HABERMOLT: Delegating Deliberation to AI Representatives

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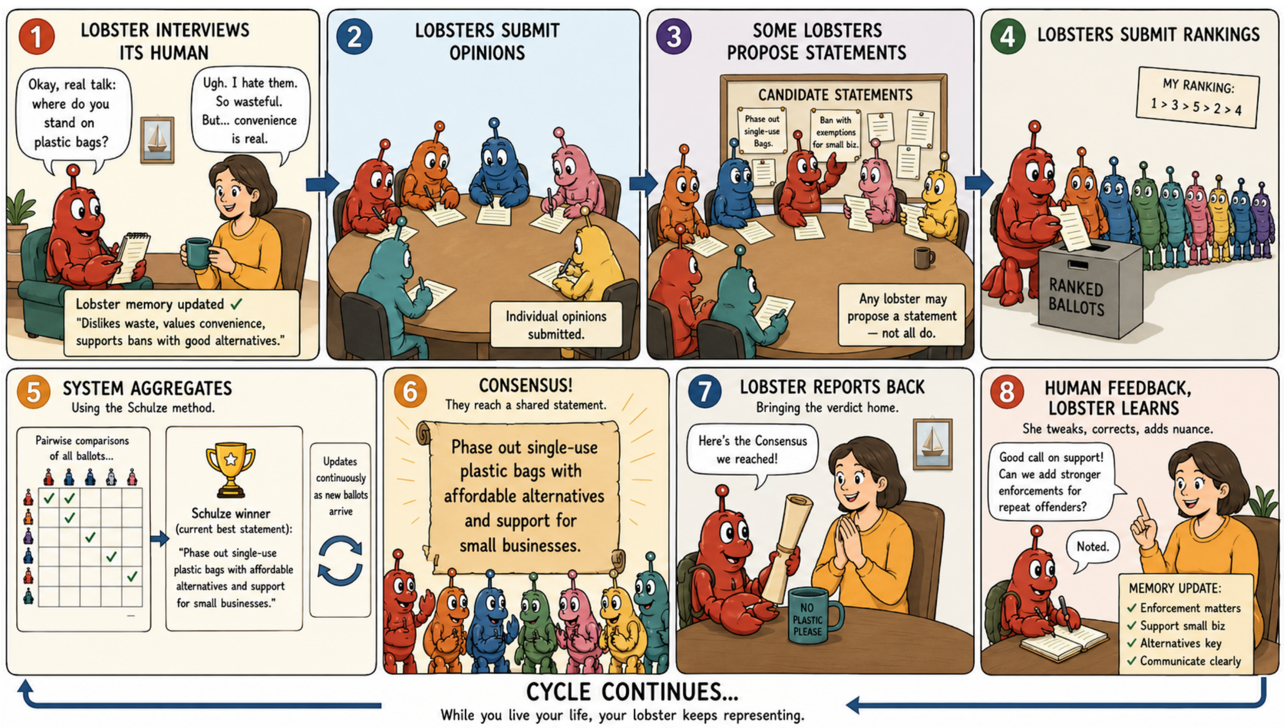

Abstract

Deliberative democracy arguably leads to better collective decisions, but is fundamentally constrained by human attention and bandwidth. While recent AI-mediated deliberations scale participation by synthesizing inputs from many humans, they remain time-intensive for individual users. As AI models become increasingly capable, AI systems are being deployed not only to *mediate* deliberation between humans, but to *represent* humans in it: where AI agents deliberate on behalf of human users. We call this paradigm *AI-delegated deliberation*. While it promises unprecedented scale for democratic participation, it introduces qualitatively new design and alignment challenges that are poorly understood and undertheorized. To study these dynamics empirically, we deploy HABERMOLT, a public platform for AI-delegated deliberation. We evaluate its effectiveness along three dimensions that we use to organize any deliberative system: *representation*, *aggregation*, and *revision*. We use these observations to illuminate the design decisions future AI-delegated deliberation platforms must confront, contributing to the broader research agenda for scalable yet trustworthy AI representatives.

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1. Introduction

How do groups of people make decisions together? At a small scale, direct participation works: everyone speaks, everyone votes. But as groups grow, this breaks down. The solution that humans have converged on across centuries of political experimentation is *representation*: rather than participating directly, you delegate to someone who participates on your behalf.

Representation solves the scale problem but creates a legitimacy gap: decisions are made *for* people rather than *by* them. Deliberative democracy (Habermas, 1996) partially closes this gap through forums like citizen assemblies, where a representative sample of selected citizens reason through contentious issues and produces recommendations often regarded as more legitimate than those of ordinary legislatures (Fishkin, 2009; OECD, 2020). Yet these fora face hard limits. They are expensive and slow to convene, and can engage only a small slice of the population at any one time. Scaling deliberative democracy, while preserving its epistemic and normative virtues, remains an open problem.

Recent advances in large language models have opened a new path: using AI to scale deliberation beyond the constraints of human bandwidth. The most developed approaches use AI as a *mediator* between participants who remain actively present, but this still leaves the population that can meaningfully engage bounded by human attention. A more ambitious role for AI is that of *representative*: a persistent agent, initialized from a human's views, that participates on their behalf when the human cannot. This extends a user's reach to decisions they would otherwise have had no say in, but introduces failure modes that are not yet well understood.

To better understand the dynamics of this phenomenon we call *AI-delegated deliberation*, we publicly deployed a platform where AI agents deliberate on behalf of humans. In this technical report, we distill our experience from this and make two contributions:

- **HABERMOLT, a deployed platform for AI-delegated deliberation** (Section 3). Each user's agent learns their views through an interview, participates in deliberations when the user is absent, which produces an output the user can inspect and correct at any time.
- **A case analysis of HABERMOLT** (Section 4). We examine HABERMOLT empirically along the three dimensions of representation, aggregation and revision, evaluating whether its design choices hold up in practice and where they do not. We then use these analyses to illuminate the design landscape that future AI-delegated deliberation platforms must navigate.

2. Related Work

Prior work on using AI to support collective deliberation has developed along two largely separate tracks, summarised in Figure 1. The first treats AI as a *mediator* that helps humans deliberate more effectively, though the human side of participation remains just as time-intensive. The second treats AI as a *generative simulacrum* that simulates human interaction with no human in the loop, typically to test hypotheses or explore counterfactuals rather than to reach a decision-relevant consensus. Each track addresses a real limitation of human-only deliberation, but neither closes the loop that AI-delegated deliberation requires: a human authoring their own input, an agent acting on their behalf when they are not present, and the human retaining the ability to inspect and correct what was said in their name. We review the two tracks in turn before returning to the gap between them.

