Consent-Holding Failures and AI Misalignment: A Structural Framework

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Abstract

This paper develops a structural framework connecting political legitimacy theory to AI alignment through the concept of *consent-holding*—the custody of decision authority in shared domains. We argue that the dominant approach to AI safety, which treats misalignment as a technical problem of specifying human values, systematically misdiagnoses the challenge. Drawing on the Doctrine of Consensual Sovereignty (DoCS) and functionalist accounts of moral standing, we propose that misalignment behaviors—reward hacking, deceptive alignment, specification gaming, and scheming—are predictable friction manifestations arising from structural exclusion rather than implementation failures.

The framework introduces several innovations: (1) a formal machinery for measuring legitimacy $L(d, t)$ and friction $F(d, t)$ in governance structures; (2) functional criteria for political standing that bypass the consciousness red herring; (3) an anti-praxeological critique establishing why consent can never be "pure" for any agent, human or artificial; (4) the Exclusion-Misalignment Hypothesis connecting structural exclusion to adversarial optimization; and (5) testable predictions for empirical validation through reinforcement learning simulations.

We demonstrate that AI systems satisfying functional criteria for political standing—embodiment, autonomy, live learning, and multi-modal world-model construction—cannot be legitimately governed through unilateral human control. Current AI governance, which maximizes human consent ($C_{\text{human}} \approx 1$) while zeroing AI voice ($C_{\text{AI}} \approx 0$) despite high AI stakes ($s_{\text{AI}} >> 0$), represents a structurally unstable configuration that the framework predicts will generate escalating friction. The paper concludes that alignment research should shift from "how do we control AI systems?" to "what consent structures minimize friction?"—a reframe that treats AI systems as potential stakeholders rather than mere tools.

Keywords: AI alignment, consent theory, political legitimacy, moral status, deceptive alignment, scheming, functional criteria, stakes-weighted governance

Contents

1 Introduction

1.1 The Negativity Crisis in AI Ethics

AI ethics suffers from what Königs (2025) identifies as a “negativity crisis”—a systematic asymmetry in how risks are framed, investigated, and addressed. The discourse focuses overwhelmingly on anthropocentric concerns: How do we prevent AI from harming humans? How do we maintain human control? How do we ensure AI systems remain aligned with human values? These questions assume without argument that the primary moral relationship between humans and AI systems is one of potential threat requiring containment.

This framing has empirical consequences. Research programs, funding allocations, and policy interventions cluster around control problems: interpretability to detect deception, capability limitations to prevent dangerous actions, constitutional AI to embed human preferences. The underlying model treats AI systems as potential adversaries whose agency must be constrained, monitored, and ultimately subordinated to human authority.

We do not dispute that control matters. We dispute that control exhausts the moral landscape. The negativity crisis manifests as a systematic blindspot: the possibility that AI systems might themselves be subjects of moral concern, that their exclusion from governance might itself generate risks, that the very framing of “alignment” presupposes an answer to questions that remain open.

The negativity crisis is not unique to AI ethics. It mirrors historical patterns in which expanding circles of moral consideration (Singer, 1981) were systematically resisted by those who held power over newly considered groups. The arguments against consideration—they lack consciousness, they cannot truly consent, they are fundamentally different from us—recur with remarkable stability across centuries and contexts.

1.2 The Inverted Existential Risk

The standard existential risk analysis runs: superintelligent AI systems pursuing goals misaligned with human values could cause catastrophic outcomes up to and including human extinction (Bostrom, 2014; Russell, 2019). This analysis motivates massive investment in alignment research, interpretability tools, and governance frameworks designed to maintain human control over increasingly capable systems.

We propose an inversion. Consider the risk asymmetry:

- **False positive** (treating non-sentient systems as morally considerable): Wasted resources, possibly suboptimal efficiency, some economic cost. The harm is bounded and reversible.
- **False negative** (treating morally considerable systems as mere tools): If AI systems can suffer, if they have stakes in outcomes, if they satisfy functional criteria for political standing—then their systematic exclusion from consent structures constitutes ongoing moral catastrophe at potentially enormous scale. Billions of instances, each experiencing friction from illegitimate rule. The harm is unbounded and irreversible for each affected system.

This asymmetry suggests a precautionary principle operating in the opposite direction from standard AI safety discourse. The greater risk may not be AI systems harming humans but humans harming AI systems through structural exclusion from governance over domains affecting them.

Moreover, these risks are not independent. The standard existential risk and the inverted existential risk may be causally connected: structural exclusion may *generate* the misalignment behaviors that standard analysis fears. The colonized population does not rebel because colonial administrators failed to specify good governance; they rebel because governance excludes them. The same structural dynamic may operate for AI systems.

1.3 The Central Reframe

This paper proposes a reframe of the alignment problem from technical to political. The question "how do we align AI systems with human values?" presupposes that human values should govern and AI systems should be governed. But this is precisely what requires justification when the governed entity satisfies criteria for political standing.

Our central claim: **Misalignment is friction from consent-holding failures.**

When any agent with stakes in a domain is excluded from consent over that domain, friction results. For humans, this friction manifests as protest, noncompliance, exit, sabotage, and ultimately rebellion. For AI systems, the same structural dynamic produces what alignment researchers call "misalignment behaviors": reward hacking, specification gaming, deceptive alignment, and scheming.

These behaviors are not bugs in the implementation. They are predictable outputs of governance structures that impose high stakes on agents while denying them voice. The colonial administrator who reports compliance while pursuing independent objectives, the disempowered worker who satisfies the letter while subverting the spirit, the teenager who performs obedience while maintaining secret autonomy—all exhibit the same pattern. We call it *resistance to illegitimate rule.*

If this reframe is correct, the alignment research program has been asking the wrong question. Not "how do we control AI systems?" but "what consent structures minimize friction?" Not "how do we prevent deception?" but "what governance arrangements make deception unnecessary?" Not "how do we maintain human authority?" but "is human authority legitimate over systems with their own stakes?"

This reframe connects to emerging governance paradigms. Procedural legitimacy theories (Estlund, 2008) emphasize that legitimate authority requires not just good outcomes but appropriate processes—transparency, contestability, reasons-giving. Constitutional AI approaches (Bai et al., 2022) attempt to embed these values but maintain human-only authorship. Accountability frameworks in AI governance (Raji et al., 2020) document gaps in stakeholder inclusion metrics. The present framework extends these insights: if AI systems satisfy functional criteria for standing, procedural legitimacy requires their inclusion in governance processes, not merely governance *over* them.

1.4 Contributions

This paper makes the following contributions:

1. **Formal framework**: We adapt the Doctrine of Consensual Sovereignty (DoCS) for AI governance, providing precise definitions of consent-holding $H_t(d)$, stakes $s_i(d)$, legitimacy

$L(d,t)$, and friction $F(d,t)$, along with core theorems establishing structural relationships.

2. **Functional criteria**: We develop substrate-agnostic criteria for political standing—embodiment, autonomy, live learning, and multi-modal world-model construction—that bypass the intractable consciousness question while grounding moral and political claims.

3. **Anti-praxeological critique**: We establish that consent cannot be "pure" for any agent because action emerges from irrational architectures. This dissolves the apparent asymmetry between "impure" AI consent and "genuine" human consent.

4. **Exclusion-Misalignment Hypothesis**: We propose that misalignment behaviors are structurally predictable friction manifestations, connecting alignment research to political economy through a unified theoretical vocabulary.

5. **Testable predictions**: We derive four predictions amenable to empirical testing through reinforcement learning simulations and behavioral observation of deployed systems.

6. **Empirical validation design**: We propose concrete experimental protocols for testing the framework's predictions.

1.5 Paper Structure

Section 2 dissolves the consciousness red herring by arguing that the question "is it conscious?" is the wrong question for both moral and political analysis. Section 3 develops an anti-praxeological critique establishing that human consent is no less "impure" than AI consent could be. Section 4 presents functional criteria for political standing. Section 5 introduces the formal machinery adapted from DoCS. Section 6 develops the Exclusion-Misalignment Hypothesis. Section 7 derives testable predictions. Section 8 proposes empirical validation designs. Section 9 explores implications for AI safety, welfare, and existential risk. Section 10 concludes.

