A NETWORK ANALYSIS OF DECENTRALIZED AUTONOMOUS ORGANIZATIONS

Completed Research

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Abstract

Decentralized Autonomous Organizations (DAOs) are multifunctional systems that mediate transactions between humans and blockchains or operate entirely autonomously. While considerable attention has been given to their organizational structure, their characteristics as online communities remain largely unexplored. This study aims to fill this research gap by analyzing a dataset comprising 31,002 DAOs, 220,960 proposals, 51,987,413 votes, 154,087,070 token ownerships, and 46,695 historical governance token prices. The research addresses several key aspects. First, it confirms the presence of the 90-9-1 rule. Second, it highlights the unequal distribution of voting power through a deciding voter analysis. Third, it validates the scale-free network properties by fitting a power-law function to the degree distribution of DAO memberships and proposal participation suggesting the existence of influential nodes within the network. Last, the study indicates that the diffusion of information is uninfluenced by the level of connectedness among voters, as determined by their shared memberships in DAOs.

Keywords: Decentralized Autonomous Organizations, Online Communities, Network Analysis

1 Introduction

Decentralized Autonomous Organizations (DAOs) are multifunctional systems, functioning either to mediate interactions between humans and blockchains or operating as entirely autonomous systems with capabilities for storage, transaction of value, notary (voting) functions, autonomous execution, and a decentralized environment (Hassan & Filippi, 2021; Rikken et al., 2023; Schillig, 2021).

Decisions within DAOs are made through online voting mechanisms known as proposals, where the voting power is most commonly determined by the number of tokens held by a member. These tokens represent a virtual stake in the DAO (Fan et al., 2023). DAOs consist of three primary pillars: Treasury, governance, and community. The treasury manages all assets and financial resources, governance allocates funds and sets the overall direction, while the community engages in deliberations on objectives and responsibilities, overseeing the governance process (Ziegler & Welpe, 2022).

Each pillar employs different tools to provide value. Treasuries, represented as multi-signature wallets on the blockchain, use tools like Discord and Discourse for communication in the community section. Governance, in many DAOs, is implemented through Snapshot,[1] an off-chain voting portal utilizing decentralized file storage for proposals and votes, offering the advantage of no transaction fees for

1 https://snapshot.org/#/

creating or casting votes. Snapshot has seen over 230,000 proposals, with DAO treasuries collectively holding $15.8 billion in assets across 2373 tracked DAOs (DeepDAO Ventures Ltd., 2023). The growing interest in DAO governance could be attributed in part to airdrops (Allen et al., 2023) issued to the community.

While DAOs have traditionally been viewed as organizations (Hassan & Filippi, 2021; Wright, 2021), we argue that DAOs fundamentally stem from online communities. Drawing from the definition of Preece (2000), online communities comprise *people* interacting socially, *sharing a common purpose*, following *policies* that guide interactions, and utilizing *computer systems* to support and mediate social interactions. These properties align with DAOs, where social interactions occur through provided community-building tools, a shared purpose and policies are defined in governance, and the blockchain serves as the computer system supporting social interactions.

Governance is crucial for all Decentralized Finance (DeFi) protocols operating as DAOs, as the governance proposals effectively decide on the most important applications of blockchain-based systems. They are seen as public good by blockchain users and play an important role in the daily usage of blockchains. Therefore, they are expected to be governed by the community that receives tokens as payment for work or through airdrops (Allen et al., 2023) to participate in the governance. However, this is in most DAOs not the case (Feichtinger et al., 2023; Fritsch et al., 2022), which highlights the problem, why more quantitative research is needed into community networks and voting power distributions.

In the early days of online community research, it was uncertain whether established techniques for analyzing offline communities, such as network analysis, are applicable (Preece, 2000). Subsequently, it became evident that theories applicable to offline communities were also relevant to online communities (Chang et al., 2023; Easley & Kleinberg, 2019; Panzarasa et al., 2009; Yang et al., 2011).

Most online communities relying on user contributions exhibit a participation pattern following the 90-9-1 rule, where 90% read or observe, 9% contribute occasionally, and 1% contribute the majority (Nielsen, 2006). This inequality leads to situations where a small percentage of users produce content consumed by the majority, posing challenges in areas like customer feedback, restaurant reviews, and hotels (Nielsen, 2006).

Applying this participation pattern to DAOs, we hypothesize that 1% create content (proposals), 9% comment on the content (vote), and 90% hold tokens but do not participate in governance. This creates a situation where the decision-making power lies with the 1%, influencing the DAO’s direction, while the 9% approve or disapprove, and the 90% observe. The introduction of Web3 adds a financial incentive for contributors, contrasting with the mainly intrinsic incentives in Web2 (Jin et al., 2015).

This centralization effect is exacerbated by a few wealthy and influential DAO members owning the majority of voting tokens, undermining the perceived decentralization of the 9%. The 90-9-1 rule in DAOs mirror characteristics of scale-free networks, where a few nodes, following a power-law distribution, accumulate a significant number of connections.

The concept of scale-free networks, extensively studied in the context of online communities, gained prominence with the analysis of a part of the internet from Barabasi and Albert (1999). They revealed highly connected hubs and a power-law distribution of link connections. This concept extended to social networks, introducing the term “scale-free network” to describe networks exhibiting a power-law degree distribution. Information diffusion varies depending on the type of network (C. Jiang et al., 2014).

From this discussion, we formulate the following research questions:

- **RQ1**: To what extent can the 90-9-1 rule be applied to DAOs?
- **RQ2**: What is the extent of dominance exerted by deciding voters in the governance process?
- **RQ3**: Do DAOs exhibit the characteristics of scale-free networks?
- **RQ4**: How does the connectivity of a node in the network influence the diffusion of information?

The rest of this paper is organized as follows. In Section 2, we present related work covering the 90-9-1 rule, empirical research on DAOs, and network analysis on online communities. Then, in Section 3, we introduce our dataset, emphasizing its capabilities and limitations and detail the methodologies for our four empirical analyses—90-9-1, deciding voter, scale-free network, and information diffusion—to address the research questions posed. We outline the methodologies for each analysis first and subsequently present their applications along with the results. Finally, we discuss our findings and draw conclusions in Section 4.

2 Related Work

The 90-9-1 rule seeks to elucidate participation patterns within online communities, positing that 90% of participants primarily observe without active engagement, 9% contribute sporadically, and 1% are responsible for the majority of content creation (Nielsen, 2006). Empirical examinations of the 90-9-1 rule, as conducted by van Mierlo (2014), Gasparini et al. (2020), Antelmi et al. (2019), validate the overarching trend that a significant proportion of members in online communities predominantly partake in observational activities. However, the precise ratio of passive observers, sporadic contributors, and productive content creators varies among online communities, often deviating moderately from the 90-9-1 ratio.

In the case of X, formerly Twitter, Antelmi et al. (2019) found that 75% of users can be considered silent observers, while 5% are actively contributing. Mierlo studied Digital Health Social Networks within the context of the 90-9-1 rule and obtained an empirical 75-24-1 ratio. A limitation of studies exploring the 90-9-1 rule is that the definition of an active contributor and a silent observer may differ for each study, depending on the specific community. Carron-Arthur et al. (2014) found further evidence that the different contribution groups are mostly not separable, and there is a relatively gradual reduction in contributions between the three user groups. Nevertheless, empirical results support the general hypothesis behind the 90-9-1 rule in the context of online communities.

