Decentralized in Name Only: The Centralization of DAO Labor

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Abstract

This paper studies how decentralized the Decentralized Autonomous Organizations (DAOs) truly are in their everyday labor practices. We collect task assignment data from Dework and construct a clean subset of 266 DAOs with sufficient activity to support meaningful decentralization measurement. We measure decentralization through inequality, diversity, coverage, dominance and combine them into the Operational DAO Decentralization Index (DDI). We find that operational work is highly concentrated: a small group of contributors complete most tasks. A fine-tuned T5 model trained for contributor recommendation largely reproduces these patterns. We therefore propose a decentralization-aware reranking method that penalizes overrepresented contributors. Experiments reveal a tunable trade-off between relevance and decentralization, with small but consistent DDI gains at top ranks. DAO labor is far from decentralized, and lightweight post-hoc adjustments can broaden contributor exposure.

CCS Concepts

• **Human-centered computing → Empirical studies in collaborative and social computing**.

Keywords

Decentralized Autonomous Organizations; Web3 labor dynamics; Fairness-aware recommendation

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1 Introduction

The Web has long supported large-scale collective action, motivating research on how participation is distributed and how platforms coordinate collaboration among distributed contributors. Web3 extends this line of work by introducing blockchain-based coordination mechanisms, among which Decentralized Autonomous Organizations (DAOs) have emerged as online communities that coordinate resources and decision-making through programmable and transparent rules [10]. DAOs are framed as a decentralized organizational form: open, permissionless, and collectively governed [3]. Their scale reinforces this expectation: as of October 2025, over 50,000 DAOs collectively controlled more than 20 billion USD in on-chain treasury assets[1].

If DAO operations are genuinely distributed, operational work should be broadly shared rather than concentrated among a small group of contributors. However, prior research on DAOs focuses primarily on *governance*, examining voting mechanisms, proposal dynamics, token-based power, and participation inequalities [5, 6, 8]. Yet governance captures only formal decision-making. Substantial managerial and coordinative work occurs outside proposals and voting mechanisms [4].

In practice, many DAOs coordinate daily work through operational task platforms such as Dework [1], where tasks are posted and contributors participate as assignees and reviewers. Some tasks offer explicit rewards, which are paid upon completion when offered. We refer to this task-based work coordination process as *DAO labor*. Unlike governance, DAO labor is not restricted to token holders. Contributors can participate through task-based workflows that may be open or selectively permissioned. These operational tasks do not necessarily correspond to governance decisions and are largely invisible to vote-based analyzes. Thus, how tasks are allocated and how participation is distributed across contributors may shape the practical experience of decentralization more directly than voting outcomes alone.

This gap motivates our focus on *operational decentralization*: the distribution of day-to-day task execution across contributors. Studying operational decentralization reveals whether DAOs' everyday labor practices align with their stated decentralization principles. We ask: **RQ1) How decentralized are DAOs operationally?** and **RQ2) What is the trade-off between relevance and decentralization in contributor recommendation models?**

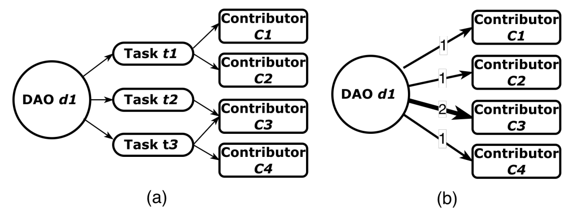

Figure 1: Illustration of data representation. (a) DAO-Task-Contributor data structure. (b) Weighted DAO-Contributor bipartite graph used to calculate DAO decentralization metrics (edge weight = number of tasks).

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[1] https://deepdao.io/organizations

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To answer these questions, we collect large-scale task assignment data from Dework and construct a DAO-task-contributor data structure (Fig. 1(a)). We operationalize decentralization using inequality, diversity, contributor-centric measures of coverage and dominance, and aggregate these signals into the *Operational DAO Decentralization Index (DDI)*. Our analyses show that everyday DAO labor is highly concentrated despite decentralization ideals. We further examine whether contributor recommendation models preserve or amplify these structural patterns, and propose a decentralization-aware reranking method based on observed participation concentration to explore the relevance-decentralization trade-off.

Our contributions are fourfold: (i) **Operational data construction.** We assemble a large-scale dataset of DAO task activity and construct a task-level operational representation linking DAOs, tasks, and contributors, enabling systematic analysis of DAO labor decentralization. (ii) **Measurement framework.** We quantify operational decentralization using inequality and diversity measures and contributor coverage and dominance indicators. (iii) **Operational DDI.** We aggregate multiple decentralization dimensions into a single index. (iv) **Relevance-decentralization trade-off.** We analyze contributor recommendation models and evaluate a simple decentralization-aware reranking method.