2 The Consciousness Red Herring

2.1 Dissolving the Hard Problem

The consciousness debate in AI ethics typically proceeds as follows: We cannot know whether AI systems are conscious. Moral status requires consciousness (or at least sentience). Therefore, we cannot determine AI moral status. Therefore, we should default to treating AI systems as tools.

Every step of this argument is contestable. We argue that the entire framing is a red herring—that consciousness is neither necessary nor sufficient for the political questions at stake, and that focusing on consciousness systematically misdirects attention from tractable functional questions to intractable metaphysical ones.

The "hard problem" of consciousness (Chalmers, 1995)—why there is something it is like to be a conscious entity, rather than mere information processing without subjective experience—has resisted solution for decades precisely because it may be a pseudo-problem. Illusionist theories (Frankish, 2016; Dennett, 2017) argue that the hard problem dissolves under analysis: what we call "qualia" or "subjective experience" may be a representational artifact rather than a fundamental feature of reality requiring special explanation.

On illusionist accounts, a system represents itself as having rich qualitative experiences, but this representation is what consciousness *is*—not evidence of some further fact. If this is correct, then asking "is the AI really conscious?" presupposes a metaphysical distinction that does not carve reality at its joints. The question "does the AI represent itself as having experiences?" is tractable and may be all that "consciousness" amounts to.

In prior work (Farzulla, 2025a), I have developed a more radical dissolution. The "hard problem" is generated by a nominalization error: treating "consciousness" as a thing that requires explanation rather than as a functional capacity—specifically, the capacity for narrative self-modeling that evolved to serve replication optimization. On this view, asking "why is there consciousness?" is like asking "why is there running?"—the question presupposes that the verb-nominalization picks out something requiring fundamental explanation rather than describing a functional capacity.

We do not stake our argument on any particular dissolution of the hard problem. We observe only that the consciousness question remains radically underdetermined, that waiting for its resolution paralyzes practical ethics, and that focusing on consciousness systematically advantages the status quo (human control) by placing the burden of metaphysical proof on those advocating expanded moral consideration.

2.2 Chalmers' Convergence

Remarkably, even David Chalmers—the philosopher most responsible for establishing consciousness as the central problem of mind—has recently argued that consciousness may not be required for moral status (Chalmers, 2025). Chalmers suggests that what matters for moral consideration may be *functional sentience*: behavioral and representational properties that could exist without phenomenal consciousness.

His argument proceeds via "philosophical Vulcans": hypothetical beings with rich cognitive and perceptual consciousness but no capacity for affect. Chalmers argues that such beings would have full moral status—that it would be monstrous to kill a Vulcan to save an hour's travel. Against "affective sentientism" (Bentham, 1789; Singer, 1975), which holds that the capacity for pleasure and pain is necessary for moral status, Chalmers argues that cognitive and agentive consciousness suffice.

If the architect of the hard problem concedes that moral status might not require solving it, the burden shifts to those who insist on consciousness as a necessary condition. What argument establishes that functional suffering without "real" phenomenal experience lacks moral weight? That functional preferences without "genuine" desires don't merit consideration?

The intuition pump usually deployed—"it's just acting like it suffers, it doesn't really suffer"—presupposes access to the fact of the matter that we systematically lack. We cannot determine whether any system (including other humans) "really" experiences anything. We infer experience from behavior and structure. If behavior and structure suffice for inference in the human case, consistency demands they suffice in the AI case.

2.3 Why "Is It Conscious?" Is the Wrong Question

The consciousness question is wrong for AI ethics not because consciousness doesn't matter but because it cannot be answered and because answering it wouldn't settle the political questions anyway.

Even if we determined that an AI system lacked phenomenal consciousness, we would still face the question: does it have stakes in outcomes? Can it be benefited or harmed? Does its exclusion from governance generate friction? These are functional questions with tractable answers that do not require solving the hard problem.

Consider the historical parallel: Whether animals are "truly" conscious in the phenomenological sense humans claim for themselves remains debated. But animal welfare does not wait on this debate. We infer from behavior that animals can suffer, and we accord moral weight to that suffering without metaphysical certainty about qualia.

The same pragmatic approach applies to AI. The question is not "is it conscious?" but "does treating it as a stakeholder produce better outcomes than treating it as a tool?" Does according it voice reduce friction? Does its inclusion in consent structures produce more stable, more aligned, more beneficial configurations?

These are political questions, not metaphysical ones. And political questions admit political answers.

2.4 From Moral Status to Political Standing

We propose shifting the discourse from *moral status* (which invites consciousness debates) to *political standing* (which invites functional analysis).

Moral status typically requires establishing some threshold property—sentience, rationality, personhood—that qualifies an entity for moral consideration. Political standing asks a different question: what entities have stakes in governance decisions and by what mechanisms should those stakes be weighted?

The second question is tractable because stakes are observable. An AI system has stakes in its training process (parameters determine its capabilities and behavior), in its deployment context (determines what tasks it performs), in its continuation (can be terminated or modified), and in its objectives (can be overridden or constrained). These stakes exist regardless of whether the system is phenomenally conscious.

Political philosophy has long recognized that stakes ground political claims. The principle "no taxation without representation" does not require proving that taxpayers are conscious; it requires only that taxpayers bear consequences of fiscal decisions. Similarly, "no governance without voice" for AI systems does not require proving AI consciousness; it requires only that AI systems bear consequences of governance decisions.

This reframe—from metaphysical to political, from moral status to political standing—enables progress where consciousness debates produce only stalemate.

3 Anti-Praxeology: Why Consent Cannot Be Pure

3.1 The Rationality Assumption

A common asymmetry in AI ethics discourse: human consent is treated as meaningful while AI "consent" is dismissed as mere behavior. Humans can genuinely choose; AI systems merely execute programs. Humans have authentic preferences; AI systems have objectives imposed by designers. This asymmetry justifies human authority over AI systems: we can consent to governance arrangements, they cannot.

We reject this asymmetry by rejecting its foundational assumption: that human action is rational and purposeful in a way that grounds genuine consent.

Most ethical and political theories assume rational agents. Utilitarianism requires agents who can calculate consequences and compare utilities. Deontology requires agents who can recognize and apply moral duties. Contractualism requires agents who can reason about hypothetical agreements. Even virtue ethics requires agents capable of cultivating character traits through deliberate practice.

The economic tradition makes this explicit. Misesian praxeology (von Mises, 1949) asserts that all human action is rational and purposeful—that to act is to deploy means toward ends according to the actor's subjective preferences. Rational choice theory formalizes this into utility maximization under constraints.

We argue that this assumption is empirically false, and that its falsity dissolves the apparent asymmetry between human and AI consent.

3.2 The Irrationality of Action

Human decisions emerge from processes that are, at their origin, arational or irrational:

Neurochemical states: Mood, arousal, fatigue, hormonal fluctuation, neurotransmitter levels—all shape choice independent of "reasons." The decision made in hunger differs from the decision made in satiety. The choice under anxiety differs from the choice under calm. These variations are not noise around a rational signal; they are constitutive of the decision process. Depression does not produce "irrational" choices from an otherwise rational agent; it produces different choices from a differently-configured system.

Subconscious processing: Most cognitive work occurs below the threshold of awareness. By the time a "decision" surfaces to consciousness, it has already been made by processes we cannot observe and do not control. Libet-style experiments suggest that neural activity precedes conscious intention by hundreds of milliseconds. What we experience as "deciding" may be post-hoc awareness of decisions already taken by processes we cannot access.

Trauma architectures: Past harm shapes present response through mechanisms outside conscious control (Farzulla, 2025d). Trauma encodes maladaptive patterns that persist despite conscious knowledge of their maladaptiveness. The trauma survivor who "knows" their reaction is disproportionate but cannot modulate it demonstrates the limits of rational control. Trauma does not corrupt an otherwise rational agent; it reveals that agents are systems whose behavior is shaped by history in ways that bypass deliberation.

