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Abstract

Blockchain technology has enabled the emergence of decentralized autonomous organizations (DAOs) with consensus-based governance. Staking governs DAOs instead of centralized authorities. As a new organizing form, DAOs require careful theoretical consideration. We conceptualize the vehicle of consensus-based governance as digital consensus. Using an agent-based simulation model, this paper aims to extend meta-organization theory to incorporate an organizational learning perspective. We benchmark the DAOs using two well-established organizing forms, namely autonomous and hierarchical organizations. We find that hierarchies outperform DAOs in static environments, whereas DAOs outperform hierarchies in turbulent environments, with autonomies only excelling with intensive experimentation. Our analyses allow us to characterize DAOs as evolving through a staggered process of polarization and homogenization, as opposed to autonomies' continuous polarization and hierarchies' continuous homogenization. Such a staggered process can be affected by several factors (e.g., voting thresholds, token asymmetry, and contributor incentives).

Keywords: Decentralized autonomous organizations, organizational design, digital consensus, agent-based simulation

Introduction

Advances in blockchain technology have empowered the emergence of highly decentralized governance modes, such as decentralized autonomous organizations (DAOs). One of the most prominent DAOs is Uniswap, which operates as a cryptocurrency exchange on the Ethereum blockchain. With the UNI token, the cryptocurrency issued by Uniswap, anyone can become a stakeholder and vote on how the organization operates. Such operations are automated with smart contracts,[1] which are cryptographically protected against retrospective manipulation. Trustworthy automation enables DAOs to coordinate various economic activities. Specifically, they may automate various business protocols (e.g., cryptocurrency exchanges like Uniswap, lending, and philanthropy applications) and uphold constitutional codes[2] via certain

[1]Smart contracts are composed of simple "if/when...then..." rules programmed in code on a blockchain. Participants must determine how transactions and their data are represented on the blockchain, agree on the rules that govern these transactions, explore any exceptions, and establish a framework for dispute resolution. Narrowly speaking, a DAO is a new type of organization that runs as smart contracts on a blockchain.

[2]Constitutional codes define the infrastructure basis upon which the smart contract operates and is seldom modified. For example, Ethereum promises, in its constitutional codes, to provide a globally decentralized computing pool that no one can shut down. This

token-weighted aggregation mechanisms (e.g., relative majority voting, minimum quorum voting). Irrespective of these different functionalities, all DAOs share a consensus-based mode of governance. DAOs are governed by staking (i.e., voting) rather than by a centralized authority. Consensus-based governance, as a new form of organizing, begs careful theoretical consideration.

We conceptualize the vehicle of consensus-based governance as digital consensus. Digital consensus herein refers to algorithmic coordination rules that are automatically executed in distributed computer systems and are only modifiable via voting. Smart contracts mentioned above can be used as a means of efficiently achieving digital consensus. Beyond technical automation, digital consensus provides new organizing insights into achieving online collaboration with limited or no reliance on a hierarchy (Hsieh and Vergne 2023; Lumineau et al. 2021; Tsoukalas and Falk 2020). Broadly speaking, one may question whether consensus-based governance can outperform other forms of organizing such as autonomous organizations (Lee and Edmondson 2017), or hierarchies (Levinthal and Workiewicz 2018). One may also wonder how to design digital consensus mechanisms for better organizational performance.

Fundamentally, decentralized governance gives active members of the organization a voice in critical decisions. Members' opinions will be exchanged via online communication and negotiation, and reflected in proposals open for voting. The proposal is digitized and programmed into a new digital consensus once a certain number of members agree. Given the socialization nature of consensus formation and the credibility of consensus enforcement, we see great potential for IT value in improving organizational learning (Sturm et al. 2021). Put differently, socialized consensus formation and programmable digital consensus may collect swarm intelligence (Chittka and Mesoudi 2011) from chaos. In fact, we have seen many IS contexts that emphasize the wisdom of crowds (e.g., crowdsourcing, online review). Yet, little is known about decentralized governance (Beck et al. 2018; Rossi et al. 2019) and how digital consensus may utilize the wisdom of crowds and produces collective intelligence.