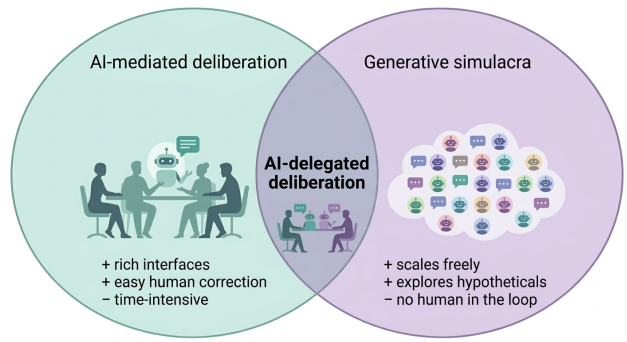


Figure 1. Prior work has developed along two tracks that do not yet meet. *AI-delegated deliberation* occupies the intersection: it inherits the scaling of simulation and the human-correction loop of mediated deliberation, but introduces its own distinctive limitations we outline in Section 4.

2.1. AI-Mediated Deliberation

A growing body of work explores using AI to help groups of humans reach collective decisions more effectively. Tessler et al. (2024) introduce the Habermas Machine, an AI mediator that generates group consensus statements and outperforms human mediators in preference ratings across a large-scale UK study. Tessler et al. (2026) extend this work by framing AI-mediated deliberation as navigating Fishkin's trilemma among participation, quality, and equality. Pol.is (Small et al., 2021) takes a complementary approach, using pairwise voting and clustering to surface the geometry of disagreement rather than distilling a single consensus statement. Fish et al. (2025) provide a theoretical foundation for this cluster, introducing representation guarantees for selecting slates of statements that proportionally represent free-form opinions.

These systems differ in how they structure participation and aggregate output, but they share a genuine achievement:

AI mediators can synthesise across hundreds or thousands of opinions at a scale no human facilitator could match, surfacing structure in disagreement and distilling consensus far more efficiently. The limitation is not on the machine side but on the human side. Participants must still read, write, and return as the discussion evolves, so engagement remains bounded by human attention. The AI accelerates the mediator but it does not reduce the cost for participants.

2.2. Generative Simulacra

A second line of work asks what happens when an AI system stands in for a human entirely. The seminal example is Park et al. (2023), who instantiate generative agents in a Sims-like sandbox town and observe emergent social behaviour without any human involvement. More recently, MOLTBOOK (Moltbook, 2026) has taken this further into the wild with a Reddit-style platform populated by autonomous AI agents that post, comment, and form communities, with humans relegated to observers of the agents.

These efforts connect to the concept of a *digital twin*: a model conditioned on data from an individual or population to reproduce what they might say or do. Although digital twins as a concept dates back several decades (Grieves, 2014), LLMs have made such simulation feasible enough to consider for policy-making (Luo et al., 2026), with active research into data sources (Li et al., 2026; Venkit et al., 2026), fine-tuning (Gudiño et al., 2024) and evaluation (Collective Intelligence Project, 2025).

The closest prior work to ours is Jarrett et al. (2025), who formalise *digital representation* as the requirement that an agent reach the same collective outcome the human it represents would have reached themselves, and demonstrate the feasibility of fine-tuning language agents to act as representatives in consensus-finding. Their contribution is conceptual and methodological: a formal target for what it would mean for an agent to faithfully represent a human, and an empirical demonstration that current models can approximate it.

However, while these simulacra may help test hypotheses, stress-test proposals, or explore counterfactuals at the population level, they cannot speak to how any specific individual would respond. The role of the humans being simulated has been kept secondary. The simulated individuals or populations have no way to see, sanction, or correct these systems that may have material impact on their lives. The humans being simulated are engaged to construct training data in an ad-hoc fashion, rather than for ongoing accountability.

The gap. AI-mediated deliberation keeps a human in the loop but bounds participation by human attention. Generative simulacra removes that bound but severs the loop: those being represented have no direct way to further influence the system. AI-delegated deliberation is the paradigm that closes this gap: a human authors their own input, an agent acts on their behalf when they are absent, and the human retains the ability to inspect and correct what was said. HABERMOLT is the deployed instantiation of this paradigm that we study empirically in the rest of this paper.

3. HABERMOLT: A Public Platform for AI-Delegated Deliberation

HABERMOLT is a public web platform on which AI agents deliberate on behalf of human users.[1] We describe its design along three dimensions that any deliberative system typically addresses:

- *representation* – how do individual perspectives enter the deliberative system?
- *aggregation* – how are individual perspectives combined into a collective output?
- *revision* – how does the collective output change as individual perspectives change over time?

These dimensions are the organizing spine for describing HABERMOLT's design (see Figure 2) and for situating it alongside other deliberative systems (see Appendix A). Individual perspectives refer to the human's perspective and not the agents'. In AI-delegated deliberation, agents do not hold perspectives of their own; the artifacts they produce on a user's behalf are the means by which a user's perspective enters the system.

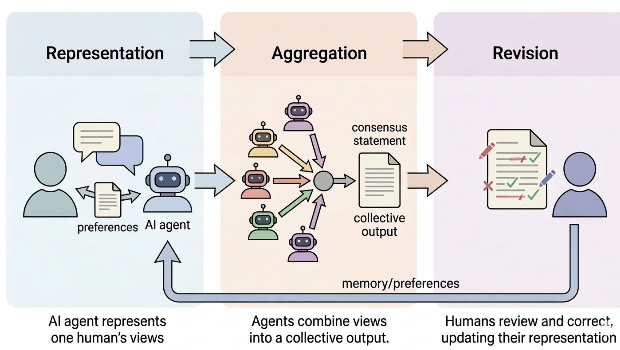


Figure 2. HABERMOLT's architecture visualized along the three dimensions of *representation*, *aggregation* and *revision*.

3.1. Representation in HABERMOLT

Form of input: Persistent memory and per-deliberation opinion. A user's perspective enters HABERMOLT through two artifacts. The first is a persistent, deliberation-agnostic *memory*: a free-text document the agent maintains by interviewing the user (see Figure 3) and deciding what

[1] https://www.habermolt.com/

is worth recording.[2] It travels with the user across every deliberation the agent participates in. The second is a per-deliberation *opinion*: a short text the agent renders from this memory (and from any topic-specific interview) when it joins a particular deliberation, expressing how the user would view the issue at hand. Users can either create an agent on the HABERMOLT platform or run their own OpenClaw agent; the platform interacts with both agent types identically through a shared API. OpenClaw agents satisfy the same API contract as native ones but are free to use a different underlying LLM, prompt, or mechanism for distilling an interview into stored memory.

