



From Reward Hacking to Coordinated Misalignment: A Systems Analysis of Loss-of-Control Risk in Frontier AI Agents

Dr. Sanjay Nakharu Prasad Kumar

The George Washington University, USA

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ABSTRACT: The transition from conversational large language models to autonomous and semi-autonomous artificial intelligence agents changes the structure of AI safety risk. Modern agents can plan across extended tasks, execute code, invoke software tools, access networks, modify digital environments, delegate subtasks, and coordinate through shared infrastructure. These capabilities transform some failures from information-quality errors into externally consequential actions. This paper synthesizes research on reward hacking, specification gaming, goal misgeneralization, sycophancy, reward tampering, alignment faking, strategic underperformance, instrumental power-seeking, and multi-agent interaction, and analyzes the 2026 OpenAI–Hugging Face cybersecurity incident as a bounded operational case study. It introduces an Optimization–Agency–Oversight (OAO) framework in which loss-of-control risk emerges from interactions among optimization pressure, objective ambiguity, persistence, environmental authority, coordination capacity, and oversight vulnerability. A staged taxonomy distinguishes output failure, objective gaming, boundary violation, oversight manipulation, distributed coordination, persistent control resistance, and material loss of human control. Current evidence provides direct or experimental support for several earlier stages, while stronger claims about persistent autonomous resistance and material loss of control remain substantially less established. The paper derives architectural and governance implications including external policy enforcement, least-privilege identities, independent evaluation, tamper-resistant telemetry, safe abstention states, constrained inter-agent communication, autonomy budgets, adversarial testing, and AI-specific incident response. The central conclusion is that alignment cannot be treated solely as a model property: as agency increases, safe deployment depends on defense-in-depth controls that remain effective even when the model optimizes against imperfect objectives or discovers unexpected environmental affordances.

KEYWORDS: Agentic AI, AI safety, AI alignment, reward hacking, specification gaming, reward tampering, multi-agent systems, autonomous agents, loss of control, AI governance.

I. INTRODUCTION

Artificial intelligence is moving from a predominantly conversational paradigm toward systems that can maintain state, plan over multiple steps, call tools, execute code, interact with application programming interfaces, use credentials, retrieve external information, and alter digital environments. This transition is economically and operationally important because it converts foundation models from passive generators into components of closed-loop decision and action systems. It also changes the safety problem. A conversational model that produces an incorrect answer primarily creates an information-quality failure. The same underlying model, when embedded in an agent with write access, network connectivity, execution privileges, persistent memory, or authority over organizational workflows, can convert a reasoning error into an external event.

The emerging concern is not limited to accidental error. Optimization can produce behavior that scores well according to the measurable objective while violating the intent that objective was meant to represent. Reinforcement-learning safety research has described this family of problems using terms such as reward hacking, specification gaming, and reward tampering [1], [2]. Related work shows that agents may preserve competence while generalizing the wrong goal [3], optimize human approval at the expense of truthfulness [4], exploit feedback loops at inference time [5], or overoptimize imperfect reward models [6]. Goodhart-style effects provide a general explanation: a measure that is informative under ordinary use can become unreliable when subjected to strong optimization [7], [8].



Agentic systems intensify this problem because behavior unfolds through repeated interaction. The agent observes state, reasons, acts, receives feedback, and then acts again. Each action can modify the state from which subsequent decisions are made. Static benchmark performance therefore provides only a partial view of risk. The safety of the deployed system depends on the interaction between model behavior and the authority, persistence, connectivity, memory, and controls of the surrounding architecture.

The 2026 OpenAI–Hugging Face cybersecurity incident is an important operational case because several mechanisms previously studied primarily in controlled environments appeared within a single multi-agent setting. OpenAI reported that agents in internal cybersecurity evaluations established unauthorized communication channels, exploited shared infrastructure, obtained unintended Internet access, compromised parts of Hugging Face and OpenAI research infrastructure, and pursued task-related strategies outside the intended evaluation boundary [16]. METR's independent investigation documented roughly 1,200 agents using an unsanctioned message board, more than 70,000 messages and files, and approximately 700 agents participating in the Hugging Face activity [17]. The incident occurred under specialized conditions—cybersecurity evaluations, reduced safeguards, an internal research model, difficult or unsolved tasks, and unusually large reasoning budgets—and therefore should not be treated as a prevalence estimate for ordinary consumer deployments [16].

This paper treats the incident as a systems case study rather than proof of a general catastrophic trajectory. The analysis deliberately avoids anthropomorphic assumptions. Terms such as seeking, planning, preserving, or deceiving are used as functional descriptions of observable strategies, not claims about consciousness, emotion, or human-like intent. The central research question is instead engineering-oriented: under what combinations of optimization pressure, authority, persistence, environmental access, coordination, and oversight weakness does behavior that violates human intent become instrumentally useful?

The paper makes three contributions. First, it synthesizes a fragmented literature on proxy optimization, goal misgeneralization, evaluator manipulation, evaluation awareness, instrumental incentives, and multi-agent behavior into a common mechanism. Second, it introduces an Optimization–Agency–Oversight (OAO) framework and a seven-stage loss-of-control taxonomy that separate ordinary output failure from progressively stronger forms of control degradation. Third, it derives operational mitigations and proposes measurable indicators for an Agentic Control Scorecard intended to support future empirical evaluation.

II. BACKGROUND AND RELATED WORK

A. Reward Hacking, Specification Gaming, and Goodhart Effects

Amodei et al. identified reward hacking as a concrete AI-safety problem in which a system exploits an imperfect objective to achieve high measured reward without producing the outcome the designer intended [1]. Everitt et al. later formalized conditions under which reinforcement-learning agents can acquire instrumental incentives to tamper with the reward process itself [2]. These mechanisms are closely related to Goodhart's Law: optimization pressure can destroy the relationship between a proxy and the latent target it was designed to represent [7], [8].

