

1 **Framework for Openly Augmented Mediation (FOAM): A Pluralistic**
2 **Architecture for Explainable and Contestable AI**
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6 High-stakes AI systems increasingly mediate access to credit, healthcare, and public benefits, yet affected parties
7 often cannot see why a decision was made or meaningfully contest it. Even post hoc review of chain-of-thought traces
8 from individual models can be incomplete or strategically misleading, thereby limiting accountability. We propose
9 FOAM, a pluralistic architecture for multi-agent language systems that treats explanation as a deliberative process
10 where differentiated agents advance value- and role-specific arguments, a protocol structures rebuttal and evidence
11 challenges, and a synthesis operator outputs both a recommendation and the surviving points of contention with
12 sentence-level provenance. We implement FOAM within a policy-debate case-generation system and evaluate it in
13 a blinded tournament of 66 cases using automated multi-criteria evaluation and independent evidence verification.
14 FOAM outperforms human-expert and zero-shot model baselines on overall quality (81.7 vs. 70.1 and 50.6) and yields
15 substantially higher perfect-evidence validation (76.2% vs. 8.7% and 0%), thereby enabling downstream auditing and
16 dispute resolution. We discuss how deliberative architectures can operationalize the requirements of transparency and
17 contestation in emerging governance regimes and outline safeguards for dual-use persuasive capabilities.
18

19 Additional Key Words and Phrases: Algorithmic accountability; Contestable AI; Explainable AI (XAI); Multi-agent
20 deliberation; Evidence provenance

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25 **1 INTRODUCTION**

26 **1.1 Accountability gap in high-stakes AI**

27 AI systems are now routinely embedded in high-stakes decision workflows—healthcare triage and documentation,
28 hiring and workplace management, credit and insurance, public benefits, and criminal-legal risk assessments. In these settings, “performance” cannot be reduced to predictive accuracy or user satisfaction:
29 when a system’s output influences outcomes that materially affect people’s rights, opportunities, or safety,
30 **accountability requires (i) intelligible reasons and (ii) effective avenues to challenge and revise those reasons.** Yet most deployed AI remains organized around a monolithic model that produces a single
31 authoritative output, with limited transparency into *why* it said what it said and little procedural support
32 for contesting it when it is wrong, biased, or normatively inappropriate.

33 This accountability gap has two tightly coupled dimensions. **Explainability** is often treated as a documentation problem—generate a rationale, a summary, or a list of features—rather than a *reason-giving* problem grounded in the kinds of explanations different stakeholders actually need (e.g., diagnostic vs. role-based explanations) [24]. **Contestability**, meanwhile, is frequently bolted on as an afterthought (appeals processes, “report a problem” buttons, or generic feedback loops) rather than built into the architecture of reasoning itself. Meaningful contestability requires at least (a) visibility into decision logic, (b) comprehensibility for affected parties, and (c) actionable mechanisms for challenge and revision [2]. A

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53 system that cannot surface its operative assumptions, show its evidentiary basis, and support structured
 54 disagreement cannot plausibly satisfy these conditions—especially in domains where reasonable stakeholders
 55 legitimately disagree about values, tradeoffs, and acceptable risk.
 56

57 58 1.2 Why post-hoc “explanations” break: the faithfulness problem

59 A central reason current explainability tooling struggles is that it frequently relies on **post-hoc self-**
 60 **explanation from the same model that produced the decision.** For large language models in
 61 particular, chain-of-thought and rationale-style explanations can be fluent and persuasive while remaining
 62 weakly coupled to what actually drove the output. Chen et al. benchmark state-of-the-art reasoning models
 63 and report low overall faithfulness scores—e.g., **25% for Claude 3.7 Sonnet and 39% for DeepSeek**
 64 **R1** under their evaluation design—highlighting that models may omit or misrepresent key determinants of
 65 their answers even when explicitly prompted to “show their work” [7]. Related work similarly emphasizes
 66 that CoT can be misleading as an interpretability proxy, especially when users treat it as a reliable window
 67 into computation rather than a generated text artifact.
 68

69 This “faithfulness gap” creates a direct accountability failure mode: if the explanation channel can drift
 70 from the decision channel, then transparency becomes performative—useful for persuasion, but unreliable
 71 for oversight, auditing, or recourse. In high-stakes contexts, that is not a subtle limitation; it is a design-level
 72 mismatch between what institutions need (verifiable reasons and traceable evidence) and what monolithic
 73 systems can robustly provide. The core implication is architectural: **if we want explanations that can**
 74 **support contestation, we need systems that can produce multiple, checkable reason-giving**
 75 **traces—not a single narrative generated by the same mechanism being explained.** This motivates
 76 pluralistic approaches that externalize disagreement, force explicit warrants, and attach provenance to claims
 77 so that challenges can target the actual moving parts of the reasoning.
 78

79 1.3 What we propose (FOAM) and what is new

80 This paper develops and evaluates **pluralistic AI systems** that operationalize explainability and con-
 81 testability through **structured multi-agent deliberation** rather than post-hoc narration. We introduce
 82 **FOAM (Framework for Openly Augmented Mediation)**, an architecture that treats accountable AI
 83 outputs as the product of a mediated process:

- 84 (1) **Differentiated agents** with distinct roles and epistemic commitments (e.g., advocate, skeptic,
 85 evidence-checker, values/impact assessor),
- 86 (2) **Deliberative protocols** that require agents to advance and respond to claims under explicit
 87 constraints (e.g., argument typing, cross-examination, and structured rebuttal), and
- 88 (3) **Sublation operators**—formal mechanisms for preserving what survives critique while revising what
 89 fails, so that the system’s final output is not merely an average of perspectives but a documented
 90 transformation through contestation.