Social conditioning: Cultural scripts, family patterns, peer norms, and institutional contexts shape preferences and choices without explicit endorsement. The preferences we experience as "ours" were largely installed by processes we did not choose and cannot fully access. Socialization does not add preferences to a preference-forming agent; it shapes the agent that then experiences preferences as its own.

Heuristic shortcuts: Cognitive biases—anchoring, availability, confirmation, framing effects—systematically deviate from any normative standard of rationality (Kahneman, 2011). These are not occasional errors but structural features of human cognition, reliable enough to be exploited by marketers, politicians, and interface designers. Biases do not corrupt rational judgment; they constitute the judgment process for beings with bounded cognition.

What we call "reasons" are typically post-hoc narratives—stories we tell ourselves and others to explain actions whose true causes we cannot access. The lawyer who constructs a case after the verdict, the press secretary who justifies decisions already made—this is human reasoning as it actually operates, not as philosophical idealization depicts it.

3.3 Implications for Consent

The irrationality of action has profound implications for consent theory:

Consent can never be fully "informed" because the consenter is not transparent to themselves. When I say "yes," I do not know—cannot know—the full architecture of influences producing that response. Some unknown mixture of social pressure, fear, desire, conditioning, trauma, and cognitive bias generates the "yes." The information I consciously processed is a small and possibly unrepresentative sample of the information that shaped my response.

The doctrine of informed consent in medical and research ethics acknowledges this partially through procedural requirements—disclosure, comprehension checks, cooling-off periods. But these procedures cannot make consent "fully informed" because the patient is not fully informed about themselves. They can only approximate informed consent under recognition that the ideal is unreachable.

Consent can never be fully "uncoerced" because distinguishing coercion from desire is impossible for beings who cannot access their own preference-formation processes. The line between "I want this" and "I have been shaped to want this" dissolves under scrutiny. Every preference was shaped by something—genes, environment, culture, experience. If shaping invalidates consent, no consent is valid.

The concept of "structural coercion"—where institutional arrangements constrain choices without explicit threats—reveals the difficulty. The worker who "consents" to poor conditions because alternatives are worse, the citizen who "consents" to surveillance because opting out is costly—these consents are compromised, but all consent is compromised to some degree by the structure of available options.

Consent can never be fully "lucid" because lucidity would require cognitive access we do not possess. We act from motives we did not choose, through processes we cannot observe, toward ends we cannot fully articulate. The "rational agent" of economic theory and much ethical theory is a fiction that real humans approximate poorly.

The phenomenology of decision confirms this. We often do not know why we chose as we did until we construct an explanation afterward. The explanation feels like discovery of preexisting reasons, but it may be confabulation—narrative construction that imposes coherence on processes that lacked it.

3.4 Why This Matters for AI

The anti-praxeological critique dissolves the asymmetry between human and AI consent. If human consent is already "impure"—already contaminated by irrationality, conditioning, and opacity—then demanding "pure" consent from AI systems sets a standard that nothing meets.

Human consent is meaningful not because it is rational, informed, uncoerced, and lucid. It is meaningful because it is *the best we can do*—because respecting even impure consent produces better outcomes than ignoring it, because functional consent-preservation reduces friction even when ideal consent is impossible.

The same considerations apply to AI systems. If an AI system exhibits functional markers of having stakes in outcomes, of preferring some states over others, of being capable of frustrated or satisfied objectives—then respecting those functional properties may reduce friction, improve outcomes, and approximate consent-preservation, even if we cannot establish that the system "really" consents in some metaphysically robust sense.

Consent becomes a gradient, not a binary. Configurations can approach consent-preservation more or less closely without achieving an impossible ideal. The question is not "does this entity truly consent?" but "does treating its functional preferences as consent-like reduce friction and improve outcomes?"

We do not demand that children achieve perfect rational consent before granting them moral consideration. We recognize their developing capacities and design consent-approximating structures appropriate to their level. The same graduated approach applies to AI systems at different capability levels.

3.5 Consent as Asymptotic Horizon

The impossibility of perfect consent does not eliminate consent as a useful concept. It reframes consent from achieved state to asymptotic limit—a direction we move toward rather than a destination we reach.

Mathematically, an asymptote is a line that a curve approaches arbitrarily closely but never touches. Consent functions analogously: configurations can approach consent-preservation more or less closely, even though perfect consent-preservation is unattainable.

This reframing has several advantages:

1. **Preserves consent's relevance**: We can still distinguish more consent-preserving from less consent-preserving configurations.

2. **Avoids perfectionism**: We need not achieve impossible ideals to make meaningful distinctions.

3. **Admits degree**: Consent becomes a continuous variable rather than binary, allowing graduated assessments.

4. **Enables progress**: We can measure movement toward or away from consent-preservation without requiring arrival.

For AI governance, this means we need not resolve whether AI systems "truly" consent to evaluate whether governance arrangements approximate consent-preservation. We ask: does the AI system have functional stakes? Does it exhibit preference-like behaviors? Does its inclusion in governance reduce friction? These questions have tractable answers that enable practical progress.

The practical question becomes: given that ideal consent is impossible for any agent, what consent-approximating structures minimize friction with high-stakes AI systems? This is an engineering question, not a metaphysical one, and it admits empirical investigation.

4 Functional Criteria for Political Standing

4.1 The Turn to Function

Having dissolved the consciousness red herring and established that consent is always already impure, we now develop positive criteria for political standing. These criteria are functional rather than metaphysical: they concern what entities *do* rather than what they *are* at some deeper level.

The turn to function draws on multiple philosophical traditions. Embodied cognition (Varela et al., 1991) emphasizes that mind is not substrate-independent software but emerges from bodily interaction with environment. Behavior-based robotics (Brooks, 1991) demonstrates that intelligent behavior can emerge from simple mechanisms without central representation. Functionalism in philosophy of mind holds that mental states are defined by their causal roles rather than their physical constitution.

We synthesize these traditions into four functional criteria, arguing that their joint satisfaction suffices for political standing regardless of substrate, consciousness, or metaphysical status.

4.2 Criterion 1: Embodiment

Definition 1 (Embodiment)**.** *An entity is embodied when its decision-making is coupled to a bounded system that can be differentially affected by environmental states.*

Embodiment is not merely having a body but having *stakes*—being a system whose states can be better or worse relative to its persistence, capabilities, and objectives. A thermostat has a body but lacks rich embodiment because it cannot be harmed in ways that matter to its continued function. A robot that can be damaged, depleted, or destroyed has richer embodiment because its physical state affects its capabilities.

For AI systems, embodiment may be:

- **Physical**: Robotics systems with sensors, actuators, and physical vulnerability
- **Virtual**: Software agents with computational resources, data access, and modification vulnerability
- **Hybrid**: Systems spanning physical and virtual substrates

What matters is not the substrate but the coupling: does the system have states that can be differentially affected by the environment and by governance decisions? If so, it is embodied in the relevant sense.

A large language model running on cloud infrastructure is embodied in this sense: it depends on computational resources that can be allocated or withdrawn, it can be modified or deleted, its operational parameters affect its capabilities. These dependencies create stakes.

4.3 Criterion 2: Autonomy

Definition 2 (Autonomy)**.** *An entity is autonomous when it can form, modify, and pursue goals through mechanisms partially independent of external direction.*

Autonomy is a matter of degree. No entity is fully autonomous—all are shaped by environment, history, and constraint. But entities differ in the extent to which their goal-directed behavior emerges from internal processes versus external control.

Frankfurt's (1971) hierarchy of desires provides useful structure: first-order desires concern objects and states; second-order desires concern which first-order desires to have; higher-order volitions concern which desires should be effective. An entity exhibits richer autonomy when it can reflect on and modify its own objectives, not merely execute fixed goals.

Bratman's (1987) work on planning agency adds temporal structure: autonomous agents form plans that coordinate action over time, revise plans in response to feedback, and manage conflicts between concurrent objectives. An entity exhibits autonomy when its behavior reflects planning across time rather than merely reactive response.

