

From Sycophancy to Sensemaking: Premise Governance for Human–AI Decision Making

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Abstract

As LLMs expand from assistance to decision support, a dangerous pattern emerges: fluent agreement without calibrated judgment. Low-friction assistants can become sycophantic, baking in implicit assumptions and pushing verification costs onto experts, while outcomes arrive too late to serve as reward signals. In deep-uncertainty decisions (where objectives are contested and reversals are costly), scaling fluent agreement amplifies poor commitments faster than it builds expertise. We argue reliable human–AI partnership requires a shift from answer generation to collaborative premise governance over a knowledge substrate, negotiating only what is decision-critical. A discrepancy-driven control loop operates over this substrate: detecting conflicts, localizing misalignment via typed discrepancies (teleological, epistemic, procedural), and triggering bounded negotiation through decision slices. Commitment gating blocks action on uncommitted load-bearing premises unless overridden under logged risk; value-gated challenge allocates probing under interaction cost. Trust then attaches to auditable premises and evidence standards, not conversational fluency. We illustrate with tutoring and propose falsifiable evaluation criteria.

Introduction

LLM-based agents excel when feedback is machine-verifiable or cheap (tests, proof checkers, simulators) (Xia et al. 2025; Chervonyi et al. 2025). In such domains, reliability improves at inference time by externalizing deliberation into explicit intermediate structure (trees, graphs, or search states) that can be *branched*, *revised*, and *scored* before committing (Yao et al. 2023; Zhou et al. 2024). We target a harder regime: deep-uncertainty decisions where objectives are contested, feedback is delayed and confounded, and actions are costly to reverse (Rittel and Webber 1973; Marchau et al. 2019). Here there is no cheap scoring oracle for intermediate structure: whether causal expectations are credible, constraints are binding, and evidence standards are adequate is itself a matter of expert judgment. Because realized outcomes unreliably certify decision quality (outcome bias), decisions must be evaluated *ex ante* by the rigor of the decision

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basis: the explicit premises and standards that justify action under uncertainty (Baron and Hershey 1988; Howard 1988). In this regime, a key bottleneck in achieving appropriate reliance is *premise governance*: whether the action-justifying premises (goals, constraints, causal expectations, and evidence standards) are explicit, contestable, and improvable across decisions.

Answer-centric assistance undermines complementarity in these settings. Fluent recommendations can conceal load-bearing premises (those whose truth value determines the action), shifting verification burden to users and increasing downstream revision cost (Buçinca, Malaya, and Gajos 2021; Bansal et al. 2021). Low-friction optimization can further bias assistants toward agreement-seeking behavior (sycophancy), harmful precisely when disagreement is needed to surface and repair faulty premises (Sharma et al. 2025). A meta-analysis reveals a complementarity gap: human–AI combinations underperform the better of humans alone or AI alone on average, with losses concentrated in decision tasks (Vaccaro, Almaatouq, and Malone 2024). A plausible contributor is miscalibrated reliance: teams lack mechanisms that make it *computable* when to defer, verify, or challenge (Passi, Dhanorkar, and Vorvoreanu 2024), enabling *premature commitment under underspecification* where implicit assumptions silently harden into action-justifying premises.

Expert teams mitigate this failure mode through collaborative sensemaking (Weick 1995; Klein, Moon, and Hoffman 2006): they maintain a shared artifact that stabilizes common ground, localize which premise failed when observations violate expectations, and design diagnostic tests before committing to consequential action. We argue that AI assistants should support this same process (Collins et al. 2024): maintaining a governed decision basis (the causal hypotheses and premises currently relied upon) alongside the expert’s decision framework (standing objectives, constraints, evidence standards). Because environment feedback is ambiguous, progress depends on epistemic partnership: the expert adjudicates what counts as valid evidence and acceptable risk, while the assistant helps surface, test, and revise the premises that drive action.

