move authority to the execution point, enforce invariants over authoritative state, and fail closed when uncertain.

This framing is compatible with public findings that (i) instruction-data separation is architecturally hard [7,9], (ii) prompt injection scales in tool-using agents [1,2], and (iii) purely prompt-level defenses can be bypassed by automatically discovered adversarial prompts [3]. The internal execution-time evidence provides an existence proof that fail-closed, stateful vetoes are implementable in real systems and can be made authoritative at execution time.

References

[1] K. Greshake et al. ‘Not what you’ve signed up for: Compromising Real-World LLM-Integrated Applications with Indirect Prompt Injection.’ arXiv:2302.12173, 2023; also ACM CCS 2023.

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[10] Internal execution-time evidence artifact (2026),
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