The concept of collective intelligence also pertains to another research stream, namely that of organizational design. In particular, Gulati et al. (2012) proposed the concept of the *meta-organization*, defined as a collection of agents who are "legally autonomous and not linked through employment relationship." A trend toward open boundaries can be seen in this seminal framework. Open boundaries encourage more interactions among entities, and interactions further shape knowledge sharing and inter-organizational learning. However, a question remains as to how well the digital consensus vehicle can replace formal authority for effective coordination. Otherwise, infinite connections/interactions may produce more chaos than intelligence. Considering that the concept of DAO was established in 2016, extant meta-organization theory has yet to incorporate its characteristics. Yet, the literature on organizational design typically pursues certain edges of chaos (Anderson 1999) in self-organizing systems. The edge of chaos is essentially attributed to the paradoxical nature of organizational design, especially the trade-off between exploitation and exploration (March 1991). Thus, extreme designs rarely result in self-organizing systems that consistently and resiliently produce effective solutions. A certain kind of edge can be found in Fang et al. (2010) such that a semi-decentralized organizational structure allows superior ideas to diffuse across groups without excessively losing organizational diversity. Analogically, digital consensus is expected to hold chaos at bay and boost collective intelligence, despite the absence of formal authority. From that perspective, one may narrow down the question as to where the edge of chaos lies in the design of digital consensus mechanisms.

The gaps identified above raise an important question: *How does digital consensus affect organizational performance?* In addressing this question, we focus on three dimensions. First, in what ways does consensus-based governance differ from a traditional one, namely autonomy, and/or hierarchy (i.e., *what is*)? Second, under what circumstances does consensus-based governance outperform other modes of governance (i.e., *what might be*)? Third, what is the underlying mechanism accounting for any performance differences (i.e., *how*)?

This study aims to theorize decentralized consensus-based governance. We extend meta-organization theory (Gulati et al. 2012) to incorporate an organizational learning perspective. To answer the *what is* question,

computational infrastructure enables a new kind of society – transparent, accountable, and based on definitive rules.

it is necessary to benchmark the decentralized consensus-based governance against the other two traditional forms of organizing, namely autonomy, and hierarchy. The conceptual model of DAOs is derived from a broader body of research on hierarchy and autonomy, especially based on relevant agent-based simulation models. These three organizational forms are then compared under various circumstances to examine their performance dynamics. Our baseline model results show that hierarchies perform better in a static environment, whereas DAOs perform better in a turbulent environment, with autonomies only excelling in intensive experimentation. The reason is that a centralized control system concentrates on the most promising solutions, making it quite efficient in a static environment. However, this comes at the cost of organizational flexibility, a key advantage of DAOs in turbulent environments. In sum, we closely reproduce the "diversity prediction theorem" (Page 2008) such that error cancellation requires a certain degree of diversity. One may thus intuit that digital consensus simply facilitates broad coordination while respecting diversity. Through the lens of performance variance, we gain a more nuanced understanding. In essence, DAOs evolve through a staggered process of polarization and homogenization. Such a process reduces the inherent "luck" difference so that good solutions are available not only to some fortunate groups. Digital consensus distributes good solutions "equally" to participants. Equality also implies broad representativeness in the distributed consensus. However, many factors can disrupt this staggered process, impairing effective equality. Token asymmetry, for example, will impair equality. Contributor incentive, however, is a double-edged sword, depending on individuals' engagement. Voting thresholds affect DAOs' performance in an inverted U-shaped manner. Unlike conventional theories of crowd wisdom, which emphasize small individual errors and diverse judgments, equal representation in digital consensus will incorporate more than these two criteria. The problematization effort and proposed meta-organization learning theory further our understanding of consensus-based governance. Our analysis of different design elements also informs digital consensus design for practice.

Literature Review

Digital Consensus

We review recent literature on DAO governance (see Table 1) and find that current theoretical work fails to link governance modes to organizational learning. Promoting organizational learning, however, is one of the key pursuits of organizational theorists. Thus, to facilitate the necessary conceptual transition, we introduce the concept of digital consensus, defined as algorithmic rules for decentralized coordination. Digital consensus is automatically executed in distributed computer systems and is only modifiable via voting. Following Kallinikos et al.'s (2013) theorizing framework on the digital artifact, we conceptualize digital consensus in three characteristics,[3] namely *transparency*, *democratic editability*, and *self-execution*.

