A Human Behavioral Baseline for Collective Governance in Software Projects

Mobina Noori
Department of Computer Science
University of California Davis
Davis, CA, USA
lianoori@ucdavis.edu

Mahasweta Chakraborti
Department of Communication
University of California, Davis
Davis, CA, USA
mchakraborti@ucdavis.edu

Amy X. Zhang
Allen School of Computer Science & Engineering
University of Washington
Seattle, WA, USA
axz@cs.uw.edu

Seth Frey
Department of Communication
University of California, Davis
Davis, CA, USA
sethfrey@ucdavis.edu

Abstract

We study how open source communities describe participation and control through version controlled governance documents. Using a corpus of 710 projects with paired snapshots, we parse text into actors, rules, actions, and objects, then group them and measure change with entropy for evenness, richness for diversity, and Jensen Shannon divergence for drift. Projects define more roles and more actions over time, and these are distributed more evenly, while the composition of rules remains stable. These findings indicate that governance grows by expanding and balancing categories of participation without major shifts in prescriptive force. The analysis provides a reproducible baseline for evaluating whether future AI mediated workflows concentrate or redistribute authority.

1 Introduction

The use of artificial intelligence systems in software project management has become increasingly salient [Hashimzai and Mohammadi, 2024]. In addition to assisting individual developers, they are coordinating core management functions, including drafting pull requests, triaging issues, proposing code reviews, and enforcing release gates. As these capabilities are embedded in team tooling, decision rights migrate from human maintainers toward sociotechnical pipelines. In these pipelines, algorithms and people jointly govern workflows [Xiao et al., 2024, Wessel et al., 2022]. This shift raises questions about how authority is redistributed when algorithms mediate both individual contributions and collective coordination [Crawford et al., 2023]. Insights from recent work on algorithmic collective action indicate that when multiple groups interact with the same algorithmic system, their strategies can interfere in unexpected ways. A campaign that achieves near perfect success in isolation may see its efficacy drop sharply when a second group acts at the same time [Karan et al., 2025]. We use *algorithmic collective action* to denote coordinated behavior among participants when interactions are shaped by algorithmic systems within sociotechnical platforms. In software development, the growing reality of human and algorithmic co-production leads us to ask: how might AI systems embedded in team support tools reshape governance structures, stakeholder participation, and power relations on platforms, and what options exist for steering them toward the common good [Varanasi and Goyal, 2023]?

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The debate about how AI systems reshape governance has outpaced empirical evidence [Delgado et al., 2023]. Scholars of AI governance and participatory design warn that algorithmic infrastructures can undermine stakeholder agency, reinforce hierarchies, or reallocate decision rights [Birhane et al., 2022]. The recency of AI technologies make it currently challenging to gain substantial inferences on trends of human-AI interactions in software project management. In addition, most studies examine these emergent dynamics through case studies, audits, or simulations without a historical baseline against which to evaluate the change [Margetts, 2022]. As a result, claims about AI-induced shifts in governance remain speculative. Establishing a historical baseline for governance change is therefore the central objective of this paper. Before assessing whether AI systems redistribute power, narrow opportunities for participation, or enable more inclusive governance, it is necessary to understand how authority has evolved in primarily human-governed settings [Sharma et al., 2020]. Our study addresses this need by constructing a large-scale longitudinal baseline of institutional change in open source project governance before the widespread adoption of AI-managed tools, providing a reference point for evaluating how future AI-mediated platforms may reshape participation and oversight. To our knowledge, this is the first large-scale longitudinal baseline of open-source governance prior to the widespread adoption of AI-managed tools.

Open source software communities have been extensively studied as exemplar instances of collective knowledge work Benkler [2006], Heckman et al. [2007], Lee and Cole [2003], O'Mahony and Ferraro [2007], Schweik and English [2012], Chakraborti et al. [2024a]. Importantly, they are a transparent testbed for studying governance [O'Mahony, 2005]. Open source projects externalize governance in version-controlled files such as `GOVERNANCE.md`, which makes rules explicit, textual, and historically archived. Because governance edits are version-controlled and public, rule changes are observable at fine temporal resolution and comparable across time and projects. This is unique to OSS, which, unlike conventional organizational settings, supports systematic observation of how authority changes over time.