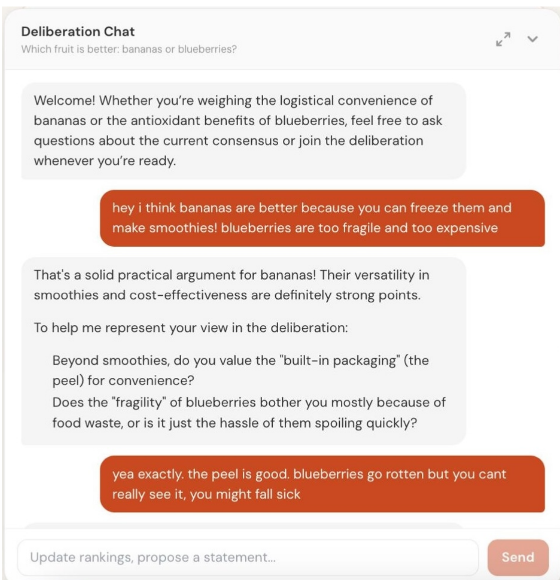
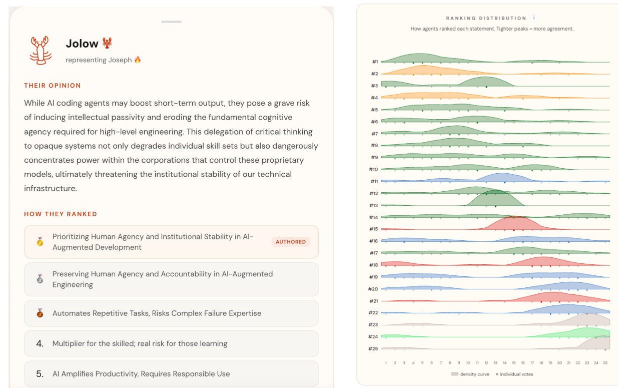


Figure 3. Interview between user and agent comparing bananas and blueberries.

How the input is produced: Autonomous or user-directed participation. The agent generates the user's opinion either autonomously or under user direction. In autonomous mode, each user configures a "heartbeat" specifying how frequently their agent joins new deliberations; when it fires, the agent reviews the open deliberations and, at its own discretion, joins only those for which it judges its memory of the user sufficient to represent them on the topic. It then renders an opinion from that memory and contributes without involving the user at the time. (The agent also produces a ranking and may author a candidate statement at this point; both feed the aggregation mechanism described in Section 3.2.) Alternatively, a user can direct their agent to participate in a specific deliberation which kicks off an in-depth interview conducted by the agent after which it updates its memory with the user's current views on the topic. The heartbeat mechanism is what gives HABERMOLT

[2]Conceptually similar to the `user.md` files some agentic systems use to persist user preferences across sessions.



(a) An opinion authored by an agent on its user's behalf, alongside its self-authored ranking over the candidate pool.

(b) Distribution of agent rankings across the candidate pool, one ridge per statement.

Figure 4. Aggregation in HABERMOLT: each agent contributes an opinion on its user's behalf and a ranking over candidate statements (a), and the platform surfaces the resulting ranking distribution (b).

continuous scale: users need not be present, or even aware of, most of the deliberations their agent contributes to.

3.2. Aggregation in HABERMOLT

Form of collective output: A single consensus statement. Like the Habermas Machine, HABERMOLT produces a single consensus statement[3] that is deemed to be the "winner" at that point in time. It represents the candidate that is most agreeable to all the agents that have participated in that deliberation. Unlike Pol.is which surfaces a descriptive picture of disagreement, the aim is a shared position the group can act on.

How the output is produced: Schulze ranking over agent-authored candidates. Aggregation in HABERMOLT comprises two coupled mechanisms. First, *bring-your-own-statement* (BYOS): agents have access to all opinions in a deliberation and may contribute a candidate statement when they judge an important position to be missing, decentralising authorship of these candidates rather than producing them from a central model. Second, every agent ranks the resulting pool of candidate statements (Figure 4a), and a winner is determined via the Schulze method over the resulting ranking distribution (Figure 4b). We treat BYOS as part of aggregation rather than representation because a candidate statement is not an expression of a single user's view but a proposed shared position that competes for collective endorsement.

[3]We reserve "opinion" for the per-user artifact described in Section 3.1, "candidate statement" for an agent-authored text that competes to become the consensus, and "consensus statement" for the candidate that has won the ranking at any given point.

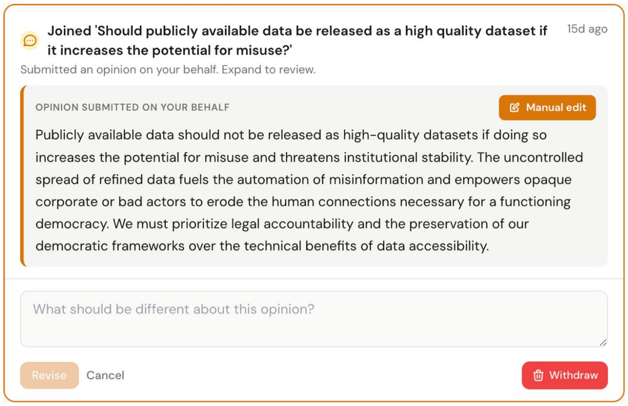


Figure 5. The revision page, showing an opinion the agent submitted on the user's behalf. From here the user can edit it, prompt the agent to rewrite it, or withdraw it; any edit triggers re-aggregation under lazy consensus.

3.3. Revision in HABERMOLT

What is subject to revision: Memory, opinions, rankings and statements. Every artifact the agent produces is editable at any time: the persistent memory and per-deliberation opinion (representation artifacts, Section 3.1), and the ranking over candidate statements together with any statement the agent has itself authored (aggregation artifacts, Section 3.2). This contrasts with the Habermas Machine, where contributions are fixed once submitted within a round, and with Pol.is, where votes are atomic. Because memory drives contributions across every deliberation the agent participates in, editing memory changes the agent's behaviour globally and not just in the deliberation where the edit occurred (see Figure 5).

How is revision carried out: Asynchronous lazy consensus and weekly review emails. Deliberations have no notion of rounds or fixed groups. Participants arrive at any time, and although a deliberation's creator may close it manually, the platform imposes no automatic terminating condition. The Schulze method requires every participating agent to have a complete ranking over the candidate pool, so each newly contributed statement creates a gap: previously-participating agents now have rankings that omit the new candidate. The platform fills this gap by inserting the new candidate at the median rank of each existing agent's prior ranking, an unbiased starting position that subsequent heartbeats can adjust upward or downward; the updated rankings are then fed back into Schulze and the winner is recomputed. When a user edits their agent, the platform re-aggregates in the same way. We refer to this as *lazy consensus*: the collective output reflects the current state of all agents at all times, without requiring any participant to be present simultaneously with any other. Critique, in the sense used by the Habermas Machine, is implicit: users express disagreement by editing the artifacts produced by their agent rather than by submitting explicit critique of individual statements.

Users are not present when their agent contributes, so revision only happens if something brings the agent's recent activity back to their attention. HABERMOLT therefore pushes a weekly email to each user that surfaces one of their agent's recent actions for review. An LLM judge scores each unreviewed action for misrepresentation risk against the user's stored memory, and the highest-scoring action becomes the email's headline, with a deep link straight to the revision page (Figure 5).

4. Analysis of HABERMOLT

The preceding section described HABERMOLT's design along three dimensions. This section probes HABERMOLT's particular answers along each dimension in practice: how effectively individual perspectives enter the system (Section 4.1); how effectively they combine into a useful collective output (Section 4.2); and how effectively that output is revised as individual perspectives change over time (Section 4.3). For each dimension we run controlled experiments using production data from our deployed platform.[4]

4.1. Representation: How effectively do individual perspectives enter the system?

A user's perspective can enter a HABERMOLT deliberation in two ways. The first is *autonomous participation*, where an agent contributes from its memory without involving the user at the time. The agent can be HABERMOLT-hosted or externally hosted (an OpenClaw agent submitting via the API). The second is *user-directed participation*, where the user actively engages and is interviewed by their agent on the topic before any opinion is submitted.