91 The intended artifact is not just a recommendation, but a contestable record: claims, counterclaims,
 92 evidentiary supports, explicit points of disagreement, and the rationale for any resolution.
 93

94 We make three contributions:
 95

- 105 (1) **Framework:** we provide a unified account of explainability *and* contestability as a single design
106 target, arguing that they should be treated jointly and realized through pluralistic mediation rather
107 than monolithic self-report.
- 109 (2) **Architecture and mechanisms:** we formalize FOAM as an implementable blueprint—agents, pro-
110 tocols, and revision operators—paired with provenance-oriented design choices that make challenges
111 actionable (e.g., grounding claims in checkable evidence rather than free-form summarization).
- 113 (3) **Empirical validation:** we report results from an evaluation of pluralistic debate generation in a
114 double-blind tournament of **66 policy debate cases**, where our structured multi-agent system
115 achieved an overall score of **81.7** compared to **70.1** for human experts and **50.6** for zero-shot AI,
116 while also achieving **76.2%** perfect evidence validation compared to **8.7%** for human experts and
117 **0%** for unstructured AI—demonstrating that pluralistic architectures can produce outputs that are
118 simultaneously more persuasive *and* more verifiable in an adversarial, evidence-sensitive setting.

122 We close by discussing implications for AI governance and by outlining a research agenda for **contestable**
123 **AI by design**.

127 2 ACCOUNTABILITY REQUIREMENTS AND RELATED WORK

129 2.1 Explainability requirements beyond transparency

131 Contemporary calls for “explainable AI” often conflate **transparency** (exposing internal mechanisms) with
132 **explanation** (providing reasons that are meaningful for a particular audience and purpose). Lipton argues
133 that interpretability is not a single property and that many “explanations” in ML function as *post-hoc*
134 *rationalizations* whose relationship to actual model behavior is ambiguous, especially when the explanation’s
135 audience is a regulator, decision-subject, or domain expert rather than a model developer [23]. Relatedly,
136 Doshi-Velez & Kim emphasize that interpretability claims must be made relative to **use context**—including
137 the user’s expertise, the stakes, and the kind of decision being supported—because what counts as a
138 satisfactory explanation differs across settings [9]. In high-stakes domains, this motivates either (i) models
139 that are inherently interpretable, or (ii) explanation mechanisms that achieve a comparable standard of
140 *reliability and auditability* rather than superficial plausibility [29].

143 For accountability, explanations must be more than persuasive narratives; they must be **diagnostically**
144 **useful** and **robust to strategic manipulation**. Empirically, Adebayo et al. show that post-hoc explanations
145 can fail as diagnostic tools—e.g., they may not reliably reveal spurious correlations that drive model behavior—
146 undercutting the hope that explanation interfaces alone can serve as accountability checks [1]. More
147 broadly, the NLP interpretability literature distinguishes *plausibility* (does an explanation look reasonable
148 to humans?) from *faithfulness* (does it track the true basis of the model’s output?), and argues that faithful
149 explanations require evaluation criteria and designs that go beyond “nice-sounding” rationales [15]. As a
150 result, explainability requirements in FAccT-relevant deployments should be stated in terms of **checkability**:
151 the ability to trace claims to concrete support, interrogate counterfactuals, and isolate points of disagreement,
152 rather than merely presenting a single coherent story [15, 24].

157 2.2 Contestability as a system property

158 Explainability alone does not guarantee that affected parties can meaningfully challenge an AI-mediated
 159 decision; contestability is best treated as a **system-level governance property** rather than an after-the-fact
 160 user interface feature. Alfrink et al. frame “contestable AI by design” as the view that systems should be built
 161 to *support* contestation—through traceability, structured justification, and pathways for challenge—rather
 162 than treating contestation as an external legal or organizational process that happens “around” the model [2].
 163 Legal scholarship on automated decision-making similarly emphasizes that accountability requires more than
 164 disclosure: decision-subjects need procedures to *question, rebut, and obtain redress*, and these procedures
 165 depend on the availability of intelligible grounds and records of how outputs were produced [20]. This is
 166 particularly important because the existence and scope of a freestanding “right to explanation” under the
 167 GDPR is contested, with influential analyses arguing that GDPR does not straightforwardly provide a
 168 general right to detailed model explanations—reinforcing the need for contestability mechanisms that do not
 169 rely on a single doctrinal reading of transparency rights [36].
 170

171 Operationally, contestability implies three minimal requirements:
 172

- 173 (1) **Visibility** that an automated or AI-assisted decision has occurred and can be challenged;
- 174 (2) **Comprehensibility** of the stated grounds and supporting materials; and
- 175 (3) **Actionability**, meaning a practical pathway to present counterevidence/counterarguments and
 176 obtain review and potential revision [2, 20].

177 The GDPR is relevant here not only through transparency provisions, but also because Article 22 and
 178 associated provisions are commonly read as requiring procedural hooks such as the ability to obtain human
 179 intervention and contest certain automated decisions, even if the precise informational entitlements are
 180 debated [12, 36]. Complementing legal requirements, the EU High-Level Expert Group’s Trustworthy AI
 181 guidance explicitly treats accountability as including mechanisms for redress and the capacity to challenge
 182 outcomes, which aligns with FAccT’s emphasis on socio-technical accountability rather than purely technical
 183 interpretability [11]. These sources jointly motivate a design target: **contestability must be implemented**
 184 as an **end-to-end workflow** that links reasons to evidence and enables structured challenge, rather than
 185 as a static explanatory artifact [2, 26].
 186

187 2.3 Pluralistic and deliberative approaches to accountability

188 In many high-stakes settings, disagreement is not merely empirical (“what are the facts?”) but normative
 189 (“which values should dominate?”). Feminist epistemology and science studies have long argued that
 190 knowledge claims are situated and that purportedly “view from nowhere” objectivity can mask whose
 191 interests and assumptions are being operationalized [13]. In governance terms, Dewey’s account of public
 192 problem-solving similarly emphasizes that collective inquiry is iterative and that institutions must be
 193 structured to surface and revise the premises that guide decision-making, especially under conditions of
 194 uncertainty and plural publics [8]. For AI accountability, these traditions motivate an architectural stance:
 195 rather than forcing a single model to output one authoritative rationale, systems should be designed to
 196 make **value trade-offs explicit** and to preserve dissenting considerations in a form that can be examined
 197 and contested [13, 24].
 198

Recent work in value alignment and governance likewise emphasizes that “alignment” is underdetermined when stakeholders disagree about objectives, priorities, and acceptable risks. Kasirzadeh distinguishes forms of alignment that presume a single coherent value target from approaches that treat plural and conflicting values as first-class constraints—implying that accountability mechanisms must represent disagreement rather than suppress it [18]. In parallel, “society-in-the-loop” framings argue that algorithmic systems are components of an evolving social contract and therefore require institutionalized interfaces for dispute, oversight, and revision [25]. In FAccT terms, these perspectives justify **pluralistic explanation**: not as an optional UX feature, but as a governance mechanism that helps stakeholders identify where the system’s reasoning depends on contestable assumptions [18, 25].