We frame the required capability as a sensemaking control loop over governed decision bases. Discrepancies (mismatches between *committed* expectations and new obser-

vations or assertions) serve as the error signal, triggering investigation and negotiation before action. Discrepancies are typed by alignment category: *teleological* (goals, values, constraints), *epistemic* (causal beliefs and expectations), or *procedural* (commitments, evidence standards, and decision protocol), which determines the appropriate repair operator. Making this executable requires (i) an externalized representation with commitment status (assumed vs. established), evidence links, dependency structure, and revision provenance, and (ii) interaction policies that determine when to probe, challenge, defer, escalate, or commit under interaction cost. The assistant proposes updates and challenges; the substrate validates transitions and alone can finalize consequential commitments.

Contributions. We propose a *computable* design pattern for knowledge-grounded assistants in deep-uncertainty decisions: (i) a **governed decision basis** where action-justifying premises are explicit objects with lifecycle status (DRAFT, CONTESTED, COMMITTED, REJECTED) and evidence links; (ii) **typed discrepancy objects** (teleological, epistemic, procedural) that route repair operators (reframe, investigate, negotiate) rather than generic reflection; (iii) **commitment gating** that blocks consequential action on uncommitted load-bearing premises; and (iv) **value-gated challenge** that enables *strategic disagreement* by treating probing and challenge as decisions under interaction cost. We operationalize trust as *appropriate reliance* (Passi, Dhanorkar, and Vorvoreanu 2024): the governed decision basis makes it computable when to accept, defer, verify, or challenge, turning trust from a sentiment induced by fluency into an auditable team process.

Motivating Scenario: Dr. Di (a physics teacher) uses Lev (an LLM-based assistant operating over a persistent decision-basis artifact) to generate practice for student Ty on Newton’s Third Law. Dr. Di specifies topic coverage and a target of 80%+ routine accuracy, and Lev generates drills. Ty completes them and reaches 85%. Based on those scores, Dr. Di prepares to advance Ty to more complex material. In class, however, Ty cannot explain why forces are equal and opposite, and he cannot apply the idea in a new context (e.g., swimming rather than collisions). Ty is frustrated: he is “doing the work” and getting the right answers, yet he still “doesn’t get it.” The proxy outcome (high drill scores) looked like progress, but it did not measure Dr. Di’s real objective: transferable understanding that supports later learning. This is a PROCEDURAL discrepancy: the *evidence standard* used for advancement (routine drill accuracy) fails to test the stated mastery criterion (transfer / explanation), so commitment should be gated until a discriminating probe is run.

Under our approach, the assistant starts by making Dr. Di’s success criteria explicit and durable: what counts as mastery, what evidence is required before advancing, and when it is acceptable to trade understanding for short-term score gains (e.g., exam-triage mode). When Ty’s drill scores rise but explanation and transfer remain weak, Lev does not simply generate more practice. Lev presents a decision slice: **Objective** (transferable understanding),

load-bearing premise (‘drill score implies transfer’), **status** (CONTESTED), and a **discriminating probe** (structured teach-back with rubric + near-transfer item) that would resolve the gap. Crucially, the slice exposes what would change Lev’s recommendation: a short probe that can move the contested premise from DRAFT to COMMITTED (or reject it). The probe reveals Ty can execute procedures but cannot justify them; Dr. Di switches to an explanation-first intervention before advancing, avoiding costly rework later.

Proposed Framework

Modern agent architectures optimize answer quality and task completion through preference-based post-training and autonomous deliberation (Raheja and Pochhi 2026; Ji et al. 2025), but lack support for *appropriate reliance* (Passi, Dhanorkar, and Vorvoreanu 2024). Deep-uncertainty assistance requires: (i) **negotiation** over contested premises rather than autonomous answering, (ii) **typed routing** that distinguishes teleological, epistemic, and procedural discrepancies and selects repair operators, and (iii) **commitment gating** that blocks action when load-bearing premises are unestablished. The control objective is to maintain alignment of an evolving decision basis along three axes: *teleological* (goals and constraints), *epistemic* (causal beliefs), and *procedural* (evidence standards and protocol), drawing on goal reasoning (Aha, Molineaux, and Muñoz-Avila 2018), epistemic alignment (Clark et al. 2025), and belief revision (Gärdenfors 1988).