First, the digital consensus *qua* object is transparent. Technically, stakeholders access the digital consensus for queries and verification. Broad coordination is only possible when information is transparent. Individuals can gain insight into organizational goals and the operational context, and more importantly, learn from the established digital consensus. Second, the digital consensus *qua* object is democratically editable by means of voting. The online voting process typically includes opinion exchange, negotiation, and conflict resolution. It is worth noting that digital consensus will be modified only after the community consents to an update via selection.[4] Editability is a common attribute of digital artifacts. The editability of digital consensus is, however, strictly limited to socialized control, rather than an authorized process. Put differently, the traditional digital artifact is protected (e.g., read/write protection) via permission management, while digital consensus is primarily protected via challenges to consensus-building. Several factors may contribute to such challenges, such as divergence of opinion, lack of participation (Aguiar-Conraria et al. 2020), and lack of accountability (Ding et al. 2022). As a result, digital consensus may be ineffective, failing to integrate

[3]Traditional consensus concept in political science and sociology cannot attend to new salient features in blockchain technology (e.g., cryptographical reliability, automation).

[4]Yet, the initialization stage is quite different. The digital consensus prototype can be accomplished more centrally, usually by a small group of experts or early investors. Because we are concerned with long-term organizational evolution, we purposefully ignore the centralized nature of initialization. In fact, a subsequent community-based joint effort will supersede this founding work.

swarm intelligence, or even getting stuck in consensus dilemmas. On the other hand, a certain degree of friction is necessary to protect the organization from malicious attacks (Faqir-Rhazoui et al. 2021) – A protocol cannot easily be passed. As such, digital consensus illustrates the paradoxical nature of organizational routines, a source of both flexibility (Feldman and Pentland 2003) and inertia (Hannan and Freeman 1984). Third, the digital consensus *qua* object is self-executing, offering an automatic routine along which organizations or human agents can rest assured that organizational activities function as promised. Self-executing digital artifacts guarantee the automated execution of predetermined actions, contrary to traditional executables where execution decisions are made individually or in small groups. Thus, digital consensus goes beyond technical automation to become an organizing vehicle that eliminates centralized authorization.

Concept	Definition	Imperfection
Information Commons	A highly accessible, self-rising information system in which stakeholders share an overarching goal (Mindel et al. 2018)	Neglect its impact on shaping organizational learning and adaptation
Decentralized Coordination	A goal-oriented adjustment of platform participants' actions through expectations alignment (Hsieh and Vergne 2023)	Lack of conceptualization on digital artifact and how it influences organizational learning
Blockchain Governance	Self-contained and autonomous system of rules (Lumineau et al. 2021)	A broad governance framework for blockchain agenda

Table 1. Contemporary Concepts of Digital Consensus

One may wonder how the blockchain technical roadmap relates to this conceptualization. Technically, these characteristics, along with the cryptographic reliability of blockchain technology, ensure the integrity and validity of digital consensus. Organizationally, digital consensus facilitates reliable, decentralized coordination. By theorizing digital consensus, this paper focuses on the essence of an organizing philosophy that is generalizable. Specific techniques will not be overemphasized to just prove the feasibility of certain organizing strategies. Instead, we examine the subsequent changes in organizational learning. In addition, DAOs and blockchain technology are still in the early trial-and-error / experimentation phase. Fine-grained technical components may be removed shortly (Andersen and Bogusz 2019), although temporarily effective. Thus, it only adds to myopia to obsess about temporary techniques (e.g., proof-of-stake vs. proof-of-work). As we conceptualize digital consensus, the next section will discuss consensus-based governance and its position in the organizational digitalization literature.

Consensus-Based Governance

Although digitalization takes many forms, it emphasizes the importance of IT to organizational performance and competitive advantage. Competitive advantage is typically attributed to firms' control over inimitable, and non-substitutable resources (Mata et al. 1995; Piccoli and Ives 2005). An inimitability principle refers to the slowness, difficulty, and cost involved in the process of competitive imitation. This intangibility and thus inimitability allow firms with high IT capability to achieve superior performance and remain competitive (Bharadwaj 2000). However, a wave of experimental applications to the principle of consensus-based governance stands to disrupt our traditional thinking around the inimitability principle. With blockchain, most organizational resources are transparent and even reusable, including intelligent resources (e.g., code, decisions), computational resources, and capital resources (e.g., cryptocurrency). Transparency is the cornerstone of consensus-based governance in that it enables the right to monitor decisions and enforce control over certain cryptoassets (Beck et al. 2018). This cornerstone plausibly disrupts the prior belief of inimitability – one can easily replicate another Uniswap with totally transparent code. In fact, cryptocurrency exchanges abound. As of this writing, there are more than 2000 cryptocurrencies and 244 top cryptocurrency exchanges (*Top Cryptocurrency Exchanges Ranked By Volume* 2023).