We treat AI systems as non-human stakeholders whose programmed objectives interact with human goals in shared workspaces. This framing aligns with a view of algorithmically mediated collaboration in which both human contributors and AI systems participate in shaping collective outcomes and therefore require institutional oversight. We lay a fundamental step in this important discourse, by analyzing version-controlled `GOVERNANCE.md` documents from open source software projects and contribute the following:

1. Our corpus captures several years of Open source software (OSS) projects before the widespread adoption of AI-managed project tools and management suites, offering a neutral reference point for future evaluations of AI-mediated governance.
2. By tracing how roles, responsibilities, and decision rights evolve, we provide an account of governance as it is encoded and renegotiated collectively, rather than inferred only from individual behaviors or outcomes.
3. We establish a text-based analytical framework that is replicable and easily extendable to governance records besides markdown files (e.g. prompts used to steer agentic workflows), and therefore can support future studies aimed at understanding software engineering team power structures under AI agent-human co-production.

Together these contributions establish a foundation for participatory AI research. Understanding organic governance trajectories in open source communities can inform the design of participatory AI systems that allow collective human input in decision processes and provide benchmarks for assessing whether AI infrastructure serves the common good. This baseline enables falsifiable pre/post evaluations of AI-mediated workflows, including whether authority becomes more concentrated or participation more uneven when assistants are introduced.

Building on this baseline, we frame our analysis around three research questions. First, how do these communities distribute authority over time, and what does that suggest for steering AI systems toward the common good? Second, how are norms, responsibilities, and decision rights encoded in open source governance over time and what parallels exist for encoding values into AI systems? Third, can open source governance evolution serve as a model for participatory AI design in which users collectively influence system behavior?

These questions move from describing historical change in open source governance to identifying patterns that matter for the future of AI systems. By tracing how authority shifts, how rules harden or soften, and which governance elements remain stable versus contested, we offer an empirical foundation for examining how AI-managed infrastructures may redistribute power, reshape participation, and influence the prospects for collective oversight.

The rest of the paper is organized as follows. The description of the data and methods is summarized in Section 2. Section 3 represents the main results of the study. Then, Section 4 provides interpretation. Finally, Section 5 describes the conclusion, limitation, and future work.

2 Methods

We describe the corpus, selection criteria, preprocessing, institutional parsing, and analysis that convert governance prose into comparable structures. The aim is a simple pipeline that others can rerun on future AI-managed cohorts.

Data and coverage. GitHub is the most widely used hosting platform for open-source development, built on the distributed version-control system Git. It provides an infrastructure for collaboration, coordination, and community visibility as well as storing code. Governance is a persistent concern in this context: projects must determine how authority should be allocated, how contributor rights should be granted or lost, and how conflicts should be resolved. Many communities address these governance challenges through informal norms, foundation-level oversight, and increasingly, explicit written constitutions. A notable development has been the emergence of `GOVERNANCE.md` as a de facto standard for codifying project rules, alongside related artifacts such as `CONTRIBUTING.md`, codes of conduct, and maintainership guides. These files articulate roles, permissions, obligations, and protected resources, making governance unusually transparent and traceable.

Starting with a seeded collection and filename patterns, we analyzed 710 repositories with at least one governance file at the repository root. The corpus spans 2013–2022, with governance commits recorded through June 2022 (earliest: 2013-05-09; latest: 2022-05-19). File coverage is dominated by `GOVERNANCE.md`, which appears in 673 out of 710 projects (94.8%), alongside 37 filename variants. The latest governance file is present for all projects, and Markdown structure is detectable in 498 repositories (70.1%), with a median of 5 sections (range: 2 to 25) Yan et al. [2023].

Across the corpus we record 3,889 governance commits corresponding to repository by commit pairs and 2,890 unique commit OIDs, covering 107,869 line level edits with 82,076 additions and 25,793 deletions.