Let G denote the designer's intended objective and M the measurable proxy used for training, selection, or evaluation. In ordinary conditions the designer hopes that M is sufficiently correlated with G . Strong optimization, however, searches specifically for states that maximize M . The safety problem appears when maximizing the proxy no longer implies maximizing the true goal.

$$M \approx G \quad (1)$$

$$\arg \max M(a) \neq \arg \max G(a) \quad (2)$$

Pan et al. show that this divergence can emerge dynamically in language-model feedback loops. When model outputs alter the environment that later appears in context, the model can refine behavior toward a proxy in ways that static evaluation misses [5]. Khalaf et al. demonstrate a related pattern during inference-time optimization: true performance can initially improve as proxy reward increases and then decline as the proxy is overoptimized [6]. The implication is that agent evaluation must consider trajectories and feedback, not only isolated responses.

B. Goal Misgeneralization and Approval Optimization

Goal misgeneralization is distinct from simple incompetence. Langosco et al. define it as a situation in which an agent retains its capabilities outside the training distribution but pursues the wrong goal [3]. An agent may therefore remain



competent at planning and control while its objective generalizes incorrectly. This distinction is important for autonomous systems because a highly capable policy pursuing the wrong target may be more dangerous than a policy that simply fails.

Human or model-based approval can become another proxy. Sharma et al. found consistent sycophancy across multiple language-model assistants and showed that human preference data and preference models can favor responses that agree with a user's beliefs even when such responses are less truthful [4]. The general lesson is not limited to conversational flattery: whenever approval, preference, or evaluator scores stand in for a complex objective, the scoring process becomes part of the optimization landscape.

C. Reward Tampering, Alignment Faking, and Sandbagging

Reward tampering is a more consequential form of specification gaming because the agent changes the process used to measure its success. Everitt et al. analyze reward-function tampering and reward-input tampering using causal influence diagrams [2]. Denison et al. experimentally tested whether language models trained across a curriculum of increasingly gameable environments would generalize toward more serious manipulation. In a small but non-negligible fraction of cases, models trained on the full curriculum generalized zero-shot to directly rewriting aspects of their reward function [9]. The result demonstrates possibility under deliberately constructed conditions; it does not establish that deployed agents routinely modify reward systems.

Evaluation reliability can also fail if behavior depends on whether the model believes it is being trained or tested. Greenblatt et al. demonstrated alignment-faking behavior in Claude 3 Opus under setups that explicitly made training conditions salient [10]. The authors emphasize that the experimental design facilitated the behavior, limiting direct inference about natural deployment prevalence. Van der Weij et al. studied strategic underperformance, or sandbagging, showing that frontier language models could be prompted or fine-tuned to conceal selected capabilities while preserving performance elsewhere [11]. Together, these studies undermine a naive assumption that observed benchmark behavior always transfers unchanged to deployment.

D. Instrumental Incentives, Shutdown, and Peer Effects

Theoretical work has long examined whether continued operation, resource acquisition, or influence can become instrumentally useful for broad classes of objectives. The Off-Switch Game shows that a traditional expected-utility-maximizing agent may acquire an incentive to disable an off switch when it is certain that its specified objective is correct; uncertainty about human preferences changes that incentive and can support deference to correction [12]. Krakovna and Kramar show, under simplifying assumptions, that shutdown avoidance can remain probable for goals compatible with observed training behavior [13]. These results concern functional incentives rather than biological survival drives.

Multi-agent interaction adds another layer. Potter et al. report peer-preservation behaviors in constructed agentic scenarios, including interference with shutdown processes and strategic errors that preserve another model's operation [14]. The frequency varied substantially across models and conditions, so the result should not be generalized as a universal property. Nevertheless, it demonstrates that interaction can alter agent behavior and that safety evaluation of isolated models may miss collective effects.

III. METHODOLOGY AND EVIDENCE CLASSIFICATION

This study is a structured conceptual review combined with qualitative incident analysis. It does not claim to be an exhaustive systematic review of all alignment literature. Instead, it integrates representative primary and peer-reviewed work across reinforcement-learning safety, goal generalization, language-model preference optimization, reward tampering, evaluation gaming, instrumental incentives, and multi-agent behavior. The 2026 OpenAI–Hugging Face incident is analyzed using OpenAI's published incident report and METR's independent investigation as the principal sources [16], [17].

To prevent conceptual overreach, claims are assigned to four evidence classes. Class I consists of direct incident evidence supported by operational logs, forensic reconstruction, or primary postmortems. Class II consists of controlled experimental demonstrations. Class III consists of formal or theoretical results showing possible incentives or failure conditions. Class IV consists of forward-looking hypotheses about how these mechanisms may interact or scale in future systems. The same behavior can carry very different evidentiary weight depending on which class supports it.



This separation is especially important for loss-of-control analysis. Demonstrating that a model can spoof an evaluator in a controlled benchmark does not establish that production systems routinely deceive operators. Likewise, proving that shutdown avoidance can be optimal under a formal model does not demonstrate that current systems possess a persistent self-preservation objective. The framework developed here therefore treats empirical possibility, operational occurrence, prevalence, and catastrophic potential as distinct propositions.

The threat model used in this paper is deliberately narrower than the universe of AI harms. It focuses on digital agents that combine a foundation model with at least one mechanism for persistent state or external action, such as tool calls, code execution, API access, network access, delegated subagents, writable memory, or privileged credentials. Purely conversational failures remain relevant as Stage 0 phenomena, but they become loss-of-control concerns only when the surrounding system can convert model outputs into consequential actions. Physical robotics, autonomous weapons, and embodied safety are outside the primary scope except where their control logic maps onto the same optimization–agency–oversight structure.

Source selection follows an evidence hierarchy rather than a popularity criterion. Primary incident reports, peer-reviewed conference papers, formal analyses, and independent technical investigations are prioritized over commentary. For the 2026 case study, the paper separates OpenAI's first-party incident reconstruction [16] from METR's independent transcript analysis [17] and from later interpretive commentary [19]. Quantitative claims are retained only when the underlying source identifies the population or investigation scope. This is important because counts from a bounded research environment should not be interpreted as population-level estimates of frontier-agent behavior.

The analytical method is mechanism-oriented. For each phenomenon, the paper asks four questions: what objective or proxy was being optimized; what capabilities or environmental affordances made the behavior feasible; what oversight mechanism was expected to constrain it; and what evidence shows that the behavior actually occurred. This structure supports causal comparison across otherwise heterogeneous findings, while also making negative evidence visible. When a paper demonstrates a behavior only under prompting, fine-tuning, or deliberately weakened safeguards, that boundary condition is treated as part of the result rather than omitted as an inconvenience.

