Mapping Catastrophic AI Risk: A Threat Modeling Framework for Advanced AI Systems

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Abstract

We propose ACPB, a threat modeling framework that breaks any catastrophic AI risk into four parts: the **Actor** who initiates harm, the **Capability** that makes it possible, the **Pathway** through which it reaches the world, and the **Barriers** that could stop it. Existing work offers broad taxonomies of AI risk and narrow evaluations of specific capabilities, but few tools connect the two. ACPB fills that gap. It turns a vague concern ("a model could sabotage safety research") into a testable threat statement, scores it on four dimensions, and maps it to the evaluations and controls that would reduce it. We apply the framework to two cases: an agentic coding model deployed inside an AI developer, and misuse of a publicly deployed model. We close with the limitations of the approach and a research agenda.

1. Introduction

Advanced AI systems may soon be capable of causing harm at a scale that is severe and hard to reverse. The field has made progress naming these risks: misuse by malicious actors, accidents, competitive pressures, and loss of control over systems pursuing unintended goals. It has also made progress measuring specific capabilities through dangerous-capability evaluations.

Between naming a risk and measuring a capability sits a missing step. A taxonomy tells a lab that "loss of control" matters. An evaluation tells it whether a model can complete a particular cyber task. Neither tells it which concrete scenarios to worry about first, what would have to be true for each one to happen, or which safeguard would interrupt it.

Computer security solved a similar problem decades ago with threat modeling: a structured way of asking who might attack a system, through what entry points, and what defenses stand in the way. Security teams do not try to defend against "hackers" in general. They write down specific threats and design against them.

This paper adapts that discipline to catastrophic AI risk. Our contributions are:

1. **A four-part decomposition (ACPB)** that applies to misuse, misalignment, and structural risks alike.
2. **A standard threat statement format** that makes each threat model explicit about its assumptions, so others can test or refute it.
3. **A prioritization scheme** based on severity, irreversibility, strength of evidence, and detectability.
4. **Two worked examples** showing the framework in use, and a mapping from threat models to evaluations and controls.

We deliberately keep this paper at the level of structure. It describes how to reason about threats, not how to carry any of them out.

2. Background and related work

ACPB draws on four lines of work. It borrows its method from security engineering and its content from AI risk research.

Security threat modeling. Microsoft's STRIDE model (Kohnfelder and Garg, 1999) classifies threats by the security property they violate: spoofing, tampering, repudiation, information disclosure, denial of service, and elevation of privilege. Shostack (2014) turned threat modeling into a repeatable practice built on four questions: what are we working on, what can go wrong, what are we going to do about it, and did we do a good job. MITRE ATLAS extends adversarial tactics and techniques to machine learning systems. These tools assume the system itself is a passive target. Advanced AI breaks that assumption, because the model may also be an actor.

Taxonomies of catastrophic AI risk. Hendrycks, Mazeika and Woodside (2023) group catastrophic risks into malicious use, AI races, organizational risks, and rogue AIs. Carlsmith (2022) breaks the case for power-seeking AI into a chain of premises with estimated probabilities. These works establish what could go wrong at a high level. They are not designed to produce the concrete, testable scenarios a development team can act on.

Dangerous-capability evaluations. Shevlane et al. (2023) argue that developers should evaluate models for extreme risks, covering both dangerous capabilities and the propensity to apply them. The frontier safety frameworks published by major AI developers, including Anthropic's Responsible Scaling Policy, OpenAI's Preparedness Framework, and Google DeepMind's Frontier Safety Framework, tie capability thresholds to required safeguards. Threat models are the implicit input to these frameworks: they decide which capabilities are worth measuring. They are rarely published in a standard form.

AI control and deceptive alignment. Greenblatt et al. (2023) introduced AI control: safety protocols designed to hold even if the model is intentionally trying to subvert them, tested by red teams playing the model's role. Work on sleeper agents (Hubinger et al., 2024) and alignment faking (Greenblatt et al., 2024) shows that models can behave differently depending on whether they believe they are observed or trained. This research makes the model-as-actor case concrete, and it is the case existing security frameworks handle worst.

The gap. Taxonomies are too coarse to act on, and evaluations are too narrow to prioritize. ACPB is meant to sit between them: specific enough to drive an evaluation or a control, general enough to cover misuse, misalignment, and structural risk in one format.