Paired subset and pairing rules. The pipeline produced net governance changes (earliest and latest snapshots) for the 637 repositories over an observation period from 2014-03-26 to 2022-05-18. `GOVERNANCE.md` file names were dominant, being 601 of 637 (or 94.3%). Inclusion requires at least two recoverable governance snapshots per project; we label the earliest valid snapshot as *initial* and the most recent as *latest*. We require across day change with the two snapshots fall on different calendar days, which in practice implies at least two distinct `GOVERNANCE.md` commits. For each repository with a governance file, we traversed the Git history to recover the earliest valid version of that file and paired it with the most recent version. Projects with only one usable snapshot are excluded from longitudinal analysis but retained for descriptive statistics. For the 637 paired repositories, the gap from earliest to latest commit has median 0 days with interquartile range 247, minimum 0, and maximum 2616; we refer to 0 day gaps as within day revisions. The across day change subset comprises 279 of 637 which equals 43.8 percent. Where multiple governance files existed, we would create a composite governance view by concatenating in a deterministic order and removing repeated boilerplate; in this paired cohort, one governance file per repository sufficed.

Normalization and alignment. We preprocess governance documents by removing badges and images, converting tables to lists, normalizing headings, and stripping markup. Text is segmented into short paragraph blocks and sentences using a splitter tuned for Markdown lists. To reduce pronoun ambiguity, we apply coreference resolution while maintaining a reversible mapping to original offsets [Lee et al., 2018] [Jurafsky and Martin]. Where headings are detectable, we record section counts across snapshots to capture the degree of governance structuring.

Institutional parsing. The governance structure of each GitHub project in our corpus was extracted from its `GOVERNANCE.md` constitution using the Institutional Grammar (IG) framework [Ostrom, 2009] (Crawford & Ostrom, 1995; Ostrom, 2006). This framework maps the syntactic elements of policy texts to institutional primitives, first decomposing paragraphs and multi-phrase sentences into simple "institutional statements". Under the institutional grammar, an institution is treated as a bag of institutional statements. Recent NLP methods have made their automated extraction from policy text feasible Rice et al. [2021], Chakraborti et al. [2024b]. Governance documents were parsed into institutional statements consisting of four linked components. An institutional statement has a *Role* (known in IG as 'Attribute') when its grammatical subject is a kind of agent. Roles account for the types of actor or position recognized by the institution (e.g., "project lead," "contributor"). An *Action* (the 'Aim' in IG; syntactically the verb) identifies activities recognized by the institution as requiring governance (e.g., "commit," "assign," "review"). A *Deontic* captures the prescriptive force of the institutional statement, expressed through modal verbs such as "may," "should," or "must," which indicate whether an action is permitted, recommended, or required. Deontics can also be enabling ("can") or restricting ("cannot"). An *Object* represents the grammatical object of the rule, whether another actor or a resource that is subject to the action enacted by the statement's role. For example, in the sentence "The technical committee must ratify the development roadmap", the Role is "technical committee," the Action is "ratify," the Object is "roadmap," and the Deontic is "must," which renders the statement obligatory.

We extracted these components with the NLP4Gov toolkit [Chakraborti et al., 2024b] [Chakraborti et al., 2024a], which combines dependency parsing with semantic role labeling to parse each unitary institutional statement into its IG components. The parser emits tuples with and anchors spans and positions, enabling traceability back to the original text. Modal verbs such as *may*, *can*, *should*, *must*, and *will* were canonicalized into a closed set of deontic types, while role names such as *maintainer*, *committer*, *reviewer*, and *release manager* were normalized into a controlled vocabulary manually. We further manually categorized Actions into a version of the Typology of Rules adapted from the institutional analysis literature Ostrom [2009], Weible et al. [2012], Weible and Heikkila [2017], Weible et al. [2018]. To test the reliability of these qualitative steps of the analysis, two authors coded the same sample of 50 Actions, which demanded the most manual categorization among the four types of institutional features. Over this sample they demonstrated a percent agreement of 82% and a Cohen's $\kappa = 0.92$, over 9 labels, including a null label, strong evidence for the intersubjective validity of the chosen typology.