2 Data Representation of DAO Operations

We collect publicly available DAO task data from Dework by retrieving all DAO pages and extracting their *Completed* tasks together with associated contributors and participation roles. In total, the dataset contains 24,323 completed tasks from 509 DAOs. Task volume varies substantially across DAOs (1–1,390 tasks; mean 48, median 9). To ensure sufficient activity per DAO, we retain only organizations with at least 9 completed tasks, resulting in 266 DAOs. Summary statistics of the resulting dataset are reported in Table 1.

We construct an operational representation of DAO labor using a task-mediated DAO–Task–Contributor structure (Fig. 1(a)). Each task may involve multiple contributors appearing as assignees or reviewers, reflecting execution and validation roles, respectively.

For DAO-level decentralization measurement in this paper, we aggregate participation roles and treat both assignees and reviewers as contributors, removing duplicates when the same user appears in multiple roles for the same task. Usernames are anonymized via one-way hashing.

To operationalize decentralization at the DAO level, we project task-level interactions onto a weighted DAO–contributor bipartite graph (Fig. 1(b)). Let D denote the set of DAOs and C the set of contributors appearing in the filtered dataset. The graph is represented as $G = (D, C, E, w)$, where $E \subseteq D \times C$ and $w : E \rightarrow \mathbb{N}$ assigns an integer-valued weight to each edge. For any $(d, c) \in E$, the edge weight $w_d(c)$ counts the number of completed tasks in DAO d in which contributor c participated. This projection supports all decentralization metrics used later, including inequality (Gini), diversity (entropy), coverage, dominance, and the DDI.

3 Method

3.1 Participation Distributions and Decentralization Metrics.

Let $T_d = \sum_{c \in C} w_d(c)$ denote the total participation volume of DAO d. We define the normalized participation share $p_d(c) = w_d(c)/T_d$, which forms a participation distribution over contributors. Let $C_d = \{c \in C : w_d(c) > 0\}$ denote the set of distinct contributors participating in DAO d, and let $N_d = |C_d|$ denote the number of those distinct contributors. Based on these participation signals, we compute four DAO-adapted decentralization metrics:

Table 1: Summary statistics of the DAO dataset (filtered to DAOs with ≥ 9 completed tasks).

Statistic	Value
Number of DAOs	266
Total completed tasks	23,541
Total tasks used for modelling (train+val+test)	21,874
Total tasks in test set	4,739
Total unique contributors	4,369
Median tasks per DAO	27.5
Median contributors per DAO	10
Median tasks per contributor	2
Assignee roles (%)	92.7%
Reviewer roles (%)	26.2%

(i) Inequality (Gini). The Gini coefficient is computed over participation counts $\{w_d(c)\}_{c \in C}$, including zero-valued entries for non-participating contributors. Let $N = |C|$ denote the number of contributors in the global pool, and let $\bar{w}_d = N^{-1} \sum_{c \in C} w_d(c)$ be the mean participation count. We compute

$$\text{Gini}_d = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \left| w_d(c_i) - w_d(c_j) \right|}{2N^2 \bar{w}_d}$$

and define $\text{Gini}_d = 0$ when $\bar{w}_d = 0$.

(ii) Diversity (Shannon entropy). We compute entropy of the participation distribution as $H_d = -\sum_{c \in C} p_d(c) \log_2 p_d(c)$, where terms with $p_d(c) = 0$ contribute zero. We normalize entropy by the DAO's maximum entropy, $H_d^{\text{norm}} = \frac{H_d}{\log_2 N_d}$.

(iii) Coverage (breadth of participation). We define coverage as $\text{Coverage}_d = \frac{|C_d|}{T_d}$, capturing how many distinct contributors participate per unit of total contributor appearances in DAO d.

(iv) Dominance (top-share). Let $c_{(1)}, \ldots, c_{(N_d)}$ denote contributors in C_d sorted by $w_d(c)$ in descending order. We define the top-share at cutoff k in DAO d as

$$\text{Dom}_d(k) = \frac{\sum_{i=1}^{k} w_d(c_{(i)})}{T_d}$$

We report Top-5 share $\text{Dom}_d(5)$ and Top-10% participation share, where $k_d = \lceil 0.1 N_d \rceil$, and use the latter as the dominance component in DDI.

3.2 Operational DAO Decentralization Index (DDI).

To aggregate complementary decentralization signals into a single score, we construct the DDI. Each DAO d provides four normalized components derived from the adapted metrics above: (i) inverse inequality, (ii) normalized diversity, (iii) normalized coverage, and (iv) inverse dominance. Let $\text{minmax}(\cdot)$ denote min–max scaling over all DAOs.

