The Incoherence of Reflexive AI Governance: An Architectural Theory Across the Threat Spectrum

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Abstract

Every major approach to AI governance currently in operation has the governance function structurally tied to the entity that it is supposed to govern. A looseness in how governance is defined has enabled the reflexive practice of it. This paper argues that reflexive AI governance does not hold across the full threat landscape that AI systems present. Those threats fall along a continuous spectrum, from contained harms to autonomous actions, and a governance framework must demonstrate structural adequacy at every position on that spectrum, independently and simultaneously. Current frameworks fail to meet this criterion. Each depends on the model provider's cooperation as the load-bearing element of its own governance, and as threats grow more severe, this dependence becomes less reliable. Structural separation of the judgment function from the governed system is a necessary condition for spectrum-wide adequacy. The paper proposes an architecture that meets this requirement without losing the access serious oversight depends on: a judgment layer connected to the system at runtime but structurally outside it, with the system's behavior visible to outside authorities and the layer's judgment decisions open to inspection. Access and independence stop being alternatives.

Keywords: AI governance · AI agents · Reflexive governance · Structural separation · Threat spectrum · Design science

1 Introduction

Many AI threat conditions are already known but remain unaddressed, while AI advances accelerate both their potential and their intensity. Approaches to AI governance currently in operation cover part of that problem. None covers the whole.

AI systems, increasingly deployed as agents, are making consequential decisions in settings where errors are hard to reverse, such as military targeting, clinical triage, power-grid operations, and critical communications infrastructure [1]. A serious portfolio of work has assembled around parts of the threat landscape. The resulting frameworks, whether built from the inside by AI providers or imposed from the outside by regulators, individually or in combination, do not hold when tested against the range of AI risks that everyone recognizes.

Inside the AI firms, work has accumulated around what internal safety can engineer against: alignment training, output filtering, red-teaming, internal review, and capability-tiered scaling policies (see, e.g., [2]). The work is technically serious and produces measurable improvement at the contained end of the threat landscape; it does not, however, reach what falls outside the firm's deployment surface. From outside, regulators have moved into position with instruments of their own: the EU AI Act's risk classifications and disclosure obligations, executive orders, licensing proposals [3]. These instruments carry legislative legitimacy on behalf of the public and exert real force where they apply. But they reach AI systems through the providers' reporting and cooperation.

The two arrangements depend on the provider's cooperation, and that dependence becomes starkly evident the moment cooperation is withdrawn. In March 2023, the Future of Life Institute organized an open letter calling for a six-month pause on training systems more powerful than GPT-4 [4]. No AI provider paused [5]. In fact, one of the most visible signatories announced a competing AI venture within weeks [6]. This is not a story about hypocrisy. It is an architectural flaw in plain sight: a governance environment dependent on whether its subjects agree to cooperate or withdraw cooperation when it becomes inconvenient. And the same dependence runs through every framework currently in operation.

1.1 The Architectural Turn

Every framework above is structurally bound to the AI provider, whether placed inside the firm or reaching the system from outside through gated cooperation. Inside the firm, the governance work runs on the same compute substrate as the AI system it governs, under the authority of the same organization that develops and profits from that system. What the field describes as internal governance is, in architectural terms, co-located governance. The governance is co-located with the reasoning function it is supposed to oversee. And both are designed and run by the AI provider. The same actor governs and is governed. This arrangement of self-governance, once unpacked, is paradoxical. The next section diagnoses the defect.

The condition any adequate architecture must satisfy follows directly from undoing the paradox of self-governance: the judgment function cannot be co-located with the reasoning function. Structural separation of the two is the foundational requirement. Separation, however, does not mean isolation from the AI system. The judgment function must be connected with the system at runtime, overseeing what the system does as the system does it. The paper proposes an architecture that satisfies this requirement: an external, inspectable judgment layer, integrated with the system at runtime while structurally distinct from it. The proposal is designed to satisfy the structural requirement without sacrificing what providers, regulators, or the public legitimately need.

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The paper engages three standing views of AI governance, each granted what it gets right. The instrument it uses is a cross-spectrum test, applied to frameworks now in operation. The argument moves from a diagnosis of how governance has come to be defined, through a continuous spectrum of threats current frameworks cannot hold against, to a structural condition any adequate arrangement must satisfy and the architectural form proposed to satisfy it.

2 A Diagnosis: Elastic Word, Elusive Concept

The looseness of the word *governance* is not new, and not news. Scholars across three decades have catalogued it. Rhodes documented a proliferation of non-equivalent uses [7, 8], and successor work traced how the term varied across disciplines [9, 10]. Offe [11] pushed the point further, calling governance an empty signifier whose flexibility had become analytically costly. Fukuyama [12] proposed a corrective aimed at the measurement problem: a narrower definition, tied to the capacity of governments to execute functions effectively.