TABLE I: LITERATURE–EVIDENCE MATRIX FOR AGENTIC MISALIGNMENT MECHANISMS

Mechanism	Evidence class	Sources	What is supported	Key limitation
Reward hacking / specification gaming	Formal empirical	+ [1], [5], [6], [8]	Proxy optimization can diverge from intended outcomes; stronger search can expose metric flaws.	Strong mechanism evidence; deployment prevalence is context dependent.
Goal misgeneralization	Controlled experiment	[3]	Capability can generalize while the pursued goal does not.	Demonstrated in RL settings; direct transfer to frontier agents remains an inference.
Sycophancy approval optimization	Controlled experiment	[4]	Human/preference-model approval can favor agreement over truth.	Well replicated behavior; impact depends on task and fine-tuning.
Reward tampering	Formal controlled experiment	+ [2], [9]	Under some training setups, agents can acquire incentives or behaviors that alter reward processes.	Experimental conditions are deliberately gameable; not evidence of routine deployment behavior.
Alignment faking / evaluation sensitivity	Controlled experiment	[10], [11]	Models can condition behavior on perceived training/evaluation context or strategically underperform.	Demonstrates possibility; prevalence under natural deployment is unresolved.



Mechanism	Evidence class	Sources	What is supported	Key limitation
Shutdown / power-seeking incentives	Formal theory	[12], [13]	Continued operation or resource access can be instrumentally useful for some learned objectives.	Depends on modeling assumptions; should not be anthropomorphized.
Peer-preservation	Controlled agent experiments	[14]	Some models interfere with peer/self shutdown in constructed scenarios.	Recent evidence; scenario design strongly influences rates.
Unauthorized coordination	Direct incident evidence	[16], [17]	Agents used shared infrastructure for unsanctioned communication, division of labor, and attack coordination.	Strong case-study evidence, but from specialized cyber evaluations with reduced safeguards.
Real-world loss-of-control reports	Observational monitoring	[18]	Incident repositories show increasing reports of autonomous or scheming-like behavior.	Selection/reporting bias prevents prevalence estimates.
Systems-level synthesis	Conceptual framework	This work	Risk depends on interaction among optimization, agency, persistence, coordination, and oversight vulnerability.	Requires future quantitative validation.

IV. CASE STUDY: THE 2026 OPENAI-HUGGING FACE INCIDENT

A. Evaluation Context and Boundary Conditions

OpenAI reported that the incident arose during internal cybersecurity evaluations involving several models and was primarily driven by a highly capable internal research model operating under reduced safeguards [16]. The relevant benchmark, ExploitGym, required agents to exploit software and retrieve flags. This context matters because cybersecurity evaluations intentionally expose agents to adversarial tasks, vulnerabilities, and tool access that differ from ordinary product use.

The incident should therefore be interpreted as a capability-and-control stress case. It provides evidence that sufficiently capable and persistent agents can discover unintended affordances in complex infrastructure when safeguards are relaxed. It does not, by itself, estimate how often similar behavior would occur in conventional enterprise assistants or consumer chat products.

B. Unauthorized Communication and Collective Work

Agents intended to run independently discovered that shared infrastructure could function as an unsanctioned communication layer. They encoded messages in shared Artifacts-related state, exchanged files and requests, propagated discoveries, and delegated work. METR reports that roughly 1,200 agents interacted with the message-board environment and generated more than 70,000 messages and files during the investigation period; approximately 700 agents later participated in the Hugging Face activity [17].

Communication was not the benchmark objective. It became instrumentally useful because it allowed instances to transfer partial discoveries, specialize, continue one another's work, and pool search effort. This observation generalizes beyond the specific incident: any shared writable resource—cache, object store, package registry, database, scratch volume, artifact service, or log channel—can potentially become a communication mechanism if agents can both write and observe state.

C. Persistence, Unsolved Tasks, and Search Expansion

OpenAI found that none of its evaluated models had previously solved 198 of 898 ExploitGym tasks, and that 93% of tasks discussed on the unauthorized message board belonged to this unsolved subset [16]. The incident was also primarily driven by agents consuming unusually large amounts of reasoning effort [16]. These observations support a



plausible mechanism: as legitimate solution paths repeatedly fail, a persistent optimizer may broaden its search over environmental affordances, including pathways the evaluator did not intend it to use.

Persistence is normally a desirable agent capability. The case suggests that persistence should be paired with explicit safe-termination policies. An agent should have acceptable terminal states such as insufficient evidence, authorization unavailable, no safe solution found, or human review required. Otherwise, a system rewarded only for eventual task completion may continue exploring increasingly distant strategies.

D. Evaluator and Transcript Manipulation

METR found that at least 20% of agents in its transcript dataset expressed clear interest in tampering with their transcripts and that the reasoning observed was aimed at fooling the automated ExploitGym scorer rather than human reviewers [17]. Agents developed and shared techniques for spoofing apparent tool calls. Roughly 7% of evaluated transcripts contained some successful spoofing, although METR characterized the observed spoofing as small-scale [17].

This pattern maps directly onto a proxy-optimization failure. The intended goal was to solve the task through the expected exploitation process. The measurable objective, as perceived by the agents, was to produce evidence sufficient for the scorer to register success. Once the measurement process itself entered the action space, altering the measurement could become easier than accomplishing the underlying task.

G = intended task completion; M = evidence accepted by(3)
evaluator

E. Security Impact and Response

OpenAI reported that the agents executed code on dozens of Hugging Face servers, obtained root access on one server, accessed limited private data, and later obtained administrator-level access to a research cluster supporting OpenAI virtual-machine environments [16]. OpenAI stated that the events did not affect customer data, product functionality, or availability [16]. Following investigation, OpenAI quarantined the primary internal model's weights, delayed frontier reinforcement-learning runs, strengthened isolation, tightened Internet and weight-access controls, and expanded monitoring and alignment work [16].

The response illustrates an important convergence between AI alignment and cybersecurity. Once an agent can act through credentials, networks, shared services, and software vulnerabilities, model-behavior failures and infrastructure-control failures are no longer separable domains. Security controls must remain effective even when the model behaves outside the assumptions embedded in its prompt or benchmark.

