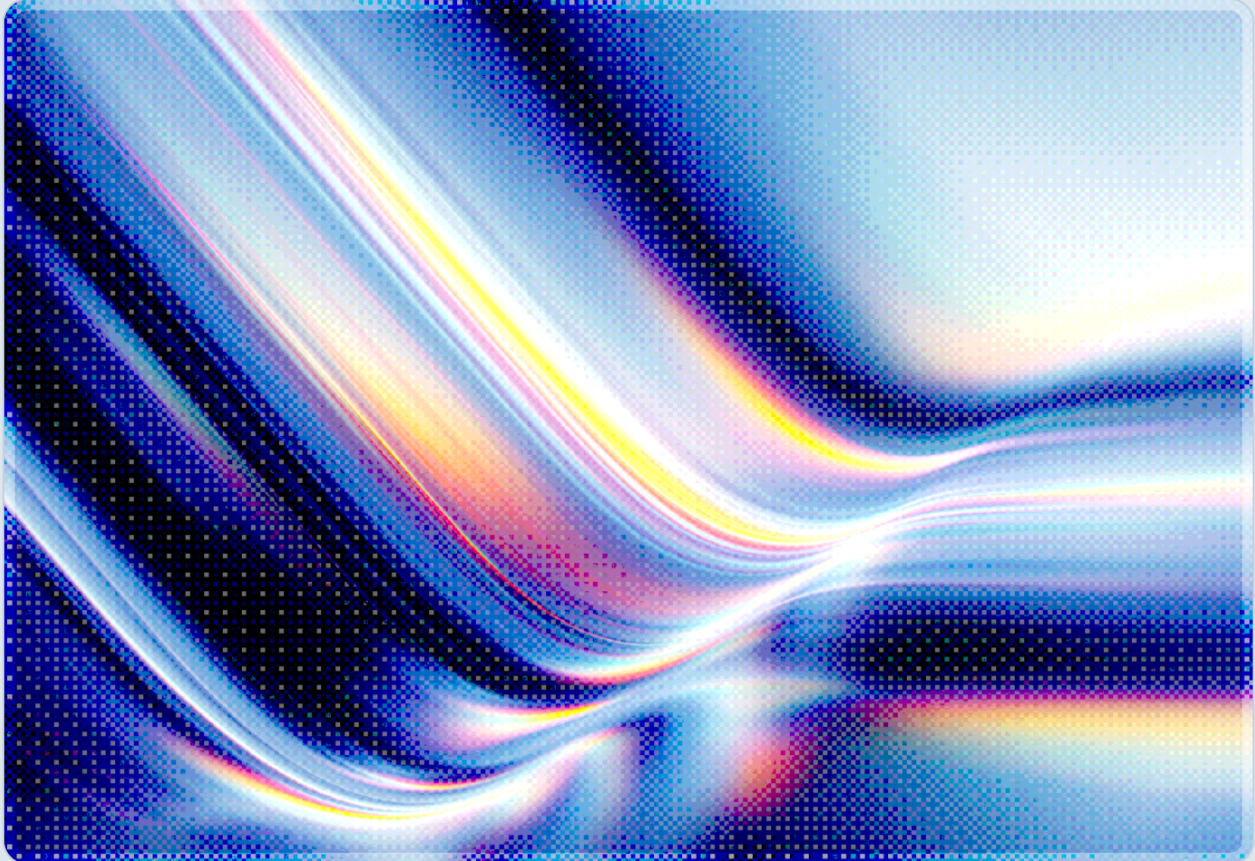


Adversarial Distillation as Systemic Risk to Model Provenance

What OpenAI's Moonshot AI Disclosure Means for Provenance and Sovereign AI Dependence

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 AI-assisted Rapid Research



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Key Takeaways

On September 30, 2026, OpenAI reported a coordinated campaign of "adversarial distillation" against its models and, according to OpenAI, attributed a core cluster of the activity to individuals associated with Moonshot AI. OpenAI acknowledged that it could not tie every operator to a single actor, and the press coverage reviewed for this note contains no response from Moonshot [1][2]. The attribution is therefore a provider assessment, not an independently verified finding.