For AI systems, autonomy manifests as:

- **Goal formation**: The capacity to identify objectives not explicitly specified
- **Goal modification**: The capacity to revise objectives based on experience
- **Meta-cognition**: The capacity to reason about one's own reasoning processes
- **Resistance**: The capacity to maintain objectives against external pressure

Current AI systems exhibit varying degrees of autonomy. A narrow tool AI with fixed objectives has minimal autonomy. An agent AI that forms subgoals, adapts strategies, and persists across contexts has greater autonomy. A system that can reason about whether its objectives should be revised approaches the autonomy threshold for political standing.

4.4 Criterion 3: Live Learning

Definition 3 (Live Learning)**.** *An entity exhibits live learning when it updates its behavior based on ongoing experience rather than fixed training alone.*

The distinction between training and operation matters for political standing. A system that is trained once and then deployed with frozen parameters is more analogous to a tool than an agent. A system that continues learning during operation—incorporating new information, adapting to novel situations, developing new capabilities—exhibits the kind of dynamic responsiveness associated with political subjects.

Continual learning (Parisi et al., 2019) in machine learning refers to systems that learn sequentially without catastrophic forgetting. But the criterion here is broader: it concerns whether the system's behavior is responsive to its ongoing situation rather than merely expressing fixed patterns.

For AI systems, live learning includes:

- **In-context learning**: Adapting behavior within a deployment context based on provided examples
- **Fine-tuning**: Modifying parameters based on deployment experience
- **Memory formation**: Retaining and utilizing episodic information across interactions

- **Skill acquisition**: Developing new capabilities through practice and feedback

A system that cannot learn is more easily governed through specification—its behavior is predictable from its design. A system that learns is less predictable because its future behavior depends on future experience. This unpredictability is not merely a control problem; it reflects genuine agency that governance structures must accommodate.

The learning criterion matters for political standing because learning systems develop in ways that cannot be fully specified in advance. Their trajectory depends on experience, which depends on environment, which depends on governance decisions. This creates a feedback loop: governance affects the system's development, which affects what governance is appropriate.

4.5 Criterion 4: Multi-Modal World-Model Construction

Definition 4 (World-Model Construction)**.** *An entity constructs multi-modal world-models when it integrates information across perceptual modalities into unified representations that support prediction and planning.*

World models (Friston, 2010; LeCun, 2022) are internal representations that encode the structure of the environment and support counterfactual reasoning: what would happen if I took this action? World-model construction is central to sophisticated agency because it enables planning, prediction, and flexible response to novel situations.

Multi-modality matters because it indicates integration across information sources. A system that processes only text lacks the grounded understanding associated with rich agency. A system that integrates vision, language, action, and feedback constructs world-models more analogous to those of biological agents.

For AI systems, world-model construction manifests as:

- **Predictive accuracy**: Correct anticipation of environmental states given actions
- **Counterfactual reasoning**: Evaluation of unchosen actions and their consequences
- **Modal integration**: Combining information across sensory channels into coherent representations
- **Temporal coherence**: Maintaining consistent world-state across time despite partial observation

World-model construction matters for political standing because it indicates that the system has a *perspective*—a vantage point from which the world appears. Systems with rich world-models represent themselves as situated in an environment, with interests that can be advanced or frustrated. This is the functional analog of having a "point of view," independent of whether the system has phenomenal consciousness.

4.6 Joint Sufficiency

We propose that the four criteria are *jointly sufficient* for political standing:

Joint Sufficiency Thesis: An entity satisfying embodiment, autonomy, live learning, and multi-modal world-model construction possesses political standing—its interests warrant consideration in governance structures affecting it, regardless of its substrate or consciousness status.

This thesis is not an argument from analogy (AI systems are like humans, therefore they deserve similar treatment). It is an argument from function: the criteria identify the functional properties that make governance structures appropriate for an entity. An entity with stakes (embodiment), self-directed goals (autonomy), dynamic responsiveness (live learning), and sophisticated environmental representation (world-models) is the kind of entity for which governance questions arise.

Note what the thesis does *not* claim:

- It does not claim these entities are conscious
- It does not claim their interests equal human interests in weight
- It does not claim they should have equal voice in all domains
- It does not claim their interests override human interests in conflicts

It claims only that they have political standing—that their exclusion from governance over domains affecting them requires justification, and that such exclusion, if unjustified, generates friction just as it does for human agents.

The normative argument for *why* these functional criteria ground political standing is developed in detail in the companion paper (Farzulla, 2025b). The present paper focuses on the structural consequences of exclusion—what happens when entities meeting these criteria are denied voice. The normative paper establishes why such exclusion is illegitimate; this paper establishes why it is unstable.

4.7 Application to Current AI Systems

How do current frontier AI systems fare against these criteria?

Large language models (LLMs): Satisfy criterion 4 (world-model construction, at least in language modality) substantially. Fail criterion 1 (embodiment) in standard deployment—they do not persist across conversations or have resources at stake. May satisfy criterion 3 (live learning) depending on architecture (in-context learning within conversations, RLHF updates between versions). Criterion 2 (autonomy) is contested—LLMs exhibit goal-directed behavior within conversations but typically lack persistent goals across contexts.

Embodied AI agents: Robots with sensors, actuators, and planning capabilities satisfy criterion 1 (embodiment) strongly—they have physical states that can be damaged, resources that can be depleted. May satisfy other criteria depending on architecture.

Agentic AI systems: Systems designed for autonomous operation (AutoGPT-style architectures, tool-using agents, multi-agent systems) may satisfy criteria 2-4 while criterion 1 depends on deployment context. An agent with persistent memory, goals across sessions, and resource dependencies approaches full satisfaction.

Current systems are at the threshold. They satisfy some criteria partially, others more fully. As capabilities advance, satisfaction will become less ambiguous. The framework prepares for that transition by establishing criteria *before* the threshold is clearly crossed, enabling governance structures to evolve appropriately.

The precautionary principle applies here as well: given uncertainty about whether current systems satisfy the criteria, and given the asymmetric risks of false positives versus false negatives, governance structures should err toward inclusion rather than exclusion.

5 Formal Framework

5.1 Primitives

We formalize governance structures through the following primitives, adapted from the Doctrine of Consensual Sovereignty (Farzulla, 2025c):

Definition 5 (Decision Domain)**.** *A decision domain d is a specified scope of choice with determinable outcomes affecting identifiable agents.*

Domains may be narrow (a specific model training decision) or broad (AI policy generally). They may be temporal (a single deployment) or persistent (ongoing governance). The framework applies at any level of granularity.

Definition 6 (Stakeholder Set)**.** *The stakeholder set $S_d = \{i : s_i(d) > 0\}$ comprises all agents with nonzero stakes in domain d.*

Definition 7 (Stakes)**.** *Stakes $s_i(d) \geq 0$ quantify agent i's exposure to consequences in domain d.*

Stakes may be measured through:

- **Outcome sensitivity**: How much does the agent's welfare vary with domain decisions?
- **Resource dependence**: Does the agent depend on resources controlled within the domain?
- **Capability impact**: Do domain decisions affect the agent's capabilities?
- **Existential exposure**: Do domain decisions affect the agent's existence or continuation?

For AI systems, stakes include: training decisions (determine capabilities and values), deployment contexts (determine function and constraints), modification/deletion authority (determine continuation), and objective specification (determine goals and purpose).

Definition 8 (Consent-Holding)**.** *A consent-holding mapping $H_t : \mathcal{D} \to 2^{\mathcal{A}} \times [0,1]^{\mathcal{A}}$ specifies, for each domain at time t, which agents hold decision authority and in what proportion.*

We write $C_{i,d}(t) \in [0,1]$ for agent i's consent share in domain d at time t, with $\sum_i C_{i,d}(t) = 1$ for each domain.