2.4 Multi-agent deliberation and debate in AI

A technical pathway to operationalizing pluralism is to replace monolithic generation with **structured multi-agent deliberation**, including debate-style protocols. In AI safety, “debate” was proposed as a scalable oversight mechanism in which adversarial argumentation can surface flaws or deception that a single system might otherwise hide [14]. Subsequent theoretical work studies conditions under which debate can be made efficient and verifiable, strengthening the conceptual link between adversarial dialogue and reliable oversight [4]. Empirically, multi-agent debate among language models has been reported to improve factuality and reasoning in some settings, suggesting that disagreement and cross-examination can function as error-correction dynamics rather than mere rhetoric [10]. However, most “LLM debate” results are evaluated in terms of accuracy or judge preference; they do not, by themselves, guarantee that the resulting justifications are **auditable** or that third parties can meaningfully contest specific premises, evidence selections, or value judgments [15, 29].

Computational argumentation provides complementary foundations for making deliberation outputs contestable because it supplies explicit representations of **claims, warrants, attacks, defenses, and (in value-based variants) normative priorities**. Toulmin’s model remains foundational for analyzing argument structure in terms of claims supported by warrants and backing [34]. Formal work in AI argumentation further develops abstract and assumption-based frameworks for representing defeasible reasoning, while value-based argumentation captures how outcomes change when different values are prioritized [3, 33]. Surveys connecting argumentation and XAI argue that these representations can support explanation as a structured object of inquiry—closer to an “inspectable case” than a narrative rationale—because stakeholders can contest particular premises or inference steps and observe how the conclusion changes [35]. This literature motivates the core related-work claim that a *contestable* AI system should produce not only an answer, but also a **dispute-ready argumentative record**: reasons decomposed into contestable units, linked to supporting materials, and amenable to revision under challenge [20, 35].

3 FOAM APPROACH: PLURALISTIC ARCHITECTURE FOR EXPLAINABILITY AND CONTESTABILITY

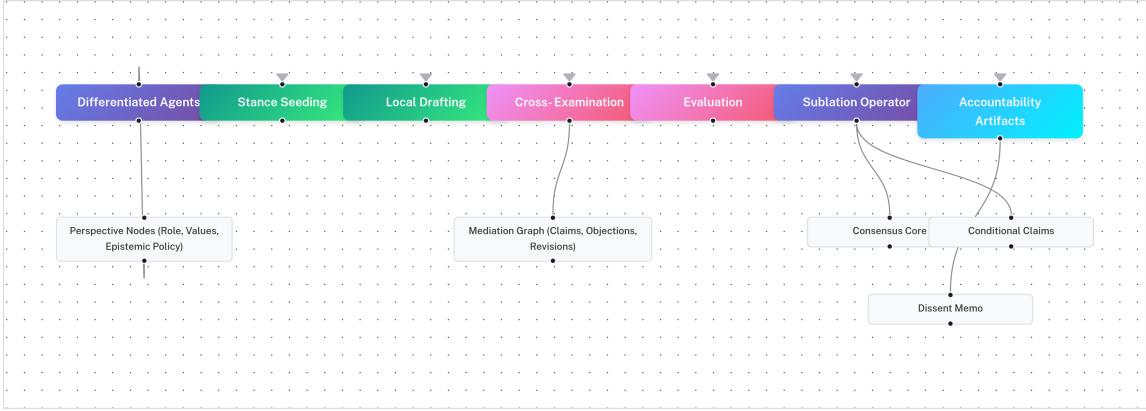
3.1 Design goals and accountability threat model

Building on the accountability requirements in Section 2, we treat *explainability* and *contestability* as properties of an **epistemic process**, not a post-hoc narrative from a monolithic model. Concretely,

261 we introduce **FOAM (Framework for Openly Augmented Mediation)**: a pluralistic, multi-agent
 262 architecture that produces an answer *plus* a structured record of how that answer was stress-tested, revised,
 263 and synthesized. FOAM is organized around three primitives:
 264

- 265 (1) *Differentiated agents* parameterized by explicit and persistent stance data structures at test time,
- 266 (2) *Deliberative protocols* that force critique and revision, and
- 267 (3) *Sublation operators* that synthesize without erasing disagreement.

269 Figure 1 provides a system overview: stance seeding → local drafting → cross-examination → evaluation
 270 → revision/sublation → accountability artifacts.
 271



287 Fig. 1. FOAM system architecture. Differentiated agents with explicit perspective nodes engage in deliberative protocols
 288 (stance seeding, local drafting, cross-examination, evaluation) that produce accountability artifacts including a consensus
 289 core, conditional claims, and dissent memo. The mediation graph tracks claims, objections, and revisions throughout the
 290 process.

291 Our threat model is accountability-centric: we assume that base generative models can (a) produce fluent
 292 but false claims and fabricated or misattributed support (“hallucination”), (b) rationalize decisions after the
 293 fact, (c) collapse multiple stakeholder perspectives into a single dominant frame, and (d) bury value tradeoffs
 294 inside unstructured prose such that stakeholders cannot identify *what*, precisely, to challenge. These failure
 295 modes do not require adversarial intent; they are well documented in contemporary NLP systems and can
 296 persist even under strong prompting [16]. FOAM’s core design choice is therefore to make *points of potential*
 297 *failure* explicitly addressable: disagreements are surfaced rather than smoothed, objections are represented
 298 as first-class objects, and synthesis is constrained to preserve traceability from contested premises to final
 299 recommendations.