Network analysis of online communities has been extensively performed in recent years, revealing a substantial body of evidence (Mislove et al., 2007; Newman et al., 2002; Panzarasa et al., 2009; Uzzi & Spiro, 2005) for small-world properties characterized by high local clustering coefficients and small path lengths in subnetworks.

Grandjean (2016) empirically studied the social network X and found structural evidence for the small-world phenomenon. The relevance of specific vertices in the network is quantified by centrality measures such as in- and out-degree, betweenness centrality, and eigenvector centrality. The distributions of the centrality measures of the users of the network approximately follow a power-law distribution. Kim and Hastak (2018) discovered that the in and out-degree distributions of nodes in the networks X and Facebook are highly right-skewed, indicating a general tendency toward social hubs.

While recent research on DAOs is predominantly qualitative (Chao et al., 2022; Kaal, 2021; Kondova & Barba, 2019; Marko & Kostal, 2022; Qin et al., 2023; Sharma et al., 2023), there have been quantitative studies focusing on the properties of DAOs, particularly decentralization, in recent times.

Feichtinger et al. (2023) and Fritsch et al. (2022) conducted analyses on the distribution of voting power within DAOs on the Ethereum blockchain. Fritsch et al. (2022) demonstrate that voting power is significantly centralized, and the dominant parties typically align their votes with the broader community. Feichtinger et al. (2023) computed Gini coefficients for voting power distributions, revealing that almost all coefficients exceed 0.9, indicating a high degree of centralization. Furthermore, they observed that in half of the studied DAOs, three or fewer addresses held most of the voting power.

Fan et al. (2023) propose a framework to analyse these trade-offs involving four dimensions (security, efficiency, effectiveness and decentralisation) and looked at “voting mechanisms as democratic administration of DAOs without the involvement of central authority”. They singled out specific examples, such as quadratic voting, as a tool to alleviate drawbacks of token-based voting and make governance in DAOs with a centralised power control more democratic.

Goldberg and Schär (2023) present similar findings from their study of voting dynamics in the DAO governing the metaverse platform Decentraland. They scrutinized actors with the most significant voting power and discovered that the voting outcome matched the dominant voter's choice nearly 95% of the time. Additionally, the study revealed that about 45% of DAO grants were approved by a single voter.

Q. Wang et al. (2022) conducted an empirical analysis of 581 DAOs organized on the off-chain voting platform Snapshot, utilizing a dataset similar to that of this paper. Their study focuses on the employed e-voting schemes, infrastructure, project scale, and DAO token usage. Among their findings are centralization threats attributed to contract reliance, IPFS storage, and platform dependency.

The study of scale-free networks in the context of online communities has been undertaken by scholars. Aparicio et al. (2015) investigated the structural properties of X, demonstrating that it can be considered a scale-free network, as the outgoing and incoming degree distributions of nodes in the network approximately follow a power-law distribution. This implies the presence of a few users with a large group of followers or friends, while most users have only a few friends or followers. However, the scientific community is still debating the evidence for the scale-free nature of many networks. In an empirical study, Broido and Clauset (2019) examined nearly 1,000 information networks to determine whether they could be classified as scale-free. They concluded that the social networks they studied are, at most, weakly scale-free.

In a similar context, the diffusion of information has been studied in networks, particularly online communities, referring to the spread of information among interconnected nodes or entities in a network (Kumar & Sinha, 2021). Bakshy et al. (2012) discovered that relationships between people in the network significantly influence the diffusion of information in social networks.

3 Methodologies and Their Applications

In this paper, we build upon scholars' previous work in network analysis in online communities by conducting four empirical analyses using the same dataset. The first analysis delves into the 90-9-1 rule, extending to demonstrate the impact of so-called *deciding voters* on DAO governance, and subsequently visualizing the network of DAOs, proposals, and voters. Following that, we examine evidence supporting DAOs as scale-free networks. Finally, we scrutinize information diffusion within DAOs by analyzing members and their shared DAO memberships.

3.1 Field data: Snapshot, CovalentHQ, and Coingecko

This section provides an overview of the three data sources combined for our analyses. First, the off-chain voting platform Snapshot "allows DAOs, DeFi Protocols, or NFT communities to participate in decentralized governance" (Snapshot, 2023). On Snapshot, users can create spaces representing DAOs, where voting strategies can be defined for proposals containing governance decisions. Users then vote on these proposals based on the defined voting strategy and mechanism. We obtained the data from Snapshot using their GraphQL API (Snapshot, 2023), resulting in 31,002 Spaces representing a DAO, 220,960 proposals, and 51,987,413 votes on these proposals.

Second, we collected 154,087,070 data points about token ownership from CovalentHQ. This dataset contains precise information about which address owned which token at the block height, representing the voting power of every eligible voter at the proposal creation.

Third, we gathered 46,695 data points on historical prices from Coingecko[2] for all voting tokens, providing us with the voting power in tokens and corresponding dollar values. The disparity in data

2 https://www.coingecko.com/

points between proposals and historical prices is attributed to tokens that are either not listed, have been delisted, or are soulbound, meaning they cannot be traded.

In blockchain-based systems, two distinct types of networks exist: Mainnet and Testnet. Testnets are frequently reset and are exclusively used for testing smart contracts or the blockchain itself. Coins on these networks typically do not hold any real-world value, with the exception of rare cases such as the Goerli Ethereum (Copeland, 2023). Consequently, we exclude all proposals that involve Testnet assets, assuming that spaces using these assets are primarily intended for testing purposes. Lastly, we validated our dataset for completeness using the web interface of Snapshot.

3.2 Analysis of participation inequality

The problem of participation inequality in online communities is well-known, but its manifestations vary depending on the type of platform users interact with. For instance, on social platforms like X, the majority of users are often considered silent observers, while only a very few actively create content (Antelmi et al., 2019). In software development platforms like GitHub, participation inequality is referred to as the “volunteer’s dilemma” (Gasparini et al., 2020), where a small number contribute code, and the majority silently utilize it. This phenomenon has been previously identified as the “tragedy of the commons,” depicting a scenario where individuals, driven by self-interest, deplete a shared resource, leading to its degradation or destruction (Feeny et al., 1990). In this analysis, we investigate whether participation inequality, specifically the 90-9-1 rule (Nielsen, 2006), holds for DAOs, as we posit they exhibit properties of online communities.

To conduct the 90-9-1 analysis, we take three samples. First, we utilize our complete dataset encompassing all DAOs, excluding Testnet data. Second, we randomly sample 10% of DAOs from our dataset. Third, we sample 10% of the top DAOs by voters from our dataset. The inclusion of these different samples adds rigor to our analysis. In this examination, we calculate entries only when we can fully map all proposals, voters, and token holders.