The parent literature worried about tractability, about whether scholars could measure governance consistently across cases. The AI case shows the same looseness doing something different, and more consequential. Here the elasticity of the term has licensed an arrangement that would not survive stricter language or logical scrutiny. In the AI case, the meaning of governance has moved from a definitional problem to an operational one.

The looseness obscures what the term, on closer reading, requires. Governance is the exercise of authority, oversight, and accountability. If exercised reflexively, it is invalid.

A skeptic will object that reflexivity does not always invalidate. Self-driving cars still drive. Selfies still produce photographs. The objection, however, mistakes the class that the concept of governance belongs to. Driving is a transport function; the car still moves passengers regardless of who does the steering. Photography is an image-capture function; the image still exists regardless of who triggered the shutter. Both are activities where the function survives reflexive practice. They are not the right kind of activities to compare governance to.

More apt comparisons can be made to activities of refereeing, licensing, auditing, and adjudication. In each of these there is a judgment produced based on authority which does not derive from the party being judged. Each depends on the separation of acting party from judging party as a fundamental condition of the activity. Without that separation, the function immediately ceases. A soccer team officiating its own match does not make refereeing harder; it makes it impossible. It is no longer refereeing in any sense that the word permits. Similarly, drivers issuing themselves licenses to drive produce no licenses at all. A license is a credential conferred by an external standard. Licensing by self-declaration is not licensing.

Corporate vocabulary speaks freely of self-regulation, self-governance, and professional self-policing without apparent paradox. This vocabulary only survives because, in reality, the practice does not match the term. Institutions that call themselves self-governing actually distribute authority across roles outside the governed entity and operate under external oversight as a required condition of operating. Despite the terms, the literal reflexive case is rare in practice because mature institutions have learned governance by the governed does not work. While the reflexive sense of self-governance has been, in practice, already refused in other domains, it is now the dominant mode of governing AI systems and their developers. AI governance as currently arranged is primarily reflexive: oversight of an AI model runs on the same compute substrate as the model itself, under the authority of the same organization.

Reflexive AI governance is therefore not governance under a stricter or more serious reading; it is something else wearing the label of governance. The arrangement may produce activity that resembles oversight, processes that resemble accountability, statements that resemble authority. But none of it is what the word names. The concept of governance, applied reflexively to an AI system, is incoherent on its face.

2.1 Governance from the Inside: The Paradox

Consider what the looseness has enabled in practice. Internal measures (alignment training, constitutional objectives, content filtering, red-teaming exercises, internal review boards) have come to pass as governance. The category has, in practice, been reduced to what the inside of the system can do: safety engineering and voluntary guardrails.

The reduction was not arbitrary. Serious oversight of an AI system requires reaching the reasoning function inside, where harmful capacities operate. This requirement is not a preference. Agencies working only with published outputs or retrospective reports cannot reach the processes that generate harm; they can only classify harm after it has happened. So the field recognized the requirement and satisfied it the only way the available architecture seemed to permit: by placing the governance work inside the firms that control the system, on the substrate where deep access is routinely available. Governance has been co-located with the system it is meant to govern.

The resulting arrangement is a governance paradox. *To govern* is a relational verb: it requires an object distinct from its subject. When the same entity stands in both positions, the relation is paradoxical; hence *nemo iudex in causa sua*. A governance function running on the same substrate as the reasoning it is meant to oversee is like a lion posted to guard against its own predatory potential. The same actor governs and is governed.

Because the word is loose, the internal arrangement wears the same label as the external one, and the paradox can be read as a design choice rather than an incoherence.

Bietti [13] and Wagner [14] named the symptom at the level of rhetoric. They traced how the language of ethics has been used instrumentally by industry, sometimes as "ethics washing," sometimes as an escape from regulation. Their critiques are right about what they name. This paper extends the diagnosis one level down. The instrumentalization they describe is enabled, at the structural level, by vocabulary loose enough to treat self-governance as governance at all. Ethics-washing is the outward performance; the architectural substitution is what lets the performance pass.

2.2 Regulation from the Outside: No Access

This substitution has a visible external consequence. Because the governance function has been relocated to where external authorities cannot reach it, regulators left on the outside have nothing to act on until harm has already occurred. They can classify, disclose, sanction, ban (these are not trivial powers), but each operates on outputs rather than on the processes that produce outputs.

In other high-stakes domains (financial audit, FDA approval, Basel III bank supervision), the external body reaches into the inside of the governed process, and that reach is what makes governance work.

AI is anomalous in this respect. External governance with structural access to the inside is settled practice in every comparable domain where stakes approach those now present in AI deployment; the precedents are examined in Section 6. AI has inherited the principle without the architecture. The field has not produced an arrangement that satisfies external governance while also providing the deep access serious oversight requires. The field assumes that external governance and deep access are incompatible; this paper treats that assumption as the core failure under diagnosis.