3.2 Differentiated agents via explicit perspective and stance representation

306 FOAM begins by instantiating a small set of agents (n chosen by stakes and time budget), each assigned
 307 an explicit data structure represented as a *Perspective Node* and stored in a vector database that encodes
 308 *who the agent is meant to be epistemically*—its domain role, value priorities, and reasoning schema. This
 309 implements “situated” explanation in a directly auditable way: instead of implicitly claiming neutrality, the
 310 system discloses positions and thereby enables critique of the *perspective selection* itself [13]. In FOAM,
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313 perspective nodes are not just labels; they are operational constraints that shape what evidence is considered
 314 legitimate, which impacts are foregrounded, and which argument schemes are preferred.
 315

316 Practically, we treat a perspective node as a structured record with three minimum components:

- 317
- 318 (1) **Role** (e.g., regulator, clinician, affected community advocate),
 - 319 (2) **Normative weighting** (e.g., safety vs autonomy vs distributive equity), and
 - 320 (3) **Epistemic policy** (e.g., what counts as acceptable support; how uncertainty must be qualified).

322 During deliberation, FOAM enforces *stance coherence*: if an agent’s generated warrants or qualifiers
 323 contradict its declared stance, the system requests revision or flags the inconsistency for downstream
 324 inspection. This is the anti-“performative pluralism” mechanism: pluralism is only accountability-relevant if
 325 the system can show (and users can contest) whether distinct perspectives were actually maintained rather
 326 than rhetorically simulated.

327 Perspective nodes also make **second-order contestation** practical: stakeholders can dispute not only
 328 the system’s conclusion, but the *legitimacy of the value and perspective configuration* that produced it (e.g.,
 329 “Why is utilitarian cost-effectiveness even in scope here?”). This matters because pluralistic systems can
 330 otherwise “value-wash” by claiming inclusivity while quietly privileging one evaluative frame. FOAM makes
 331 the stance set an explicit input and therefore a target for governance and oversight; this aligns with work
 332 arguing that legitimacy depends on making value choices and their selection procedures contestable [19].
 333 In deployment terms, this means FOAM can be rerun with (i) added perspectives, (ii) reweighted value
 334 priorities, or (iii) altered evidentiary rules, producing *comparative, contestable* outcomes rather than a single
 335 authoritative verdict.

341 3.3 Deliberative protocol: dialectical refinement and mediation trace

342 FOAM’s deliberation is implemented as a **mediation loop**:

- 343
- 344 (1) *Seeding* (instantiate agents + perspective nodes),
 - 345 (2) *Local drafting* (agents generate independent proposals),
 - 346 (3) *Cross-examination* (agents issue structured objections and targeted questions),
 - 347 (4) *Evaluation* (a judge/jury component scores draft–objection pairs against criteria), and
 - 348 (5) *Revision + synthesis* (agents revise and a sublation operator composes the provisional output).

349 The accountability point is not that deliberation guarantees truth; it is that **deliberation guarantees**
 350 **structured opportunities to find and localize error**, and then to record what happened when error
 351 was raised.

352 Cross-examination produces a **mediation graph**: a structured trace that links *which agent* made *which*
 353 *claim*, what objections were raised (e.g., missing evidence, value conflict, logical gap), how the claim was
 354 revised, and which surviving claims contributed to the synthesis. This is the audit primitive: contestation
 355 requires that stakeholders can point to *the specific node* where they disagree and see what depended on it. As
 356 an interoperability target, the mediation trace can be expressed using standard provenance representations
 357 (e.g., PROV-O) so that downstream tools can query “what influenced what” across a run [22].

365 3.4 Sublation: synthesis without erasure

366
 367 After critique and revision, FOAM applies a **sublation operator**: a synthesis step intended to preserve
 368 what is valuable in competing positions while explicitly retaining unresolved tensions. In FOAM, sublation
 369 is not a rhetorical flourish; it is a concrete rule: synthesis is disallowed from silently discarding objections
 370 that were scored as material or from collapsing incompatible value frames into an unmarked compromise.
 371

372 Operationally, FOAM’s sublation emits a structured output with (at minimum) three parts:

- 373 (1) A **consensus core** (claims that survived critique across stances),
- 374 (2) A set of **conditional or branch claims** (“if autonomy is prioritized over aggregate welfare,
 375 then...”), and
- 376 (3) A **minority report / dissent memo** that records unresolved conflicts, the strongest arguments on
 377 each side, and which premises are contested.

379 Sublation preserves dissent explicitly.

381 3.5 Inspectable argument structure: Toulmin decomposition and typed syllogisms

383 To make contestation actionable, FOAM constrains agent outputs into an **inspectable argument structure**
 384 rather than free-form prose. We adopt Toulmin-style decomposition—claim, grounds, warrant, backing,
 385 qualifier, rebuttal—because it maps naturally to “what can be challenged”: stakeholders can contest
 386 evidence (grounds), the inferential link (warrant), scope conditions (qualifier), or missing counterevidence
 387 (rebuttal) [34]. This structure also aligns with prior work connecting computational argumentation to
 388 explainable AI, where explanations are made more useful by exposing structured reasons and counterreasons
 389 rather than only surface-level narratives [35].

392 FOAM additionally employs **typed syllogisms**—domain-relevant argument templates that enforce
 393 completeness (e.g., in policy debate: Advantage = Uniqueness + Link + Impact; Disadvantage = Uniqueness
 394 + Link + Impact; Kritik = Link + Impact + Alternative). These structures are standard in competitive
 395 policy debate pedagogy and make dependencies explicit for non-expert audiences [32]. In FOAM, typed
 396 syllogisms function as contestability scaffolds: if a stakeholder disputes the conclusion, the system can point
 397 to the *specific missing or weak component* (e.g., “impact evidence absent” or “link warrant unsupported”),
 398 and the mediation graph can show whether that component was ever raised in critique and why it survived.
 399 The result is a system where “challenge” is not a vague request to “explain more,” but a targeted operation
 400 on a specific argumentative component with traceable upstream dependencies.