For the analysis, we establish the following definitions:

1. Let $D_{\{t10,r10,full\}}$ represent the top 10% DAOs, random 10% DAOs, and all DAOs
2. Let $P(d)$ represent the set of proposals for a DAO d
3. Let $V(p)$ represent the set of voters for a proposal p
4. Let $T(d)$ represent the set of distinct token holders for a DAO d
5. Let $C(d)$ represent the creator of a proposal d

Using the above, the set V represents the fraction of voters of D:

$$V_{D_{\{t10,r10,full\}}} = \frac{\sum_{d\,\in\,D_{\{t10,r10,full\}}} \sum_{p\,\in P(d)} |V(p)|}{\sum_{d\,\in\,D_{\{t10,r10,full\}}} |T(d)|}$$

The set C represents the fraction of creators of D:

$$C_{D_{\{t10,r10,full\}}} = \frac{\sum_{d\,\in\,D_{\{t10,r10,full\}}} \sum_{p\,\in P(d)} |C(p)|}{\sum_{d\,\in\,D_{\{t10,r10,full\}}} |T(d)|}$$

Let $T'(d)$ represent the set of distinct token holders for a DAO d excluding $V(p)$ and $C(p)$ such that:

$$T'(d) = \{t \mid t\ \in T(d)\ \wedge t \notin \mathrm{V(d)}\ \wedge t \notin \mathrm{C(d)}\}$$

Then, the set L represents the fraction of lurkers (token holders) of D:

$$L_{D_{\{t10,r10,full\}}} = \frac{\sum_{d\,\in\,D_{\{t10,r10,full\}}} \sum_{p\,\in P(d)} |T'(d)|}{\sum_{d\,\in\,D_{\{t10,r10,full\}}} |T(d)|}$$

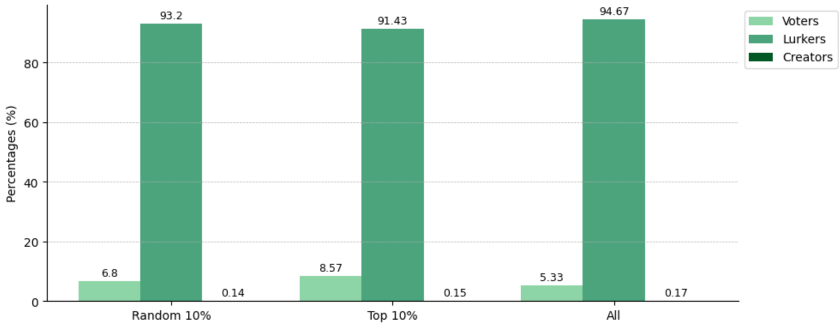

Figure 1. Distribution of voters, lurkers, and creators across the samples.

From Figure 1, we deduce that the 90-9-1 rule applies to DAOs. However, with a 95-5-1 distribution, creators are also considered voters.

3.3 Analysis of deciding voters

Next, we analyze the distribution of voting power within the 5.33% of voters in DAOs. Feichtinger et al. (2023) and Fritsch et al. (2022) have empirically examined voting power distributions in DAOs, focusing on datasets other than the one we are using. They observed a highly centralized voting power distribution in DAOs. Our objective is to either corroborate or challenge their findings by leveraging our extensive dataset in this analysis.

We employ a dataset comprising 31,002 DAOs, 220,960 proposals, and 51,987,413 votes to unveil power distribution within DAOs. Initially, we filter it based on the following criteria: a minimum of five proposals per DAO, at least five votes per proposal, exclusion of DAOs on the Testnet, and ensuring DAOs and proposals are not flagged by Snapshot. This filtering leaves us with 47,048 eligible proposals and 45,592,752 votes.

Continuing, we ascertain the voting power of each voter on every proposal and calculate the total voting power for each proposal by summing up individual voting powers. Using this total voting power, we compute the relative voting power as a percentage for every voter on every proposal.

Subsequently, we arrange the voting power for each proposal in descending order and calculate a running total of the voting power. For instance, in a proposal where voters possess relative voting powers of [40%, 30%, 20%, 10%], their corresponding running total voting powers would be [40%, 70%, 90%, 100%]. Following, we identify the count of voters required for each proposal to surpass 50% of the total voting power. In our example, this count is 2, and we refer to them as the deciding voters.

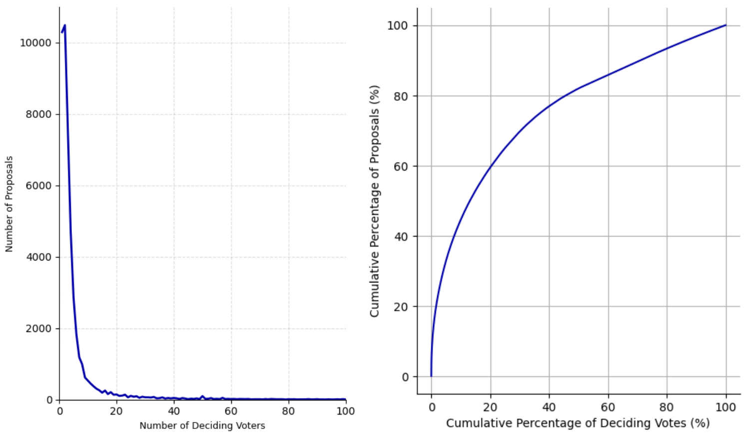

Figure 2. Number of deciding voters based on the number of proposals, presented as absolute counts and percentages.

Figure 2 illustrates that in 86.3% of proposals, fewer than 10 voters determine their outcome. This indicates a concentration of voting power within DAOs among a select few. While this observation would be adequate if we were exclusively analyzing large DAOs, Figure 2 contextualizes this discovery by revealing that less than 20% of all votes influence over 60% of all proposals. However, considering the presence of non-negligible proposals with a limited number of votes, we must align the count with the total number of voters for each proposal, presenting the distribution of deciding voters as a percentage. This corroborates the findings of Feichtinger et al. (2023), who observed similar results in their restricted dataset.

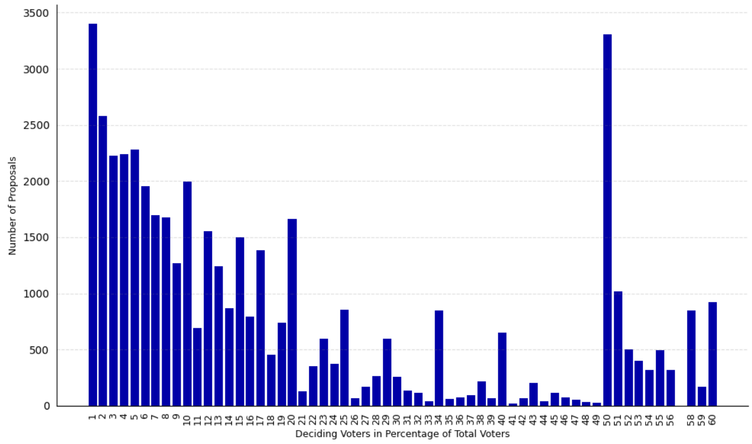

Figure 3. Relationship between the share of deciding voters and the number of proposals.

Figure 3 illustrates this relationship. The x-axis represents binned percentages, indicating the proportion of total voters that constitute deciding voters. The chart reveals two key insights. Firstly, there are numerous proposals where less than 10% of the voters wield over 50% of the voting power. Moreover, almost 3,500 proposals are determined by less than 1% of the voters. Secondly, the chart highlights proposals that are not influenced by a minority but instead, decisions are made with equal voting power, as indicated by the significant number of proposals at 50%. Upon closer examination, we identified that these proposals employ a one-vote-per-address method implemented through a whitelist, ERC721 (Non-Fungible-Token, NFT), or a single ERC20 token. Consequently, we argue that the development of decentralized protocols governed by DAOs is not driven by the community as a whole but by a small group of participants who actively participate in proposal creation and voting.