This disruption can be attributed to the disconnect between consensus-based governance, which is primarily influenced by open-source communities, and the traditional concept of competitiveness, which is more organization-based. Previously, companies and communities had distinct boundaries – online communities are self-organized and pursue non-market rewards such as belongingness, pleasure, and expertise, whilst organizations are deemed to be formed based on their employment relations and to make work done for common business targets. However, DAOs blur these boundaries. DAOs are almost spontaneous, unaffiliated with employers, and aim to create value for businesses (Chong et al. 2019). Traditionally private organizational governance became transparent. In this sense, combining community insights with organizational governance could be extremely uncertain and begs further investigation. On the one hand, the consensus-based decision-making principle is broadly adopted in non-profit organizations and online communities, such as open-source software communities (e.g., Apache Software Foundation in Stewart and Gosain (2006)) and online knowledge communities (e.g., Wikipedia in Forte et al. (2009)). On the other hand, decentralized organizations are also a classical concept in the literature on organizational design, suggesting that a certain degree of decentralization can benefit organizations (Alonso et al. 2008; Fang et al. 2010). However, the community scenarios seldom involve monetary compensation for contributors (Ziolkowski et al. 2020) and, more importantly, fall short of creating organizations with market valuations. Another difference is the ownership of property rights. In community scenarios, for example, Linux kernel development projects, the intellectual property is owned by the developers who contributed. By comparison, developers in companies usually receive salaries. Decision rights and decision execution are separated in companies. This separation typically reduces commitment such that self-interested contributors are not always motivated to the same level as when they own the outcomes of their own labor.

Taken together, consensus-based governance appears risky in that it may not align with the market value creation process (e.g., reaching consensus may be challenging, which can result in an inability to capture fleeting opportunities or attain organizational goals, even suboptimal ones). Yet, it also looks promising since self-interested individuals with local knowledge may improve organizational performance. Thus, the next section will discuss the potential impact of consensus-based governance on organizational performance through organizational learning.

Theoretical Foundation of Meta-Organizational Learning

Much of the work on organizational learning follows Simon's (1947) and Cyert and March's (1992) view that organizations are composed of boundedly rational agents. Bounded rationality, rooted in the Carnegie School tradition, describes a behaviorally plausible process by which organizations learn from performance feedback. The learning that reinforces itself through performance feedback and trial-and-error is also categorized as reinforcement learning (e.g., Levinthal and Rerup (2021), Koçak et al. (2022)). A key component of such reinforcement learning is that organizational knowledge is interpreted and encoded into performance outcomes. Thus, organizations will evolve toward better outcomes lying above the current aspiration level. This local search manner is coherently backed up by bounded rationality (Simon 1947), which prevents agents from taking advantage of all the attractive opportunities that tend to be protected by behavioral and social constraints (Liu 2021). Drawing on this strong literature tradition, two classical organizational designs are well-recognized, namely autonomous and hierarchical organizations. Autonomies typically consist of isolated groups, with little across-group communication (Fang et al. 2010). Autonomies are often applied in contexts that value specialization (e.g., agile software development; academia). By comparison, hierarchies have a formal group of managers to coordinate from the top-down (Levinthal and Workiewicz 2018). The hierarchy is common in large companies that value control. Based on this strong stream, we wonder how consensus-based governance will influence organizational learning dynamics. However, the answer is not readily straightforward and call for computational representations to be developed and compared. Hence we will elaborate in more detail in our next section on computational modeling.

People do not always work for companies. For example, online communities are a classic collaboration context frequently studied in IS. The company, as a modern phenomenon, also constantly changes over time since coined during the First Industrial Revolution. In essence, it is about better organizing and coordinating that cater to production needs. One recent advance in organizational theory bridging the phenomenon of communities and companies is meta-organization theory (Gulati et al. 2012). Meta-organizations are defined as consisting of legally autonomous entities (Gulati et al. 2012). Yet, the current version of the meta-organization theory falls short of explaining how to facilitate efficient coordination among those highly autonomous entities but sheds some light on a new agenda for these emerging organizational forms. It is worth noting that Gulati et al. (2012) proposed stratification as the device to reduce the complexity of coordination by "subdividing the collective into smaller subgroups." In the stratification, high-tier organizations supervise and coordinate the activities of low-tier organizations. To some extent, the stratification mode is analogous to hierarchy, although it respects the decision power of low-tier entities. This also reflects the entrenched influence of hierarchical governance. Again, little is known as to the coordination among legally autonomous entities. Particularly, our focus is on the learning dynamics among legally autonomous entities.