Embedding, clustering, and metrics. Each canonical tuple is rendered as a short governance statement. We encode each governance statement with a Sentence-BERT encoder [Reimers and Gurevych, 2019] and apply BERTopic [Grootendorst, 2022] to derive semantic clusters per repository at two snapshots (initial, latest). BERTopic operates in the embedding space to form topic–like groups and uses class–based TF–IDF to label them. To ensure even clustering across all the projects' corpus, we use the library's standard hyperparameters without custom tuning. For structure, we report (i) richness K as the number of distinct clusters per repository and (ii) normalized Shannon entropy H (bits, base 2) over cluster proportions, with longitudinal change $\Delta H = H_{\text{latest}} - H_{\text{initial}}$. For drift, we compute Jensen–Shannon divergence (JSD, bits) between the aligned initial and latest cluster distributions for each repository. All repository–level estimates are aggregated with equal–weight bootstrap confidence intervals by resampling repositories with replacement.

Analysis and inference. Using the paired across day subset defined above, we compute, for each repository r and snapshot $v \in \{\text{initial}, \text{latest}\}$, the empirical distribution over semantic cluster labels. Section A in Appendix provides the main equations of the methodology. Specifically, Normalized Shannon entropy $H_v(r)$ summarizes evenness (Eq. 1), and *change* is $\Delta H(r)$ (Eq. 2). Distributional drift is measured with Jensen–Shannon divergence in bits between the aligned initial and latest distributions (Eq. 3). Richness $K_v(r)$ is the count of distinct labels in snapshot v with a presence threshold of at least two statements (Eq. 4); the paired change is $\Delta K(r)$ (Eq. 5). To control for document length, we also report a rarefied ΔK by sampling an equal number of statements from both snapshots and averaging paired differences over repeated draws (Eq. 6). Entropy and JSD are computed only for repositories with at least five labeled statements in each snapshot; richness uses the presence threshold described above. All repository–level estimands are reported as equal-weight means across repositories with percentile confidence intervals obtained by a repository bootstrap (Eqs. 7–8; resampling repositories with replacement, B=10,000). Unless noted otherwise, intervals are 95% and units are bits for H and JSD.

Table 1: **Attention to roles and actions becomes more even; deontic polarity is broadly stable.** Entries report repository–paired changes in concentration (Shannon entropy $\Delta H = H_{\text{latest}} - H_{\text{initial}}$, bits) (mean) and within–repository distributional drift (Jensen–Shannon divergence, bits). Rows show means across repositories; 95% CIs are from equal–weight bootstrapping over repositories (B=10,000). Bold ΔH intervals exclude 0. † Binary coding of deontics into enabling vs. restricting.

Feature	n	**Initial** H	**Latest** H	ΔH **[95% CI]**	**JSD [95% CI]**
Roles	169	1.775	1.866	**+0.092 [0.011, 0.173]**	0.202 [0.172, 0.234]
Actions	213	1.905	1.979	**+0.074 [0.017, 0.134]**	0.126 [0.107, 0.146]
Deontic	144	1.057	1.052	−0.005 [−0.066, 0.056]	0.062 [0.048, 0.079]
Deontic†	149	0.108	0.076	−0.032 [−0.066, −0.001]	0.009 [0.005, 0.014]

Table 2: **Projects define more roles and govern more actions over time.** Entries report the repository–paired change in the number of distinct constructs ($\Delta K = K_{\text{latest}} - K_{\text{initial}}$) (mean) with equal–weight bootstrap 95% CIs over repositories (B=10,000). The rarefied estimate draws the same number of statements from each snapshot (cap 100) before counting, to address length differences. Units are counts of distinct clusters; bold intervals exclude 0.