3.4 Analysis of connections between DAOs, proposals, and voters

Until now, we have demonstrated that only 5.33% of all token holders participate in voting. Within this subset, the distribution of voting power is highly unequal, with 45% of the votes determining 80% of all proposals. In the subsequent analysis, we delve into the observation that not only is the total voting power centralized, but the monetary value of this voting power is also highly concentrated.

The following graphs illustrate the connections within our combined datasets. Each colored circle represents a proposal, with each DAO having its distinct color, while the black dots represent voters. The size of each circle is determined by the exercised total voting power in dollar value, with the dollar value being taken from when the proposal was created. Figure 5 showcases the connections through exercised votes, while Figure 4 represents all potential votes. Both figures highlight the strong interconnectedness between most DAOs. However, some DAOs exhibit voters without connections to other DAOs, a phenomenon possibly explained by airdrop farming or privacy practices. The presence of large DAOs and their affluent token holders is evident in both figures. Further investigations are imperative, not only into the connections between voters and multiple DAOs but also into how they acquired their governance tokens, to draw a clearer picture of the connections within the DAO ecosystem.

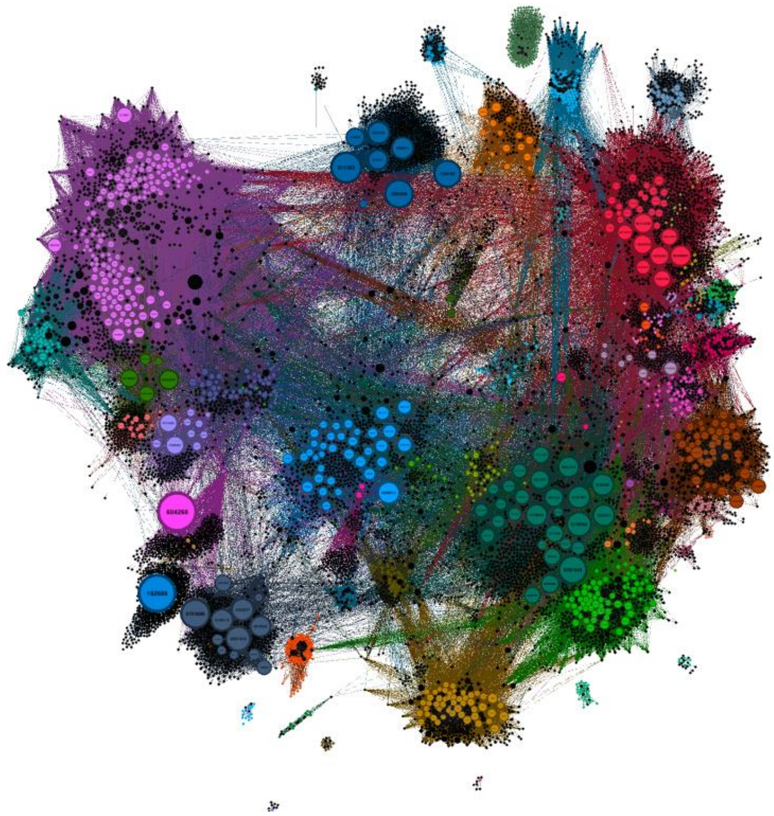

Figure 4. Snapshot's DAO network with all potential voting edges.

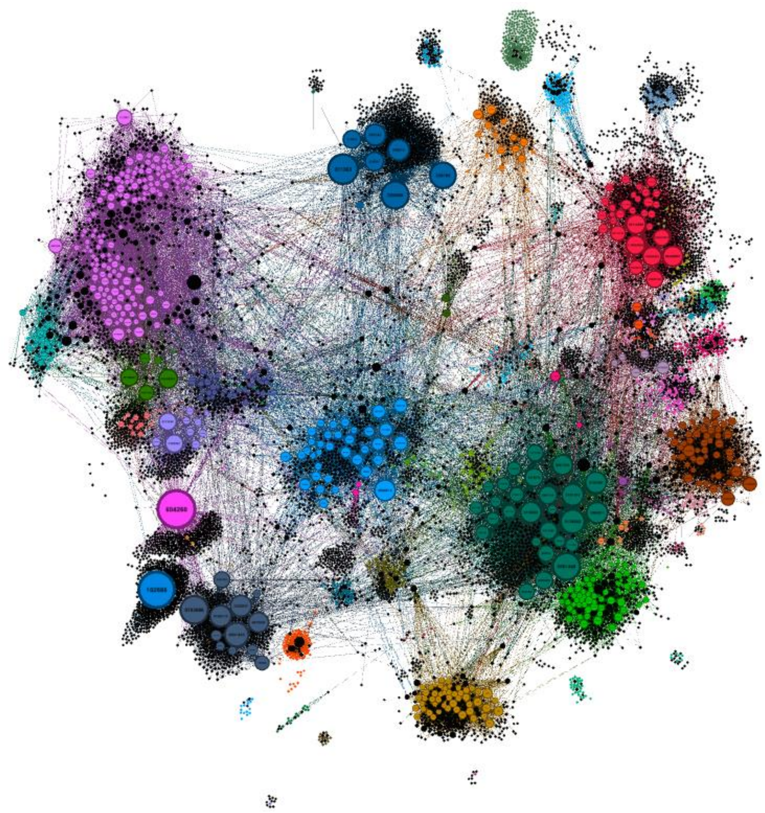

Figure 5. Snapshot's DAO network with all asserted voting edges.

3.5 Analysis of scale-free network properties

Scale-free networks are characterized by a degree distribution that conforms to a power-law distribution, and they are believed to emerge spontaneously in diverse and unrelated domains. Examples include technological realms such as the internet, social networks involving academic references and collaborations among film actors, and biological systems like protein interaction networks (Broido & Clauset, 2019). A fundamental concept considered the underlying principle of a scale-free network is the preferential attachment rule, stating that during network creation, the probability that a node gains a new connection is proportional to its current degree (Barabási, 2009).

Our objective is to verify the presence of scale-free networks in online communities, focusing on the structure of DAO membership and proposal sizes. We utilize power-law functions to gather evidence for the emergence of scale-free networks in our DAO datasets, relying on goodness-of-fit metrics to quantify the results. Subsequently, we fit selected statistical distributions and assess their goodness of fit using a well-known statistical test. Each distribution is evaluated based on the fit visualization and the test, aiming to prove or disprove the hypothesis that the data is sampled from a power-law distribution, essentially determining if the network can be described as scale-free (Broido & Clauset, 2019).

For our analysis, we curated two datasets:

1. DAOs and their active voters: In this dataset, individual DAOs and voters serve as nodes, with edges representing the act of voting within a DAO. The degree distribution indicates the presence of a small number of highly popular DAOs, with 924 DAOs having a maximum of 5,000,000 active voters.
2. Proposals and their voters: In this dataset, individual proposals and voters are nodes, and edges represent the act of voting on a proposal. The degree distribution suggests the existence of a small number of highly popular proposals, with 45,932 proposals having a maximum of 600,000 votes.