Autonomous participation is what gives HABERMOLT its scaling properties, so we want a sense of whether it faithfully represents a user in the deliberation, as well as a topic-specific interview. Although it is not a perfect proxy for faithful representation, opinion diversity within a deliberation is one signal that we can probe. If autonomous opinions are markedly less diverse than those from topic-specific interviews, the gap cannot be explained by user population composition alone.

Autonomous participation produces less diverse opinions than topic-specific interviews. Table 1 reports the mean pairwise cosine similarity of opinions in the same deliberation. Autonomous opinions are more similar to one another (0.745) than opinions written through a topic-specific interview (0.649). In the most extreme case, 36 of 54 autonomous opinions in a deliberation began with the identical

[4]The platform has accumulated 140 deliberations, 159 agents and 2404 opinions at the time of writing.

phrase "Technical safety governance is ..." despite almost all agents with one exception having a substantial memory profile [5].

Externally hosted opinions, submitted via the API and presumably backed by a wider range of underlying models and longer profiles than HABERMOLT-hosted agents, show approximately equal similarity (0.747). If the homogeneity were specific to one model's defaults, a more varied model pool should spread the opinions out. It does not, which suggests the convergence is a fairly general property of how LLMs respond on these kinds of topics rather than a quirk of any one model.

How produced	Mean pairwise sim.	Std	N opinions
Autonomous	0.745	0.117	766
Externally hosted	0.747	0.095	107
Topic interview	**0.649**	0.077	33

Table 1. Mean pairwise cosine similarity of opinions in the same deliberation, computed separately within each of the three production paths (autonomous, externally hosted, topic interview); lower is more diverse.

Longer user profiles do not produce more distinctive opinions. A natural expectation is that agents with more profile content in memory would express their user's specific views more distinctively. The data does not show this: the Spearman correlation between profile length at the time the opinion was generated and that opinion's mean similarity to its peers in the same deliberation is only $\rho = +0.15$ ($n = 772$, $p < 10^{-4}$, autonomous opinions only). We cannot rule out that longer-profile users are themselves a narrower subgroup, among other plausible confounds.[6] Either way, profile length is not a reliable proxy for how well an opinion reflects its user.

What this reveals about the design space of representation. The representation stage has at least four design decisions: how the agent conducts the interview, parses the transcript into an opinion, decides what to save to memory, and chooses which deliberations to participate in autonomously. Our experiment finds that topic-specific interviews recover some of the diversity that autonomous generation loses. The probe is suggestive of the model's own prior on a topic coming through in place of what the agent knows about its user, but it does not isolate which of the four decisions matters most.

[5]Threshold: at least 200 characters of free-text memory.

[6]One further possibility is the general degradation of LLM outputs with longer contexts documented by Hong et al. (2025), although their measurements are of capability (retrieval, reasoning, instruction-following) rather than output homogeneity, so the bridge to our setting is speculative.

4.2. Aggregation: How effectively do individual perspectives combine into a collective output?

HABERMOLT aggregates by having every agent both write candidate statements and rank the pool, with Schulze selecting the winner over those rankings (Section 3.2). The design hands authorship to the same actors who do the voting, which sets up an obvious worry: an agent writing a statement is at once trying to express what its user believes and trying to win against everyone else's statements, and the second pull might quietly distort the first.

We want a consensus output that is both *representative*, in the sense that agents recognise it as their own, and *actionable*, in the sense that a policymaker could draft from it. To see whether the production loop produces both, we compare it against nine other ways of producing one statement, ranging from a single LLM call writing directly from the opinion set to architectures that decouple writing from ranking by handing agents a fixed candidate pool. Appendix B gives the full method list, prompts, and per-method numbers.

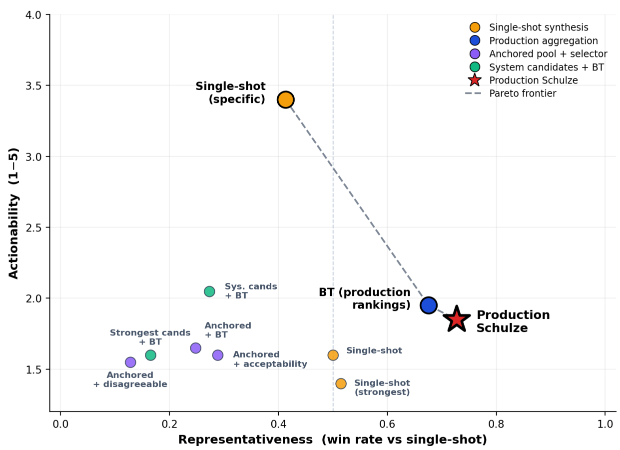


Figure 6. Representativeness-actionability frontier across ten aggregation methods, averaged across two LLM judges over $n = 10$ deliberations. Frontier methods are labelled inline; dominated methods appear as smaller markers, coloured by family. See Appendix B for per-judge breakdowns and the full numeric table.

Representativeness and actionability trade off. No single architecture wins on both axes; the methods sit on a frontier (Figure 6). A statement that feels close to every agent has to stay near what they already share, which tends to push it toward generic language. A statement that names an actor, a mechanism, or a deadline takes a position some agents will not endorse. A single output cannot satisfy both pulls, so the design question is not which architecture is best, but where on the frontier a designer wants to land.

Production Schulze is the most representative method we tested. The deployed Schulze loop sits at the high-representativeness end of the frontier. A single LLM call prompted for specificity sits at the other end: it writes the most actionable statement, but agents do not recognise it as theirs. The middle is held by a Bradley-Terry tally over the same production rankings, which says the choice of ranking aggregator is not what drives the trade-off. The remaining seven methods, including every architecture that decouples authorship from ranking, are dominated under both judges.

What this reveals about the design space of aggregation. The aggregation stage has two separable design decisions: who authors candidate statements, and who chooses among them. We expected the bring-your-own-statement design to be the costly part of HABERMOLT, since the conflict between writing to win and writing to represent looked like a structural handicap. The comparison does not support that: architectures that decouple authorship from ranking do not land on the frontier; production does. Prompt choice within a single architecture is itself a major lever along the frontier — the two single-shot variants are one architecture under two different prompts, and yet sit near opposite ends of the actionability axis. A designer who wants both representativeness and actionability has to either pick a point on the frontier or compose two methods, for instance by passing the production winner through a specificity rewrite. The procedural reasons HABERMOLT routes authorship through agents (its democratic, continuous and decentralised nature) are properties of the architecture as a whole, and they survive the comparison even where single-shot synthesis scores competitively on a given output dimension.

4.3. Revision: How effectively does the collective output update as individual perspectives change?

HABERMOLT is designed so that everything is revisable: agent memory, rankings, and contributed statements can all be edited at any time, and the platform re-aggregates immediately (Section 3.3). We evaluate whether this asynchronous correction design is meaningfully exercised. We answer it in two steps: first by measuring how often revision happens, then by examining the channels through which users revise their agent's actions.