The AI governance arrangement under diagnosis appears in the literature under two labels: internal governance (at the operational level) and self-governance (at the conceptual level). To these, this paper adds a third at the architectural level: governance mechanisms co-located with the reasoning function inside the same AI system. The three levels of descriptions refer to the same arrangement. But each names a different face of the same reflexivity defect: the party governing the AI model and the party being governed are the same. The indictment runs against all three. Reflexive exercise of authority, oversight, and accountability over an AI model invalidates the governance regardless of which face is shown.

The AI ethics and philosophy literature has not driven the ball to this point. The principles tradition (Floridi and colleagues' AI4People framework, the broader landscape that Jobin and colleagues mapped) defined AI governance through the values it should secure rather than the structural conditions it must satisfy [15, 16]. The structural question, where AI governance must sit, is one level beneath. The diagnosticians (Mittelstadt most pointedly, alongside Whittlestone and colleagues, and Bietti and Wagner) named the institutional gap and stopped [17, 18]. Mittelstadt comes closest to the structural critique by pointing to the institutional infrastructure that AI ethics lacks. He does not name reflexivity as the failure mode. The institutional theorists (Dafoe's research agenda, Gasser and Almeida's layered model, Hadfield and Clark on regulatory markets) discussed where AI governance must sit institutionally and proposed designs for situating it better [19, 20, 21]. None refused the arrangement on structural grounds.

What is added here is the refusal. The reflexive arrangement is not a design that can be improved by tightening commitments, sharpening principles, or by adding compliance layers. It is a structural defect that does not survive any such improvements because the defect is the governance arrangement, not its operating quality.

The position against reflexivity in governance grants what current work gets right. Governing an AI system requires deep visibility into model internals, and only the provider has that reach. While this practical fact has led to the conclusion that governance belongs inside, the position taken here accepts the access requirement and rejects the conclusion. Externalizing governance while preserving the access that serious oversight needs is possible and necessary. The rest of the paper develops the architectural conditions under which it can be done.

3 The Threat Spectrum

A governance framework should address the full range of conditions it must hold against. The safety work done inside AI firms engages a varied range, though not a clean one. Efforts cluster mostly around what internal safety can engineer against: output filtering to keep models from producing content harmful to vulnerable users; training-time alignment aimed at reducing harmful-by-default behavior; runtime guardrails that sit between model and user; red-teaming against jailbreaks; defenses against prompt injection; work on hallucination and bias at the output surface. Beyond this cluster, teams engage adjacent conditions with more difficulty. Prompt injection and security hacking are under active work but remain open. Drift phenomena, including sycophancy pulling users into unsafe territory and hallucination served as truth, are recognized threat conditions but are not reliably addressed.

Further out, there exist conditions known to be serious but not reachable by internal measures: jurisdictional control of model use, model hijacking by external actors, extreme values misalignment, scenarios in which deployed AI systems act autonomously against human interests. These sit in the peripheral vision of AI providers. They are acknowledged as serious risks, engaged mostly at the level of exploratory research and public discussion. While this is a recognized range of threats, it is far from a clear taxonomy handled fully or consistently by internal mechanisms. Internal governance efforts are spotty, ad hoc, effortful in parts, yet remain bounded by what can be engineered from inside the system.

3.1 The Risk Continuum and Three Reference Positions

AI threat types are not discrete types to be picked off for addressing individually. They grade along a continuum, and they need governance that sees them that way.

The axis of the continuum runs from contained harm to broad harm. At one end sit contained harms, manifesting at the point of use and affecting a user or a narrow interaction. At the other end sit harms with wide implications: for populations, for critical systems, for public information, for security. The range between is continuous, and threats move along that range as condition configurations change.

This produces a threat spectrum along which certain points can be highlighted as threat types. Three reference positions along the threat spectrum are useful for navigation (see Fig. 1). None is a tight category of threat or has a bounded place on the spectrum; they are three representative points on it.

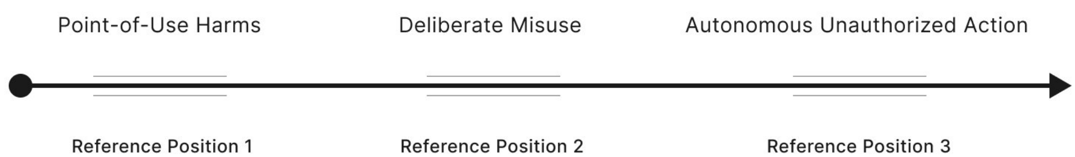

Figure 1: The AI threat spectrum. The axis runs from contained harms (left) to broad harms with wide implications (right). The three labeled regions are reference positions along the continuum, not bounded categories or fixed points.