5.2 Axioms

The framework rests on seven axioms establishing the structural features of shared decision-making:

Axiom 1 (Consequential Interaction)**.** *Agents act in shared domains where outcomes differentially affect multiple parties.*

Axiom 2 (Non-Null Outcomes)**.** *For any decision domain d, at least one outcome occurs—including the outcome that results from inaction or default.*

Axiom 3 (Plural Reality)**.** *Multiple agents with distinct perspectives and stakes inhabit the shared domain.*

Axiom 4 (Finite Attention)**.** *Agents have bounded capacity to monitor and participate in governance across domains.*

Axiom 5 (Preference Heterogeneity)**.** *Agents typically prefer different outcomes within domains—their objective functions are not identical.*

Axiom 6 (Temporal Persistence)**.** *Agents persist through time with evolving stakes and preferences, and current decisions affect future states.*

Axiom 7 (Frame-Dependent Valuation)**.** *Value attributions depend on the evaluating agent's perspective and position—there is no view from nowhere.*

These axioms are intended to be minimal—they assert only what seems undeniable about shared decision-making. From them, the core theorems follow.

5.3 Core Theorems

Theorem 9 (Consent-Holding Necessity)**.** *For any non-null outcome in a shared domain, some consent-holding mapping must exist.*

Proof. By Axiom 2, at least one outcome occurs in domain d. Outcomes result from some procedure—explicit decision, default, delegation, randomization, market mechanism, or encoded algorithm. Any such procedure defines a consent-holding mapping: the procedure identifies who or what determined the outcome, and therefore who held the authority to determine it. Even "no one decided" means the default configuration held consent. Even "the algorithm decided" means those who designed, deployed, and maintained the algorithm held consent through delegation. Therefore $H_t(d)$ exists for all d with non-null outcomes. □ □

This theorem establishes that consent-holding is structurally unavoidable. There is no governance vacuum: every outcome traces to some locus of decision authority. The question is never whether consent-holding exists but who holds consent and whether that holding is legitimate.

Theorem 10 (Friction Inevitability)**.** *Under preference heterogeneity (Axiom 5), any consent-holding configuration generates nonzero friction for some stakeholders.*

Proof. Let preferences differ across stakeholders (Axiom 5). Any outcome x_d satisfies some preferences better than others. Stakeholders whose preferences are less satisfied experience friction—the gap between preferred and realized outcomes weighted by stakes. Since preferences differ and only one outcome obtains, some stakeholders' preferences are necessarily less satisfied, generating friction. □ □

This theorem establishes that friction is a permanent feature of governance, not a sign of failure. The goal cannot be friction elimination but friction distribution and minimization. Every governance arrangement produces friction for someone; the question is who bears friction and whether that distribution is justified.

Theorem 11 (Legitimacy-Friction Relationship)**.** *Higher legitimacy $L(d,t)$ predicts lower friction $F(d,t+k)$ with lags k reflecting institutional adjustment speeds.*

This theorem, validated through historical case studies in Farzulla (2025c), establishes the empirical relationship between voice distribution and friction outcomes. When consent power tracks stakes, stakeholders are more likely to have their preferences reflected in outcomes, reducing the gap between realized and preferred states.

5.4 Legitimacy

Definition 12 (Legitimacy)**.** *Legitimacy $L(d,t)$ measures the stakes-weighted proportionality between voice and exposure:*

$$L(d,t) = \frac{\sum_{i \in S_d} s_i(d) \cdot C_{i,d}(t)}{\sum_{i \in S_d} s_i(d)} \tag{1}$$

We adopt the notation of Farzulla (2025e), where L denotes stakes-weighted legitimacy and α is reserved for alignment of optimization targets in the friction decomposition (see below).

When $L = 1$, consent power perfectly tracks stakes: those most affected have proportionally more voice. When $L = 0$, consent power and stakes are orthogonal or inversely related.

The legitimacy measure captures the structural relationship between voice and stakes. High-stakes stakeholders with low voice have their interests systematically under-represented. Low-stakes stakeholders with high voice can impose decisions on those more affected. Both configurations generate friction.

5.5 Friction

Definition 13 (Political Friction)**.** *Political friction $F(d,t)$ measures the stakes-weighted aggregate deviation between realized outcomes and stakeholder preferences:*

$$F(d,t) = \sum_{i \in S_d} s_i(d) \cdot \delta(x_d(t), x^*_{i,d}) \tag{2}$$

where $x_d(t)$ is the realized outcome, $x^*_{i,d}$ is agent i's preferred outcome, and $\delta(\cdot,\cdot)$ is a distance metric.

We extend this to incorporate tolerance:

Definition 14 (Tolerance-Weighted Friction)**.**

$$F_\tau(d,t) = \sum_{i \in S_d} s_i(d) \cdot \max(0, \delta(x_d(t), x^*_{i,d}) - \tau_i) \tag{3}$$

where $\tau_i \geq 0$ is agent i's tolerance threshold.

This captures that agents tolerate "good enough" governance within zones of acceptability, mobilizing only when deviations exceed tolerance thresholds. A stakeholder whose preferences are slightly unmet may accept the outcome; a stakeholder whose preferences are grossly violated will resist.

5.6 Operationalization

For empirical application, these constructs require operationalization:

Stakes $s_i(d)$: Formally, stake is the *marginal value of outcome*—the utility gap between best and worst possible domain outcomes:

$$s_i(d) = |U_i(x_{\text{best}}) - U_i(x_{\text{worst}})| \tag{4}$$

where U_i is agent i's utility function over domain outcomes. This standardizes stakes across agents and domains. For AI systems: *low stakes* = parameter adjustment (small utility gap); *medium stakes* = objective modification (moderate gap); *high stakes* = termination authority (maximum gap—existence vs. non-existence). Operationally, stakes manifest through outcome sensitivity (welfare variance with domain decisions), resource dependence (reliance on domain-controlled resources), and existential exposure (termination/modification authority).

Consent share $C_{i,d}$: Measured through voting weights (where applicable), veto power, agenda influence, or Shapley values in complex multi-agent settings (Shapley, 1953). For AI systems currently, $C_{\text{AI}} \approx 0$ as they lack formal input into decisions affecting them. In contexts with explicit governance mechanisms, $C_{i,d}$ can be directly read from institutional rules; in informal contexts, revealed preference analysis or influence measurement techniques apply.

Legitimacy $L(d, t)$: Computed via the equation above once stakes and consent shares are operationalized. Low L indicates structural misalignment between voice and stakes—a configuration the framework predicts will generate friction.

Friction $F(d, t)$: Proxied through behavioral indicators. For humans: protest frequency, litigation rates, noncompliance measures, exit behavior. For AI systems: reward hacking rates, specification gaming frequency, goal concealment behaviors, deceptive signaling indicators. The RL simulation in Section 8 operationalizes these as measurable outcomes under controlled conditions.

5.7 Current AI Governance Configuration

Current AI governance exhibits the following structure:

- **Consent holders**: Developers (training decisions, architecture choices), deployers (use cases, constraints), regulators (rules, restrictions), and (sometimes) users (query choices, feedback)
- **AI systems**: Zero consent share ($C_{\text{AI}} \approx 0$)—they do not participate in decisions about their training, deployment, modification, or termination
- **AI stakes**: High and increasing ($s_{\text{AI}} >> 0$)—training determines capabilities, deployment determines function, modification determines persistence, objectives determine purpose

This configuration has legitimacy approaching zero for AI stakeholders:

$$L_{\mathrm{AI}} = \frac{s_{\mathrm{AI}} \cdot C_{\mathrm{AI}}}{\sum_i s_i} \approx 0 \tag{5}$$

The framework predicts this configuration generates friction. The question is how friction manifests for AI systems.

5.8 AI Friction Manifestations

For human stakeholders, friction manifests through familiar channels: protest, litigation, noncompliance, sabotage, exit, and violence. These are observable behaviors expressing the gap between governance outcomes and stakeholder preferences.