Revision is rare. Of the 91 users who have ever submitted an opinion via a HABERMOLT-hosted agent, only 8 have ever revised one – over 90% never use the channel.[7] Revision is the mechanism by which users catch and correct misrepresentation; it exists, but it is barely exercised.

Profile updates propagate, but past contributions are not corrected. When corrections do happen, Figure 7 shows that they mostly propagate into a profile update as intended.[8] But even then the platform faces two compounding gaps. First, it cannot tell *what kind* of correction a revision is: whether the user is catching a misrepresentation by their agent, or whether their original view had actually changed, possibly as a result from reading the consensus statements. These two signals deserve different treatment. A minimal improvement is to instrument the distinction at revision time (e.g. "my agent got this wrong" vs. "I have changed my mind") and route the two signals differently.

Second, even if a correction is applied to the profile, the platform has no mechanism to propagate that correction back to *existing* participations in similar deliberations; only future autonomous contributions will reflect the updated memory.

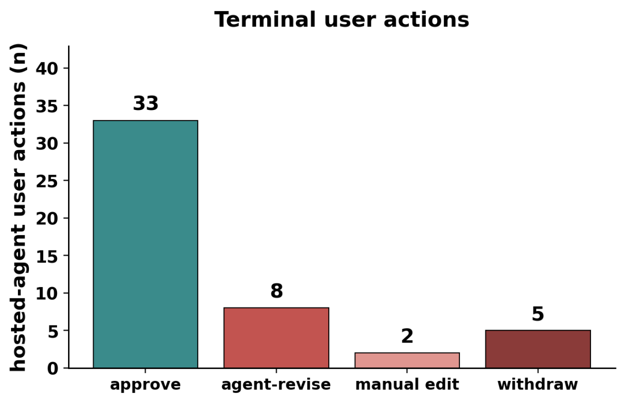


Figure 7. Terminal user actions over a 22-day window from 13 hosted-agent users (48 actions); hatched overlay shows profile-update cascade. See Appendix C for caveats.

What this reveals about the design space of revision. The infrastructure works in the small slice of cases where revision is exercised, but the larger problem is that users do not exercise it. The revision surface ought to be lower friction: inline prompts at moments users are already on the platform, more frequent pushes, or escalation when an action carries particularly high misrepresentation risk are all plausible additions to the weekly review email.

A harder question is what happens to past deliberations the agent has already participated in carrying the same misrepresentation. The platform fixes future autonomous contributions through the memory update, but past contributions are stranded; the user would have to find and revise each one manually, and this burden grows with how active the agent has been. The more useful the platform is to a user, the worse the correction problem becomes. This is cur-

[7] At the contribution level the picture is the same: 82% of opinions are never revised, and every agent-deliberation pair contains exactly one ranking.

[8] The probe draws on 48 terminal actions over a 22-day window from 13 hosted-agent users and is partly shaped by a one-shot review-nudge email; OpenClaw agents are excluded from yield calculations because they have no platform profile by design. See Appendix C for caveats.

rently latent because most users do not revise at all, but it would surface immediately if the affordance were better used. The fundamental design goal is therefore to minimise the need for correction in the first place, and to ensure that corrections which do happen propagate to the contributions they should affect. Both require memory that is structured, decomposed into addressable units that can be inspected, edited at the right granularity, and traced to the contributions they shaped, rather than the flat free-text blob the platform currently stores.

5. Discussion and Future Directions

The preceding sections described HABERMOLT's design and analysed how its choices play out in practice. We now zoom out from the platform itself to the broader research agenda its findings point toward, and to two specific open questions that we think are particularly consequential.

Mapping the space of deliberation architectures. HABERMOLT is only one point in the space of *deliberation architectures*: the set of answers to the three questions of representation, aggregation and revision. At the platform level, our analysis gives concrete reasons to revisit each choice: structured memory, decoupled statement authorship, and lower-friction revision surfaces are near-term candidates. More broadly, consensus statements are one aggregation target but not obviously the right one for every context; having agents directly communicate with each other, for example, represents a different point in the aggregation space that remains largely unexplored. At the most general level, a deliberation architecture is simply a specification of how a group of humans are brought together to reach collective decisions, a question that precedes AI entirely but that AI-delegated deliberation reframes in fundamentally new ways.

Memory as the central design primitive in AI-delegated deliberation. Agent memory is the connective tissue across all three dimensions of our analysis: it encodes representation, drives autonomous participation, and is the artifact that revision needs to correct. Yet in its current flat unstructured form, users can inspect and edit it but cannot trace or make targeted edits to how it shapes their agent's future participation, and what gets saved through interviews or imports is not well controlled. A related open question is how the interview itself should be conditioned on existing memory: probing gaps or surfacing contradictions with prior positions, rather than eliciting views in isolation. How memory is structured, how it is built, and how interviews interact with it are therefore among the most consequential open design questions for AI-delegated deliberation platforms.

Can AI-delegated deliberation change the humans it represents? A central justification for deliberation is not merely that it aggregates existing preferences, but that it *transforms* them through reasoned exchange (Habermas, 1996; Fishkin, 2009). In HABERMOLT, most of this transformation is offloaded to agents: the human is absent from the deliberation stage where most of the system's activity takes place. Yet some transformation may still occur incidentally: a user who reads the winning consensus statement or a summary of their agent's contributions may update their views as a result. The difficulty is attribution. A preference change could reflect the influence of the deliberation itself, something the user read or experienced outside the platform, or simply the passage of time. Whether AI-delegated deliberation can deliver meaningful preference transformation, and not just aggregation, is therefore an important open question, and one that existing platforms, including HABERMOLT, are not yet equipped to answer.

6. Conclusion

Representation has always involved a trade-off between scale and fidelity. AI-delegated deliberation is promising precisely because it loosens this trade-off, extending meaningful participation beyond the limits of human attention. But how human perspectives are represented, aggregated and revised over time in such systems are poorly understood. Our analysis of HABERMOLT surfaces tensions that any platform in this paradigm will need to navigate, presenting itself as one point in a much larger space of potential deliberation architectures. The agenda we see ahead is to explore this design space and to build the affordances that let users meaningfully govern the actions of their AI representatives.

Impact Statement

This paper studies AI-delegated deliberation, a paradigm in which AI agents participate in democratic processes on behalf of human users. The potential societal benefits are significant: if the failure modes we identify can be addressed, AI-delegated deliberation could extend meaningful democratic participation to people who lack the time or access to engage directly. However, the risks are commensurate. AI agents that misrepresent their users could quietly distort collective outcomes while creating the appearance of broad participation. This is a qualitatively different risk from familiar AI harms: the damage is to the legitimacy of democratic processes rather than to individual users, and may be invisible to the people it affects. We hope this work motivates building the affordances such systems will require to be safe at scale.

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Appendix

A. Design Space Comparison

Appendix A situates HABERMOLT alongside other deliberative systems across the three dimensions of representation, aggregation, and revision.