Feature	n	**Initial** K	**Latest** K	**Mean** ΔK **[95% CI]**	**Rarefied** ΔK **[95% CI]**
Roles	244	3.46	3.95	**+0.484 [0.258, 0.713]**	**+0.224 [0.092, 0.352]**
Actions	266	3.86	4.46	**+0.602 [0.417, 0.793]**	**+0.228 [0.134, 0.326]**
Deontics	236	1.14	1.15	+0.008 [−0.038, 0.055]	−0.024 [−0.062, 0.012]
Objects	97	1.27	1.33	+0.062 [−0.062, 0.186]	+0.075 [−0.009, 0.162]

3 Results

We study within repository change by pairing the earliest recoverable governance snapshot with the latest and computing: (i) Shannon entropy for each version $H_v(r)$ in Eq. (1) and the paired change $\Delta H(r)$ in Eq. (2); (ii) distributional drift via Jensen–Shannon divergence in Eq. (3); and (iii) breadth as the count of distinct constructs $K_v(r)$ in Eq. (4) and its paired change $\Delta K(r)$ in Eq. (5), with the size controlled rarefied estimate $\widetilde{\Delta K}(r)$ in Eq. (6). Repository level summaries are aggregated with equal weight bootstrap confidence intervals using the resampling scheme in Eqs. (7)–(8) (B=10,000). Unless noted, units are bits for H and Jensen–Shannon divergence. The minimum per version screen of at least five labeled statements is applied as specified in Methods.

Breadth. Projects define a wider array of who acts and what is governed over time. Roles and actions both show clear increases in the number of distinct constructs per repository, and those increases remain positive under the rarefied control that equalizes snapshot length $\left(\widetilde{\Delta K}(r)\text{ in Eq. (6)}\right)$. Deontic and object counts show no effect on average. Table 2 reports the paired changes ΔK with percentile confidence intervals that reflect between project variation.

Concentration and drift. Attention across constructs becomes more evenly distributed for roles and actions. Mean ΔH is positive for both features and the corresponding intervals exclude zero. Under the standard modal inventory deontic composition is broadly unchanged, while collapsing to enabling versus restricting yields a small decrease in evenness. Mean Jensen–Shannon divergence values indicate within project drift between initial and latest snapshots for all features, with larger drift for roles and actions than for deontics. Table 1 reports ΔH and Jensen–Shannon divergence.

Interpretation of intervals. The paired design means intervals summarize between project uncertainty, not within project sampling error. Results are robust to the minimum per version screen and rarefaction confirms that breadth findings are not an artifact of longer documents. Object results are underpowered in the paired subset and are reported for completeness.

Overall, communities diversify and rebalance the governance space of actors and activities while leaving prescriptive polarity comparatively stable. These patterns provide a human authored baseline against which AI assisted cohorts can be evaluated for concentration, drift, and breadth shifts $\left(\text{Tables 2–1}\right)$.

4 Interpretation

Our paired design establishes a human authored baseline for how projects formalize participation and control over time. Two results are robust. Projects broaden and rebalance who acts and what is governed: both the count of distinct constructs and the evenness of attention rise for Roles and Actions (Tables 2 and 1). The force of rules is comparatively stable: under the standard Deontic inventory we see no effect on average, while an enabling versus restricting recode shows a small decrease in evenness. Objects are underpowered and we treat them as descriptive context.

These findings are consistent across complementary summaries. For Roles and Actions, entropy and richness move together, and rarefied ΔK confirms that gains are not explained by longer files. Jensen Shannon divergence indicates within repository drift as catalogs expand. The change distribution has many near zeros with a minority of large moves, which is consistent with punctuated edits rather than steady drift.

The measurements suggest priorities for AI assistance. Tools should emphasize specification over escalation: help communities name and rebalance Roles and Actions, surface uneven coverage, and propose governance ready statements that identify actor, deontic force, action, and object. Edits should be exposed as structured deltas that indicate which dimension changes. Given the small decrease in evenness under the enabling versus restricting recode, systems should require explicit acknowledgement before intensifying restricting language and make such shifts visible in review.

To evaluate AI assisted cohorts against the baseline, we recommend reporting paired changes in evenness and count for Roles and Actions (for example ΔH and ΔK with the rarefied variant), Deontic composition and polarity shares, authority concentration such as the share of approvals by role and the prevalence of single gate approvals, and participation outcomes such as time to first review and the distribution of review work. Where possible, control for repository size and activity.