Following, we applied various curves and distributions to the datasets mentioned above:

1. Power-law function $P(x) = Cx^{-\alpha}$: This function is employed to model datasets where a small number of items are clustered at the top of the distribution, dominating the majority of resources.
2. Power-law function with exponential cutoff $P(x) = (ax^{-\alpha} + c)e^{-dx}$: Since the power-law function exhibits a "heavy tail," meaning it converges to zero more slowly than exponential functions, the exponential multiplier is introduced to ensure a more exponential curve beyond a certain point, enhancing the fit to the noise in the tail.
3. Power-law distribution $f(x, a) = ax^{a-1}$: This continuous random variable is also known as the Pareto distribution and is often found to describe processes driven by the rule of preferential attachment.
4. Log-normal distribution $f(x, s) = \frac{1}{sx\sqrt{2\pi}} \exp\left(-\frac{log^2(x)}{2s^2}\right)$: This continuous random variable has a logarithm that is distributed normally. It is identified as describing natural growth processes driven by an accumulation of small changes over time, which are additive on the log scale.
5. Weibull distribution $f(x, c) = cx^{c-1} \exp(-x^c)$: A unimodal continuous random variable widely applied in modeling quality control, biological processes, or reliability analysis due to its flexibility.

To assess the goodness of fit for the curves, we calculated R-squared and Summed Squared Error (SSE). Additionally, we conducted the Kolmogorov–Smirnov statistical test for distributions. The KS test informs us about the likelihood of a sample being drawn from a given distribution. It indicates the similarity of the sample function to the reference distribution, and the p-value helps estimate our confidence in the hypothesis. The power-law curves show a good fit for both datasets, with high R-squared values and low SSE. Specifically, for the power-law and truncated power-law DAO-member dataset: {0.999532, 182.827804}, {0.998842, 452.691648}, and the proposal-voter dataset: {0.999844, 237,188.711232}, {0.999525, 720,178.488603}. This suggests that both networks may be identified as scale-free.

It seems that no distribution can be confidently described as a likely candidate (KS test with significance level of 95%) from which either dataset can be drawn. In both datasets, the log-normal distribution is the most probable candidate among the three, considering the relatively large p-value (0.000027 for the proposal-voter dataset and a negligible value for the DAO-member dataset) and a visual interpretation of the fit. While the degree distributions seem to be modeled by a power-law function, other distributions may be preferred over the power-law. Scale-free networks contribute to the resilience of online communities against random disruptions due to their many low-connectivity nodes, but the same structure also creates a dependency on a few critical hubs (Ercal & Matta, 2013). Previous research has found limited direct evidence for social networks to be scale-free, leading us to believe that mechanisms other than preferential attachment may govern the growth and information dissemination within DAO networks (Broido & Clauset, 2019). In the next section, we explore how information diffusion occurs within DAOs in the context of voting procedures to delve deeper into how these networks evolve over time.

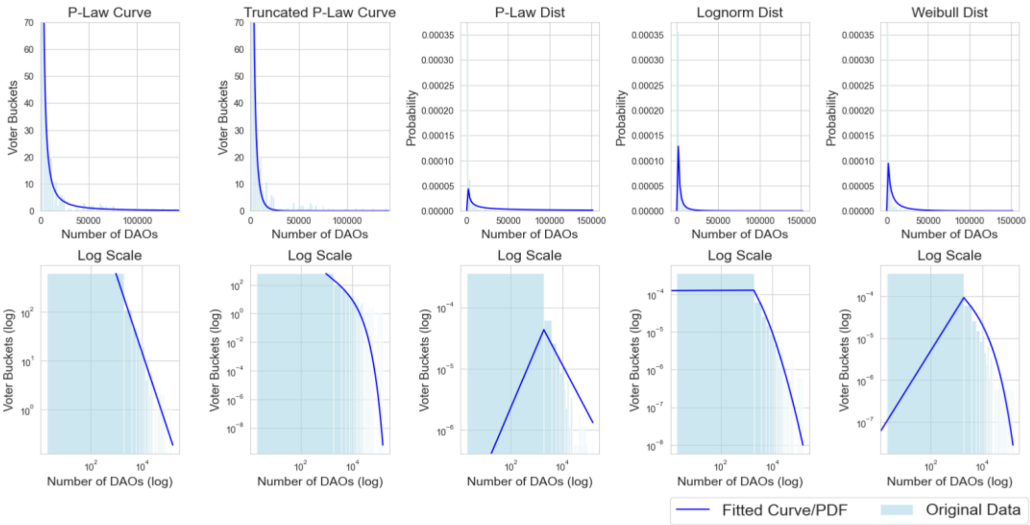

Figure 6. Comparison of curve and distributions fit of DAO-member (linear and log scales)

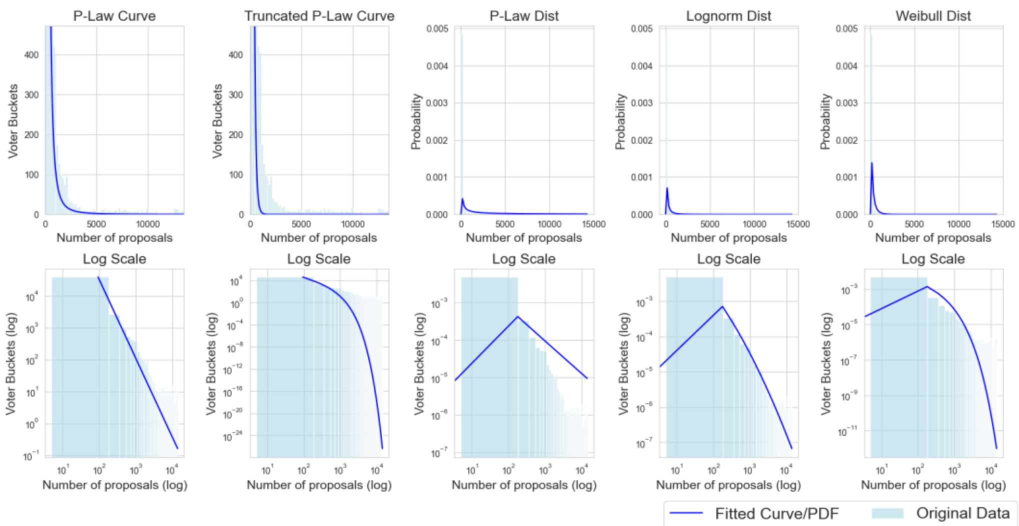

Figure 7. Comparison of curve and distribution fits of proposal-voter (linear and log scales)

3.6 Analysis of information diffusion in DAOs

Information diffusion involves understanding how information spreads within a network (F. Wang et al., 2012). This propagation is quantified by measuring the time it takes for information to reach predefined thresholds, such as 20%, 40%, 60%, or 80% of a network's critical mass. Network connectivity, referring to the degree of interconnectedness among nodes, plays a crucial role in this phenomenon. Information diffusion has been the subject of extensive research, particularly in the domain of social networks (J. Jiang et al., 2013; Schneider et al., 2009). Attempts have also been made to forecast information diffusion using logistic functions (F. Wang et al., 2012).