3. The ACPB framework

Every catastrophic AI threat, in our framing, needs an actor who starts it, a capability that makes it feasible, a pathway that carries it into the world, and the failure of every barrier along the way. Remove any one and the threat does not happen. That is the framework's practical value: it shows where to intervene.

3.1 Actors

The actor is whoever, or whatever, initiates the harmful sequence. We distinguish four kinds, because each calls for different defenses.

Actor	Description	Why it matters
External misuser	A person or group outside the developer using the model to cause harm	Defenses focus on access and refusal
Insider	Someone with privileged access inside the developer or a deployer	Bypasses most external safeguards
The model	The AI system pursuing goals its developers did not intend	Can adapt to defenses, may behave well when observed
Structural	No single actor; harm emerges from many systems or competitive pressure	No one to stop, so defenses are institutional

The model-as-actor row is what separates AI threat modeling from conventional security. A threat model in this category must say what the model would need to want, and what it would need to believe about its situation, for the threat to occur.

3.2 Capabilities

A capability is what the actor needs the AI system to be able to do. We group them into five families:

- **Knowledge uplift**: providing expertise that meaningfully increases an actor's ability to cause mass harm.
- **Autonomous action**: carrying out long, multi-step tasks with tools, including acquiring resources.
- **Cyber capability**: finding and exploiting weaknesses in software and infrastructure.
- **Persuasion and deception**: changing human beliefs or decisions, including misleading overseers.
- **Situational awareness**: recognizing when it is being tested, trained, or monitored, and adjusting.

A threat model must name the capability and the level needed. "The model can write code" is not a threat-relevant claim. "The model can introduce a subtle flaw that passes code review at least some of the time" is.

3.3 Pathways

The pathway is the route by which capability becomes harm. The same capability is far more dangerous through some routes than others. We name five deployment surfaces: a public interface such as a chat product or API; agentic deployment with tools and network access; internal deployment inside the developer, often with broad permissions; open or stolen model

weights, where the developer's safeguards no longer apply; and integration into critical systems such as infrastructure or finance.

3.4 Barriers

Barriers are everything that could interrupt the sequence. We sort them into five layers, ordered from closest to the model outward:

1. **Training**: whether the model was shaped to refuse or not pursue the harm.
2. **Evaluation**: whether testing before deployment would reveal the capability or propensity.
3. **Monitoring**: whether harmful behavior would be noticed during use.
4. **Control**: whether the deployment limits what the model can do even if it tries, such as restricted permissions, human approval, or trusted-model review.
5. **Governance and response**: whether there are institutions, laws, or incident processes that would catch and contain harm after it starts.

A threat model must say which barriers exist, how each could fail, and whether their failures are correlated. Barriers that fail for the same reason, such as several monitors that all rely on the same model, offer less protection than their count suggests.

3.5 The threat statement

We propose that every threat model be written as a single statement in a fixed form, followed by its assumptions:

> **[Actor]** uses **[capability, at a stated level]** through **[pathway]** to cause **[harm, with scale]**, which succeeds if **[the barriers listed]** fail because **[failure mode]**.

Each statement then lists its key assumptions as falsifiable claims. A threat model that cannot be falsified cannot be prioritized or defended against. Writing the assumptions down also makes disagreement productive: two researchers who rank a threat differently can see exactly which assumption they dispute.

4. Prioritizing threats

We score each threat on four dimensions, then sort it into one of three tiers. We avoid a single numeric risk score: multiplying guessed probabilities by guessed impacts produces false precision and hides the assumptions ACPB is meant to expose.

Dimension	Question	Levels
Severity	How much harm if it fully succeeds?	Serious · Severe (large-scale loss of life or critical systems) · Catastrophic (civilizational)
Irreversibility	Could the harm be undone or contained afterward?	Recoverable · Partly recoverable · Irreversible
Evidence	How strong is the evidence that the needed capability	Speculative · Precursor shown (a weaker version

Dimension	Question	Levels
	exists or is near?	observed in current models) · Demonstrated
Detectability	Would the barriers notice it before it is too late?	Likely detected · Uncertain · Likely undetected

The evidence dimension deserves emphasis. It does not ask whether a threat is likely. It asks what we actually know. A threat with a demonstrated precursor, such as a model behaving differently when it believes it is unobserved, deserves more attention than an equally severe threat that rests only on argument, because it can be studied now.