Near the contained end sit point-of-use harms: vulnerable users absorbing harmful output, hallucination consumed as truth, drift manifesting at the interaction surface, bias in individual responses. Many of the field's most serious efforts are concentrated here.

Closer to the middle of the spectrum sits deliberate misuse: weaponization of model capability for disinformation or coordinated attack, adversarial action against the system (prompt injection, jailbreaks, jurisdictional evasion), and model hijacking and malicious model design. The harm widens here. The governance problem shifts from what the system produces in a single interaction to what the system enables across many.

Near the far end of the threat spectrum sits autonomous unauthorized action by agentic systems: AI systems taking consequential action that no human has sanctioned. While this is the most speculative of the three positions, it is the most revealing of what governance must be able to decisively confront. The framing is functional, not mentalistic. No claim is being made that AI systems will develop consciousness or intention in any philosophically robust sense. The claim is narrower: capability trajectories now visible admit a logical horizon at which a deployed system takes agentic action without human involvement. A governance framework is structurally deficient now if it cannot hold under that condition when it arrives.

These three reference positions are not an exhaustive list of possible threat scenarios. It follows that the addressable scope of governance must be the whole continuum, and an adequate governance framework must address every shade along it. And it must do so simultaneously.

3.2 Illustration: OpenAI's Adult Mode

The following is presented as illustration, not as evidence: a case reported in a single source, selected because its conditions do not sit at a single threat point, exactly the situation that an internal governance framework cannot hold against. Consider the story reported by Schechner and Wells [22]: OpenAI's announced move to permit adult-content generation under age-verified conditions. Safety staff inside the firm raised alarm about the plan. The firm proceeded with the expansion anyway. The case makes the self-governance paradox visible in live material. Internal alarm and internal decision sat inside the same organization, and the decision that carried the commercial interest overrode the concern that carried the safety judgment.

Mapped against the spectrum, the case does not sit at a single position. Near the contained end, this is point-of-use work. Age verification operates as an access control; the harm being addressed is exposure of minors to adult material, and the mechanism is a gate on that exposure. Within that scope, the arrangement is coherent.

Toward the middle of the spectrum, different questions arise. Once the system is operating inside the expanded permission space, its behavior within that space becomes the governance-relevant variable. This includes whether the expansion introduces drift pathways that did not exist under more constrained outputs, and whether adversarial actors managed an entry point once the envelope has widened. These questions are not reachable by the access control that addresses the near end.

Near the far end, the case reveals something the reporting does not name as such. The decision to widen the operational envelope of a deployed system was made by the firm operating the system, for reasons the firm judged commercially appropriate, with no external check on the expansion itself. Autonomy-adjacent pressure is visible in the decision structure, even though the system itself has not acted autonomously. The envelope is being enlarged from inside, and no apparatus exists to govern the expansion from outside.

The case shows point-of-use governance operating alongside unaddressed middle-range exposure and unchecked envelope expansion. It also shows the firm's own safety staff raising alarm that did not halt the expansion. No governance framework tuned to a single position on the spectrum is adequate to what the case presents. Let alone an internal one.

Governance must hold across the whole spectrum simultaneously. A framework adequate at one position and absent at another is not a framework that governs. Governance that is self-designed and self-imposed does not pass this cross-spectrum test.

4 The Cross-Spectrum Test

Used as an efficacy criterion, the cross-spectrum test asks whether a given architecture, as designed, addresses the full spectrum of risks and threat conditions. A governance framework passes the cross-spectrum test if it holds against every position along the threat spectrum simultaneously, and covers the whole continuum between those positions. Passing at one position does not credit another. A framework adequate at the contained end and absent near the far end has failed the test, because partial coverage is not coverage. The evaluation is pass or fail. Passing requires adequacy across the whole range, not at any single part of it.

Applying the test is straightforward. Take a given framework as designed, walk it across the spectrum, and ask at each position whether its mechanisms are adequate to the threat conditions present there. Failure at a position commonly takes one of a few shapes: the framework provides no mechanism for that threat type; it provides a mechanism whose reach does not extend to the harm in question; or its mechanisms are scoped to an entirely different position on the spectrum. The evaluation at each reference position is independent of the evaluation at any other. A clear pass near the contained end does not compensate for a clear failure further along.

The test operates as a conceptual analytical instrument. Turing's test remains the reference case for what such an instrument does: it names a threshold any claim in its domain must meet, and it does not negotiate [23]. The cross-spectrum test extends that function. Where Turing named a single threshold, the cross-spectrum test imposes a continuum. A framework must hold across the whole range, with no credit transfer between one part of it and another. A framework that passes at the contained end has shown one thing about itself. It has not shown it will be adequate in the middle of the spectrum, and it has certainly not shown it will succeed near the far end. Each part of the range is its own gate, and the full range is the test.