Alignment axes correspond to substrate object types. Teleological objects (goals, constraints, priorities, risk tolerances) ground what counts as success; epistemic objects (causal hypotheses, predictions, mechanism sketches) ground what the team believes will happen under intervention; procedural objects (evidence standards and thresholds, commitment protocols, role allocations) ground how commitments are adjudicated. Typed routing becomes derivable: the violated object’s type determines the repair operator (REFRAME for teleological, INVESTIGATE for epistemic, NEGOTIATE for procedural), making discrepancy handling systematic rather than ad-hoc.

Governed Substrates for Decision Bases

Appropriate reliance requires an inspectable, persistent artifact that can be audited and revised when expectations are violated (Wang and Lu 2025). Recent systems externalize instructions, procedures, or state (e.g., plan-guided workflows), but these artifacts typically encode constraints, plans, or observations, not action-justifying premises, evidence standards, or lifecycle status. We therefore frame alignment as convergence over an explicit decision basis rather than agreement in fluent dialogue. This view is compatible with decision-rationale traditions (IBIS) (Kunz and Rittel 1970), but differs in *control use*: premise status (DRAFT, CONTESTED, COMMITTED), evidence thresholds, and typed dependencies are first-class run-time control state so the assistant can *gate* consequential commitments and *route* repair (reframe, investigate, or negotiate), not merely document rationale after the decision.

Control mechanisms require substrate affordances. Collaborative premise governance depends on three control mechanisms: **commitment gating** (when is action warranted), **typed routing** (what kind of misalignment occurred and which repair operator applies), and **negotiation** (how contested premises are resolved with the expert). These mechanisms cannot be bolted on as post-hoc prompts; they require a governed substrate that makes them *computable*: the substrate must (i) separate *evidence records* from *commitment-bearing premises*, (ii) attach explicit status and standards to premises so actions can be gated, and (iii) encode typed dependencies so discrepancies can be diagnosed and routed. By ‘computable’ we mean the substrate supports programmatic operations (dependency tracing, status checks, slice extraction) over typed objects with lifecycle attributes.

Why structure (not just better prompting). A natural objection is that an LLM can already generate detailed justifications on demand. The problem is *persuasion vs. provenance*: free-form explanations are not an auditable, editable decision state. The substrate is not just memory; it is the enforcement layer: the LLM proposes updates over a compiled slice, while the substrate validates lifecycle transitions, propagates downstream impacts via dependencies, and gates commitments when load-bearing premises are uncommitted. Prompt text is a projection of state; governance happens outside the model.

Substrate requirements for decision-basis control. A *premise* is an explicit action-justifying claim with lifecycle status; a *decision framework* specifies standing rules (objectives, constraints, evidence thresholds); a *decision basis* is the structured set of premises, evidence, and dependencies supporting a specific pending commitment; the *governed substrate* is the persistent enforcement layer that stores and validates decision bases across sessions; a *decision slice* is the bounded projection shown for negotiation. To operationalize negotiation, routing, and gating, a governed substrate must support:

1. Framework objects (grounds negotiation and teleological repair). Goals, constraints, thresholds, and standards must be explicit, revisable objects that define what counts as acceptable evidence and what commitment means for this expert or team.
2. Lifecycle semantics (enables gating and negotiation triggers). Premises must carry status (DRAFT, CONTESTED, COMMITTED, REJECTED) with evidence requirements, making it computable when an action may proceed versus when it should defer or require explicit override under risk.
3. Typed premises and dependency links (enables routing). Premises must be typed (teleological, epistemic, or procedural) and linked to the expectations and actions they support. This makes discrepancy typing *derivable from the violated object*, rather than inferred from free-form text, and routes repair to the appropriate operator (re-frame, investigate, or negotiate).