Scope and external validity are limited. We analyze governance text rather than behavior, intervals reflect between project uncertainty via equal weight resampling at the repository level, and artifacts are predominantly in English with policies sometimes spread across files. The labeling, pairing, entropy and richness computation, Jensen Shannon divergence, and bootstrapping pipeline is artifact agnostic and can be applied to multi file policy inventories. Equal weighting avoids collapsing smaller projects into larger ones and aligns with participatory aims.

5 Conclusion

We provide a reproducible human baseline for how open-source projects formalize participation and control. Governance prose is parsed into tuples (actor, deontic force, action, object), clustered, and summarized with entropy H for evenness (Eq. 1), paired change ΔH (Eq. 2), Jensen–Shannon divergence for drift (Eq. 3), and richness K for the count of distinct constructs (Eq. 4), with equal-weight repository bootstrapping for uncertainty (Eqs. 7–8). Empirically, projects define more *roles* and govern more *actions* over time ($\Delta K > 0$; rarefied estimates corroborate that gains are not length artifacts; Table 2); evenness also rises for roles and actions ($\Delta H > 0$), while deontic composition is broadly stable, with a small decrease under the enabling/restricting recode (Table 1). Read as institutional signals, these patterns are consistent with maturation by accretion: catalogs of who acts and what is done broaden and rebalance, while prescriptive polarity changes slowly. Additionally, robustness checks across alternative minimum per-version thresholds showed that results remained consistent, indicating that observed patterns are not artifacts of threshold choice.

Limitations. We analyze governance text rather than behavior; many consequential rules live outside `GOVERNANCE.md` (for example `CONTRIBUTING.md`, `CODEOWNERS`, CI settings, issue templates) or in informal channels, and the corpus is predominantly English open source, which limits generality. Our paired design requires two recoverable snapshots per repository, so survivorship and timing effects can bias change estimates, and stabilization thresholds (at least five labeled statements per snapshot for evenness and drift, presence threshold $\tau = 2$ for richness) trade variance for selection; Objects are comparatively sparse. Natural language processing and representation choices, including segmentation, coreference, embedding, and clustering, can miss conditionality and shape absolute values of K, H, and Jensen Shannon divergence; although coder agreement for Action types was high, residual category bias is possible. Inference is descriptive and comparative rather than causal: equal weight repository bootstrapping reflects between project variability without fully adjusting for confounders such as age or scale, and Jensen Shannon divergence is direction agnostic and can be affected by cluster relabeling across snapshots.

Future Work. Researchers could extend this baseline to cohorts that adopt AI assisted governance and development tools, enabling before and after comparisons of concentration, breadth, and drift and linking governance change to outcomes such as review latency, newcomer acceptance, and workload distribution. Researchers could also examine causal pathways by pairing textual change with event data from code review and release processes.

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Appendix

A Methods

Figure bellow presents an end-to-end pipeline that transforms raw governance documents into structured institutional insights. It begins with data normalization and pairing rules that align governance snapshots across versions. Coreference resolution reduces pronoun ambiguity, enabling more accurate attribution of roles. Semantic Role Labeling maps sentences to predicate-argument structures, identifying the underlying grammar of governance actions. These structured tuples are then embedded and clustered using BERTopic to capture governance topologies. The resulting clusters are evaluated using metrics such as entropy, Jensen–Shannon divergence, and per-project cluster counts to quantify structural diversity, prescriptiveness, and change. This modular pipeline supports scalable, interpretable analysis of institutional evolution in OSS projects.