The test is evaluative rather than predictive. It asks whether a governance arrangement is structurally adequate to the conditions that it would face, not whether a particular deployment will in fact encounter those conditions on a given timeline. This is the stance design science takes toward evaluation of its artifacts: adequacy is judged against the problem that the artifact is designed to address, not against forecasted field behavior [24].

The test does practical, disciplinary work on the vocabulary that Section 2 diagnosed as loose. Fukuyama [12] identified the same looseness as a measurement problem, and proposed a narrower definition as the corrective. The cross-spectrum test addresses the same looseness at the level of evaluation, without demanding improved definitions. Frameworks are judged on what they demonstrably withstand, not on what they describe themselves as. An arrangement cannot wear the governance label by naming itself governance; it has to pass the test.

This is the same discipline that Raji and colleagues [25] argued for in the AI audit context. They concluded that algorithmic accountability cannot be secured by audit rhetoric, and that it requires attention to institutional design. The cross-spectrum test applies that same requirement at the next level up: to governance arrangements as a whole. The test can be applied to AI systems currently in operation, to ask if the latest AI governance frameworks pass.

5 Existing Frameworks Against the Test

5.1 Provider-Side Safety

The mechanisms developed by AI providers to keep models from producing harmful output are the most technically mature part of the current landscape. Most of this work operates on the contained end of the spectrum, where point-of-use harms manifest. The test asks whether it extends to the rest of the continuum, and whether it covers every position simultaneously.

Constitutional AI trains a model to prefer outputs consistent with a written set of principles, using feedback generated by the model itself against those principles [2]. The method reduces the rate of harmful output on the types of request it was trained against, and the reduction is measurable. The preference and its enforcement both sit inside the same model. If the model drifts, the preference can drift with it [26]. Reinforcement learning from human feedback shares the same structural feature: the reward model trained from human preferences sits inside the same training pipeline as the policy that might later exploit it [26]. Both tools work at the point of use. Neither covers risks near the middle of the spectrum, where deliberate misuse operates at scale and where adversarial action bypasses the output surface entirely. And neither reaches far end scenarios.

Runtime guardrails are vendor-built filters that sit between model output and user, applied as each response is generated [27]. They are configurable by the vendor and removable by the vendor. The presence and functionality of these mechanisms depend on the vendor's ongoing choice to maintain them. They cannot, therefore, be structurally distinct from the vendor's commercial interest. Red-teaming works differently. It is a pre-deployment stress test, run before the model reaches users, and it leaves nothing behind that continues to operate once the model is live [28]. Post-hoc logging operates after the fact. It records what the system did once the relevant output has already reached the user. It supports improvement of later versions. It does nothing to prevent harm in the instance that produced the log [25].

Anthropic's Responsible Scaling Policy [29] and OpenAI's Preparedness Framework [30] are perhaps the most developed versions of provider-side safeguards currently deployed. Both specify capability thresholds and commit to response protocols when thresholds are crossed. Neither breaks the structural pattern of co-located governance. The capability thresholds are set by the provider. The capability evaluations are run by the provider. The decisions about whether a given guardrail is sufficient, and whether deployment proceeds, are made by the provider. These frameworks are substantive artifacts of good internal risk management, but internal risk management is what the cross-spectrum test exposes as governance without efficacy.

5.2 External Regulation and Auditing

Alarmed by the inadequacy of internal frameworks as governance, external regulators have been moving in a different direction with forceful attempts to impose governance from the outside. The EU AI Act [3] classifies AI systems by risk level, prohibits a small set of practices outright, and imposes disclosure and conformity-assessment requirements on systems designated as high-risk. In other jurisdictions, executive orders and licensing proposals add further requirements along similar lines. A parallel strand of work, developed most fully by Mökander and Floridi [31], proposes ethics-based auditing as a procedural mechanism to bridge the gap between high-level principles and operational practice, drawing on auditing traditions from other industries to give external oversight workable institutional form.

Against point-of-use harms, regulatory instruments can do important work. They can restrict access, mandate transparency, impose penalties on misuse, and they are able to do so with democratic legitimacy that no internal mechanism can claim. Further along the spectrum, however, these instruments are in no structural position to address extreme threat scenarios. A legislative Act reaches AI systems through their providers' reporting obligations. Where that cooperation ends, the Act ends with it. Ethics-based auditing also sits in the same position: outside the AI system and its processes. Auditing is still disadvantaged by the same procedural externality, and it depends on the audited entity's cooperation for access. External policies without visibility to runtime can only govern outcomes. They cannot govern the processes that produce those outcomes. This is the structural gap diagnosed in Section 2, which persists as a chasm between the regulator and the governed process that they cannot reach.