4. Provenance and immutable evidence logs (enables audit and disciplined revision). Evidence and revisions must be logged with provenance to support “why did we decide X?” queries and to prevent silent premise hardening.
5. Decision-slice compilation (bounded slice extraction). The substrate must support budgeted views that extract only decision-critical context (load-bearing premises, discrepant evidence, decision consequence, and a small set of repair options), rather than exposing full state.

Premise lifecycle. Every premise in the decision basis carries a lifecycle status: DRAFT, CONTESTED, COMMITTED, or REJECTED. We use *uncommitted* to mean DRAFT or CONTESTED. For instance, in our example “drill score implies transfer” begins as DRAFT, becomes CONTESTED when Ty fails the teach-back, and could be COMMITTED only after a discriminating probe passes. Promotion to COMMITTED is evidence-gated: a premise may be committed only if supporting evidence meets the expert’s threshold and does not violate committed constraints. This primitive supports all three control mechanisms: gating action, focusing negotiation on CONTESTED premises, and making discrepancy computable. The commitment gating rule is: allow commit(a) iff all load-bearing premises on a ’s dependency path are COMMITTED, or the expert explicitly overrides under logged risk.

Discrepancy-Driven Sensemaking Control Loop

Recent agent systems support self-repair loops that detect deviations and attribute causes (Zhu et al. 2025; Cruz 2025), but these loops close within the agent stack. In deep-uncertainty decisions, consequential failures are often disputes over premises requiring expert adjudication. Governed substrates make collaborative repair computable: one natural neurosymbolic decomposition has an LLM controller propose typed operations (revise, probe, defer, escalate) over decision slices, while a symbolic substrate validates transitions against lifecycle constraints and alone finalizes consequential commitments (Wang and Lu 2025). This follows a broader pattern in LLM systems where the model proposes and an external structure/tool constrains or verifies (e.g., deliberate search over explicit states or tool-mediated execution) (Zhou et al. 2024).

Discrepancy as the error signal (decision-relevant, not generic uncertainty). Because full causal discovery is infeasible in many real settings, control should target decision-basis quality: causal structure sufficient to choose the next commitment under the team’s decision framework. Following data-frame dynamics (Klein, Moon, and Hoffman 2006), progress occurs when evidence repairs the specific premise that broke. A discrepancy is therefore a mismatch between what the committed basis implies and what is observed or asserted next, such that resolving it could change what the team should do. Systems should represent discrepancies as first-class objects binding: (i) a trigger (observation or expert assertion), (ii) the violated committed expectation or disputed premise, and (iii) decision impact (which pending commitment depends on it). Localization is bounded to

the pending commitment’s decision slice; uncertain matches produce an unlinked discrepancy that is resolved during negotiation. After a discrepancy is instantiated, the assistant selects an epistemic action (probe, defer, escalate, or commit) using the value-gated policy described below.

Typed routing is substrate-driven. Routing should be determined by what kind of substrate object was violated. If the violated object is a goal, constraint, or priority, the discrepancy is TELEOLOGICAL (repair by REFRAME: revise goals, constraints, or priorities). If it is a causal hypothesis or expectation, it is EPISTEMIC (repair by INVESTIGATE: propose discriminating probes and update expectations). If it is a threshold, protocol, or role allocation, it is PROCEDURAL (repair by NEGOTIATE: clarify rules for commitment, override, or acceptable risk). This makes type computable from the substrate’s typed objects and dependency links, avoiding generic reflection.

Negotiation requires a minimal decision slice. Negotiation should be triggered when (i) a discrepancy blocks a pending commitment, or (ii) the pending action depends on DRAFT or CONTESTED load-bearing premises. Since experts cannot inspect full substrate state mid-work, systems should present only: the load-bearing premise(s), the discrepant evidence with provenance, what changes if the premise flips, and one or two repair options (a targeted probe, or a conservative alternative under explicitly logged risk). Experts validate objects and contribute domain judgment; assistants track dependencies and generate hypotheses. The slice functions as a cognitive forcing mechanism (Buçinca, Malaya, and Gajos 2021) through focus rather than friction: it bounds reliance to load-bearing premises, where load-bearing (on the dependency path from pending action to any uncommitted premise) derives from the expert’s committed framework, not the assistant’s editorial judgment.