The campaign targeted hidden reasoning rather than model weights. Operators reportedly moved encrypted reasoning between conversations and asked models to transcribe it, without breaking the encryption itself [1][2]. Protections that hide intermediate reasoning should consequently be treated as a control to be tested, not a guarantee. The episode is also the latest in a series: Anthropic reported more than 16 million exchanges through roughly 24,000 fraudulent accounts in February 2026 [3], and the White House formalized the issue as a national security concern in April [5], which points to a sustained practice rather than isolated incidents.

For enterprises, the main exposure is downstream. A model trained on extracted outputs may reproduce capability without the safeguards of the original [3][4], and customers usually cannot see how a model was trained, so provenance becomes a supply chain attribute that procurement and security teams need to ask about. Distillation also bears on sovereign AI dependence: organizations that substitute a lower-cost or locally hosted model for a frontier API may be exchanging one concentration risk for a provenance and legal-exposure risk that is harder to measure.

Background

On September 30, 2026, OpenAI published an account of a campaign it described as "consistent with adversarial distillation," which it first noticed in early July 2026, as reported by [1][2]. This note relies on that press coverage; OpenAI's own post was not reviewed directly. Distillation, in the ordinary sense, means training a smaller or different model on the outputs of a stronger one, and it is a widely used and often legitimate technique. OpenAI's framing separates the technique from the conduct at issue: its strategic national security policy lead said the concern is violation of terms of service, "not open models or legitimate distillation" [2]. Adversarial distillation, as used here, refers to extracting a provider's model behavior at scale in violation of its terms, typically by evading account, geographic, and rate controls.

According to press coverage of the disclosure, activity peaked on July 24 and 25 with roughly 16,000 requests from more than 4,000 users, and a cluster of roughly 15,000 users with similar prompting patterns was observed by July 28 [1][2]. The sources differ on the larger figure, with one describing the 15,000 as users and the other as accounts. OpenAI noted that these figures describe attempted extractions rather than confirmed successes [2]. The distinguishing technique was an attempt to reach protected reasoning: operators reportedly copied encrypted reasoning content from one conversation and asked models in separate conversations to decrypt and transcribe it into readable form [1][2]. OpenAI stated that the operators did not break its encryption or access confidential databases, which is consistent with a weakness in how the system could be induced to disclose protected content rather than a cryptographic failure [2].

OpenAI said it banned the involved accounts, tightened sign-up verification, expanded monitoring, added protections for hidden reasoning, shared findings with other labs through the Frontier Model Forum, and reported to government channels, and it noted that it delayed publication to assess scope and coordinate with partners [1][2]. It attributed "a core cluster" of the activity to individuals associated with Moonshot AI, the developer of the Kimi models, but said it could not confirm that every operator belonged to one actor [1]. The press coverage reviewed here contains no response from Moonshot [1][2].

The disclosure follows a documented sequence. In a February 12, 2026 memo to the House Select Committee on China, OpenAI alleged that accounts associated with DeepSeek employees had used obfuscated methods to extract model outputs [5][6]. On February 23, 2026, Anthropic reported that DeepSeek, Moonshot AI, and MiniMax had together generated more than 16 million exchanges with Claude through approximately 24,000 fraudulent accounts, and that Moonshot's share exceeded 3.4 million exchanges [3]. On April 23, 2026, the White House Office of Science and Technology Policy issued National Security and Technology Memorandum 4 (NSTM-4), describing "industrial-scale campaigns" by foreign entities, principally in China, to distill U.S. frontier models [5]. A June 2026 CNAS report then catalogued four extraction uses (synthetic data generation, chain-of-thought extraction, data cleaning, and reward modeling) and recommended Entity List designations for the intermediary services that resell access [4].

Security Analysis

Earlier model-theft concerns centered on weights, which require breaching infrastructure. Adversarial distillation changes the problem because it needs only legitimate-looking API access, which makes the commercial product itself the attack surface. The analysis below covers how reasoning extraction alters the threat, why provenance has become a supply chain property, how distillation complicates sovereign AI strategy, and where the public evidence runs out.