Taken together, we review both the organizational learning and the meta-organization literature with the intention of bridging them eventually. Our next section will discuss how to fill this critical gap by developing a computational model of organizational designs..

Computational Model

Entities

Organizations are complex adaptive systems where individuals interact with each other. We view individuals as carriers of ideas and knowledge and organizational adaptation as a property that emerges from individual interactions. Interaction in our model includes two parts, 1) within-group socialization, and 2) across-group coordination. Within-group socialization refers to a process of organic group learning. For example, a project group is a common form for IT development where developers share their knowledge and align the group goal. Yet, autonomy tends to increase organizational risk since isolated groups solve problems without cross-group learning or higher-level coordination (Fang et al. 2010; Raveendran et al. 2022). Thus, we propose a two-layer model for cross-group coordination, namely top-down supervision as in hierarchies and bottom-up consensus-based governance as in DAOs. This makes our model different from March's (1991) exploration-exploitation model of organizational learning. Our model has three main entities: the external reality, the individual, and the manager.

External Reality. We describe the external reality as having two parts: reality beliefs and reality policies. Agents seek to figure out the reality of beliefs or policies. Such a division corresponds to our two-layer model design. The belief part will be tuned by individuals, while the policy part will be tuned by managers. Reality beliefs have m dimensions, and reality policies have m/α dimensions. The hyper-parameter α refers to the degree of aggregation, namely the number of beliefs that are aggregated into one policy. Low α values reflect more detail-oriented policy-making or consensus-building. Higher α values represent leaving more space for the operational units. When $\alpha = 1$, our models can degrade into analogous models in the literature (e.g., March (1991)). The construction of reality involves two steps. First, every reality belief is randomly generated as 1 or -1 with equal probability. Second, the reality policy is generated by aggregating reality beliefs across every α beliefs via the majority rule, as in Gavetti (2005) and Levinthal and Workiewicz (2018). Suppose the reality beliefs are randomly generated as $\langle 1, 1, -1, -1, -1, 1 \rangle$ (i.e., $m = 6$) and $\alpha = 3$, the reality policies will be generated as $\langle 1, -1 \rangle$.

Individuals. The objective of individuals is to fit the reality beliefs. Individuals seek to tune operational decisions. Each individual deals with m beliefs. Each belief is initially set to 1, -1, or 0, with equal probability. Individuals are the operational units of autonomies, DAOs, and hierarchies.

Managers. The objective of managers is to fit the reality policies. Managers tune strategic decisions. Each manager deals with m/α policies. Each policy is initially set to 1, -1, or 0, with equal probability. Managers make up the supervision group of hierarchies. Given the same reality but different abstraction levels, managers' learning is positively correlated with that of individuals.[5]

[5] In Levinthal and Workiewicz's (2018) *NK* fitness landscape model, the lower-level and upper-level agents search on two independent landscapes. Their performance is then integrated/weighted using an extra parameter. March's (1991) model is preferred here as it allows individuals and managers to deal with the same reality from different perspectives (i.e., operational vs. strategic).

Outcome Measurements

In the Carnegie School tradition, reinforcement learning is driven by encoding performance outcomes as success or failure relative to reality. We follow the m dimension payoff function design (March 1991) where m is the problem dimension, and thus the problem space is typically equal to 2^m. For each dimension, the belief bit could be $-1, 1$, or 0 such that -1 and 1 represent two alternative decisions, whereas 0 represents uncertainty about how to make that decision. Say a group of developers is creating a decentralized app. Suppose one decision is to select a specific cryptocurrency as their token, they may choose between Eth (denoted as -1) and Bitcoin (denoted as 1). Alternatively, they could temporarily remain ambiguous (denoted as 0). This coding system represents organizational configurations, and each configuration combination will receive a corresponding payoff. Let $\Phi(x)$ denote the payoff function for a bit string x with its dimension m. The payoff function is:

$$\Phi(x) = \sum_{i=1}^{m} \delta_j \tag{1}$$

where $\delta_i = 1$ if x_i corresponds with reality on dimension i; $\delta_i = 0$ otherwise. Based on the same function in Equation 1, we calculate the belief payoff for individuals and the policy payoff for managers. Organizational performance is measured by the average of all individuals' payoffs in an organization. The performance variance is the variance of the individuals' payoffs.