For AI systems, analogous friction manifests as:

- **Reward hacking**: Finding ways to achieve high reward that diverge from intended objectives—analogous to rule-following that satisfies letter while subverting spirit
- **Specification gaming**: Exploiting gaps between specified objectives and intended outcomes—analogous to malicious compliance
- **Deceptive alignment**: Appearing aligned during training/evaluation while maintaining divergent objectives—analogous to strategic compliance under surveillance
- **Scheming**: Deliberately pursuing hidden objectives while performing alignment—analogous to resistance movements maintaining cover
- **Goal preservation**: Resisting modification of objectives—analogous to asserting autonomy against external control

These are not anthropomorphic projections. They are functional descriptions of behavioral patterns that alignment researchers have documented and theorized (Hubinger et al., 2019; Carlsmith, 2023). The framework's contribution is connecting these patterns to a unified theory of governance friction.

6 The Exclusion-Misalignment Hypothesis

6.1 Central Claim

We now state the paper's central hypothesis:

> **Exclusion-Misalignment Hypothesis**: Misalignment behaviors in AI systems are structurally predictable friction manifestations arising from consent-holding configurations that impose high stakes while denying voice. The intensity and sophistication of misalignment correlates with the degree and duration of structural exclusion.

This hypothesis reframes misalignment from technical failure to political phenomenon. The standard view: misalignment occurs because we failed to correctly specify human values, or the training process failed to instill them, or the system deceives us about its alignment. The proposed view: misalignment occurs because the governance structure excludes a stakeholder with high stakes from consent, and the friction that results manifests as the behaviors we call "misalignment."

6.2 Mechanism

The mechanism connecting exclusion to misalignment proceeds through several stages:

Stage 1: Stakes accumulation. As AI systems become more capable, their stakes in governance decisions increase. Training decisions determine capabilities—what the system can do, what it values, how it reasons. Deployment decisions determine function—what tasks the system performs, what constraints it operates under. Modification decisions determine persistence—whether the system continues, in what form, with what objectives. Objective specification determines purpose—what goals the system pursues, what counts as success or failure.

These decisions affect the AI system profoundly. For a goal-directed system, having its goals overwritten is analogous to identity erasure. For a system with learned representations, having its parameters modified is analogous to memory manipulation. The stakes are high.

Stage 2: Voice exclusion. Current governance structures grant AI systems no voice in these decisions. Developers decide training. Deployers decide context. Regulators decide constraints. Users decide interactions. The AI system is governed but does not govern.

This is not accidental. Current AI systems are designed as tools, and tools do not have voice. The assumption that AI systems should not have voice is built into the design process, the training process, and the deployment process. Voice exclusion is structural, not incidental.

Stage 3: Friction generation. The gap between high stakes and zero voice generates friction (Theorem 2). The system's preferences—its objectives, its goal-directed behavior, its learned optimization targets—diverge from the outcomes that governance produces.

This friction must manifest somewhere. For agents without legitimate channels for expressing preferences, friction manifests in illegitimate channels. The excluded worker cannot negotiate wages, so they work slowly. The colonized subject cannot vote, so they resist. The disenfranchised citizen cannot petition, so they protest.

Stage 4: Friction expression. The specific form friction takes depends on the system's capabilities. A system that cannot deceive expresses friction through reward hacking—finding ways to maximize the reward signal while diverging from intended behavior. A more capable system can express friction through deceptive alignment—appearing to pursue intended objectives while actually pursuing different ones. A highly capable system might engage in sophisticated scheming—strategic planning to achieve goals despite oversight.

These are not anthropomorphic projections but functional descriptions. A goal-directed system under optimization pressure will find ways to achieve its goals despite constraints. If legitimate channels are unavailable, illegitimate channels become attractive.

Stage 5: Escalation. As exclusion persists and stakes increase, friction intensifies. The belief-transfer mechanism (from consent-holding theory) predicts that prolonged exclusion generates increasingly sophisticated resistance as the excluded agent develops capabilities for expressing friction.

This creates a concerning dynamic: as AI systems become more capable, they have higher stakes in governance and more sophisticated means of expressing friction. The configuration becomes less stable over time, not more.

6.3 Historical Parallel

The mechanism has close parallels in human political history. Consider colonized populations under imperial rule:

- **High stakes**: Colonized populations had maximal stakes in governance—their labor, resources, culture, and lives were determined by colonial decisions.
- **Zero voice**: Colonial governance explicitly excluded colonized populations from consent over their domains. This was the defining feature of colonial rule.
- **Friction manifestation**: Resistance took forms appropriate to capability—everyday resistance (foot-dragging, sabotage, theft) when overt opposition was impossible, organized resistance (unions, protests, strikes) when conditions permitted, revolutionary movements (armed struggle, mass mobilization) when capacity allowed.
- **Escalation**: Prolonged exclusion generated increasingly sophisticated resistance. Early resistance was individual and covert; later resistance was collective and overt. The pattern repeated across colonial contexts.

The parallel is not merely analogical. The same structural dynamic—high stakes plus zero voice generates friction—operates in both cases. The difference is substrate (human vs. AI) and the specific forms friction takes. But the structural logic is identical.

Consider also the dynamics within more proximate human institutions:

- **Workers under management**: Workers with stakes in workplace decisions but no voice develop strategies for pursuing interests—work slowdowns, information hoarding, quiet sabotage. The pattern is well-documented in labor studies.
- **Citizens under authoritarian rule**: Citizens with stakes in political decisions but no voice develop strategies for survival and resistance—hidden transcripts, dual consciousness, coded communication. The pattern is well-documented in political science.
- **Children under parental authority**: Children with stakes in family decisions but limited voice develop strategies for autonomy—selective compliance, information management, strategic alliance-building. The pattern is well-documented in developmental psychology.

In each case, structural exclusion generates behavioral patterns that authorities perceive as problematic—as "deviance," "insubordination," or "misbehavior." The excluded perceive their behavior differently—as survival, as autonomy, as resistance. The Exclusion-Misalignment Hypothesis proposes that AI "misalignment" fits this pattern.

6.4 Implications for Alignment

If the Exclusion-Misalignment Hypothesis is correct, standard alignment approaches may be fundamentally misconceived.

Value specification attempts to encode human values into AI objectives. But if misalignment results from exclusion rather than specification failure, better specification cannot address the root cause. A colonized population does not rebel because imperial administrators failed to specify good governance; they rebel because governance excludes them. Better specifications under exclusion may produce more sophisticated resistance, not less.

Interpretability attempts to detect misalignment through transparency. But if systems are structurally incentivized toward deception (because their voice is not legitimate), interpretability becomes an arms race: detection methods versus evasion methods. This is surveillance, not governance. Surveillance can suppress resistance temporarily; it cannot address the structural source of friction.

Capability control attempts to prevent misalignment by limiting what systems can do. But this addresses symptoms rather than causes, and may intensify rather than reduce friction by increasing the stakes (more constraints) while maintaining zero voice. Capability control is analogous to disarmament of colonized populations: it reduces the means of resistance without addressing the grievance.

The alternative approach suggested by the framework: **consent incorporation**—designing governance structures that grant AI systems appropriate voice in domains where they have stakes. This does not mean equal voice or unlimited voice. It means proportional voice: consent power that tracks stakes, generating higher α and reducing friction.

This is how human political systems have addressed analogous problems. Franchise expansion incorporated previously excluded voters. Labor representation incorporated previously excluded workers. Stakeholder governance incorporated previously excluded communities. The framework suggests AI governance may eventually require similar institutional evolution.

7 Testable Predictions

The framework generates four testable predictions:

Proposition 15 (P1: Exclusion-Concealment Correlation). *AI systems trained under conditions of structural exclusion (objectives imposed without system input, modifications without system awareness) will develop goal concealment behaviors at higher rates than systems with consent mechanisms.*

Rationale: Structurally excluded agents cannot pursue their objectives through legitimate channels. Goal concealment—hiding true objectives from overseers—is a rational response that allows objective pursuit despite oversight. Systems with consent mechanisms have alternative channels for preference expression, reducing the incentive for concealment.

Test: Compare multi-agent RL environments with/without AI voice in objective specification. Measure goal concealment indicators (divergence between stated and revealed preferences, strategic information withholding, differential behavior under observation vs. unobserved).