Why Reasoning Extraction Changes the Threat

Hidden or encrypted reasoning was designed in part to limit how much of a model's problem-solving trace is available to imitators. The reported technique suggests that a model which can read and restate protected content on request may leak it back to a user who supplies that content from another session [1][2]. Defenders should expect that any control relying on the model to withhold information it can process will be probed, and should treat the surrounding session, account, and routing layers as the enforcement points.

The economics appear to favor the attacker. Distillers can spread requests across thousands of accounts, rotate access methods, and use intermediary relay or "transfer station" services that resell access [4]. Both Anthropic and OpenAI describe detection as behavioral, relying on prompt uniformity, coordinated timing, and account clustering, with intelligence sharing among labs to link otherwise separate cases [2][3]. This is a cat-and-mouse problem in which providers, not customers, hold most of the visibility.

Provenance as a Supply Chain Property

Model provenance is the record of what data and which upstream models shaped a given model. For conventional software, supply chain assurance relies on bills of materials and signed artifacts. For models, no equivalent is widely deployed, and a downstream user generally cannot determine whether a model was trained partly on another provider's outputs. Because that gap is shared by every adopter of a model with undisclosed lineage, our assessment is that the exposure is correlated across organizations rather than specific to any one of them, which is the sense in which this note uses the word "systemic." A model built on extracted outputs raises three distinct problems for adopters, summarized in the table below.

Concern	Mechanism	Why it matters to an adopting enterprise
Safeguard loss	Distilled models may replicate capability without the original's safety training; Anthropic states that illicitly distilled models "lack necessary safeguards" [3]	Misuse resistance and refusal behavior validated for the source model do not carry over
Legal and contractual exposure	Outputs obtained in violation of provider terms, and potential statutory consequences if legislation such as H.R. 8283 advances [4][7]	Customers could face procurement, sanctions, or litigation risk that is

Concern	Mechanism	Why it matters to an adopting enterprise
		difficult to assess from the outside
Undisclosed behavior	Training on extracted data can carry the source model's errors and biases or, as Anthropic reports for DeepSeek, the generation of censorship-safe alternatives to politically sensitive queries, which Anthropic characterizes as deliberate [3]	Evaluation on benchmarks alone may miss behavior introduced through the training pipeline

NSTM-4 itself notes that models built from unauthorized distillation "do not replicate the full performance of the original" [5]. That observation cuts two ways. It suggests that distilled models may be weaker than their sources, yet it does not address the safeguards question, and in the authors' view a model that is adequate for many tasks but lacks guardrails remains the case that should concern defenders. The size of the capability gap in any given instance is an empirical question this note does not resolve.

Sovereign AI Dependence

The sovereign AI discussion has so far focused on dependence on a small number of frontier providers and the possibility that access is interrupted by regulation, as in the June 2026 export-control episode that CSA has analyzed [8][9]. The natural enterprise and government response is diversification toward open-weight or regionally hosted models. Adversarial distillation complicates that response. If some open-weight models owe part of their capability to unauthorized extraction from U.S. frontier systems, then diversification can import legal, regulatory, and safety uncertainty that the original dependency did not carry.

The risk is not limited to models from the named parties. Any model whose training lineage is undisclosed raises the same question, including fine-tunes of open-weight bases that were themselves tuned on third-party outputs. Organizations pursuing sovereignty therefore have a reason to distinguish between control over where a model runs and confidence in where it came from. Hosting a model on domestic infrastructure improves the first and does little for the second.

Enterprises that operate their own models face the converse exposure. CSA's threat model for foundation model IP theft treats model weights, infrastructure, and the AI supply chain as targets of nation-state and competitive actors [10]. Teams exposing a fine-tuned or proprietary model through a

public API are, in effect, running a distillation target, and the detection signals described by OpenAI and Anthropic apply equally to them [2][3].