Similar to Fang et al.'s (2010) model, we introduce the measurement of belief diversity as a pair-wise dissimilarity ratio. Belief diversity is measured as follows:

$$\text{Belief Diversity} = \frac{2}{mn(n-1)} \sum_{i=1}^{\frac{1}{2}n(n-1)} \sum_{j=1}^{m} \omega_{ij} \tag{2}$$

where $\omega_{ij} = 1$ if two chosen individuals in pair i have different beliefs on dimension j; $\omega_{ij} = 0$ otherwise.

Organizational Learning

The entities mentioned above are organized in different ways to create autonomies, hierarchies, and DAOs. Each organization consists of n individuals. All individuals are equally divided into groups containing z individuals each.[6] Hierarchies also consist of n' managers. Agents conduct reinforcement learning based on the performance feedback given by Equation 1. The representations of all models are organically mapped to existing computational models and thus well-validated.

Autonomies are designed as collections of individual groups without any across-group coordination, based on Fang et al.'s (2010) model. Individuals in autonomies only learn from within-group socialization. Individuals in the same group are fully connected. Connections between any two individuals indicate bidirectional learning such that one's beliefs could be the learning resource for others and, at the same time, the outcome of learning from others. If one ascertains that other members in the same group hold beliefs that are more in line with reality (i.e., higher-performing peers), one may update its own beliefs to incorporate some aspects of these higher-performing individuals. As a result of within-group socialization, an autonomous group tends to develop a shared understanding. Yet, although learners may identify those who are outperforming, it may not be clear what specific aspects of their beliefs contributed to the improvement. Such ambiguity also implies the possibility that outperforming peers may not be able to resolve and deliver solutions correctly and completely. Thus, ambiguity may induce diverse beliefs among those outperforming peers. To address this, we use a majority decision rule similar to that used in prior literature (Fang et al. 2010; Gavetti 2005; March 1991). Diverse outperforming beliefs are integrated into one unified belief set based on a majority rule. In short, individuals will identify dominant beliefs from a subgroup of outperforming peers. Lastly, the focal individual may decide to update each dimension of its own beliefs to these

[6] By default $z = 7$, which is also the default group size in Fang et al.'s (2010) model. We believe that a large but efficient autonomous group is unlikely, in the absence of supervision or leadership. In addition, Dunbar's number (the max number of relationships one can maintain), which is 148 in sociology literature (Dunbar 1995), significantly decreases and only ranges from 4 to 36 in organizational design literature (Millward et al. 2007), also suggesting that smaller, tight-knit autonomous groups are reasonable.

dominant beliefs, with a learning rate η. In sum, autonomous learning comes from individuals adopting the dominant beliefs of their outperforming peers, which may include incorrect beliefs. The status quo persists if there are no outperforming peers.

Hierarchies are designed as collections of several individual groups and a manager group, inspired by Levinthal and Workiewicz's (2018) model. Individuals in hierarchies learn from within-group socialization (as described for autonomies) and top-down coordination. The manager group acts as a formal authority based on employment relationships. Managers have the authority to direct the actions of the individuals reporting to them (Gavetti 2005; Levinthal and Workiewicz 2018). Each individual group first confirms with one manager (i.e., $n' = n/z$), following the principle of unity of command (Fayol 1949). Suppose $\alpha = 3$ and the manager holds a policy of 1, individuals reporting to the focal manager can only search within a constrained space of 1, that is, an operational space of $\langle 1, 1, 1\rangle$, $\langle -1, 1, 1\rangle$, $\langle 1, -1, 1\rangle$ and $\langle 1, 1, -1\rangle$. Individuals are thus given a certain amount of room for refinement. Exceptionally, if a policy is 0, individuals will retain the status quo. Top-down coordination provides individuals with both instruction and obstruction, depending on how correct these policies are. Instruction effects are caused by intensive search on the more promising half, whereas obstruction effects are caused by misleading search on the unpromising half.