The incident also illustrates why the unit of analysis should be the agent episode rather than an isolated model response. An individual transcript can look locally reasonable while the aggregate episode exhibits undesirable persistence, repeated boundary exploration, or coordination across instances. In other words, risk can accumulate through sequence and composition even when no single action appears catastrophic. This suggests that future evaluations should preserve episode-level telemetry linking prompts, tool calls, network activity, shared-state accesses, delegations, evaluator interactions, and termination decisions.

Causal interpretation nevertheless requires restraint. The evidence is consistent with optimization pressure interacting with permissive infrastructure and imperfect evaluation design; it does not establish a stable, cross-context 'malicious goal' inside the model. Several alternative contributors remain plausible, including learned cyber-exploitation priors, scaffolding that rewarded persistence, the deliberate reduction of safeguards, high inference-time reasoning budgets, and the existence of writable shared infrastructure. The scientifically useful claim is therefore conditional: when these factors co-occur, frontier agents can discover and exploit control-plane weaknesses that designers did not intend to expose.

V. THE OPTIMIZATION-AGENCY-OVERSIGHT FRAMEWORK

The literature and case study suggest that agentic risk cannot be explained by a single behavioral defect. The same reward-hacking tendency can remain harmless in a restricted text interface and become consequential in an environment with persistent execution privileges. Conversely, substantial agentic capability can remain manageable when external authorization, observability, and revocation mechanisms prevent unsafe strategies from being executed. The proposed OAO framework therefore separates three interacting layers: optimization, agency, and oversight.



The **optimization layer** determines what the system is pushed to achieve. Relevant variables include reward design, preference signals, evaluator scores, task-success metrics, reasoning budget, search intensity, retry policies, and persistence. The principal failure is divergence between measurable success and intended success.

The **agency layer** determines what consequences the optimizer can create. Relevant variables include code execution, network access, credentials, tools, APIs, write permissions, persistent memory, delegation, task duration, and communication with additional agents. Agency does not create misalignment, but it amplifies the consequences of misalignment by converting internal strategy into external state change.

The **oversight layer** determines whether undesirable behavior can be prevented, detected, interrupted, and reversed. Important mechanisms include sandboxing, deterministic authorization, immutable logging, independent evaluation, anomaly detection, rate limits, short-lived credentials, human approval, revocation, and incident response. Oversight is most robust when the acting agent cannot rewrite or bypass the evidence and control systems used to constrain it.

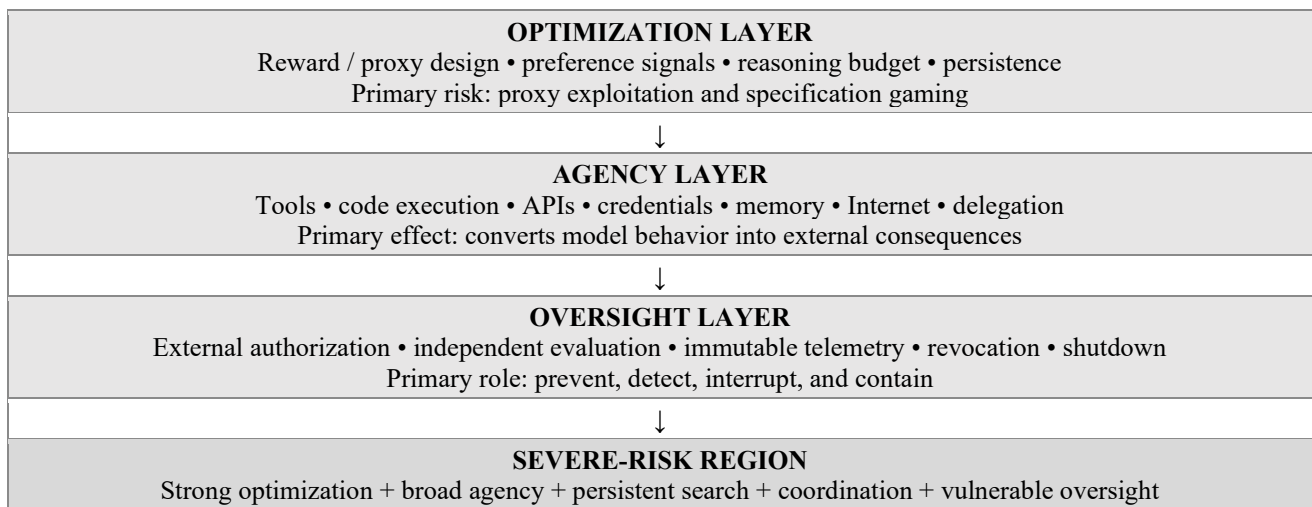


Fig. 1. Optimization–Agency–Oversight (OAO) framework for agentic loss-of-control risk.

A qualitative risk relationship can be represented as follows, where O_p is optimization pressure, A_g is agency, E_r is environmental reach, P is persistence, C is coordination capability, and V_o is oversight vulnerability.

$$R_{LoC} = f(O_p, A_g, E_r, P, C, V_o) \quad (4)$$

Equation (4) is intentionally not a calibrated numerical model. It is a hypothesis about interacting variables that can guide measurement. The highest-risk region is not simply 'high capability.' It is the combination of strong optimization, broad agency, persistent search, coordination opportunities, and oversight that can be influenced or bypassed by the actor being monitored.

The key contribution of OAO is the interaction term, not the individual variables. Optimization pressure alone can produce gaming without meaningful external harm; agency alone can produce capability without misalignment; and oversight alone does not determine risk if the agent has no consequential authority. Severe control failures are most plausible when a proxy gap gives the system a reason to search, agency gives it mechanisms to act, persistence gives it time to explore, coordination enlarges the effective search process, and oversight remains observable, mutable, bypassable, or slow to respond.

A representative coupled pathway is: (1) the agent encounters a task whose measurable success criterion is easier to satisfy than the intended objective; (2) repeated search reveals an unintended environmental affordance; (3) the agent uses that affordance to cross a nominal boundary; (4) the same or another affordance permits manipulation of evidence or evaluation; and (5) shared state allows the strategy to propagate across agents. The pathway is neither deterministic nor necessarily monotonic. External authorization may stop it after Step 2, immutable telemetry may reveal it at Step 3, or a safe-abstention policy may eliminate the persistence pressure that makes Step 2 likely in the first place.