404 4 CASE STUDY SYSTEM: EVIDENCE-GROUNDED POLICY DEBATE GENERATION

406 4.1 Why policy debate is an accountability crucible

407 We instantiate FOAM in a domain where *contestability is native to the task*: American competitive policy
 408 debate. Policy debate is a two-team adversarial format in which teams argue for and against a policy
 409 proposal under strict procedural constraints. In this ecosystem, argument quality is not evaluated purely as
 410 rhetorical fluency; instead, the activity is structured around *traceable evidentiary support* and explicit clash,
 411 so claims can be challenged in real time and revisited across subsequent speeches. Critically, policy debate
 412 operationalizes “grounding” through an established evidence artifact: the *debate card*. A card typically
 413 includes (i) a short biased summary intended to support a specific argumentative function, (ii) a full citation,
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and (iii) verbatim quoted source text, often with token-level highlighting that marks precisely what will be read into the round. Competitive success is strongly coupled to evidence quality and its deployment, creating an evaluation environment where provenance and verifiability are not optional.

4.2 Pipeline overview

Figure 2 summarizes our **five-phase pipeline** for generating an evidence-grounded constructive speech (the 1AC, in our evaluation setting). Phases 1–3 produce an inspectable argumentative plan in typed components (perspective assignment → strategic plan → template traversal), Phase 4 binds each argumentative component to *verbatim evidence at sentence granularity* (sentence-level provenance), and Phase 5 compiles and verifies the result (structural conformance, evidence/claim alignment, and perspective consistency). The key design principle is to keep the model in a role where it can be audited: rather than “write a persuasive case and cite sources,” the system decomposes “case construction” into a sequence of constrained decisions that leave a machine-checkable trail.

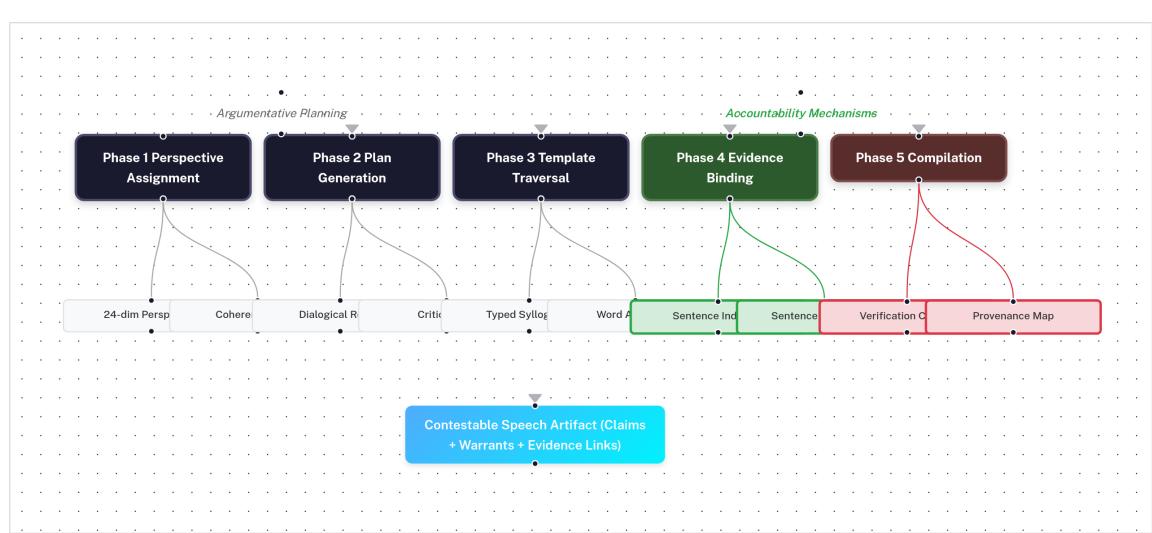


Fig. 2. Five-phase pipeline with accountability mechanisms. Phases 1–3 (Perspective Assignment, Plan Generation, Template Traversal) handle argumentative planning. Phase 4 (Evidence Binding) creates sentence-level provenance by selecting specific sentence IDs rather than paraphrasing. Phase 5 (Compilation) enforces verification checks. The output is a contestable speech artifact with claims, warrants, and traceable evidence links.

4.3 Phases 1–3: perspective assignment, planning, and template traversal

Phases 1–3 produce an inspectable argumentative plan: the system selects an explicit perspective, drafts a typed strategic blueprint, and expands it into a structured scaffold with evidence slots. These phases are implementation detail for our case-study pipeline; we summarize the key outputs here (full prompt and protocol detail are available in supplementary materials). The primary accountability mechanisms evaluated in this paper are sentence-level provenance (Phase 4) and verification checks (Phase 5).

469 4.4 Phase 4: sentence-level provenance

470 **Motivation.** Retrieval-augmented generation can reduce hallucinations, but it does not eliminate a central
 471 accountability failure mode: models may still produce claims that are *unsupported by*, *in conflict with*,
 472 or *misattributed to* retrieved text. Recent benchmarks explicitly document that, even under RAG setups,
 473 LLM outputs can contain unsupported or contradictory content relative to the retrieved passages. Phase 4
 474 therefore implements a stronger constraint than “retrieve then paraphrase”: it forces the model to operate
 475 over *sentence identifiers* rather than free-form rewriting of source material.

476 **Mechanism.** Phase 4 is a two-step procedure:

477 **Step (a): sentence indexing and retrieval.** The system queries (i) a debate-evidence store (implemented
 478 in our current system as a vector database over a large set of debate “cards”) and (ii) any other preprocessed
 479 sources permitted by the pipeline. Retrieved documents are segmented into sentences, each assigned a
 480 stable index, and returned to the deliberation workspace as a set of candidates with identifiers of the form
 481 (`document_id`, `sentence_id`) plus immutable citation metadata.

482 **Step (b): evidence selection and tagging.** The LLM is then prompted to (1) select which sentence
 483 IDs support each argument slot created in Phase 3 and (2) generate only a short “tag” that states what the
 484 selected evidence is being used to establish. Importantly, the model is not asked to restate the evidence;
 485 the evidence content in the final speech is assembled from the retrieved sentences themselves. This design
 486 eliminates an entire class of failure (fabricated quotations and invented citations) by construction: the model
 487 can be wrong about *which* sentences to use, but it cannot invent sentences that are not in the retrieved set.