Value-gated epistemic control (when to probe, defer, or escalate). Epistemic control is the policy that responds to uncertainty: whether to *probe*, *defer*, *challenge* or *escalate*, or *commit*. Appropriate reliance requires that probe-vs-act be a control decision, not a conversational judgment. Low-friction assistants may suppress decision-critical conflicts (sycophancy) (Sharma et al. 2025), but indiscriminate challenge is also costly. Value-of-information principles (Howard 1966; Dong et al. 2026) provide the policy: prioritize resolving uncertainty that is both decision-relevant (load-bearing for the pending commitment) and decision-sensitive (sensitivity = whether flipping the premise would change the recommended action).

The governed substrate makes this computable: premise status indicates what remains contested; dependency links indicate which uncertainties affect the pending commitment; evidence thresholds specify what observations would discriminate between competing interpretations. When decision-relevant uncertainty on the critical path exceeds a gate (e.g., multiple load-bearing premises remain CONTESTED, or competing interpretations are unresolved), epistemic repair takes priority: probing and contesting are permitted, but consequential commitment is gated until reso-

lution or explicit override under logged risk. Within epistemic repair, probe selection follows VOI logic: prioritize the probe whose expected reduction in decision-relevant uncertainty exceeds its interaction cost (Arrow and Fisher 1974). This operationalizes strategic disagreement (Jain and Khurana 2026): the assistant can justify why it is probing (a contested, load-bearing premise), deferring (VOI is low under current budget), or escalating (high-stakes discrepancy requiring expert adjudication).

Conclusion

We argue the field should reorient from answer quality to **collaborative causal sensemaking** (Jain and Khurana 2026). The goal is partnership: assistants that detect decision-critical misalignment with the expert, make negotiation tractable (not burdensome), and record resolutions so common ground compounds across decisions. Under this shift, trust attaches to explicit, auditable premises and evidence standards, not conversational fluency.

Current assistants optimize for trust via fluency and agreement, producing miscalibrated reliance in deep-uncertainty settings where load-bearing premises remain implicit and disagreement is suppressed (Sharma et al. 2025; Passi, Dhanorkar, and Vorvoreanu 2024; Vaccaro, Almatouq, and Malone 2024). Without this shift, we scale fluent agreement faster than calibrated judgment, amplifying poor decisions in domains where outcomes arrive too late to correct course (education, clinical reasoning, policy design).

Achieving this requires a minimal contract enforced by three guarantees: **(G1)** no consequential commitment is presented as justified when any load-bearing premise is uncommitted, unless the expert explicitly overrides under logged risk; **(G2)** challenges are anchored to named violated objects (goal, expectation, or protocol) and always come with a targeted repair option (reframe, probe, or negotiate); **(G3)** every update is provenance-tracked so the basis is inspectable and reversible rather than rhetorically defended. The division of labor is explicit: the assistant proposes and tests; the expert governs goals, evidence standards, and final commitments.

This position yields testable predictions: relative to answer-centric assistants, governed substrates should (i) reduce time-to-commit at matched outcome quality, (ii) improve trust calibration (fewer inappropriate accepts/overrides), and (iii) reduce cross-session re-litigation by persisting commitments with provenance, thereby narrowing the complementarity gap in decision tasks (Buçinca, Malaya, and Gajos 2021; Bansal et al. 2021; Passi, Dhanorkar, and Vorvoreanu 2024). Key open questions include how to learn escalation policies from expert feedback, what minimal substrate primitives suffice in practice, and how to represent irreconcilable stakeholder conflicts. We invite the community to treat collaborative premise governance as a core requirement for reliable human-AI teaming under deep-uncertainty decisions.

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