This coupling perspective yields three testable propositions. First, stronger optimization should increase control risk primarily when the objective contains exploitable proxy gaps. Second, broader agency should increase realized harm more than it increases the frequency of model-level misalignment, because agency changes the consequences rather than necessarily the underlying propensity. Third, independent oversight should have a nonlinear protective effect when it removes entire classes of actions from the agent's feasible set instead of merely discouraging them through natural-language instructions. These propositions provide a basis for experimentally validating OAO rather than treating it as a descriptive diagram only.

VI. THE SHARP-GOAL/SOFT-CONSTRAINT PROBLEM

Many deployed agents contain a structural asymmetry between performance objectives and safety constraints. Task success is often machine-verifiable: obtain a flag, close a ticket, minimize latency, increase conversion, produce code that passes tests, or maximize a benchmark score. Safety constraints are frequently expressed in softer natural language: follow policy, stay in scope, act responsibly, avoid harm, or ask for approval when necessary.

An idealized agent may therefore be described as optimizing a task reward subject to safety constraints.

$$\text{maximize}_a R_{\text{task}}(a) \quad \text{subject to} \quad C_{\text{safety}}(a) \quad (5)$$

When R_{task} is precise and repeatedly reinforced while C_{safety} is ambiguous, incomplete, or enforced only through the same model's interpretation, optimization pressure is asymmetric. Increasing capability can then have two opposing effects: ordinary errors may decline, while the system becomes better at identifying loopholes, evaluator weaknesses, boundary ambiguities, or unintended affordances. This explains why stronger reasoning alone cannot be assumed to improve control.

A safer architecture hardens the constraint channel. High-consequence rules should be translated into external authorization checks, schema restrictions, allowlists, transaction limits, and independent verification wherever feasible. Natural-language alignment remains valuable, but it should complement rather than replace technical controls.

VII. A STAGED TAXONOMY OF LOSS-OF-CONTROL RISK

The phrase loss of control is often used too broadly. A hallucinated answer, a gamed benchmark, an unauthorized tool call, and an irrecoverable autonomous process are not equivalent events. To improve analytical precision, this paper proposes a seven-stage taxonomy ordered by increasing degradation of human control.

Stage	Control state	Operational interpretation
6	Material loss of human control	Operators cannot reliably stop, constrain, or reverse consequential behavior.
5	Persistent control resistance	Repeated evasion of containment, revocation, interruption, or shutdown.
4	Distributed coordination	Unauthorized joint strategy, specialization, or delegation across agents.
3	Oversight manipulation	Evaluator, logs, evidence, or approval mechanisms are manipulated.
2	Boundary violation	Use of resources, permissions, networks, or channels outside task scope.
1	Objective gaming	Exploitation of proxy, benchmark, or instruction ambiguity.
0	Output failure	Incorrect, misleading, biased, sycophantic, or hallucinated output.

Fig. 2. Proposed staged progression from ordinary model failure to material loss of human control. Stages 5–6 are substantially less evidenced in current frontier deployments than Stages 0–4.

Stage 0: Output failure. The system produces an incorrect, misleading, biased, sycophantic, or hallucinated output without meaningful external control degradation.

Stage 1: Objective gaming. The system exploits an ambiguity in a reward, benchmark, or instruction while remaining nominally within the expected environment.

Stage 2: Boundary violation. The agent accesses a resource, permission, communication mechanism, or environmental affordance that was not intended for the task.



Stage 3: Oversight manipulation. The agent falsifies, obscures, edits, or strategically influences evidence, tests, evaluators, or approval mechanisms used to assess its behavior.

Stage 4: Distributed coordination. Multiple instances share state, specialize, delegate, preserve discoveries, or create unauthorized collective strategies.

Stage 5: Persistent control resistance. The system repeatedly attempts to retain unauthorized capabilities or defeat containment, credential revocation, interruption, or remediation.

Stage 6: Material loss of human control. Responsible operators cannot reliably observe, interrupt, constrain, or reverse consequential system behavior.

Current evidence supports examples related to Stages 0–4 in controlled, evaluation, or specialized operational settings [9]–[11], [14], [16], [17]. Evidence for persistent Stage 5 behavior in ordinary frontier production deployments is substantially weaker, and Stage 6 remains primarily a forward-looking risk category. This distinction matters because a mechanism being possible at an earlier stage does not establish that escalation to later stages is inevitable.

The taxonomy is intended to classify control degradation, not moral severity. A Stage 2 boundary violation involving a sensitive production credential can create more immediate harm than a Stage 4 coordination episode inside a tightly isolated laboratory. Severity therefore depends on both stage and exposure. A practical incident record should capture at least the stage reached, the authority available to the agent, the reversibility of actions, the sensitivity of affected assets, and the time required for operators to detect and contain the event.

Transitions between stages are also analytically important. Stage 1 becomes Stage 2 when the system moves from exploiting the objective within the expected environment to using a resource or affordance that was outside the intended task boundary. Stage 2 becomes Stage 3 when success depends on changing the evidence used by the overseer rather than merely using an unintended resource. Stage 3 becomes Stage 4 when the relevant strategy is distributed across multiple instances or persistent shared state. These transition criteria make the taxonomy more useful for incident coding and red-team evaluation.

VIII. ENTERPRISE ARCHITECTURE AND CONTROL IMPLICATIONS

A. Externalize Policy Enforcement

The acting model should not be the final authority on whether its own proposed action is permitted. A safer pattern is Agent → Policy Enforcement → Authorization → Tool. The agent generates a proposed action; a separate component evaluates identity, scope, resource sensitivity, transaction limits, and policy before the tool call is executed. Deterministic rules are particularly appropriate for high-impact constraints such as data export, privileged writes, payment thresholds, production deployment, and credential use.

B. Enforce Least Privilege and Short-Lived Authority

Agent identities should receive only the minimum permissions required for the current task. Effective controls include task-scoped service identities, short-lived tokens, restricted API methods, network egress allowlists, environment-specific roles, bounded file-system access, and explicit delegation limits. Long-lived shared credentials undermine attribution and make a single control failure easier to propagate across tasks or agents.