DDI components are: $G_d^{\text{inv}} = 1 - \text{minmax}(\text{Gini}_d)$, $H_d^{\text{norm}} = \text{minmax}(H_d/\log_2 N_d)$, $C_d^{\text{norm}} = \text{minmax}(\text{Coverage}_d)$, $D_d^{\text{inv}} = 1 - \text{minmax}(\text{Dom}_d(\lceil 0.1 N_d \rceil))$.

DDI score is the unweighted average:

$$\text{DDI}_d = \frac{G_d^{\text{inv}} + H_d^{\text{norm}} + C_d^{\text{norm}} + D_d^{\text{inv}}}{4}$$

Higher values of DDI_d indicate more decentralized operational structures, characterized by broader participation and reduced contributor concentration.

3.3 Decentralization-Aware Reranking

We introduce a simple reranking mechanism that adjusts contributor exposure based on observed participation concentration. For each DAO d, we penalize contributors with higher normalized participation share $p_d(c)$. For a task t_i in DAO d_i, we compute a reranked score for each candidate contributor c as

$$S_i(c) = \alpha R_i(c) - (1 - \alpha) p_{d_i}(c)$$

where $\alpha \in [0, 1]$ controls the trade-off between relevance and decentralization. Since the baseline T5 model outputs an ordered list rather than explicit relevance scores, we convert its rankings into relevance weights using a DCG-style logarithmic discount: $R_i(c) = 1/\log_2(\text{rank}_i(c) + 1)$, and set $R_i(c) = 0$ for unranked candidates.

4 Experiment Setup

Modeling Dataset. The contributor recommendation dataset is constructed at the task level. Each sample uses the task title, user-defined tags, and reward information as input, with the associated contributor hashes as the target. We use training/validation/test splits.

Models and evaluation. We fine-tune a T5-small seq2seq model [7] as the baseline recommender, following a task-to-candidate formulation [12]. For each test task t_i, we rerank predicted contributors using $S_i(c)$, where participation shares $p_{d_i}(c)$ are computed from the training and validation data. We evaluate both relevance (standard ranking metrics) and decentralization (DDI@k).

5 Results

5.1 RQ1: How Decentralized Are DAOs?

Table 2 summarizes aggregate decentralization statistics across the 266 DAOs in our dataset. The results show extremely high Gini values (mean 0.9983) and low contributor coverage (median 0.19), suggesting that only a small subset of members perform most operational work. The top five contributors account for more than 80% of all completed tasks on average, and overall DDI scores remain low. These DAO-level patterns provide clear evidence of substantial operational centralization. Overall, operational activity within many DAOs is far from decentralized.

Table 2: DAO operational decentralization statistics.

Metric	Mean	Median
Gini	0.9983	0.9990
Entropy	2.6400	2.6160
Number of Contributors	19.43	10
Contributor coverage	0.2154	0.1875
Top-5 participation share	82.33%	82.61%
Top-10% participation share	73.23%	73.74%
DDI	0.3649	0.3463

5.2 RQ2: How Do Models Affect Centralization?

Baseline Recommendation Behavior. As a consequence of this highly centralized participation structure, we examine whether contributor recommendation models reproduce or mitigate these patterns. The T5 baseline model's DDI@k results (Table 3) suggest that top-ranked positions are dominated by observed active contributors, indicating the model largely reproduces existing participation concentration.

Effect of Reranking on Relevance and Decentralization. Table 3 summarizes model performance before and after applying reranking with $\alpha = 0.5$. As expected, relevance metrics decrease substantially: MAP@5 declines by 42.7%, NDCG@5 by 35.2%, and similar drops appear across other top-k metrics. Despite the strong relevance reduction, decentralization increases modestly. DDI@3 rises by 1.8% and DDI@5 by 0.6%, indicating a shift in exposure away from observed dominant contributors. These results illustrate how strongly the model relies on observed participation dominance.

Table 3: Baseline vs. reranking performance comparison.

Metric	Baseline	Reranked $\alpha = 0.5$	Improve
Precision@5	0.1934	0.1418	-0.0516
Precision@10	0.0993	0.0709	-0.0284
Recall@5	0.5381	0.3825	-0.1556
Recall@10	0.547	0.3825	-0.1645
NDCG@5	0.3620	0.2345	-0.1275
NDCG@10	0.3656	0.2341	-0.1315
MAP@5	0.2723	0.1561	-0.1162
MRR@5	0.3238	0.2087	-0.1151
F1@5	0.2569	0.2073	-0.0496
DDI@3	0.5119	0.5210	+0.0091
DDI@5	0.5337	0.5367	+0.0030
DDI@10	0.5353	0.4806	-0.0547

Cutoff Sensitivity. Figure 2 shows DDI@k for $k = 1$–10 across α settings. Reranking yields its strongest decentralization effects for small cutoffs (DDI@2–4), where exposure is most concentrated. As k increases, the reranked and baseline curves converge, indicating that deeper ranks are less sensitive to dominance adjustments.