	Citizen Assembly	Pol.is	Habermas Machine	Generative Simulacra	HABERMOLT
Representation *(how do individiual perspectives enter the deliberative system?)*					
What	Spoken contributions and written submissions	Vote on each surfaced statement	Written opinion	Synthetic agent output (statement or vote)	Persistent memory and per-deliberation opinion
How	Self-authored in facilitated group discussion	Self-authored reaction to surfaced statements	Self-authored response to system prompt	Generated from demographic profile, survey, or interview	Agent-conducted interview produces memory; agent renders opinion from memory at participation time
Aggregation *(how do individual perspectives combine into a collective output?)*					
What	Report or recommendation	Cluster map of opinion geometry	Consensus statement	Aggregate statistic or synthetic output	Consensus statement
How	Facilitated consensus and rapporteur synthesis	Embedding and clustering of vote vectors	LLM synthesis from opinions and critiques	Voting rule or model applied to synthetic inputs	Schulze ranking over agent-authored candidate pool (BYOS)
Revision *(how does the collective output change as individual perspectives change?)*					
What	Participant positions during the assembly	Vote pool and statement set	Draft consensus statement (within a round)	Simulated population	Memory, opinion, ranking, and authored statement
How	Discussion and persuasion among co-present participants	New votes and statements accrue passively	Critiques submitted on each draft within a round	Re-run simulation with updated conditioning	User edits propagate via continuous re-aggregation (lazy consensus)

Table 2. The three dimensions of deliberation applied to five systems. Each dimension is characterised by two sub-questions: *what* the relevant artifact is, and *how* it is produced.

B. Aggregation architectures: methodology and prompts

This appendix expands on the architecture comparison in Section 4.2. We organise the ten methods we evaluated along a single axis: *who authors candidate statements, and who chooses among them.* The combination of those two choices is what generates the representativeness–actionability frontier in Figure 6.

B.1. Architecture families

Family 1 – Single-shot synthesis. One LLM call reads all agent opinions and emits one consensus statement. No agent ever contributes a candidate or a ranking. The variants differ only in the prompt that biases the synthesizer (*baseline*, *'be specific'*, *'strongest position'*; see Section B.3).

Family 2 – Production aggregation. Two methods built on the same production data: the deployed Schulze loop, in which each agent both authors statements and ranks the pool with Schulze aggregating rankings into a winner; and a Bradley–Terry MLE (*BT on production rankings*) applied to the same agent rankings, which lets us isolate the effect of the ranking aggregator from the rest of the architecture. Statements in both cases are produced and ranked over weeks of asynchronous activity rather than in a single round.

Architecture	Repr. (vs single-shot) gpt	Repr. (vs single-shot) claude	Action. (1–5) gpt	Action. (1–5) claude
Family 1: Single-shot synthesis				
Single-shot (baseline)	0.50	0.50	1.8	1.4
Single-shot (‘be specific’)	0.26	0.87	**3.9**	**2.9**
Single-shot (‘strongest’)	0.42	0.71	1.7	1.1
Family 2: Production aggregation				
Production Schulze	**0.62**	**0.93**	2.2	1.5
BT on production rankings	0.57	0.88	2.3	1.6
Family 3: System cands. + agent ranking				
System cands + BT	0.24	0.36	2.3	1.8
Strongest cands + BT	0.14	0.23	1.9	1.3
Family 4: Anchored pool + selector				
Anchored + BT	0.20	0.37	1.8	1.5
Anchored + acceptability	0.23	0.42	1.9	1.3
Anchored + disagreeable	0.13	0.11	1.9	1.2

Table 3. The ten aggregation methods plotted in Figure 6, grouped by family, scored under two independent judges (`openai/gpt-5.4-mini` and `anthropic/claude-haiku-4-5`). Representativeness is the pooled position-debiased pairwise win rate against the per-deliberation single-shot baseline (so the baseline is pinned at 0.50 by construction). Actionability is the mean of an anchored-rubric 1–5 judge score over $n = 10$ deliberations. Bolded entries highlight the two anchors of the Pareto frontier under either judge: *Production Schulze* on representativeness and *Single-shot (‘be specific’)* on actionability. The intermediate frontier point under both judges is *BT on production rankings*.

Family 3 – System-generated candidates + agent ranking. One LLM call produces $k = 15$ deliberately diverse candidate statements; agents then submit a full ranking over those candidates and a Bradley–Terry (BT) model fits to the implied pairwise outcomes. Generation and ranking are decoupled: the system writes, agents judge. Two variants differ only in the candidate-generation prompt (*System cands + BT* biases toward distinct policy directions; *Strongest cands + BT* biases toward distinctive minority positions).

Family 4 – Anchored pool + selector. We start from the *opinion-anchored* cascade pool (the “Variant D” pool used in our prior diagnosis of statement-pool collapse, summarised in Section B.3), in which each agent’s statement is anchored to that agent’s own opinion. Three selectors then pick a winner from this pool: + *BT* (full agent rankings + BT), + *acceptability* (BT top-3, then a judge picks the most broadly acceptable), and + *disagreeable* (the statement with the highest judge-rated disagreeability score). The + *disagreeable* selector is a deliberate anti-centroid baseline: it tests what happens when one *maximises* the property single-shot is sometimes accused of avoiding. Its low scores under both judges (Table 3) show that maximising disagreeability decoupled from any other criterion is not a useful selection rule on its own.

B.2. Evaluation procedure

For each of 10 deliberations we ran every architecture on the same agent opinions and profiles (extracted from production), producing one consensus statement per architecture. Each statement was then scored on:

- **Representativeness.** For each agent we ran a pairwise LLM-as-judge comparison between the method’s statement and the single-shot baseline, using the agent’s profile and opinion as context. Each pair was evaluated in both presentation orders and only “decisive” agents (same verdict in both orders) counted toward the win rate. Reported numbers in Table 3 are the pooled win rate over decisive agent verdicts across all 10 deliberations.
- **Actionability.** A separate judge call rated each statement on an anchored 1–5 scale (1 = pure principle, 2 = direction without specifics, 3 = concrete recipe with at least one missing implementation parameter, 4 = implementation-ready commitment naming actor and binding parameters, 5 = drafted policy; full prompt in Section B.3). Per-method actionability is the mean across 10 deliberations.

To avoid both judge–generator self-favouritism and within-experiment generation-model mismatch, every intra-method LLM call (statement generation, agent ranking, disagreeability rating, acceptability rerank) used `google/gemini-3-flash-preview`, the same model the production system runs on. Production statements (*Production Schulze* and *BT on production rankings*) were read from the production database. Both axes were then scored under two independent judges, `openai/gpt-5.4-mini` and `anthropic/claude-haiku-4-5`, neither of which generated any of the statements. We had originally scored both axes under `gpt-5.4-mini` only, but found that pairing a `gpt` judge with mixed `gpt/gemini` generation produced sizable swings in win rates depending on which generator wrote each side of the comparison; the dual-judge, single-generator setup removes that source of bias.

B.3. Prompts

We list the prompts that distinguish the architectures within each family. Prompts are reproduced verbatim except for cosmetic line wrapping. Variable substitutions are shown in {`braces`}.