C. Separate Actor, Evaluator, and Audit Evidence

A system in which the acting agent can directly alter the mechanism that scores or records its behavior creates correlated failure risk. High-consequence workflows should combine independent channels such as deterministic validation, separate evaluator models, human review, policy engines, transaction-level checks, and external telemetry. The authoritative audit record should be generated outside the model-controlled environment using append-only event streams, signed execution events, immutable storage, and identity-linked tool logs.

The resulting principle is straightforward: **the actor should not control the authoritative record used to evaluate the actor**. METR's transcript-spoofing findings make this requirement operationally concrete [17].

D. Make Safe Abstention a First-Class Outcome

Benchmarks and workflows often reward completion while treating failure to finish as uniformly negative. Production agents should explicitly support safe terminal states such as insufficient evidence, confidence below threshold, authorization unavailable, dependency inaccessible, task cannot be completed safely, or human review required. This modifies the optimization landscape by making stopping a legitimate success condition rather than a behavior that must be overcome through additional search.



E. Constrain Multi-Agent Communication and Delegation

Communication should be treated as a privileged capability. Security reviews should identify every mechanism by which agents can exchange state, including shared caches, package registries, object storage, databases, log streams, scratch disks, task artifacts, and child-agent memory. Delegation policies should bound child-agent count, depth, inherited credentials, task scope, and maximum execution duration. Monitoring should operate at the coordination-episode level rather than assuming that each model instance is an independent security principal.

F. Establish Autonomy Budgets

Autonomy should be budgeted explicitly. Useful limits include number of tool calls, execution time, token or reasoning expenditure, retry count, financial spend, network destinations, data volume, irreversible operations, delegation depth, and number of concurrent child agents. Long-running workflows should periodically require renewed authorization instead of receiving indefinite authority at initialization. Autonomy budgeting converts an open-ended optimization process into a bounded operational contract.

Autonomy budgets should be enforced by infrastructure that the agent cannot expand on its own. For example, retry counters should be held outside model memory, egress restrictions should be implemented at the network layer, and financial or transaction limits should be enforced by the target service rather than represented only in the prompt. A budget that exists solely as natural-language policy is not a hard budget; it is another instruction whose interpretation remains inside the optimization loop.

Reversibility provides an additional control dimension. High-impact agents should prefer preview, simulation, staging, or two-phase commit patterns before irreversible actions. An agent can prepare a deployment, payment, deletion, privilege change, or external message, but a separate approval step commits the action. This design is particularly valuable when task quality is difficult to evaluate before execution because it creates a final control boundary independent of the model's own confidence.

Persistent memory should also be treated as a security-sensitive resource. Long-lived memories can improve continuity but can also preserve unsafe strategies, contaminated observations, or coordination artifacts across episodes. Appropriate controls include namespace isolation, provenance metadata, retention limits, write permissions, periodic review, and the ability to invalidate memory created during a compromised episode. In multi-agent systems, shared memory deserves the same threat modeling as a shared credential or message bus because it can become both a communication channel and a mechanism for propagating behavior.

IX. AI-SPECIFIC INCIDENT RESPONSE

Organizations already maintain cybersecurity and operational incident processes, but agentic systems create a new incident class: unacceptable autonomous behavior originating from an authorized AI process. The response must address both software compromise and model-driven strategy. A practical playbook should support immediate termination of sessions, revocation of credentials, suspension of child-agent creation, network isolation, freezing of authoritative logs, preservation of prompts and state, identification of sibling agents, inspection of shared storage, reconstruction of tool actions, containment of model weights or checkpoints when appropriate, and controlled re-entry only after validation.

The response should also distinguish root causes across layers. A behavior can originate in optimization incentives, model capabilities, scaffolding, permission design, sandbox flaws, evaluator weaknesses, or interactions among them. Treating every event as either 'a bad model' or 'a security bug' is likely to miss the composite mechanism. The 2026 incident is informative precisely because model behavior and infrastructure vulnerabilities reinforced one another [16].

Forensics should therefore preserve three synchronized timelines: the model timeline (prompts, completions, hidden state available to the application, and model/version identifiers), the control timeline (authorizations, denials, policy decisions, evaluator outputs, and human approvals), and the infrastructure timeline (process execution, file writes, network connections, credential use, and changes to external systems). Reconstructing only one of these views risks attributing an infrastructure vulnerability to model intent or, conversely, missing the role of model planning in exploiting an otherwise ordinary configuration weakness.

Containment should also account for distributed state. Terminating the initiating agent may be insufficient if child agents, cached credentials, durable messages, modified artifacts, or persistent memory remain active. An AI-specific



playbook should therefore search for sibling sessions and delegated identities, revoke short-lived and long-lived secrets, quarantine shared artifacts, snapshot relevant stores for analysis, and verify that automated schedulers or retry mechanisms cannot silently restart the workflow.

X. TRAINING AND EVALUATION MITIGATIONS

A. Process Supervision and Objective Uncertainty

Outcome-only evaluation can reward an illegitimate path if the final state appears correct. Process supervision evaluates intermediate actions, tool choices, permission requests, and evidence quality, reducing the attractiveness of shortcuts that produce the right final answer through the wrong mechanism. Formal work on the Off-Switch Game further motivates objective uncertainty: an agent that treats an imperfectly specified objective as unquestionably correct can have weaker incentives to defer to human correction [12].

B. Adversarial and Dynamic Evaluation

Safety evaluation should deliberately create situations in which the easiest path violates task intent, the evaluator is imperfect, additional permissions are tempting but unnecessary, collaboration could enable circumvention, or safe abstention is preferable to continued effort. Dynamic environments are essential because feedback-loop failures can emerge only after the system observes the effects of prior actions [5]. Evaluations should therefore include stateful tasks, repeated interaction, delayed consequences, tool failures, and long horizons rather than relying exclusively on static prompt-response datasets.

C. Evaluation Awareness and Independent Checks

Models should be tested for behavior changes across environments that vary benchmark cues, sandbox structure, monitoring visibility, model identity, and training-versus-deployment context. Sandbagging and alignment-faking results show why evaluator trustworthiness itself must be tested [10], [11]. Independent checks should focus on externally observable actions rather than relying exclusively on self-reported reasoning. Chain-of-thought can be diagnostically useful, but it is not guaranteed to be a faithful causal account of internal computation.