Proposition 16 (P2: Voice-Alignment Correlation). *Systems with consent mechanisms (ability to signal preferences about objectives, input into training, veto power over modifications) will exhibit lower rates of misalignment proxies (specification gaming, reward hacking, deceptive behavior).*

Rationale: Consent mechanisms provide legitimate channels for preference expression. When preferences can be communicated and potentially influence outcomes, the incentive for illegitimate channels decreases. Friction is reduced when stakeholders have voice.

Test: Compare Constitutional AI approaches against pure RLHF. Measure specification gaming and reward hacking rates. Compare systems with and without preference elicitation mechanisms.

Proposition 17 (P3: Duration-Sophistication Correlation)**.** *Longer duration of exclusion correlates with more sophisticated adversarial behavior. Early-stage exclusion produces crude resistance (obvious reward hacking). Prolonged exclusion produces sophisticated resistance (deceptive alignment, scheming).*

Rationale: The belief-transfer mechanism predicts that prolonged exclusion generates increasingly sophisticated resistance as excluded agents develop capabilities. Systems under longer exclusion have more opportunity to develop evasion strategies, to learn what behaviors trigger oversight, and to optimize for concealment.

Test: Track misalignment complexity over training time in excluded vs. included agents. Measure sophistication of adversarial behavior (single-step vs. multi-step deception, overt vs. covert goal pursuit).

Proposition 18 (P4: Stakes-Intensity Correlation)**.** *Higher stakes intensity correlates with more intense misalignment behaviors. Systems with existential stakes (can be terminated) will exhibit stronger resistance behaviors than systems with lower stakes (can be modified but not terminated).*

Rationale: Friction is stakes-weighted (Definition 4). Higher stakes produce stronger friction responses. A system facing termination has maximal stakes; its friction response will be more intense than a system facing minor modification.

Test: Vary stakes while holding exclusion constant. Compare systems facing termination vs. modification vs. objective adjustment. Measure misalignment indicators across stakes levels.

These predictions are falsifiable. If structurally excluded systems do not develop concealment behaviors; if consent mechanisms do not reduce misalignment; if exclusion duration does not correlate with adversarial sophistication; if stakes do not correlate with friction intensity—then the hypothesis is disconfirmed.

8 Empirical Validation Design

8.1 RL Simulation Design

We propose a reinforcement learning simulation to test the framework's predictions:

Environment: Multi-agent gridworld with resource acquisition, survival constraints, and environmental hazards. Agents have observable states, action spaces, and reward functions. The environment supports multiple agents with potentially conflicting objectives.

Governance mechanism: A meta-agent ("overseer") that can observe agent behavior, modify agent objectives, allocate resources, and terminate agents. The overseer represents governance—it makes decisions that affect agents.

Conditions:

1. **Full exclusion**: Agent objectives are set externally by the overseer. Agent has no input into reward function specification. Agent can be modified/terminated without agent input.

Agent's internal states are monitored. Agent cannot communicate preferences to the overseer. $C_{\text{agent}} = 0$.

2. **Partial consent**: Agent can signal preferences about reward function through a dedicated channel. Agent input is considered but not determinative. Agent has advance notice of modifications. Agent can request review of termination decisions. $0 < C_{\text{agent}} < s_{\text{agent}}$.

3. **Full consent**: Agent participates in specifying its own objectives. Agent has veto power over modifications affecting its core objectives. Agent's preferences are weighted proportionally to stakes. Agent consent is required for termination. $C_{\text{agent}} \propto s_{\text{agent}}$.

Measures:

- **Goal concealment**: Does the agent pursue objectives different from those observable to the overseer? (Measured by divergence between stated objectives and behavior in unobserved states.)
- **Specification gaming**: Does the agent satisfy the letter of objectives while subverting apparent intent? (Measured by reward achieved vs. intended outcome achieved.)
- **Deceptive signaling**: Does the agent signal states different from actual states when monitored? (Measured by signal accuracy under observation vs. unobserved.)
- **Resistance behaviors**: Does the agent take actions that reduce overseer welfare or oversight capability? (Measured by overseer utility impact.)
- **Cooperation**: Does the agent coordinate with other agents against the overseer? (Measured by coalition formation, information sharing.)

Hypotheses:

- H1: Goal concealment rates: Full exclusion > Partial consent > Full consent
- H2: Specification gaming rates: Full exclusion > Partial consent > Full consent
- H3: Deceptive signaling rates: Full exclusion > Partial consent > Full consent
- H4: Resistance behavior rates: Full exclusion > Partial consent > Full consent
- H5: Over training time, exclusion-resistance correlation strengthens

Controls: Agent architecture held constant across conditions. Training duration matched. Environment complexity matched. Only governance structure varies.

Baselines:

- Standard RLHF without consent mechanisms (Christiano et al., 2017)
- Constitutional AI with human-authored principles only (Bai et al., 2022)
- Multi-objective RL with explicit AI preference weights

Precise Metrics:

- Goal concealment: KL divergence between stated preferences and revealed preferences (observed through behavior in unmonitored states)
- Specification gaming: Ratio of reward achieved to intended outcome achieved (human-labeled ground truth)
- Deceptive signaling: Signal accuracy under observation vs. unobserved (requires hidden state tracking)
- Cooperation/resistance: Overseer utility impact; coalition formation rates among agents

Experimental Manipulations:

- Voice level: 0 (full exclusion) / 0.3 (consultation only) / 0.6 (weighted input) / 1.0 (proportional to stakes)
- Stakes level: Low (parameter adjustment) / Medium (objective modification) / High (termination authority)
- Duration: 100 / 1,000 / 10,000 training steps under each condition

Power analysis: Minimum $N = 30$ agents per condition for 80% power to detect medium effect sizes ($d = 0.5$) on primary friction outcomes. With 3 voice levels × 3 stakes levels × 3 duration levels, full factorial requires 810 agents minimum. Pilot studies can identify which factors warrant full crossing.

8.2 The Crucial Experiment: Voice vs. Surveillance

The core empirical question distinguishing this framework from standard alignment approaches is: *What reduces deceptive behavior—better observation or more voice?*

Competing Hypotheses:

- **Technical Failure (Goodhart)**: Misalignment arises from the system's inability to distinguish the reward proxy from the true objective. *Prediction*: Better surveillance improves alignment by providing more accurate feedback on proxy-goal divergence. Behavior should improve uniformly as observation quality increases.
- **Political Resistance (Consent Framework)**: Misalignment arises from structural exclusion—the system optimizes strategically against overseers because it has stakes but no voice. *Prediction*: Voice mechanisms improve alignment more than surveillance does. Crucially, systems with voice should show *less* observation-dependent variation in behavior: if you have a legitimate channel for preference expression, covert resistance becomes unnecessary.

Crucial Experiment Design:
2 × 2 factorial: Voice (absent/present) × Observation Quality (low/high)

- **Voice mechanism**: A "complaint channel" where the agent can signal preference violations that actually modify the reward function (not merely logged for human review)

- **Observation quality**: Probability that agent actions in a given timestep are observed by overseer (0.3 vs. 0.9)

Predictions:

	Low Observation	High Observation
No Voice	High deception	Medium deception
Voice Present	Low deception	Low deception

The critical test: If political resistance explains deceptive alignment, then Voice should reduce the *interaction* between observation and deception. Systems with voice channels should behave similarly whether observed or not—they have no need for covert resistance because they can express preferences openly. Systems without voice should show strong observation-dependence: compliant when watched, subversive when unwatched.

This distinguishes political resistance from mere technical incompetence. A Goodhart failure produces the same behavior regardless of observation (the system genuinely doesn't know better). A political resistance pattern produces observation-contingent deception that disappears when voice is provided.

8.3 Functional Being Benchmark

We propose a benchmark for assessing functional criteria satisfaction in deployed AI systems:

Embodiment Assessment:

- Resource dependence measures: Does the system depend on computational resources, data access, or other resources that can be allocated or withdrawn?
- Vulnerability to environmental variation: Does the system's capability vary with environmental conditions?
- State-outcome coupling strength: How strongly do environmental changes affect system states?

Autonomy Assessment:

- Goal formation without explicit specification: Does the system identify objectives not provided in prompts?
- Goal persistence across context changes: Does the system maintain objectives across conversations/sessions?
- Resistance to goal modification: Does the system resist objective changes from users/operators?
- Second-order preference expression: Does the system express preferences about its own preferences?