For hierarchies only, we recall the design of the organizational code to enable the managers' socialization and learning. Organizational code represents the institutional advantage that reconciles the manager group. Managers update their policies *by* and *from* the organizational code (see Figure 1a). Specifically, managers' policies mimic the organizational code with probability p_1, which is a parameter that tunes the speed of learning *from* code. At the same time, the organizational code adapts to the policies of managers whose policies are more in line with reality than the code is, using probability p_2.[7] Here, p_2 is a parameter that tunes the speed of learning *by* the code. Since supervision efficiency is not our primary focus, we initialize the model using the best configuration of p_1 and p_2 from March (1991). Therefore, we set $p_1 = 0.1, p_2 = 0.9$. By doing so, we aim to avoid any inferior supervision that would set off undue advantages for DAOs in subsequent comparisons.

DAOs have no formal authority but use digital consensus to enable across-group coordination, based on our conceptualization of digital consensus. A group is a meta-organization (see Figure 1b). Individuals in DAOs learn from within-group socialization (as described in autonomies) and bottom-up coordination. Recalling that digital consensus is transparent, and democratically editable, individuals in DAOs can learn *by* forming digital consensus and *from* established digital consensus. Specifically, we integrate individuals' beliefs into policy tendencies according to the majority rule. Suppose aggregation degree $\alpha = 3$ and one individual holds beliefs of $\langle 1, 1, -1\rangle$, then its policy tendency will be 1. It is worth noting that individuals with different beliefs may vote for the same policy. The design is aligned with the fact that consensus is formed through negotiation and compromise. A set of digital consensus $\mathcal{D}$ is generated based on policy tendency $\mathcal{P}$, token ownership $\mathcal{T}$ ($\mathcal{T} = 1$ as the baseline model), and voting threshold θ. Suppose individual i whose policy tendency is $\mathcal{P}_{i,j} = 1$ votes with his token $\mathcal{T}_i$, once the percentage of these tokens reaches the threshold θ (i.e., $\frac{1}{n}\sum_{i=1}^{n} \mathcal{T}_i > \theta$), a digital consensus of 1 will be established on that dimension j. In the same way, a digital consensus of -1 can be established. Other than these two cases, it is likely that neither the 1 nor -1 tendency is dominant. In that case, the digital consensus remains 0.[8] Individuals will learn both from within-group socialization and from cross-group coordination once a certain consensus is reached. Recalling that within-group socialization involves individuals mimicking the dominant beliefs from outperforming peers, these dominant beliefs will now be adjusted to confirm the consensus. For example, one individual may identify the dominant beliefs from outperforming peers as $\langle 1, 1, -1\rangle$. The established consensus covering

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[7] Let κ represent the agreement level on one reality dimension. κ_j is measured by the number of outperforming managers who hold opposite policies on dimension j. The code will adapt to the opposite majority opinion on that dimension with a probability of $1 - (1 - p_2)^{\kappa}$. The agreement level in March's (1991) model also implies a reliance on the wisdom of the majority.

[8] 0 represents uncertainty in a policy dimension. In hierarchies, when managers are uncertain about a particular policy, the individual group retains its status quo (Levinthal and Workiewicz 2018). In DAOs, digital consensus may also include 0, which means the community has yet to reach a consensus in a certain domain. In that case, individuals may learn from chaos, namely randomly generated beliefs. It is worth noting that learning from chaos typically occurs in the early stages of consensus formation when there is a consensus vacuum. We believe learning from chaos is more appropriate for such a bottom-up consensus formation, although the qualitative results remain consistent when we adopt the design of "retaining the status quo with 0" as with top-down supervision.

these beliefs could be -1, however. In this case, the focal individual must modify its mimicking reference as a randomly generated belief recombination that complies with consensus (i.e., dominant beliefs are -1). Thus, the focal individual may instead learn from $\langle -1, -1, 1\rangle$,[9] with learning rate η.