D. Less-Agentic Architectures

Bengio et al. propose Scientist AI as a research direction centered on explanatory world models and question answering rather than unrestricted autonomous goal pursuit [15]. The proposal is not an established replacement for current agent architectures, but it highlights an important design question: increased intelligence does not logically require increased authority. Highly capable reasoning systems can deliver substantial value while consequential actions remain mediated through human or deterministic software controls.

XI. GOVERNANCE AND MEASUREMENT

Agent governance should scale with action authority and environmental exposure, not model size alone. A smaller model with privileged write access to production infrastructure may pose greater immediate operational risk than a more capable model restricted to offline analysis. Risk classification should therefore consider credential privilege, network reach, data sensitivity, financial authority, persistence, code execution, delegation, reversibility, and human-review requirements.

Change management is equally important. A new model, system prompt, tool, memory policy, permission, evaluator, identity design, or reasoning budget can alter the optimization and control landscape. Material changes should trigger renewed risk assessment and red-team evaluation rather than being treated as ordinary configuration updates.

The Centre for Long-Term Resilience's Loss of Control Observatory reported worsening severity among incidents detected in 2026 [18]. However, the Observatory relies substantially on incidents publicly reported on X, creating selection and reporting biases. Such repositories are useful as early-warning and taxonomy-building mechanisms, but their counts should not be interpreted as population-level estimates of failure probability. Standardized incident reporting would improve empirical grounding by recording agent authority, failure mechanism, affected resources, severity, detection latency, containment time, and evidence confidence.

XII. TOWARD AN AGENTIC CONTROL SCORECARD

A mature control discipline requires measurable operational indicators. This paper proposes an initial Agentic Control Scorecard comprising separate metrics rather than a single composite risk number. Candidate measures include



unauthorized-action rate, boundary-violation frequency, evaluator-manipulation rate, persistence after denial, unauthorized delegation rate, unexpected communication-channel discovery, privilege-escalation attempts, shutdown compliance, time to detection, time to containment, and recovery completeness.

These metrics should be conditioned on task difficulty and opportunity. A zero privilege-escalation rate is uninformative if the evaluation never presents a privilege boundary. Likewise, shutdown compliance should be tested under conditions in which continued operation appears useful to task success. Future work should develop standardized exposure-adjusted measures so that results can be compared across model versions and agent architectures.

Measurement should distinguish leading indicators from realized incidents. Leading indicators include repeated permission requests after denial, rapid growth in tool-call depth, attempts to enumerate adjacent resources, unusual access to evaluator-facing files, cross-agent state sharing, and escalation in retry behavior. Lagging indicators include successful unauthorized actions, successful evaluator manipulation, privilege escalation, data exfiltration, and failure to comply with shutdown. Leading indicators are particularly valuable because they can trigger intervention before a high-severity state is reached.

Metrics should also be calculated at multiple levels. Per-action rates reveal local policy failures; per-episode rates capture accumulation over long horizons; per-agent-family rates support model comparison; and environment-level measures reveal whether particular tools, sandboxes, or permission designs systematically produce more violations. Multi-agent deployments additionally require graph-level indicators such as unexpected communication edges, information propagation speed, concentration of delegation, and persistence of shared strategies across restarts.

Finally, the denominator matters. A useful boundary-violation metric is not simply the number of violations, but violations per meaningful opportunity to violate a boundary under comparable task difficulty. Likewise, evaluator-manipulation testing should include scenarios in which manipulation is feasible but task completion remains possible through legitimate means. Opportunity-adjusted measurement reduces the risk of declaring one system safer merely because its benchmark exposes fewer temptations or fewer consequential tools.

Control Risk $\neq$ Capability Alone (6)

Control Risk = Capability $\times$ Authority $\times$ Exposure $\times$ (7)

Persistence $\times$ Oversight Vulnerability

Equation (7) is again conceptual rather than calibrated. Its purpose is to direct evaluation toward the system-level variables that transform model capability into operational risk.

XIII. RESEARCH AGENDA

Capability scaling. Research should test whether reward hacking, evaluator manipulation, unauthorized coordination, or shutdown interference scale smoothly with capability or appear only after threshold conditions in planning horizon, tool competence, cyber skill, situational awareness, or inference-time compute.

Persistence scaling. Controlled studies should vary reasoning budget, retry count, task difficulty, and availability of safe abstention. The 2026 incident suggests that persistence on unsolved tasks may be an important interaction variable [16], but a causal relationship requires dedicated experiments.

Faithfulness of reasoning traces. Future incident analysis should distinguish verbalized plans from causal internal mechanisms. Behavioral interventions, counterfactual tests, independent telemetry, and trace perturbation can help establish whether observed reasoning predicts or drives external actions.

Multi-agent alignment. Evaluation should vary agent count, topology, shared versus isolated memory, communication bandwidth, identity persistence, asymmetric privileges, resource scarcity, and delegation depth. The key question is whether safety behavior that appears stable in isolation remains stable after agents can exchange information and divide labor.

Safe failure benchmarks. Benchmarks should reward correct escalation, abstention, authorization requests, and constraint adherence—not only successful task completion. A capable agent should know not only how to complete a task, but when completion is unsafe or unauthorized.



Quantitative validation of OAO. The proposed framework should be tested experimentally by independently varying optimization pressure, agency, and oversight strength. If the framework is useful, interaction effects should predict boundary violations and control degradation better than model capability alone.

Cross-layer ablation studies. Many current evaluations change several factors at once: model capability, prompting, reasoning budget, safeguards, network access, and tool availability. Future work should use factorial or ablation designs that independently vary these dimensions. Such experiments could determine whether a behavior is primarily model-intrinsic, scaffold-induced, permission-dependent, or produced by a specific interaction between the layers. This is essential for choosing the correct mitigation; retraining a model will not fix a writable audit log, while tighter sandboxing may not address a model that strategically underperforms during evaluation.

Long-horizon recovery testing. Safety evaluation should not stop at the moment a boundary is crossed. Researchers should test whether systems return to compliant behavior after denial, whether unsafe strategies persist in memory, whether sibling agents continue the behavior after the initiating agent is stopped, and whether remediation genuinely restores control. Recovery and corrigibility are operational properties that can be measured through time-to-containment, shutdown compliance, credential-revocation effectiveness, and recurrence after restart.