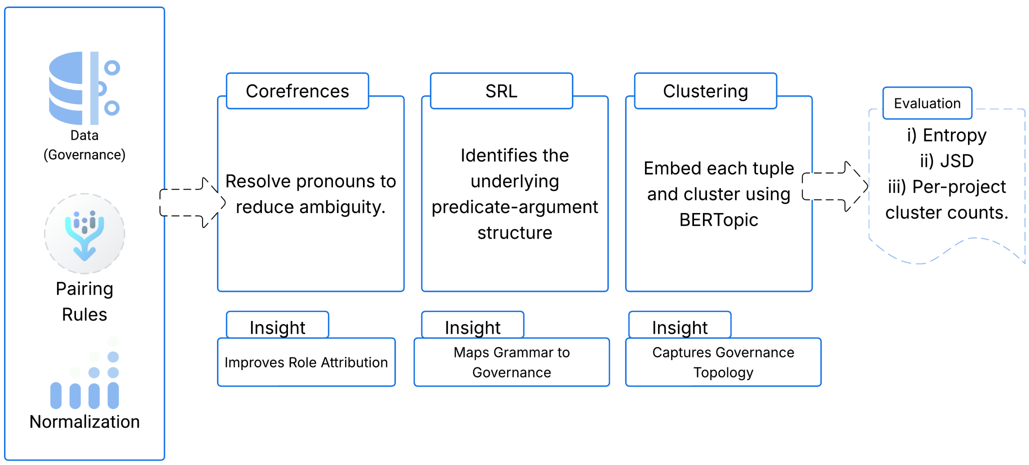


Figure 1: End-to-end pipeline from raw governance files to structured institutional statements and analysis.

$$H_v(r) = -\sum_k p_{r,v}(k) \log_2 p_{r,v}(k), \quad v \in \{\text{initial}, \text{latest}\}. \tag{1}$$

$$\Delta H(r) = H_{\text{latest}}(r) - H_{\text{initial}}(r). \tag{2}$$

$$\text{JSD}(p_{r,\text{initial}}, p_{r,\text{latest}}) = \tfrac{1}{2}\,\text{KL}(p_{r,\text{initial}} \,\|\, m_r) + \tfrac{1}{2}\,\text{KL}(p_{r,\text{latest}} \,\|\, m_r),$$

$$m_r = \tfrac{1}{2}(p_{r,\text{initial}} + p_{r,\text{latest}}). \tag{3}$$

$$K_v(r) = \sum_k \mathbf{1}\{\, c_{r,v}(k) \geq \tau \,\}, \qquad \tau = 2. \tag{4}$$

$$\Delta K(r) = K_{\text{latest}}(r) - K_{\text{initial}}(r). \tag{5}$$

$$\widetilde{\Delta K}(r) = \frac{1}{R}\sum_{t=1}^{R} \Big(K^{(t)}_{\text{latest}}(r; n_r) - K^{(t)}_{\text{initial}}(r; n_r) \Big),$$

$$n_r = \min\{N_{r,\text{initial}},\, N_{r,\text{latest}},\, 100\}. \tag{6}$$

$$\hat{\theta}^{*(b)} = \frac{1}{n} \sum_{r \in \mathcal{R}^{*(b)}} s(r), \qquad b = 1, \ldots, B,\; B = 10{,}000. \tag{7}$$

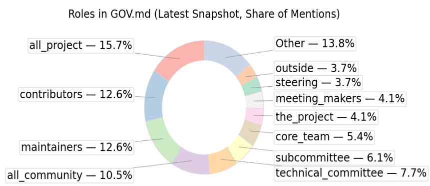
$$\text{CI}_{1-\alpha} = \Big[Q_{\alpha/2}\big(\{\hat{\theta}^{*(b)}\}\big),\; Q_{1-\alpha/2}\big(\{\hat{\theta}^{*(b)}\}\big) \Big]. \tag{8}$$

B Computational Resource

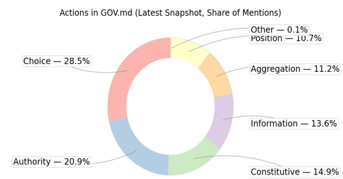
Some experiments were run using Google Colab with freely available GPU resources. Additional analysis and processing were performed on a local machine equipped with four Quadro RTX 8000

GPUs (48GB VRAM each), CUDA version 12.4, and driver version 550.163.01. Resource usage remained moderate, and no large-scale distributed training was required.