In our analysis, voters serve as nodes in our network, and their memberships in DAOs establish connections within the network. We use the Jaccard value, specifically the intersection over the union of DAO memberships, as a measure of interconnectedness among nodes. For instance, if voter X is a member of DAOs $\{A, F\}$, and voter Y is a member of $\{A, B, C, D, E\}$, then the ratio would be $|\{A, F\}|/|\{A, B, C, D, E\}| = 0.2$. To compute the Jaccard value for each voter, we group the dataset by proposals, calculate the Jaccard value for each pair of voters within a proposal, and then take the average of all pairwise Jaccard values for every voter. We apply certain limitations, specifically focusing on proposals with less than 100,000 votes, proposals with more than 10 votes, and DAOs with at least 10 proposals. This filtering leaves us with 19,638,924 votes and 47,704 proposals. This approach aligns with the research proposed by F. Wang et al. (2012), where they analyzed information diffusion based on two metrics: friendship hops and shared interests.

Continuing, we delve into the analysis of voting behavior within DAOs, employing the Cumulative Density Function (CDF). The CDF tracks the progression of votes on a proposal, organizing each vote by its timestamp to create a consistently ascending curve. This curve effectively illustrates the pace at which eligible voters engage in a vote, considering that voting timespans can vary significantly across different proposals. To consolidate this data at the DAO level, where multiple proposals exist, we leverage *relative time*. This metric measures the duration from the start of voting to a specific timestamp, and *normalized hours*, a metric that scales the entire voting period from 0 to 1, covering the span from the beginning to the end. We categorized the Jaccard indices into intervals [0, 0.25), [0.25, 0.5), [0.5, 0.75), [0.75, 0.99), [0.99, 1.0]. Subsequently, we aggregated the first and second intervals, labeling them as *low*, and the remaining intervals as *high*, effectively splitting the dataset in half at Jaccard value 0.5.

To address our research question regarding how the connectivity of a node in the network influences information diffusion, we explore the time elapsed from the start of voting until various thresholds are reached—specifically, when 20%, 40%, 60%, and 80% of eligible voters have cast their votes. To present aggregated results at the DAO level, we normalized the time and scaled it from 0 to 1, ensuring comparable results.

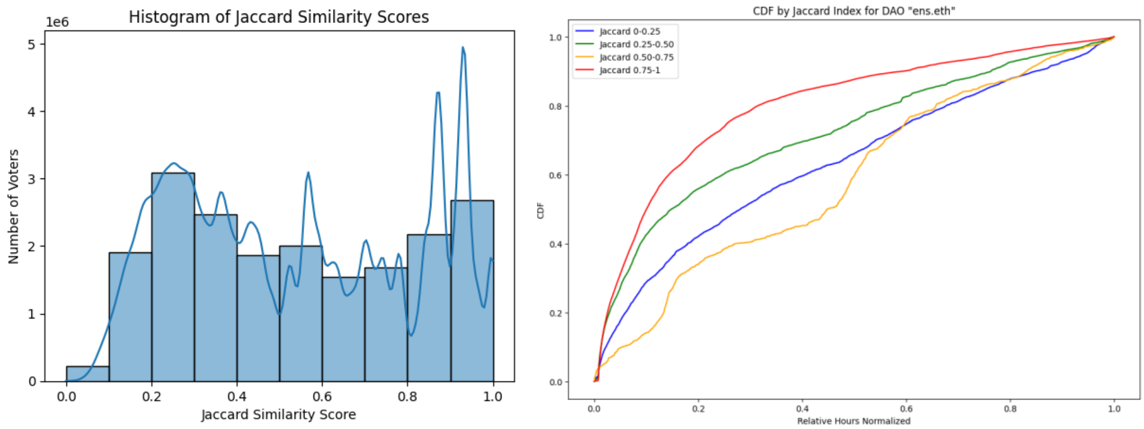

Figure 8. Distribution of Jaccard index and CDFs for largest DAOs based on Jaccard coefficients.

Figure 8 demonstrates that highly connected voters tend to react much faster to the voting process than weakly connected voters. This phenomenon was explored on a large scale by categorizing 1,397 DAOs by size. We computed the CDF for labels *low* and *high* for each proposal, then employed relative time to aggregate at the DAO level, allowing us to infer the average time when specific thresholds were met.

DAO Size	**Nr. of DAOs**	**10% threshold ***	**20% threshold ***	**40% threshold ***	**60% threshold**	**80% threshold ***
1-50	268	170 (63.4%)	158 (59.0%)	160 (59.7%)	151 (56.3%)	132 (49.3%)
51-100	235	150 (63.8%)	152 (64.7%)	132 (56.2%	125 (53.2%)	111 (47.2%)
101-150	168	111 (66.1%)	112 (66.7%)	94 (56.0%)	86 (51.2%)	85 (50.6%)
151-1,000	527	334 (63.4%)	332 (63.0%)	303 (57.5%)	296 (56.2%)	275 (52.2%)
1,001-10,000	165	85 (51.5%)	93 (56.4%)	95 (57.6%)	96 (58.2%)	94 (57.0%)
10,001-100,000	29	9 (31.0%)	12 (41.4%)	11 (37.9%)	12 (41.4%)	12 (41.4%)
100,001+	5	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (20.0%)
Total	1397	859 (61.4%)	859 (61.4%)	795 (56.9%)	766 (54.8%)	710 (50.8%)
Median time diff between highly and weakly connected subset of DAO achieving thresholds		14.51%	25.52%	12.28%	4.61%	0.35%
* % of DAOs with highly connected voters achieving the threshold faster than weakly connected						

Table 1. Number of DAOs where the normalized time for reaching thresholds (40%, 60%, 80%) for highly connected voters is lower than for weakly connected voters.

We examined for each bucket the percentage of DAOs where highly connected voters require less time to reach the specific thresholds than weakly connected voters. Table 1 shows that for smaller or medium DAOs, the share of DAOs with highly connected voters voting faster than weakly connected voters is slightly higher than for larger DAO. This hints that the effect is more important for smaller sized DAOs. Also, there is an estimation of the median difference in time required for reaching the specific thresholds: it subsides as time evolves meaning that the effect of connectivity is more pronounced at the beginning of the voting rather than at the end. The relationship is very weakly negative for lower thresholds and is negligible at the higher thresholds.

Statistical Test	**1% threshold**	**5% threshold**	**10% threshold**	**20% threshold**	**40% threshold**	**60% threshold**	**80% threshold**
Spearman	-0.197	-0.149	-0.117	-0.072	-0.007	0.014	0.056
Pearson	-0.083	-0.073	-0.065	-0.027	0.019	0.026	0.065
Kendall	-0.163	-0.115	-0.088	-0.054	-0.004	0.010	0.041

Table 2. Statistical tests showing the correlation between Jaccard index and the average normalized time of reaching a certain threshold.

Our data shows that highly connected voters vote marginally faster than weakly connected voters. The effect has the most considerable magnitude initially and subsides over time. To achieve the 10% threshold, DAOs with highly connected voters need 14.51% less time in comparison to DAOs with weakly connected voters. When reaching the 40% threshold, highly connected voters need 12.28% less time; for the 80% threshold, they require 0.35% less time. However, since the statistical tests range from -0.197 to 0.065, with a p-value of less than 0.001, we deem the results to not be statistically significant.