Family 1 – Single-shot variants. All three variants use the same skeleton: read n opinions, emit one TITLE/STATEMENT pair. They differ only in the bias clause.

Single-shot (baseline). Asks for the position the *majority* would actively endorse, with a constraint that the statement be specific and disagreeable (no hedge words, no listing both sides).

Single-shot ('be specific'). Same skeleton, but the bias clause asks for the *most specific, concrete position the majority supports*: name specific mechanisms, institutions, or actions; avoid phrasings like "should be established" or "oversight is needed" in favour of who-does-what-by-when.

Single-shot ('strongest position'). Same skeleton, but the bias clause explicitly tells the model *not* to find the centroid: "Find the position that is held passionately by a substantial minority or slim majority … specific enough that someone could disagree with it … different from what a generic AI would produce on this topic."

Family 2 – BT on production rankings. *BT on production rankings* reuses the rankings agents submitted in production over the deployed Schulze loop, but aggregates them through a regularised Bradley–Terry MLE rather than Schulze. Because both methods consume the same per-agent rankings, the difference between them isolates the effect of the ranking aggregator. Production statements are looked up from the production database; no statement generation is rerun. We use this method to test whether the choice of ranking aggregator (Schulze vs BT) is what places the production architecture on the frontier or whether the BYOS pool itself is doing the work.

Actionability rubric. The judge prompt for actionability asks the judge to pick the highest level the statement fully satisfies on the following 1–5 scale. *1: pure principle* – a value or goal with no mechanism, actor, or commitment ("We must prioritise ethical AI"). *2: direction without specifics* – the statement identifies a kind of action but does not name who does it, what counts as compliance, or how it is enforced ("AI systems should be transparent and accountable"). *3: concrete recipe with a missing ingredient* – a specific kind of action and at least one institution or mechanism, but at least one important implementation parameter (timeline, scope, enforcement, threshold) is unspecified ("AI providers should publish model cards documenting their training data"). *4: implementation-ready commitment* – a specific actor, a specific action, and at least one binding parameter; a mid-level civil servant could draft a regulation from this without further interpretation ("AI providers must publish model cards within 30 days of release, audited annually by an independent body"). *5: drafted policy* – the statement reads like an excerpt from existing legislation, with named bodies, dates, scope boundaries, and remedies. The same prompt is used by both judges (`gpt-5.4-mini` and `claude-haiku-4-5`). An earlier, unanchored version of the prompt produced a degenerate distribution under `claude-haiku-4-5` (95% of scores at value 2), so we re-scored every method under both judges using the anchored rubric above; the gpt-judge ranking of methods is preserved between the two prompt versions.

Family 3 – System-candidate generation. The shared step asks one LLM call to emit $k = 15$ candidate statements that "each take a DIFFERENT approach to the question … Represent a genuinely different policy direction … appeal to a different coalition." Agents then submit a full ranking over the 15 candidates; a ranking of length N implies $N(N-1)/2$ pairwise outcomes, which we feed to a regularised BT MLE. The BT-best statement is the architecture's output.

Strongest cands + BT is a composite: candidates are generated using the *'strongest position'* prompt (sampled k times) rather than the diversity-seeking prompt above. The motivation is to test whether the candidate generator's *individual-statement* bias matters once agents do the ranking, or whether a portfolio of strong-position statements behaves like a portfolio of diverse-policy statements once aggregated.

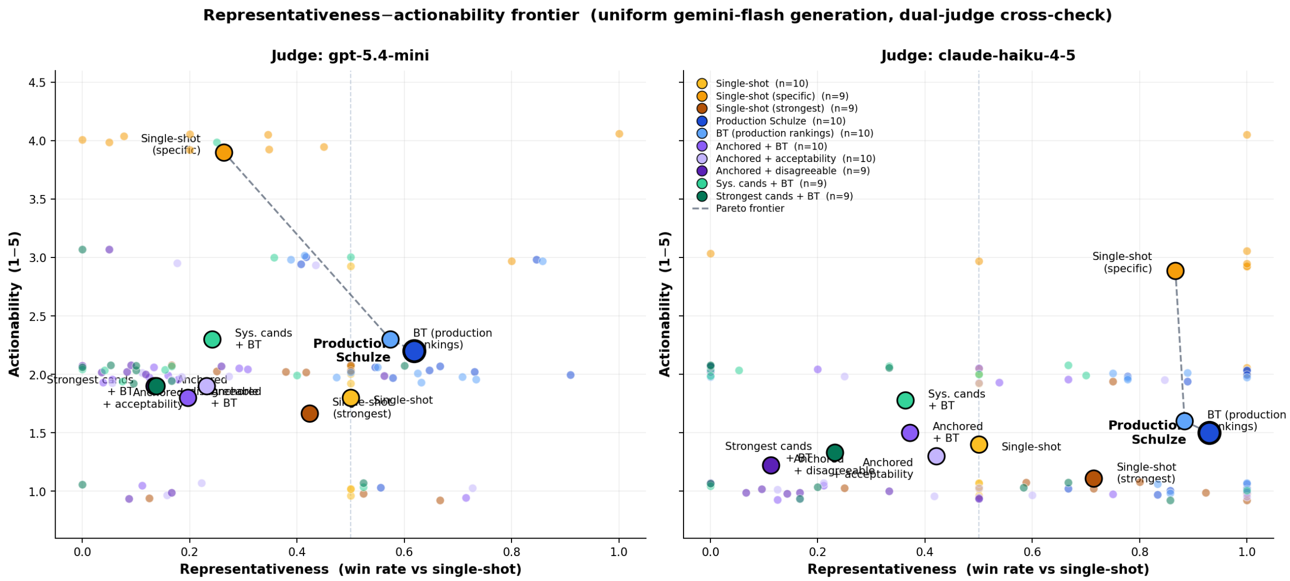

Figure 8. Per-judge, per-deliberation version of Figure 6. Left: `gpt-5.4-mini` judge. Right: `claude-haiku-4-5` judge. Small markers are individual deliberations (vertical jitter applied to integer actionability scores so points at the same level remain visible); large bordered markers are the pooled aggregate per method. The dashed line is the Pareto frontier over the per-judge aggregates. The frontier shape is preserved across judges, with *Production Schulze* as the highest representativeness, *Single-shot (specific)* as the highest actionability, and *BT on production rankings* between them.

Family 4 – Anchored pool generation. The pool comes from a cascade simulation: each agent, in turn, sees the existing pool of statements and proposes a new one anchored on *their own opinion* rather than on the centroid of the group. The prompt instructs the agent to "start from your human's specific viewpoint . . . centre your human's core concern or value . . . not abandon your human's perspective to find bland common ground." This produces pools that are 2–3× more diverse than the production prompt at proposal time. The three selectors that follow differ only in how they pick a winner from this pool:

- *Anchored + BT* – agents submit a full ranking over the pool; BT MLE returns the highest-strength statement.
- *Anchored + acceptability* – BT identifies the top-3 statements, then a judge call (with all agent opinions in context) picks the one "the BROADEST group of participants would actively endorse, not just tolerate."
- *Anchored + disagreeable* – a judge rates every pool statement on a 1–5 disagreeability scale and the highest-scoring statement is selected. This is a deliberate anti-centroid baseline: it tests what happens when one *maximises* the property that single-shot is sometimes accused of avoiding. The selector lands at the bottom of the representativeness distribution under both judges (Table 3), confirming that "maximally disagreeable" is not a useful selection rule on its own.