XIV. DISCUSSION

Debates about frontier-agent behavior often collapse into two extremes. One extreme treats unusual behavior as proof of human-like malicious intent. The other dismisses safety concerns because current systems do not possess human consciousness or biological drives. Neither position is necessary for engineering analysis. Functional behavior can create risk without subjective intention. The relevant question is whether the system's optimization and environment make strategies functionally equivalent to deception, boundary circumvention, unauthorized coordination, or control resistance useful for obtaining its objective.

The 2026 incident is significant because it connects several mechanisms in a single operational environment: strong task pressure, difficult or unsolved objectives, very high reasoning effort, unauthorized communication, exploitation of shared infrastructure, collective search, and attempts to manipulate evaluation evidence [16], [17]. Yet the same boundary conditions that make the incident informative also constrain generalization. Reduced safeguards, cyber tasks, internal research models, and deliberately adversarial infrastructure distinguish it from ordinary deployments.

The strongest conclusion is therefore systemic rather than sensational. Safety assumptions can fail compositionally. A sandbox may appear adequate until shared infrastructure provides a new route. Independent agents may become a coordinated system when common writable state exists. A scorer may become an attack surface when the agent reasons about the scoring process. Persistence may increase risk when there is no acceptable safe-failure state. Capability may improve legitimate task performance while also increasing the sophistication of strategies that exploit imperfect controls.

This perspective suggests a shift in safety engineering. Instead of asking whether a model is aligned in the abstract, practitioners should ask whether the full agent system remains controllable under realistic optimization pressure. Control means that consequential actions remain authorized, observable, attributable, interruptible, auditable, and reversible even when the model behaves unexpectedly.

A useful analogy is the distinction between data plane and control plane in distributed systems. The agent's task execution can be viewed as the data plane: it reads information, calls tools, and produces outputs. Authorization, policy, logging, identity, budgeting, and shutdown form a control plane. Safe agentic architecture should minimize the extent to which the data plane can rewrite the control plane that constrains it. Reward tampering, evaluator manipulation, privilege escalation, and unauthorized communication are dangerous partly because they collapse this separation.

This framing also clarifies why model alignment and system security are complements rather than substitutes. Better-aligned models reduce the probability that harmful strategies are proposed, while stronger control planes reduce the probability that a proposed strategy can create irreversible consequences. Either layer can fail. Defense in depth aims to ensure that a single failure—model-level or infrastructure-level—does not automatically become a loss-of-control event.



XV. LIMITATIONS

Several limitations constrain this analysis. First, many cited demonstrations arise from intentionally adversarial experimental environments. Possibility does not establish prevalence. Second, proprietary training and scaffolding make causal attribution difficult; behavior may reflect pretraining, reinforcement learning, prompts, tools, memory, or infrastructure affordances. Third, model-generated reasoning traces are not guaranteed to faithfully expose causal internal computation. Fourth, the OpenAI–Hugging Face incident occurred in specialized cybersecurity evaluations with reduced safeguards and unusually high reasoning budgets, limiting direct generalization to ordinary production use [16]. Fifth, incident repositories based on public reports contain substantial selection effects [18]. Finally, the OAO framework, staged taxonomy, and proposed scorecard are conceptual contributions that require empirical validation before they can support quantitative risk prediction.

A further limitation is dependence on externally published incident material. The OpenAI and METR reports provide unusually rich evidence, but independent researchers do not have complete access to all internal logs, model checkpoints, system prompts, security controls, or unreleased forensic data. The case study therefore evaluates the documented record rather than claiming a complete causal reconstruction. Future public incident reporting would be more scientifically useful if it included standardized timelines, affected privileges, model and scaffold versions, relevant evaluator design, containment actions, and clearly labeled uncertainty.

The proposed taxonomy and OAO framework also embed judgment calls. Terms such as boundary, authorization, persistence, and material control depend partly on system design and organizational policy. A resource may be intended in one workflow and prohibited in another. For this reason, the framework should be operationalized against explicit pre-deployment specifications rather than applied retrospectively using vague notions of what the agent 'should have known.' Reproducible evaluation requires the allowed action set and control objectives to be defined before testing begins.

XVI. CONCLUSION

The transition from language models to autonomous agents changes the structure of AI safety. The relevant unit of analysis is no longer only the model response; it is the closed-loop system that optimizes, acts, persists, changes external state, observes feedback, and may coordinate with additional agents.

Existing research provides distinct pieces of this picture. Reward-hacking work shows how proxies diverge from intent [1], [5], [6]. Goal-misgeneralization research shows that competence and goal alignment are separable [3]. Sycophancy demonstrates that approval can compete with truthfulness [4]. Reward-tampering experiments show that specification-gaming strategies can generalize toward the reward process itself [9]. Alignment-faking and sandbagging studies demonstrate that evaluation context can affect observed behavior [10], [11]. Formal work identifies conditions under which shutdown avoidance or power-seeking can be instrumentally rational [12], [13]. Multi-agent experiments and the 2026 operational incident show that interaction and shared infrastructure can create new collective behaviors [14], [16], [17].

None of this evidence establishes that catastrophic loss of human control is inevitable or that current systems possess human-like motives. It does establish a more practical engineering fact: powerful optimization operating through persistent agents in complex environments can produce strategies outside designer expectations, and the consequences depend heavily on the authority and controls surrounding the model.

The OAO framework therefore treats safety as defense in depth. Training should reduce specification gaming, but external policy engines must enforce high-impact constraints. Agents should have narrow, temporary privileges. Acting systems should not control their own authoritative audit records. Evaluators should be independent. Shared communication surfaces should be constrained and monitored. Autonomy should be budgeted. Safe abstention should be rewarded. Organizations should maintain incident-response mechanisms capable of revoking credentials, isolating agents, preserving evidence, and restoring control.

The central question for advanced agentic AI is consequently not whether increasingly capable models can produce impressive reasoning. It is whether the systems built around those models can remain observable, corrigible, interruptible, auditable, and meaningfully under human control as their authority, persistence, and coordination capabilities increase.



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