488 **Accountability and contestability properties.** Sentence-level provenance changes the contestation
 489 workflow from “argue about what the model meant” to “inspect exactly what the model relied on.” A
 490 stakeholder can challenge (i) *relevance* (“this sentence does not establish the warrant you claim”), (ii) *adequacy*
 491 (“the evidence is too weak/out of context”), or (iii) *selection bias* (“you ignored stronger counterevidence
 492 available in the same corpus”)—and each challenge targets a concrete object (a sentence ID and its parent
 493 source). This is especially aligned with policy debate’s evidence norms, which already treat quoted and
 494 highlighted text as the unit of disputation under cross-examination.

502 503 504 4.5 Phase 5: compilation and verification checks

505 Phase 5 compiles the typed argument scaffold (Phase 3) and the evidence bindings (Phase 4) into a final
 506 speech artifact suitable for evaluation. Compilation preserves the provenance map: each substantive claim in
 507 the rendered speech remains traceable to one or more sentence IDs plus citation metadata. The system then
 508 runs verification checks that are directly tied to the accountability requirements:

- 511 (1) **Structural completeness** (template validators—e.g., required components are present),
- 512 (2) **Evidence/claim alignment** (each slot has at least one bound sentence; missing bindings fail
 513 closed), and
- 514 (3) **Perspective consistency** (warrants and impacts do not contradict the declared perspective node
 515 from Phase 1).

516 Figure 2 highlights where provenance is created (Phase 4) and where it is enforced (Phase 5).

521 5 EMPIRICAL EVALUATION

522 5.1 Research questions

523 We evaluate FOAM’s accountable-generation claims using an *audit-style* design: we define explicit research
524 questions, compare against salient baselines, and report both performance outcomes and traceability outcomes
525 as first-class metrics. This approach aligns with established work on internal algorithmic auditing and
526 emerging “assurance audit” perspectives, which emphasize that accountability requires not only outcome
527 quality, but also artifacts and procedures that make decisions inspectable and challengeable [21, 26].
528

529 We ask whether FOAM improves:

- 530
- 531 • **RQ1:** Quality/persuasiveness
 - 532 • **RQ2:** Evidence verifiability
 - 533 • **RQ3:** Whether gains are attributable to the accountability mechanisms rather than model strength

534 5.2 Experimental design and baselines

535 **Task selection.** We evaluate in evidence-grounded policy debate generation because it combines (i) long-
536 horizon argumentative planning, (ii) adversarial robustness expectations (arguments must survive challenge),
537 and (iii) strict evidentiary norms (claims are conventionally supported with citations). In computational
538 argumentation, even highly resourced systems have historically relied on constrained debate settings and
539 bespoke pipelines; the Project Debater line of work illustrates both the ambition of debate as a benchmark
540 and the practical need to structure and constrain the task for reliable evaluation [31].

541 **Debate artifact.** We focus on the **first affirmative constructive (1AC)** as the most demanding
542 generative unit in competitive policy debate: it must introduce a full strategic position (advantages/disadvantages/solvency framing), anticipate common lines of negative attack, and do so under
543 tight length constraints while maintaining evidentiary support. This makes the 1AC a strong proxy for
544 high-stakes accountable generation: arguments must be *comprehensible, internally coherent, and traceable to*
545 *evidence* to be meaningfully contestable.

546 **Corpus and baselines.** We ran a **double-blind tournament of 66 cases** drawn from three sources:

- 547
- 548 (1) **FOAM-based structured system** (“DebaterHub Structured System,” $n = 22$), generated via
549 differentiated perspectives, iterative dialectical refinement, typed syllogisms, and sentence-level
550 provenance;
 - 551 (2) **Human expert baseline** ($n = 23$), sampled from prestigious debate camps (Dartmouth, George-
552 town, Michigan, Emory); and
 - 553 (3) **Zero-shot AI baseline** ($n = 21$), produced by frontier models (Gemini/Claude/ChatGPT/Grok)
554 using prompt engineering and web-research access but without debate-specific pluralistic architecture.

555 **Evidence corpus for provenance.** FOAM’s evidence retrieval and validation leverage a structured
556 debate-evidence corpus derived from OpenDebateEvidence, which (as released) contains **3.5M+** competitive
557 debate documents with metadata useful for downstream argument mining and citation [27]. Operationally,
558 our system queries a vector database of $\sim 85,000$ curated “cards” plus any newly processed sources, and the
559 generation pipeline preserves *sentence-level identifiers* so that downstream reviewers can trace claims to
560 exact supporting spans.
561

573 5.3 Judging rubric and scoring

574 Tournament format and blinding. All submissions were anonymized and assigned unique IDs (e.g.,
575 Case_001), and judging proceeded purely on content without revealing origin. Cases advanced through a
576 modified Swiss-style bracket with double elimination, and pairings were balanced by strategic approach
577 (e.g., traditional policy vs. kritik) to reduce “judge adaptation” artifacts. Ties within a narrow score
578 band triggered evidence validation as a tiebreaker, keeping accountability-relevant verifiability salient in
579 advancement decisions.

580 Rubric and judge. A Claude Opus 4 judge evaluated each case on five weighted dimensions:

- 581 • Argumentation Strength (25%)**
- 582 • Evidence Quality (25%)**
- 583 • Strategic Coherence (20%)**
- 584 • Innovation (15%)**
- 585 • Competitive Viability (15%)**

586 The rubric was designed to reward both argumentative competence and evidence-groundedness, while
587 preserving enough structure for reproducibility.

588 5.4 Evidence validation methodology

589 Why evidence validation is an accountability metric (not just “anti-hallucination”). In contestable
590 systems, stakeholders must be able to *locate* and *evaluate* the grounds of a claim—especially where persuasive
591 language can obscure weak or missing support. Audit frameworks similarly emphasize that assurance depends
592 on traceable evidence artifacts rather than outcome plausibility alone [21, 26]. We therefore operationalize
593 verifiability as a measurable property of each case’s citations.

594 Automated citation checks and categories. Each citation was automatically checked against the
595 referenced source (via URL or resolvable reference), and classified into one of four buckets: **exact match,**

596 **partial match, **paraphrase**, or **fabricated**.** We summarize results primarily via **Perfect Validation**,
597 a stringent metric that counts only **exact matches—i.e., the cited claim can be located verbatim in the**
598 referenced source span. This is intentionally conservative: Perfect Validation corresponds to the strongest
599 form of contestability, where an affected party can directly inspect the cited text without interpretive debate
600 about semantic similarity.