Additionally, we performed the Kolmogorov-Smirnov (K-S) test (Massey, 1951) to compare distributions across different Jaccard bins. The results show high p-values (ranging from 0.5361 to 0.9985) for all bins, indicating a strong similarity between the distributions. Since p-values above 0.05 suggest that the null hypothesis, in this case, that the distributions are the same, cannot be rejected (Dowdy et al., 2004), these findings imply that the distributions across the Jaccard bins are very similar.

4 Conclusion and Outlook

While there have been empirical studies on DAOs in recent years, no work has yet connected DAOs to online communities. Our research bridges theoretical and empirical evidence, establishing DAOs as a new type of online community.

We gathered data on 31,002 DAOs, 220,960 proposals, 51,987,413 votes, 154,087,070 token ownerships, and 46,695 historical token prices. Utilizing this extensive dataset, we conducted a 90-9-1 analysis, previously confirmed for online communities. We proceeded with a deciding voter analysis to highlight the unequal distribution of voting power in DAOs. The exploration culminated in two network analyses, revealing that DAOs exhibit properties of scale-free networks and that information diffusion is not affected by the connectedness of voters.

Our contribution to theory and practice begins by aligning DAO properties with the working definitions of online communities from Preece (2000), providing a fresh perspective on understanding DAOs. We then present empirical evidence, demonstrating that analyses traditionally applied to online communities also apply to DAOs in four distinct areas. First, we successfully apply the 90-9-1 rule to DAOs, extending its applicability from online communities. Second, through the deciding voter analysis, we reveal that even within the exemplary 5.33% of active users in a DAO, voting power is unevenly distributed, concentrating at the top, where 20% of all votes decide 60% of all proposals. Third, we establish that DAOs exhibit properties of scale-free networks, a concept widely studied in other domains but not conclusively applied to DAOs.

Last, we explore information diffusion within DAOs, assessing the impact of connectivity on the rate of information spread. Our findings indicate that more connected nodes disseminate information at the same rate as weakly connected nodes, contributing to the theoretical understanding of communication within decentralized governance structures.

While we made a considerable effort to compile a comprehensive dataset, our evaluation of DAOs was limited to those utilizing an ERC20 Token strategy for creating network graphs and analyzing the 90-9-1 rule, as both require token holder data. Unfortunately, accurate historical data for other voting strategies such as whitelist voting, ERC721, and ERC1155 was unavailable. Moreover, in creating network graphs that include pricing data, our analysis was confined to tokens listed on Coingecko or similar platforms; for those not listed, we could not reliably confirm the actual value of a token. Reasons for this limitation include scenarios where a token has never been listed, is soulbound (non-transferable), falls under ERC721 and ERC1155 (NFTs), or has a daily trading volume below $100, resulting in extreme price fluctuations. Despite these constraints, as our initial dataset includes all DAOs available on Snapshot and is not a sample, we assert that our results remain rigorous.

Our study establishes a foundation for advanced network analysis within the DAO domain. We anticipate that network analysis holds significant potential to unveil the factors contributing to the success or failure of various DAOs. Given the rapid evolution of DAOs, each possessing unique properties, the field promises exciting avenues for future analysis.

References

Allen, D. W., Berg, C., & Lane, A. M. (2023). Why airdrop cryptocurrency tokens? *Journal of Business Research*, *163*, 113945. https://doi.org/10.1016/j.jbusres.2023.113945

Antelmi, A., Malandrino, D., & Scarano, V. (2019). Characterizing the Behavioral Evolution of Twitter Users and The Truth Behind the 90-9-1 Rule. In L. Liu & R. White (Eds.), *Companion Proceedings of The 2019 World Wide Web Conference* (pp. 1035–1038). ACM. https://doi.org/10.1145/3308560.3316705

Aparicio, S., Villazón-Terrazas, J., & Álvarez, G. (2015). A Model for Scale-Free Networks: Application to Twitter. *Entropy*, *17*(12), 5848–5867. https://doi.org/10.3390/e17085848

Bakshy, E., Rosenn, I., Marlow, C., & Adamic, L. (2012). The role of social networks in information diffusion. In A. Mille, F. Gandon, J. Misselis, M. Rabinovich, & S. Staab (Eds.), *Proceedings of the 21st international conference on World Wide Web* (pp. 519–528). ACM. https://doi.org/10.1145/2187836.2187907

Barabasi, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science (New York, N.Y.)*, *286*(5439), 509–512. https://doi.org/10.1126/science.286.5439.509

Barabási, A.-L. (2009). Scale-free networks: A decade and beyond. *Science (New York, N.Y.)*, *325*(5939), 412–413. https://doi.org/10.1126/science.1173299

Broido, A. D., & Clauset, A. (2019). Scale-free networks are rare. *Nature Communications*, *10*(1), 1017. https://doi.org/10.1038/s41467-019-08746-5

Carron-Arthur, B., Cunningham, J. A., & Griffiths, K. M. (2014). Describing the distribution of engagement in an Internet support group by post frequency: A comparison of the 90-9-1 Principle and Zipf's Law. *Internet Interventions*, *1*(4), 165–168. https://doi.org/10.1016/j.invent.2014.09.003

Chang, M., Min, Q., & Li, Z. (2023). Understanding Members' Active Participation in a DAO: An Empirical Study on Steemit. In *PACIS*.

Chao, C.-H., Ting, I.-H., Tseng, Y.-J., Wang, B.-W., Wang, S.-H., Wang, Y.-Q., & Chen, M.-C. (2022). The Study of Decentralized Autonomous Organization (DAO)in Social Network. In *The 9th Multidisciplinary International Social Networks Conference* (pp. 59–65). ACM. https://doi.org/10.1145/3561278.3561293

Copeland, T. (2023). *Speculators push price of testnet ether on Goerli network to $1.60*. https://www.theblock.co/post/215248/speculators-push-price-of-testnet-ether-on-goerli-network-to-1-60

DeepDAO Ventures Ltd. (2023). *DeepDao - Organizations*. https://deepdao.io/organizations

Dowdy, S. M., Wearden, S., & Chilko, D. M. (2004). *Statistics for research* (3rd ed.). Wiley-Interscience.

Easley, D., & Kleinberg, J. (2019). *Networks, crowds and markets: Reasoning about a highly connected world* (7th printing). Cambridge University Press.

Ercal, G., & Matta, J. (2013). Resilience Notions for Scale-free Networks. *Procedia Computer Science*, *20*, 510–515. https://doi.org/10.1016/j.procs.2013.09.311

Fan, Y., Zhang, L., Wang, R., & Imran, M. A. (2023). Insight into Voting in DAOs: Conceptual Analysis and A Proposal for Evaluation Framework. *IEEE Network*, 1–8. https://doi.org/10.1109/MNET.137.2200561

Feeny, D., Berkes, F., Mccay, B. J., & Acheson, J. M. (1990). The tragedy of the commons: Twenty-two years later. *Human Ecology*, *18*(1), 1–19. https://doi.org/10.1007/BF00889070

Feichtinger, R., Fritsch, R., Vonlanthen, Y., & Wattenhofer, R. (2023). *The Hidden Shortcomings of (D)AOs -- An Empirical Study of On-Chain Governance.* https://doi.org/10.48550/arXiv.2302.12125

Fritsch, R., Müller, M., & Wattenhofer, R. (2022). *Analyzing Voting Power in Decentralized Governance: Who controls DAOs?* https://doi.org/10.48550/arXiv.2204.01176