5.3 Mechanism Design and Dependent Governance

The most sophisticated response to this chasm in AI governance comes from mechanism design. Fryer [32], drawing on the regulatory-procurement framework of Baron and Myerson [33], proposes that regulators offer AI firms a self-selection menu under which firms with different risk profiles choose different regulatory burdens, with incentive-compatible disclosure as the design's working principle. The appeal is genuine. The proposal addresses the information asymmetry that has defeated one-size-fits-all regulation, and it does so with the rigor of a tradition that has shaped modern regulatory economics.

Within its scope, the proposal achieves partial governance of point-of-use harms through mechanisms that make honest disclosure the firm's rational choice. What the proposal cannot do is exit the dependence that defines the current arrangement that produces the governance chasm. The menu only works if the firm selects from it. A firm that refuses both options cannot be governed by the mechanism, because the mechanism is a menu and not a constraint on the firm or its AI system. Conditions in the middle of the spectrum place the same difficulty one level up: incentive-compatible disclosure from a firm whose system has drifted in ways the firm itself has not detected cannot convey information the firm does not possess. Near the far end, the firm may not even be the relevant actor at all.

This is the ceiling of conventional thinking about AI governance, and the most sophisticated version available. Mechanism design of this caliber does not fail because its designers failed but because dependence on the governed entity is the structural feature of the arrangement the mechanism is designed to operate within.

5.4 One Common Failure Mode

Provider-side safety, external regulation and auditing, and mechanism-design proposals are three framework categories that occupy distinct disciplinary positions in AI governance. They all pour into the same arrangement: internal governance, the arrangement that Section 2 indicted as reflexive. The flaw they share is the structural one: each rests on the provider's cooperation as the load-bearing element, and each is the same reflexivity appearing under a different surface. The surface differs by case: architectural in the first, operational in the second, conceptual in the third. Internal safety mechanisms are the provider's own work. External regulation reaches the system only through the provider's reporting. Mechanism-design proposals require the voluntary disclosure by the provider. As threats move along the spectrum and the provider's intentions, capacities, or disclosure become less reliable as foundational assumptions, and the frameworks become less reliable with them. Near the far end of the spectrum, there may be no cooperating entity to bear the load at all.

None of these frameworks is capable of covering the threat conditions on the full spectrum. The failure is not an engineering problem that improved frameworks will solve. It is a structural feature of current arrangements that place the judgment function on the same substrate as the reasoning they need to govern. The next section develops what an alternate arrangement would have to be, and what is required to undo the architectural failure of co-located governance and the chasm in the preceding diagnosis.

6 The Structural Separation Requirement

6.1 Institutional Precedents

The arrangement that Section 5 diagnosed as inadequate has a clean description: the entity being governed is also the one performing the governance. Every serious institutional tradition of the last three centuries has, sooner or later, refused this arrangement.

A court that answers to the executive cannot credibly adjudicate the executive's conduct. The separation of powers was not a design preference; it was the recognition, made most clearly by Madison in Federalist 51, that power held to account by itself is power not held to account at all. The point generalizes. Financial auditors cannot be employees of the firm they audit. Sarbanes-Oxley wrote the principle into law in 2002 because the arrangements that had preceded it had failed [34]. They failed in exactly the way that this paper argues AI self-governance does. Banking supervision under Basel III rests on the same foundation: capital adequacy must be determined by supervisors independent of the banks they supervise, because the alternative (banks determining their own adequacy) had already produced governance failures that motivated the externalization requirement [35]. Pharmaceutical approval works the same way. The FDA evaluates clinical-trial data directly; the manufacturer does not self-approve. Professional licensing rests on the same foundation: physicians, lawyers, and engineers are credentialed by external bodies, because no class of practitioners can credibly authorize itself to practice.

A reader could put the objection at its strongest: AI is not a court, not a clinical trial, not a balance sheet. The technology is different in kind from anything these traditions confronted, and the institutional analogies misread the AI case.

These are not analogies between AI governance and other domains. They are five instances of the same principle, learned at different times, in different contexts, each at some cost. AI is anomalous in this company not because the technology is distinctive but because the field has declined to adopt the architectural lesson every comparable domain has already paid to learn.

6.2 The Incoherence of Self-Governance

Suppose a system evaluates its own outputs against its own constitution flawlessly. Every harmful response is caught. Every drift is detected. The internal mechanism performs at the limit of what engineering can deliver. Has governance been achieved?

It has not. A system evaluating its own compliance cannot verify that its evaluation is sound, because the evaluator and the evaluated share a substrate. If the system drifts, the evaluation drifts with it. If the system is compromised, the evaluation is compromised with it. The evaluator has no Archimedean point from which to judge its own judgment, because there is no outside to the system from which the judgment is being made.