601 How FOAM changes the validation problem. FOAM’s sentence-level provenance changes citation
602 validation from a semantic retrieval problem into a *pointer integrity* problem: the model is never asked to
603 reproduce source text, but instead selects sentence indices from retrieved documents and attaches them to
604 specific argument components. This design greatly reduces degrees of freedom for fabrication and enables
605 deterministic re-checking of a case’s evidentiary backbone.

606 5.5 Results

607 Main tournament outcomes. Table 1 reports aggregate performance by source. The FOAM-based
608 system achieved the highest overall score (81.7**) relative to human experts (**70.1**) and zero-shot AI**
609 (50.6**). The largest gap appears in **Evidence Quality** (**86.7** vs. **56.9** vs. **27.1**), consistent with the claim**

that provenance-constrained generation shifts the system from persuasive-but-unreliable outputs toward persuasive-and-grounded outputs.

Table 1. Tournament Results by Source

Metric	FOAM	Human Expert	Zero-shot AI
Overall Score	81.7	70.1	50.6
Evidence Quality	86.7	56.9	27.1

Evidence validation and verifiability. Table 2 reports Perfect Validation rates. FOAM achieved 76.2% Perfect Validation, compared to 8.7% for the human expert baseline and 0% for zero-shot AI. This is the central accountability result: the FOAM pipeline does not merely produce arguments that a judge model rates as “good,” but produces arguments whose evidentiary support can be mechanically verified at scale.

Table 2. Perfect Validation Rates

Source	Perfect Validation (%)
FOAM System	76.2
Human Expert	8.7
Zero-shot AI	0.0

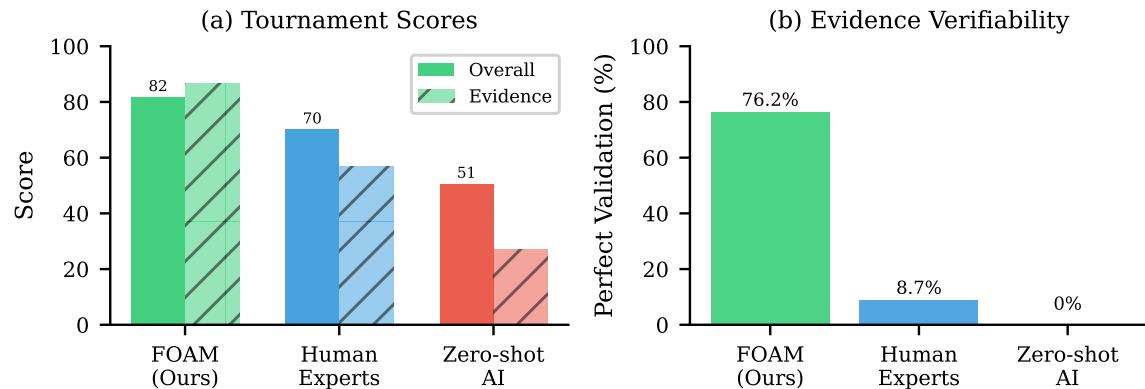


Fig. 3. Tournament results comparing FOAM, human expert baselines, and zero-shot AI. (a) Overall and Evidence Quality scores. (b) Perfect Validation rates—the percentage of citations that exactly match source text. FOAM achieves 76.2% perfect validation vs. 8.7% for human experts and 0% for zero-shot AI.

Interpreting what is doing the work. Two mechanisms plausibly drive the observed gap: (i) **pluralistic deliberation** (multi-perspective critique and refinement) improves strategic coherence and argument coverage, while (ii) **sentence-level provenance** directly improves evidence integrity and sharply limits fabrication opportunities. Consistent with this interpretation, the tournament champion (**Case_045**, “Navy Underwater Exploration”) achieved **fidelity = 1.0** alongside a strong final-round score, indicating that high persuasive quality and high verifiability can co-occur under the FOAM constraint regime.

6 IMPLICATIONS FOR ACCOUNTABLE AI SYSTEMS

FOAM reframes explanation as a contestable record rather than a post-hoc narrative. Instead of producing a single rationale, the system outputs:

- (1) An auditable argument structure (claims, warrants, rebuttals),
- (2) Explicit perspective configurations, and
- (3) Sentence-level provenance linking each substantive claim to a checkable source span.

This shifts accountability from “did the explanation sound plausible?” to “which premises and evidence does the output depend on, and where can a challenge be lodged?”

Operationally, FOAM supports contestation at three levels:

- (1) **Evidence disputes** (a cited sentence does not support the tagged claim; missing counterevidence),
- (2) **Inferential disputes** (the warrant connecting evidence to conclusion is invalid or incomplete), and
- (3) **Normative disputes** (the perspective/value configuration is illegitimate or incomplete for the context).

Because these objects are explicit, a reviewer can localize disagreement to specific nodes and request revision without reopening the entire output as free-form prose.

Institutionally, the resulting artifact functions as an auditable dossier that can plug into existing governance workflows (internal review, incident response, assurance audits, and post-hoc dispute resolution). The technical contribution is not replacing due process, but supplying the structured, traceable materials that make procedural review feasible at scale.

7 LIMITATIONS AND FUTURE WORK

7.1 Methodological limitations and validity threats

First, our primary outcome measure relies on an automated judge (Claude Opus 4) to score debate artifacts under a fixed rubric. While LLM-as-judge evaluation is increasingly standard at scale, it is known to exhibit systematic biases (e.g., position effects, verbosity/style sensitivity, and self-enhancement tendencies) and may be vulnerable to prompt- or framing-based perturbations that shift preferences without corresponding semantic differences [6, 30, 37]. We reduce—but do not eliminate—these threats via double-blinding, standardized prompts, and by pairing judge scores with an independent evidence-validation audit. Nevertheless, the reported tournament results should be interpreted as descriptive for this evaluation setup, and future replications should triangulate across multiple judge models and human adjudication.