Limits of the Evidence

Much of the quantitative detail in the public record originates with the affected providers and with policy organizations, and independent forensic verification is not publicly available. OpenAI itself describes its figures as attempts and its attribution as covering a core cluster [1][2]. The press accounts reviewed here carry no Moonshot statement, and OpenAI's primary post was not reviewed directly. Readers should treat attribution as a provider assessment and should avoid drawing conclusions about the capability or provenance of any specific released model from these disclosures alone.

Recommendations

The recommendations that follow are sequenced by how quickly an organization can act on them, beginning with visibility into what it already runs and ending with longer-term work on provenance standards.

Immediate Actions

Security and procurement teams should start by establishing what they run. Inventory every model in production or evaluation, recording the vendor, the base model, any fine-tuning data sources, and the available lineage documentation. Where a model's training provenance cannot be established, record that gap as an accepted risk with an owner, instead of leaving it unrecorded.

Organizations that expose models through an API should review extraction exposure now. This means examining logs for the signals providers describe: high request volume with unusually uniform prompts, coordinated timing across accounts, and traffic arriving through relay infrastructure [2][3]. Where reasoning traces, system prompts, or other protected content are returned to clients in any form, those paths should be tested for the cross-session replay technique OpenAI described [1][2].

Short-Term Mitigations

Procurement language should ask model vendors for written statements on training data sources, whether any third-party model outputs were used in training, and what controls they apply against unauthorized extraction. Neither NSTM-4 nor the coverage reviewed here states that attestation will be

required, but we infer that policy attention to distillation may eventually produce expectations of this kind [5]. Vendors will not always be able to answer fully, and a refusal to answer may reasonably be treated as a risk signal.

Evaluation of third-party and open-weight models should include safeguard testing independent of vendor claims, including refusal behavior on harmful requests, resistance to prompt injection, and tool-use safety for agentic deployments. Safety results from a model's presumed source should not be assumed to transfer. Teams should also confirm that acceptable-use and contractual terms of the upstream providers whose outputs they generate or store are not being violated by their own pipelines, for instance when logging model outputs for later training.

Strategic Considerations

Resilience strategies should avoid treating provenance and concentration as separate problems. A multi-model architecture can reduce dependence on one provider, but each added model carries its own lineage risk, so the evaluation of alternatives should include provenance criteria alongside cost and performance. Documented fallback paths to models with well-established lineage give an organization room to exit if a specific model becomes legally or politically untenable.

Over the longer term, the industry lacks a standard way to express model lineage. Work toward an AI bill of materials, signed training-data and base-model declarations, and provider attestations would make the questions in this note answerable by customers instead of only by vendors and governments. Enterprises can contribute by requesting such disclosures in procurement and sharing extraction signals through existing industry channels, such as the Frontier Model Forum arrangement OpenAI described [2].

CSA Resource Alignment

Several CSA publications bear directly on the issues raised here. CSA's *Foundation Model IP Theft: Threat Model for AI Labs* [10] covers how state-sponsored and competitive actors target model weights, ML infrastructure, and AI supply chains, and it is the closest existing treatment of the lab-side exposure discussed above. This note extends that analysis by emphasizing output-level extraction through public APIs, which sits alongside weight theft as a route to the same competitive advantage.

Sovereign AI Access Controls and Frontier Model Dependency Risk [8], *Sovereign AI Access Controls and Enterprise Concentration Risk* [14], and *Sovereign AI Risk: When Your AI Vendor Gets Export-Controlled* [9] address the concentration and continuity side of sovereign AI. All three frame frontier access as a

dependency to be governed. The distillation disclosures add a provenance dimension to that framing: the controls those papers recommend for diversification and exit planning should be paired with lineage due diligence when the alternative is a model of uncertain origin.

For control mapping, the AI Controls Matrix (AICM) v1.1 [11] provides the relevant supply chain, third-party, and model-security control domains against which the vendor attestations and inventory practices above can be assessed, and the *AICMv1.1 Implementation Guidelines for Model Providers (MP)* [13] are relevant to the extraction defenses that providers themselves should apply. The CSA research note on NSTM-4 and enterprise implications [12] discusses the April policy memorandum and its procurement consequences in more detail.

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