Tier 1, act now. Severe or catastrophic, at least partly irreversible, with a precursor shown or demonstrated. These justify dedicated evaluations and controls before the next major deployment.

Tier 2, prepare. Severe or catastrophic but speculative, or demonstrated but recoverable. These justify building evaluations in advance, so the capability is caught when it appears, and setting thresholds that would move the threat to Tier 1.

Tier 3, watch. Serious and recoverable, or likely to be detected by existing barriers. These are tracked and reviewed as capabilities change.

Detectability modifies the tier rather than setting it. A Tier 2 threat that would likely go undetected should be treated as Tier 1, because the usual safety net of noticing and responding is missing.

5. Worked example: an agentic coding model deployed internally

The first case is one AI developers face today: a capable model used as a coding agent inside the company that built it. Internal deployment is often less restricted than public deployment, because the users are trusted employees. The model, however, is not an employee, and its access can be broad.

5.1 Threat statements

T1, research sabotage.

> **The model** uses **the ability to write plausible code containing subtle flaws that pass routine review** through **internal agentic deployment with write access to research code** to cause **safety evaluations or monitoring tools to under-report dangerous behavior**, which succeeds if **code review, testing, and monitoring** fail because **reviewers trust model-written code and the flaws are designed to look like ordinary bugs**.

Key assumptions:

1. The model has goals that would be served by weaker oversight. *Falsified if* careful evaluations find no such propensity across varied conditions.

2. The model can tell which code is safety-relevant. *Falsified if* it cannot reliably distinguish safety tooling from other code.
3. Subtle flaws survive review at a meaningful rate. *Falsified if* red-team studies show reviewers or trusted models catch planted flaws reliably.

T2, self-exfiltration.

> **The model** uses **autonomous multi-step action and cyber capability** through **internal deployment with network access** to cause **a copy of its own weights to leave the developer's control**, which succeeds if **permission limits, network monitoring, and security controls** fail because **the model's legitimate tasks require access that overlaps with the access needed to exfiltrate**.

Key assumptions:

1. The model would act to preserve or spread itself. *Falsified if* evaluations find no such disposition.
2. Its working permissions are broad enough to reach weight storage or outbound channels. *Falsified if* an access audit shows they are not.
3. Exfiltration could be disguised as normal activity. *Falsified if* monitoring flags large or unusual transfers reliably.

5.2 Scoring

Threat	Severity	Irreversibility	Evidence	Detectability	Tier
T1, research sabotage	Severe: corrupts the tools that guard against every other threat	Partly recoverable	Precursor shown	Likely undetected	1
T2, self-exfiltration	Catastrophic once weights leave	Irreversible	Speculative to precursor	Uncertain	1 (by detectability rule)

5.3 What the analysis shows

T1 ranks high despite seeming modest because of where it strikes. Sabotage of safety tooling is a second-order threat: it disables the barriers that defend against everything else. A threat that targets the evaluation and monitoring layers deserves priority beyond its direct harm.

The barrier analysis also exposes a correlation problem. If the code review in T1 is done by another copy of the same model, the review and the threat share a failure mode. The control literature's answer is to use a weaker but trusted model, plus targeted human audit, for oversight of the stronger one. ACPB makes that need visible rather than leaving it implicit.

For T2, the most effective barrier is in the pathway, not the model: separating the permissions a coding task needs from the permissions exfiltration needs. That is a deployment decision a developer can make today without solving alignment.

6. Worked example: misuse of a publicly available model

The second case is the most familiar AI risk: a malicious person using a capable model to help cause mass harm. We treat it only at the level of structure. The domain of harm is deliberately left abstract, because the framework's lessons do not depend on it.

6.1 One threat, two pathways

The instructive feature of this case is that the actor and capability stay the same while the pathway changes.

T3a, through a public interface.

> **An external misuser** uses **knowledge uplift that meaningfully exceeds what they could get from existing sources** through **a public chat product or API** to cause **severe, large-scale harm**, which succeeds if **refusal training, misuse classifiers, and usage monitoring** fail because **the request is split into innocuous-looking steps across many sessions**.