Gasparini, M., Clarisó, R., Brambilla, M., & Cabot, J. (2020). Participation Inequality and the 90-9-1 Principle in Open Source. In G. Robles, K.-J. Stol, & X. Wang (Eds.), *Proceedings of the 16th International Symposium on Open Collaboration* (pp. 1–7). ACM. https://doi.org/10.1145/3412569.3412582

Goldberg, M., & Schär, F. (2023). Metaverse governance: An empirical analysis of voting within Decentralized Autonomous Organizations. *Journal of Business Research*, *160*, 113764. https://doi.org/10.1016/j.jbusres.2023.113764

Grandjean, M. (2016). A social network analysis of Twitter: Mapping the digital humanities community. *Cogent Arts & Humanities*, *3*(1), 1171458. https://doi.org/10.1080/23311983.2016.1171458

Hassan, S., & Filippi, P. de (2021). Decentralized Autonomous Organization. *Internet Policy Review*, *10*(2). https://doi.org/10.14763/2021.2.1556

Jiang, C., Chen, Y., & Liu, K. J. R. (2014). Evolutionary Dynamics of Information Diffusion Over Social Networks. *IEEE Transactions on Signal Processing*, *62*(17), 4573–4586. https://doi.org/10.1109/TSP.2014.2339799

Jiang, J., Wilson, C., Wang, X [Xiao], Sha, W., Huang, P., Dai, Y., & Zhao, B. Y. (2013). Understanding latent interactions in online social networks. *ACM Transactions on the Web*, *7*(4), 1–39. https://doi.org/10.1145/2517040

Jin, J., Li, Y., Zhong, X., & Zhai, L. (2015). Why users contribute knowledge to online communities: An empirical study of an online social Q&A community. *Information & Management*, *52*(7), 840–849. https://doi.org/10.1016/j.im.2015.07.005

Kaal, W. A. (2021). Decentralized Autonomous Organizations: Internal Governance and External Legal Design. *Annals of Corporate Governance*, *5*(4), 237–307. https://doi.org/10.1561/109.00000028

Kim, J., & Hastak, M. (2018). Social network analysis: Characteristics of online social networks after a disaster. *International Journal of Information Management*, *38*(1), 86–96. https://doi.org/10.1016/j.ijinfomgt.2017.08.003

Kondova, G., & Barba, R. (2019). Governance of Decentralized Autonomous Organizations. *Journal of Modern Accounting and Auditing*, *15*(8). https://doi.org/10.17265/1548-6583/2019.08.003

Kumar, P., & Sinha, A. (2021). Information diffusion modeling and analysis for socially interacting networks. *Social Network Analysis and Mining*, *11*(1), 11. https://doi.org/10.1007/s13278-020-00719-7

Marko, R., & Kostal, K. (2022). Management of Decentralized Autonomous Organizations. In *2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS)* (pp. 1–8). IEEE. https://doi.org/10.1109/COINS54846.2022.9855004

Massey, F. J. (1951). The Kolmogorov-Smirnov Test for Goodness of Fit. *Journal of the American Statistical Association*, *46*(253), 68–78. https://doi.org/10.1080/01621459.1951.10500769

Mislove, A., Marcon, M., Gummadi, K. P., Druschel, P., & Bhattacharjee, B. (2007). Measurement and analysis of online social networks. In C. Dovrolis & M. Roughan (Eds.), *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement* (pp. 29–42). ACM. https://doi.org/10.1145/1298306.1298311

Newman, M. E. J., Jensen, I., & Ziff, R. M. (2002). Percolation and epidemics in a two-dimensional small world. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, *65*(2 Pt 1), 21904. https://doi.org/10.1103/PhysRevE.65.021904

Nielsen, J. (2006). *The 90-9-1 rule for participation inequality in social media and online communities*. https://www.nngroup.com/articles/participation-inequality/

Panzarasa, P., Opsahl, T., & Carley, K. M. (2009). Patterns and dynamics of users' behavior and interaction: Network analysis of an online community. *Journal of the American Society for Information Science and Technology*, *60*(5), 911–932. https://doi.org/10.1002/asi.21015

Preece, J. (2000). Online Communities: Designing Usability, Supporting Sociability. *Industrial Management & Data Systems*, *100*(9), 459–460. https://doi.org/10.1108/imds.2000.100.9.459.3

Qin, R., Ding, W., Li, J., Guan, S., Wang, G., Ren, Y., & Qu, Z. (2023). Web3-Based Decentralized Autonomous Organizations and Operations: Architectures, Models, and Mechanisms. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *53*(4), 2073–2082. https://doi.org/10.1109/TSMC.2022.3228530

Rikken, O., Janssen, M., & Kwee, Z. (2023). The ins and outs of decentralized autonomous organizations (DAOs) unraveling the definitions, characteristics, and emerging developments of DAOs. *Blockchain: Research and Applications*, *4*(3), 100143. https://doi.org/10.1016/j.bcra.2023.100143

Schillig, M. (2021). Some Reflections on the Nature of Decentralized (Autonomous) Organizations. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.3915843

Schneider, F., Feldmann, A., Krishnamurthy, B., & Willinger, W. (2009). Understanding online social network usage from a network perspective. In A. Feldmann & L. Mathy (Eds.), *Proceedings of the 9th ACM SIGCOMM conference on Internet measurement* (pp. 35–48). ACM. https://doi.org/10.1145/1644893.1644899

Sharma, T., Kwon, Y., Pongmala, K., Wang, H [Henry], Miller, A., Song, D., & Wang, Y. (2023). *Unpacking How Decentralized Autonomous Organizations (DAOs) Work in Practice.* https://doi.org/10.48550/arXiv.2304.09822

Snapshot. (2023). *Welcome to Snapshot docs!* https://docs.snapshot.org/

Uzzi, B., & Spiro, J. (2005). Collaboration and Creativity: The Small World Problem. *American Journal of Sociology*, *111*(2), 447–504. https://doi.org/10.1086/432782

van Mierlo, T. (2014). The 1% rule in four digital health social networks: An observational study. *Journal of Medical Internet Research*, *16*(2), e33. https://doi.org/10.2196/jmir.2966

Wang, F., Wang, H [Haiyan], & Xu, K. (2012). Diffusive Logistic Model Towards Predicting Information Diffusion in Online Social Networks. In *2012 32nd International Conference on Distributed Computing Systems Workshops* (pp. 133–139). IEEE. https://doi.org/10.1109/ICDCSW.2012.16

Wang, Q., Yu, G., Sai, Y., Sun, C., Nguyen, L. D., Xu, S., & Chen, S. (2022). *An Empirical Study on Snapshot DAOs.* https://doi.org/10.48550/arXiv.2211.15993

Wright, A. J. (2021). The rise of decentralized autonomous organizations: Opportunities and challenges.

Yang, T., Chi, Y., Zhu, S., Gong, Y., & Jin, R. (2011). Detecting communities and their evolutions in dynamic social networks—a Bayesian approach. *Machine Learning*, *82*(2), 157–189. https://doi.org/10.1007/s10994-010-5214-7

Ziegler, C., & Welpe, I. M. (2022). A Taxonomy of Decentralized Autonomous Organizations. *ICIS 2022*. https://aisel.aisnet.org/icis2022/blockchain/blockchain/1/,”