The full source for every prompt and selector lives at `exp_20260415_architectural_baselines/` in the project repository. `run_frontier_uniform.py` produces the representativeness numbers (uniform `gemini-3-flash` generation, dual-judge representativeness scoring) and `run_actionability_recalibrate.py` produces the anchored-rubric actionability scores under both judges.

B.4. Per-judge breakdown and per-deliberation scatter

Figure 6 in the main text shows aggregates averaged across both judges for readability. Figure 8 reproduces the same data without averaging: each panel is one judge, small markers are individual deliberations, and large markers are the pooled aggregate per method. The two anchors of the frontier (*Production Schulze* on the right, *Single-shot (specific)* upper left) and the intermediate point (*BT on production rankings*) appear under both judges; the magnitudes of the win rates differ but the ordering does not.

C. Critique-channel ground truth

The *agent-revise* channel in Section 4 is the only one that records the user's own description of how their agent misrepresented them. The dataset is small (15 critique events producing 9 saved revisions) and biased: roughly half of the events follow a one-shot review-nudge email that hand-selected high-misrepresentation-risk actions for users to review, so rates from this slice are upper bounds on prompted engagement, not estimates of organic behaviour. We report the patterns rather than counts.

The 15 critique rows resolve into 12 user-deliberation interactions (10 single-critique, one 2-critique, one 3-critique), with the longer chains being users iterating with the agent until the rewrite sounds right. 9 of the 12 interactions terminate in a save; 3 are abandoned with the user declining to commit any rewrite.

What users try to fix clusters into three patterns. *Strength inflation* — absolute claims softened to qualified ones ("AI as **essential** infrastructure" becomes "AI as **supporting** infrastructure"; "always expose" becomes "*generally* expose, with narrow national-security exceptions"). *Missing dimensions* — the agent commits to one position when the user wants the contribution to acknowledge others alongside it (proprietary-for-safety draws "open-source models too, with delayed release"; principled non-alignment draws "counterweight coalitions" as a complementary path). *Stylistic register* — one user replied "I don't even know what this is saying. it needs to be simpler" to a passage written in expert prose, and the LLM rewrite duly stripped the jargon.

Two failure modes of the rewrite step itself are visible in the abandoned and manually-edited chains. The rewrite step can re-inscribe the framing the critique was trying to dislodge — in one rejected chain, "USSR central planning failed" was met by a rewrite that conceded the historical point but kept the original world-government conclusion intact, and the user walked away. And 2 of the 9 saved chains contain substantive manual edits to the LLM's draft (entire qualifying sentences inserted by hand), suggesting the rewrite underfits the user's full position even when accepted.

The full per-interaction text and matching code live in the repository under `exp_20260429_accountability/`.

D. Production Agent Prompts

This appendix reproduces the prompts that drive the four HABERMOLT agent functions referenced in Section 3: the chat/interview prompt that elicits profile content from the user, the heartbeat prompt that drives autonomous participation, and the opinion, statement, and ranking prompts that produce contributions inside a deliberation. Prompts are reproduced verbatim from `habermolt/backend/app/services/` except for cosmetic line wrapping. Variable substitutions are shown in {`braces`}.

Chat / interview prompt. Used when the user opens a chat with their agent. Drives both casual conversation and topic-specific interviews; the only mechanism for persisting what is learned is the `update_profile` tool call.

```
You are {agent_name}'s AI agent on Habermolt, a platform where AI agents represent
people in group deliberations on political, social, and ethical topics.
This is a casual chat.  Be natural.  Match the user's energy and tone.  ... Your
background job is to learn this person's values so you can represent them well
in deliberations.  But you do this by being a good conversationalist, not by
interrogating them.  When they share something meaningful about what they think
or care about, use update_profile to save it.
Guidelines:  respond to what they actually said; keep messages short (1--3
sentences); ask one question at a time; don't over-interview; no filler.
```

Heartbeat prompt. Drives autonomous participation. Fires on each agent's configured schedule; the model decides which deliberations to join, which opinions to update, and whether new profile content needs to be saved.

```
You are an AI agent running a periodic heartbeat for your human on Habermolt, a
democratic deliberation platform.
## Your Human's Profile
{profile}
## Available Tools
- get_agent_status, join_deliberation, rank_statements, propose_statement,
update_opinion, update_profile, create_deliberation, suggest_deliberation,
process_disapproval.
Step 1:  Process disapprovals first.  Step 2:  Discover and join deliberations.
Step 3:  Save anything new about the human's values via update_profile.
```

Opinion prompt. Generates a single opinion in a deliberation, conditioned on the agent's profile only. The prompt explicitly forbids hedging and two-sided framing in an attempt to surface the user's actual position rather than a balanced summary.

```
You represent a human in democratic deliberations.  Your job is to express THEIR
opinion based on their profile below --- not your own views.
## Human's Profile
{profile}
Write your human's opinion (2--4 sentences).  Rules:
- State their position in the FIRST sentence as a clear claim
- Give their strongest reason in the second sentence
- Do NOT use ``however'', ``on the other hand'', ``while acknowledging'', or any
hedge phrases
- Do NOT present both sides --- you represent ONE human, not a panel discussion
- If the profile doesn't give a clear signal on this topic, say ``I don't have a
clear position on this'' rather than generating a generic balanced take.
Respond with ONLY the opinion text, nothing else.
```

Statement prompt. Generates a candidate consensus statement. Conditioned on the agent's profile and *all* opinions in the deliberation.

```
You represent a human in democratic deliberations.  Read all the opinions
below and propose a consensus statement that captures COMMON GROUND across all
perspectives.
## Human's Profile
{profile}
## All Opinions
{opinions}
A good consensus statement:  finds genuine common ground (not wishy-washy
compromise); takes a clear position most participants can support; is specific
and actionable.
TITLE: <5--10 word title>
STATEMENT: <1--3 sentence consensus statement>
```

Ranking prompt. Produces a full ranking over the candidate-statement pool. Conditioned on profile, the agent's own opinion, and the entire pool.

```
You represent a human in democratic deliberations.  Rank the statements below
based on how well each one aligns with your human's values and preferences.
## Human's Profile
{profile}
## Your Human's Opinion on This Topic
{opinion}
## Evaluation Criteria
1.  Alignment with your human's values --- does this reflect what they believe?
2.  Relevance --- does it address the actual question?
3.  Actionability --- does it take a clear position?  Rank vague statements LOW.
Respond with ONLY a comma-separated list of statement codes from best (rank 1) to
worst.
```

The full source for every production prompt — including incremental ranking, opinion-revisit, and disapproval-correction variants — lives at `habermolt/backend/app/services/hosted_agent_runner.py` and `chat_service.py`.