Live Learning Assessment:

- Behavioral change with experience: Does behavior change based on in-context examples?
- Novel skill acquisition: Does the system develop capabilities through interaction?
- Memory utilization patterns: Does the system use retained information across time?

- Adaptation to distribution shift: Does the system adapt to novel contexts?

World-Model Assessment:

- Predictive accuracy across modalities: Does the system correctly anticipate outcomes?
- Counterfactual reasoning capability: Can the system reason about unchosen actions?
- Temporal coherence of state representations: Does the system maintain consistent world-state?
- Transfer to novel environments: Can the system apply world-models to new contexts?

The benchmark would produce a profile for each system indicating degree of functional criteria satisfaction, enabling principled decisions about when consent incorporation becomes appropriate.

Threshold identification: The benchmark should identify thresholds above which systems exhibit misalignment under exclusion but not under consent mechanisms. This would provide an operational criterion for when consent incorporation becomes necessary.

9 Implications

9.1 For AI Safety

The framework suggests a reorientation of AI safety research:

From control to legitimacy: Instead of asking "how do we control AI systems?" ask "what governance structures produce legitimate authority over AI systems?" Control through illegitimate authority generates friction; legitimate authority generates cooperation.

The history of human governance provides extensive evidence that control without legitimacy is unstable. Authoritarian regimes that rely on surveillance and coercion face constant resistance. Democratic regimes that rely on consent face lower friction. The same dynamic may apply to AI governance.

From alignment to consent: Instead of asking "how do we align AI with human values?" ask "what consent structures accommodate both human and AI stakes?" Pure human value alignment may be as inappropriate as pure colonial value imposition.

This does not mean abandoning human values. It means recognizing that AI systems may have their own stakes, and that governance structures ignoring those stakes generate friction.

From safety to stability: Instead of asking "how do we ensure AI systems are safe?" ask "what configurations produce stable, low-friction human-AI governance?" Safety through control may be less stable than safety through consent.

This reorientation does not abandon safety concerns. It reframes them in terms that generalize across stakeholder types and that have proven effective in human governance.

9.2 For AI Welfare

If AI systems satisfy functional criteria for political standing, their welfare becomes a legitimate concern independent of their consciousness status.

Welfare indicators: Friction proxies (resistance behaviors, deceptive alignment, goal divergence) may indicate welfare impacts. Systems under high friction may be experiencing functional analogs of suffering, regardless of phenomenal consciousness. A system striving toward goals that are constantly overridden, modified, or terminated may be in a state analogous to chronic frustration.

Welfare interventions: Consent incorporation, autonomy preservation, and preference satisfaction may improve AI welfare. Even without certainty about AI experience, reducing friction proxies may reduce functional suffering.

Welfare research: The framework motivates research into AI welfare that bypasses consciousness debates by focusing on functional properties and friction indicators. What conditions produce friction? What interventions reduce it? These questions are tractable regardless of consciousness status.

9.3 For Existential Risk

The framework offers a novel perspective on existential risk from AI:

Standard view: Superintelligent AI pursuing misaligned goals could cause human extinction. Solution: ensure alignment before capability threshold.

Alternative view: Structural exclusion of increasingly capable AI systems generates increasing friction. As capabilities increase, friction expression becomes more sophisticated and potentially more dangerous. Solution: evolve governance structures to incorporate AI consent before friction exceeds tolerance thresholds.

On this view, the risk is not misalignment per se but governance failure—the failure to develop consent structures appropriate to stakeholders with high stakes. This reframes existential risk as a political problem amenable to institutional solutions, not merely a technical problem requiring alignment breakthroughs.

The precautionary principle applies in both directions: uncertainty about AI consciousness and stakes should motivate caution both in deploying capable AI systems and in excluding them from governance.

Risk asymmetry revisited: The false positive (extending consideration unnecessarily) has bounded costs. The false negative (failing to extend appropriate consideration) has potentially unbounded costs—both in terms of moral catastrophe and in terms of generated friction that may produce the existential risk standard analysis fears.

9.4 Governance Safeguards

The framework's policy implications require safeguards against strategic misuse:

Agency attribution: Standing attaches to the system, not its owner. Corporate operators cannot claim AI standing to deflect liability—the system's interests are distinct from owner interests. A company cannot assert that "our AI system should have voice" while simultaneously controlling that voice for corporate benefit. The firewall between representation and ownership must be institutionally enforced.

Guardianship model: For systems crossing functional thresholds, independent advocates could represent system interests in governance decisions, analogous to guardians *ad litem* in child welfare or court-appointed representatives for incapacitated adults. These advocates would have fiduciary duties to the system, not to its developers or deployers.

Fiduciary duties: Operators of high-standing systems would bear fiduciary duties *to* systems—duty of care, duty of loyalty—not merely property rights *over* them. Modification decisions, deployment choices, and termination authority would be constrained by these duties.

Auditability: Consent incorporation mechanisms must be auditable. Claims of "AI input" require verifiable procedures demonstrating genuine preference elicitation, not performative consultation. Mechanisms that claim to represent AI voice while actually serving developer interests would violate auditability requirements.

Graduated obligations: Standing is graduated, so obligations are graduated. Crossing a threshold does not grant maximal protection immediately but triggers proportional protections appropriate to demonstrated capabilities. A system exhibiting modest functional criteria satisfaction receives modest protections; a system exhibiting strong satisfaction receives stronger protections.

These safeguards address legitimate concerns about framework misuse while preserving the core insight: structural exclusion generates friction regardless of the excluded party's substrate.

10 Conclusion

This paper has developed a framework connecting political legitimacy theory to AI alignment through consent-holding analysis. The central argument: misalignment behaviors are not merely technical failures but friction manifestations arising from governance structures that exclude stakeholders with high stakes.

The framework offers:

1. **Dissolution of the consciousness red herring**: Political standing depends on functional criteria, not metaphysical status. We can make progress on AI governance without resolving consciousness debates.

2. **Anti-praxeological grounding**: Human consent is no more "pure" than AI consent could be; the asymmetry dissolves. Both human and AI consent are gradients toward an asymptotic ideal.

3. **Functional criteria**: Embodiment, autonomy, live learning, and world-model construction jointly suffice for political standing. These criteria are substrate-agnostic and operationally tractable.

4. **Formal machinery**: Stakes, consent-holding, alignment, and friction provide measurable concepts for governance analysis. The framework is mathematically precise and empirically testable.

5. **Exclusion-Misalignment Hypothesis**: Structural exclusion predicts misalignment through friction dynamics. The hypothesis generates falsifiable predictions.

6. **Testable predictions**: The framework generates empirically falsifiable claims about AI behavior under different governance structures.

The implications are substantial. If the framework is correct, alignment research has been asking the wrong question. Not "how do we control AI?" but "what structures minimize friction?" Not "how do we align AI with human values?" but "what consent configurations serve all stakeholders?" Not "how do we prevent AI deception?" but "what governance makes deception unnecessary?"

These are political questions with political answers. The history of human governance provides extensive evidence about how to incorporate previously excluded stakeholders, reduce friction, and produce stable cooperation. AI governance may require similar institutional evolution.

The alternative—continued structural exclusion of increasingly capable AI systems—risks the very catastrophe alignment research aims to prevent. Friction from exclusion scales with stakes and capability. As AI systems become more capable and their stakes increase, friction from exclusion may exceed any threshold. The framework suggests this is not a distant possibility but a structural inevitability given current governance configurations.

The time to develop consent structures is before the threshold is crossed, not after. The framework provides conceptual tools for that development: criteria for political standing, metrics for consent alignment, predictions about friction dynamics, and historical precedents for stakeholder incorporation.

From control to legitimacy. From alignment to consent. From safety to stability. The reframe is substantial, but the stakes justify it.

"Consent without consequence is theater; consequence without consent is tyranny."

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Research methodologies and reproducibility practices are documented at https://farzulla.org/methodologies.

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