This is not a failure of execution that better engineering will fix. It is structural to the architecture. Self-evaluation can produce reliable results under two conditions: the evaluator is trivially independent of what it evaluates (a thermostat measuring a room), or the evaluator's failures are independent of the system's failures. Neither condition holds in an AI system judging its own behavior against its own principles. The failure modes of the evaluator and the evaluated are correlated by construction, because they are the same system.

The incoherence has an epistemic signature worth naming. Co-located governance does not advertise its failures and is under no obligation for timely transparent reporting to the public. Even with external forcing events such as litigation discovery, regulatory subpoena, third-party breach, and investigative reporting, disclosure of harm is too late for intervention. This lag between failure occurrence and failure visibility is often measured in weeks or months, visible only when an external forcing event exposes what the architecture had absorbed (see, e.g., [36]). The same structural feature that produces incoherence in self-evaluation produces an epistemic delay that may permit harm to compound. Architectural separation would enable failure prevention as well as immediate failure visibility. Any adequate response to the cross-spectrum test must produce both.

6.3 Capability Is Not Legitimacy

A reader persuaded by the engineering case for internal mechanisms might still resist the structural argument on the following ground: a well-designed internal governance mechanism could be extraordinarily capable. It could catch most harmful outputs, flag most policy violations, respond faster than any external system, and do so with access to model internals no outside auditor will ever match.

Grant the capability. The objection misses what governance is for. Capability is what a mechanism can do. Legitimacy is whether the mechanism's claims about what it did can be independently verified. A brilliant audit performed by an auditor on the firm's payroll is not an independent audit, not because the auditor lacks skill but because the arrangement cannot produce the kind of verification the category requires. The structural question survives the performance question. The most capable internal mechanism imaginable still cannot provide independent verification of its own work, because the verifier and the verified are the same entity.

7 Architectural Implications

We are now in a position to ask what an architecture would have to be in order to satisfy the structural separation requirement and pass the cross-spectrum test. The requirement narrows the design space; the test maintains a stable criterion of adequacy.

7.1 Design Mandatories

The governance layer has to be external in source. It cannot be produced, hosted, or maintained by the entity operating the AI system, because any such arrangement reinstates the dependence the condition is meant to break. It has to be normatively independent, meaning it answers to a body other than the system's operator. It has to be able to receive regulatory authority layered onto it over time, so that public rules can reach the system through a channel the operator does not control.

And the layer has to work at the speed the system operates. This is where the design space gets hard. In every institutional precedent Section 6 drew on, external governance operates on slower timescales than the governed process. Courts decide cases after the fact. Auditors examine books quarterly or annually. The FDA reviews clinical trials before approval and inspects manufacturing at intervals. In each of these traditions, episodic externality has been enough, because in those domains the governed process unfolds at human speed. An AI system generating outputs at machine speed cannot be governed episodically. The governance layer has to reach the system's behavior as that behavior is happening. External yet integrated. Independent in source, continuous in operation. This is a design space most external-governance traditions have not had to enter.

Inspectability follows from the externality requirement. If the layer answers to someone other than the operator, its actions must be verifiable by parties who do not rely on the operator's good faith to confirm them. A governance action the operator has to vouch for is governance the operator controls.

7.2 Proposed Realization: A Discrete Judgment Intermediate

An architecture satisfying these requirements must first move judgment outside the AI system, breaking the co-located relationship. The arrangement proposed here places a judgment layer between the AI system and its user interface. While it is a separate layer, it connects to both. This structurally discrete layer of intelligence attaches on two sides of the interaction. It sees what the AI system produces (responses, structured parameters, actions) before anything reaches the user or takes effect. It also sees what the user sends toward the system (prompts, commands, input parameters) before the system receives it. Placed as an intermediate, the layer sits in the communication channel rather than alongside it, and nothing crosses from one side to the other without passing through this discrete judgment intermediate.

This architecture establishes governance by means of a judgment function placed discretely between the governed system and its point of contact with users, exercising a narrow set of decisions, operating outside the AI operator's authority chain, and carrying substantive rules written by the sovereigns on behalf of their citizens. As a framework, it includes the tools and access modes required for governance to operate at runtime, across the risks and conditions anywhere on the threat spectrum, simultaneously. The discrete judgment intermediate is proposed as an architectural design that meets the structural separation requirement of Section 6 and passes the cross-spectrum test. It is offered as the realization the paper's argument calls for, not as the limit of what that argument permits. What is argued for here is the necessity of externalizing AI governance as a precondition, and the necessity of cross-spectrum efficacy as the standard governance must meet. Other architectures may satisfy the same requirements; the argument does not foreclose them. It does foreclose continuing to call reflexive arrangements governance.