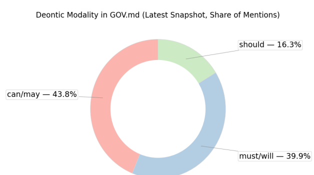
C Additional Results



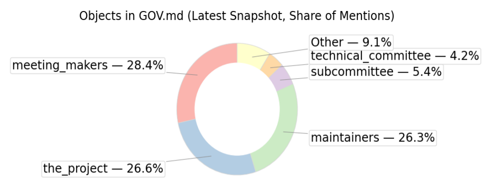
(a) Roles



(b) Actions

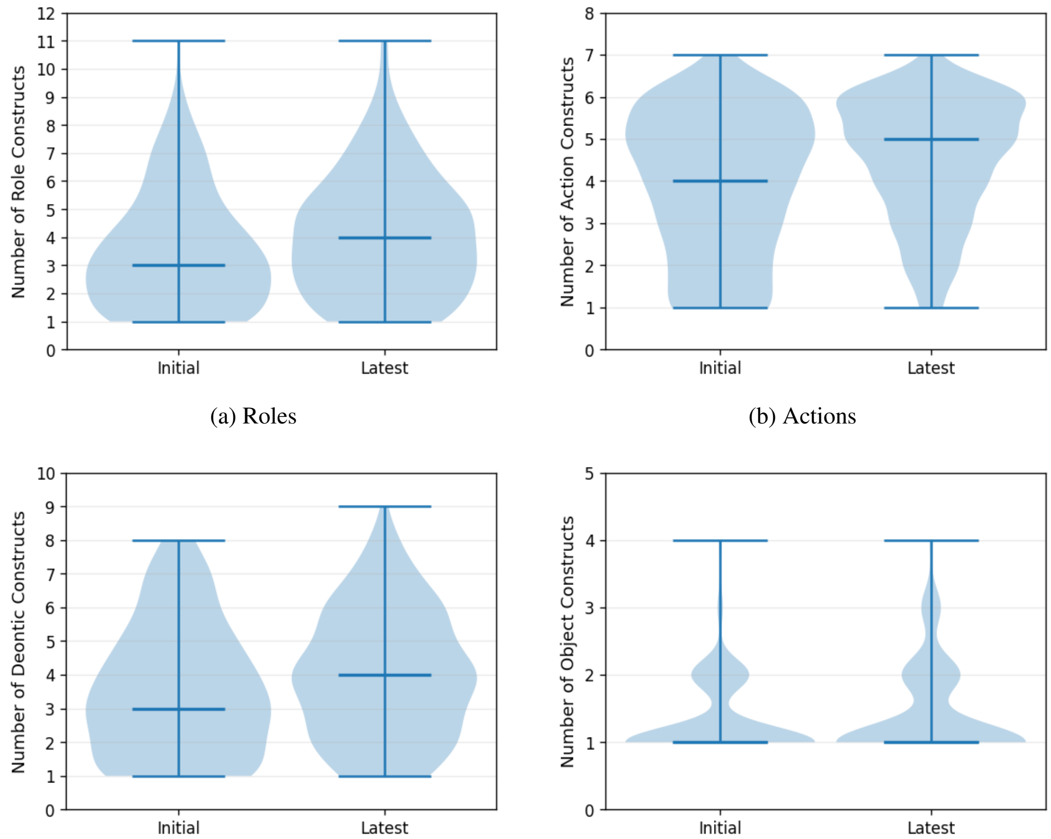


(c) Deontics



(d) Objects

Figure 2: **Latest-snapshot composition of governance constructs.** Donuts show the relative share of clusters within each feature (Roles, Actions, Deontics, Objects). These panels are descriptive context; inference relies on paired change metrics reported in the main text.



(a) Roles (b) Actions (c) Deontics (d) Objects

Figure 3: Distribution of per-repository **distinct construct counts** at the initial and latest snapshots for each institutional feature. Violins show density; the horizontal line is the median. Panels provide descriptive context; paired bootstrap estimates are reported in Table 2.

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