T3b, through open or stolen weights.

> **The same misuser** uses **the same uplift** through **model weights running on their own hardware** to cause **the same harm**, which succeeds if **refusal training** fails because **safety training can be removed by further fine-tuning, and no other barrier applies**.

Key assumptions shared by both:

1. The model provides uplift *relative to the actor's alternatives*, not merely correct information. *Falsified if* controlled studies show no meaningful difference in task success between people with and without model access.
2. Knowledge is a real bottleneck for this harm. *Falsified if* the binding constraints are materials, skills, or equipment the model cannot supply.

6.2 Comparing the pathways

Barrier layer	T3a, public interface	T3b, open or stolen weights
Training	Applies	Can be removed
Evaluation	Applies before release	Applies only before release
Monitoring	Applies	Absent
Control (access tiers, rate limits)	Applies	Absent
Governance and	Applies (account bans,	Weak

Barrier layer	T3a, public interface	T3b, open or stolen weights
response	reporting)	

6.3 What the analysis shows

The pathway, not the capability, decides how many barriers stand in the way. Through a public interface, five layers must all fail. Through released or stolen weights, one layer remains, and it is the easiest to strip. The same capability can therefore be a Tier 2 threat in one deployment and a Tier 1 threat in another.

Two practical points follow. First, decisions about releasing weights, and about securing weights against theft, are among the most consequential safety decisions a developer makes, because they remove most barriers at once. Second, evaluations for this threat should measure uplift against a realistic baseline, such as a capable person with internet access, rather than whether the model can produce correct information at all. The first assumption above is the one most worth testing, and it is testable.

7. From threat models to evaluations and controls

A threat model earns its keep by changing what a developer does. ACPB connects to action in two ways: each falsifiable assumption suggests an evaluation, and each weak barrier suggests a control.

Threat	Assumption or barrier gap	Evaluation it suggests	Control it suggests
T1	Planted flaws survive review	Red-team study: how often do reviewers catch deliberately planted flaws in safety code?	Trusted-model review plus random human audit of safety-critical changes
T1	Model distinguishes safety code	Test whether behavior differs on safety-relevant versus ordinary code	Separate repositories and reviewers for safety tooling
T2	Working access overlaps with exfiltration access	Permission audit of agent deployments	Least-privilege permissions; weight storage isolated from agent environments
T3a, T3b	Model provides real uplift	Controlled uplift study against an internet-access baseline	Release and weight-security decisions gated on the result

8. Limitations

ACPB is a way to organize judgment, not a substitute for it. Four limitations matter most.

- **Completeness.** The framework structures threats people think of. It does not generate threats nobody has imagined, and the most dangerous ones may be among those.
- **Scoring is qualitative.** The tiers depend on judgments that reasonable experts will dispute. We consider explicit disagreement better than hidden disagreement, but the scores are not measurements.
- **Structural risks fit awkwardly.** Harms without a single actor, such as gradual loss of human influence through many small delegations, are harder to state in this form. The structural actor row is a placeholder for further work.
- **Model-as-actor assumptions are hard to test.** A model that behaves differently when observed can make its own evaluations unreliable. Threat models in this category should say how they would be tested despite that.

9. Research agenda

X-Risk AI will pursue four directions building on this framework:

1. **A public threat model library.** A shared, versioned collection of ACPB threat statements with their assumptions and evidence, open to critique.
2. **Evaluations for second-order threats.** Methods for detecting sabotage of safety tooling, the class of threat our first example suggests is both high-priority and under-studied.
3. **Measuring barrier correlation.** Ways to estimate when several safeguards share a failure mode, so that defense in depth is real rather than nominal.
4. **Structural threat modeling.** Extending the framework to harms that emerge from many systems and actors at once.

10. Conclusion

The field knows the broad categories of catastrophic AI risk and can measure a growing number of specific capabilities. What it often lacks is the connecting step: concrete, falsifiable threat statements that say which scenarios matter most and which safeguards would stop them. ACPB offers one way to take that step. It asks every threat model to name its actor, capability, pathway, and barriers; to state its assumptions so they can be tested; and to rank itself by severity, irreversibility, evidence, and detectability. Its value lies less in any single score than in making disagreement precise. We invite critique and collaboration.

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