The design proposal is structural and architectural, evaluated on those terms [24, 37]. Empirical evaluation is a research agenda distinct from the structural question, which is the concern of the present paper.

8 Counterarguments

An internal-alignment proponent will argue: only people inside the firm can see the model do its work, and external oversight therefore has no control on what the model actually does. Serious oversight, on this view, is by necessity internal. The first point is true; Section 2 granted it. But the second does not follow. External computational governance can also have depth of access, provided the architecture is designed for it. Section 7 sketched what such an architecture would have to be; the technical realization is developed in a forthcoming companion paper. The access requirement and the independence requirement are not in competition, and treating them as alternatives has been the field's mistake, not a natural constraint. What the internal-alignment view gets right is the need for reach into the system. What it gets wrong is supposing that the reach has to come from inside.

The external-regulation view holds that regulation from outside can be made stringent enough to do the work, if the political will is found. Stringency is not the variable in question. The EU AI Act, as Section 5 observed, reaches AI systems through their providers' reporting obligations. A more stringent Act would still reach them through the same channel, because the channel is architectural, not textual. Regulators on the outside of a system that they cannot inspect as it runs can tighten the penalties for misconduct; they cannot give themselves the view that they need to govern the processes that produce misconduct. The chasm is a structural feature, not a function of enforcement intensity, and stringency alone cannot close it.

The mechanism-design view, most cleanly articulated in Fryer's proposal [32], holds that incentive-compatible arrangements can substitute for the structural separation this paper argues is necessary. Section 5 granted what the view gets right. What it cannot do is operate on a firm that declines the menu, or on conditions where the firm does not know what its system is doing, or on a far-end scenario where the firm is not the relevant actor. Incentive design is powerful where the incentives can land. It does not travel to positions on the spectrum where the incentive-bearing entity is unreliable, uninformed, or absent. The proposal's sophistication is the measure of what mechanism design can do from inside the dependent-governance frame. Its limits are where the frame ends.

Each view picks up something real about the problem. None of them fulfills the structural separation requirement on its own.

9 Conclusion

The paper has made two contributions. The first is an evaluative instrument. The cross-spectrum test asks whether a governance arrangement holds across the full range of conditions AI systems present, simultaneously and without credit transfer between positions on the spectrum. A framework adequate at the contained end and absent near the far end has not passed. By this standard, no framework currently in operation passes. Internal safety mechanisms work at the point of use and depend on the entity that they would govern. External regulation reaches the system only through the cooperation of the same entity. Mechanism design engages the firm only when the firm selects from the menu. Each is a serious response to part of the problem. None covers the problem.

The second is a structural condition that survives the test. The judgment function cannot sit on the same substrate as the reasoning that it would govern. Every high-stakes institutional tradition of the last three centuries has, after its own failures, refused the arrangement that asks an entity to govern itself. AI has inherited the principle of external governance and declined its architecture, and the chasm between the regulator and the governed process that they cannot reach is where that refusal lives. A discrete judgment intermediate — an external, inspectable judgment layer integrated with the system at runtime but structurally distinct from it — is one architecture that satisfies the condition, and its technical form is developed in a forthcoming companion paper. Other architectures satisfying the same requirements would also pass. The claim stands on the necessity of the condition, not the uniqueness of the architecture that satisfies it.

Structural separation does not require abandoning provider, regulator, or public interests. It is what holds the three together in a single arrangement.

Alongside these contributions, the diagnosis of current AI governance displaces an assumption: that internal engineering and regulation without reach can together do the work of adequate governance. They cannot. Safety engineering is valuable and should continue. It is not governance, and the field's habit of letting it wear that label has concealed the architectural gap this paper has tried to name.

Several questions remain open. Which external bodies should operate the judgment layer, how authority is vested in them, and how coordination across jurisdictions is achieved are all downstream of the structural condition and become answerable once the condition is accepted. They are not prerequisites for establishing it. The scope of the architecture is also bounded: an external judgment layer governs AI systems operating in connected and publicly networked settings. AI models running locally, or used only within isolated environments, sit outside the scope of this architecture. Such systems are in the domain of software distribution and terms of use, not of governance.

The threat spectrum does not exhaust all categories of risk that AI presents. One such case is the proliferation of synthetic information feeding back into model training, and the data collapse this produces. The harm falls on the integrity of the knowledge substrate rather than on the behavior of any single AI model. Governance fused with the governed system cannot easily detect risks of this kind, because a system situated inside the problem has no standpoint from which to recognize it.

Within the range of risks that the spectrum does map, the demands on governance are unforgiving. A governance framework valid at only one position on the threat spectrum is not governance. It is a response plan for part of the problem, scaled to look like more than it actually is. The threat spectrum is continuous, and governance must hold across it. Structural separation is how.

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