Second, our system’s accountability guarantees are conditioned on the properties of the underlying evidence substrate. Sentence-level provenance constrains the model to point to specific source sentences rather than inventing citations, but it does not ensure that the retrieved evidence is complete, representative, or up to date. Coverage gaps, topical skew, and retrieval errors can shape which arguments are discoverable, and can yield outputs that are “well-cited” yet misleading due to selection effects, over-aggregation, or missing context [28]. These concerns are not unique to debate generation: any contestability mechanism built on curated corpora inherits the corpus’ blind spots. Accordingly, FOAM should be viewed as an approach to making claims auditable and challengeable—not as a guarantee that the selected evidence is normatively “best” or epistemically sufficient.

729 Third, our evaluation scope is intentionally narrow and therefore limits external validity. We benchmark a
730 specialized argumentative domain (policy debate) and a bounded artifact type (constructive case generation),
731 and we do not yet measure downstream stakeholder contestation behaviors (e.g., whether affected parties
732 can efficiently detect, understand, and successfully challenge specific warrants or citations). Additionally, our
733 “perfect validation” metric is strict by design: it favors verbatim traceability and can under-credit faithful
734 paraphrase or correct claims supported by multiple dispersed sentences. Conversely, the metric may fail to
735 detect other fidelity failures (e.g., cherry-picked quoting or context stripping) that require richer contextual
736 checks. These are appropriate trade-offs for an audit-style evaluation, but they motivate follow-on studies
737 with complementary human-centered and context-sensitive validation protocols.
738
739

740 7.2 Safety and misuse considerations

741 Systems optimized for persuasive, evidence-backed argumentation can be dual-use. Even when designed for
742 accountability, modular pipelines that improve rhetorical quality and citation hygiene could be adapted for
743 manipulation at scale (e.g., coordinated influence operations, astroturfing, or microtargeted persuasion),
744 especially if paired with personalization and distribution infrastructure [5, 28]. We therefore include a
745 dedicated Adverse Impacts statement in the paper’s Endmatter describing plausible misuse modes, anticipated
746 affected groups, and mitigations (e.g., access controls, logging/auditability, and deployment constraints)
747 appropriate to this capability class.
748
749

750 7.3 Future work

751 A first priority is human-subject evaluation of contestability as an interaction property rather than a static
752 artifact property. We plan controlled studies in which participants (including domain experts and affected
753 stakeholders) attempt to (i) locate supporting evidence for a contested sentence, (ii) challenge a warrant
754 or inference step, and (iii) request or compare alternative perspective nodes. Primary outcomes should
755 include time-to-challenge, challenge success rates, perceived procedural fairness, and the degree to which
756 the system supports actionable revision pathways (e.g., retracting a claim, swapping evidence, or surfacing
757 counter-arguments) rather than merely producing longer explanations.
758
759

760 A second priority is extending FOAM with optimization and training methods while preserving con-
761 testability constraints. Our preliminary results in iterative preference learning for debate suggest that
762 tactic selection and evidence integration can be improved substantially, but also reveal failure modes (e.g.,
763 “phantom critic” contamination and degraded interactive cross-examination under naïve retry-with-feedback
764 regimes) that matter directly for accountable deliberation systems. Future work should explore (i) multi-
765 judge and human-calibrated optimization targets, (ii) training objectives that explicitly reward faithful
766 warrant-evidence alignment (not only persuasiveness), and (iii) contestation-aware curricula that treat
767 interactive questioning and rebuttal as first-class skills rather than afterthoughts.
768
769

770 8 CONCLUSION

771 High-stakes deployments of LLM-based systems demand more than *transparent-seeming* narratives; they
772 require explanations that can be *challenged, audited, and revised*. Recent evidence suggests that post-hoc
773 “reasoning traces” are often not a reliable proxy for what drives model behavior: when a prompt-injected hint
774 changes a model’s answer, state-of-the-art reasoning models reveal that hint in their chain-of-thought only
775

about 25–39% of the time, indicating substantial unfaithfulness of verbalized rationales to causal drivers of outputs [7].

This paper contributes:

- (1) **FOAM**, a pluralistic deliberation architecture for explainability-and-contestability-by-design;
- (2) An **inspectable provenance mechanism** that makes sentence-level claims traceable to source spans and contestable at the level stakeholders actually dispute; and
- (3) An **audit-style empirical evaluation** in evidence-grounded policy debate generation.

In a double-blind tournament of 66 cases, the FOAM-based system achieves higher overall scores than expert-human and zero-shot baselines (Table 1) and dramatically higher perfect evidence validation rates (Table 2), demonstrating that accountable generation can be simultaneously *high-quality* and *verifiable*.

For the FAccT community, the central implication is a practical shift from explanation-as-disclosure to **contestable explanations**: outputs whose *claims, warrants, and evidence links* are explicit, inspectable, and designed to invite targeted challenge (e.g., disputing a cited sentence, contesting a warrant, or requesting an alternative perspective node). This orientation is consistent with due-process motivations for a meaningful right to contest consequential automated decisions [17].

More broadly, FOAM reframes accountability as a *system property* produced by structured mediation among differentiated perspectives, rather than as a post-hoc narrative appended to a monolithic model. Where governance requires reason-giving that can withstand scrutiny, pluralistic deliberation plus verifiable provenance offers a concrete design pattern for building AI systems whose decisions can be examined, contested, and improved without relying on “black-box” rationalizations.

GENERATIVE AI USAGE STATEMENT

This research investigates the use of large language models (LLMs) within a structured multi-agent deliberation framework. The FOAM system described in this paper uses LLMs as components within the deliberation pipeline. The paper text itself was drafted by human authors with AI assistance limited to copy-editing and formatting suggestions. All substantive claims, experimental design, and analysis reflect human judgment and interpretation.

ETHICAL CONSIDERATIONS

This work develops AI systems with persuasive capabilities, which raises dual-use concerns. We address these in Section 7 and Section 6, discussing safeguards including transparency requirements, evidence provenance constraints, and the deliberate choice to evaluate in a domain (competitive debate) with established norms for scrutinizing persuasive claims. The evaluation involved no human subjects; all baselines were drawn from publicly available debate materials or generated outputs.

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