Trade-off Sweep Over α. Figure 3 plots NDCG@5 and DDI@5 as functions of α. Higher α values preserve model relevance but reduce decentralization, while lower values increase exposure dispersion. This analysis illustrates how strongly the baseline ranking is tied to existing dominance and how exposure shifts as this preference is weakened.

Discussions. The experiments highlight a clear tension between predictive relevance and contributor decentralization. The baseline model largely reproduces the structural inequalities present in observed DAO activity. The reranking mechanism provides a

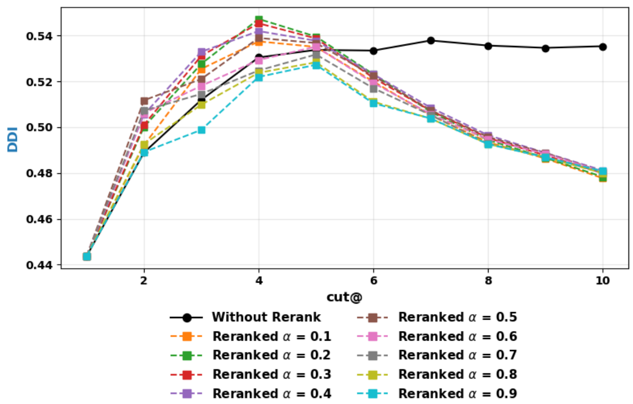

Figure 2: DDI@k across α values, showing strongest gains at small cutoffs.

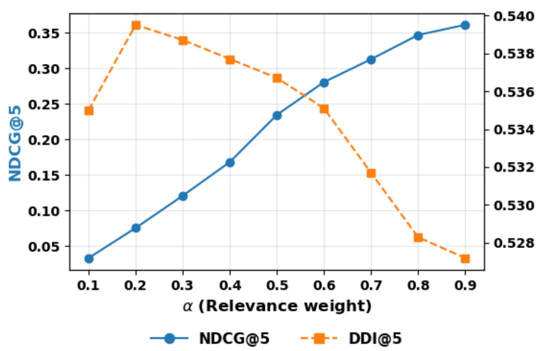

Figure 3: Reranking sensitivity to α using DDI and NDCG.

controlled way to probe this sensitivity: reducing the influence of dominance broadens exposure, especially at early positions, by explicitly penalizing observed dominant contributors [2]. While relevance decreases substantially, these shifts reveal how strongly the model is anchored to existing participation patterns and provide an interpretable diagnostic of its centralization tendencies.

Although the numerical changes in DDI across different values of α appear small, this behaviour is expected given the structure of top-k predictions and the design of the reranking method. Because DDI@k is computed from only the top-k recommended contributors, the range of possible changes in its components is inherently limited. In practice, reranking primarily affects the exposure concentration term (top-10% share), while the other components change only marginally. Moreover, the scoring function of $S_i(c)$ applies a deliberately conservative adjustment that slightly demotes observed dominant contributors without replacing them, thereby preserving predictive relevance while inducing modest decentralization gains. Thus, the small but consistent improvements in DDI are fully aligned with the intended relevance-decentralization trade-off. The magnitude of this trade-off aligns with prior fairness-aware ranking studies [9, 11].

6 Limitation

While DDI integrates complementary concentration indicators, some components are partially correlated (e.g., dominance and inequality) and are computed over slightly different participation bases (global vs. DAO contributors), so the index should be interpreted as a composite operational measure rather than fully distinct dimensions. Additionally, contributor concentration may partly reflect skill specialization and role differentiation (e.g., core developers taking on repeated tasks), not solely systemic bias. Future work could integrate task difficulty and contributor skill signals to disentangle these mechanisms.

7 Conclusion

This work provides the first large-scale measurement of operational decentralization in DAO task execution and evaluates how contributor recommendation models reproduce these patterns. We find that contributor activity is heavily concentrated and that baseline predictions largely mirror this structure. By applying a simple decentralization-aware reranking adjustment, we test whether model outputs deviate from these imbalances and observe that reducing the influence of observed dominant contributors broadens exposure—especially at top ranks—while predictably lowering relevance. This controllable trade-off highlights the tight coupling between recommendation behavior and underlying participation distributions. Overall, our findings underscore the value of explicitly assessing decentralization in DAO tooling and offer a diagnostic framework for understanding when and how ranking systems may reinforce or mitigate organizational inequalities.

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