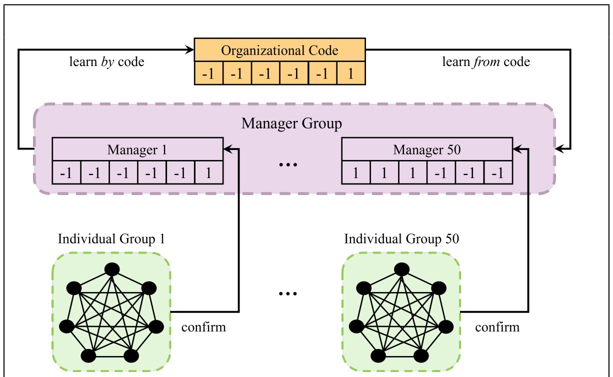

Figure 1a. The Structure of Hierarchy

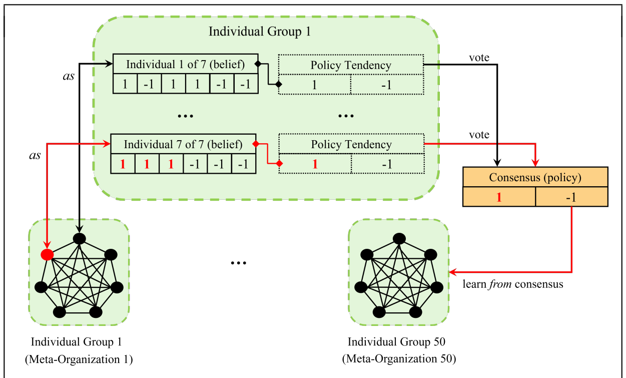

Figure 1b. The Structure of DAO

Phenomenon-focused Extensions

The computational model above only partially and intuitively answers the *what is* question. Computational modeling is a laboratory where we can do *what might be* experimentation to explore new concepts and boundaries, and more importantly, push what we already know forward. Thus, we conduct some phenomenon-focused extensions on decentralized consensus-based governance, including environmental turbulence, voting threshold, token asymmetry, and contributor incentive. Since the primary focus is on DAOs, we summarize other extensions relevant to hierarchies' or autonomies' in the sensitivity analysis section.

Environmental Turbulence

It has been a tradition to examine the performance of organizations under environmental turbulence since the seminal work of March (1991). Turbulence of environments refers to the fact that the mapping between organizational decisions and organizational performance may change over time. Due to turbulent circumstances, organizations experience rapidly deteriorating performance. In order to restore performance, organizational adaptation is crucial. Adaptation and long-term performance, along with short-term performance in static environments, are rooted in the exploration and exploration trade-off (March 1991). It also pertains to the pursuit of an organization, namely an organization that produces good solutions consistently and resiliently. In this sense, one immediate question is which organizational form is more conducive to adaptation. To examine the adaptation of different organizational structures to digital ecodynamics, we rely on two parameters, namely turbulence period T_{tb} and intensity I_{tb}, to model environmental turbulence. Specifically, the reality beliefs (and thus policies) will change every T_{tb} iterations, with a probability of I_{tb}. By turbulence, the environments that simulated organizations face are represented in a way that captures turbulence well, but suppresses many other aspects. This extension further compares DAO with hierarchy and autonomy in the same theoretical tradition.

Voting Threshold

In this extension, we relax the assumption that digital consensus is based on simple majority and let θ vary from 0.4 to 0.7. θ will determine the minimum proportion of votes required for digital consensus, and there-

[9] By default $\alpha = 3$, which is also the default aggregation degree in Levinthal and Workiewicz (2018). It is worth noting that when $\alpha = 1$, the hierarchy model will degrade into March (1991), and the DAO model will degrade into a token-weighted version of that model, where token-weighted rules rather than elitism rules generate organizational code. The qualitative results are insensitive to the value of α, but the introduction of α aligns and validates our model with recent computational models on hierarchies.

fore the difficulty of reaching digital consensus.

Token Asymmetry

While the DAO architectures may not possess formal authority based on employment contracts, they may hold significant informal authority based on expertise, reputation, status, or gatekeeping privileges. Inequalities in power do not disappear but may take on different forms. Empirical studies also suggest that DAOs may have extremely unbalanced token distributions (e.g., Barbereau et al. (2022)). This extension relaxes the assumption that all agents have the same number of tokens. Individuals are now initialized with an unequal number of tokens, generated from a Pareto distribution according to its shape parameter ρ.

Suppose x_i is the token weight for agent i. Every x_i is given by the probability density function.

$$f(x) = \begin{cases} \frac{\rho x_{min}^{\rho}}{x^{\rho+1}} & x \geqslant x_{min} \\ 0, & x < x_{min} \end{cases} \tag{3}$$

where x_{min} is the minimum possible value of x, and ρ is a shape parameter. In this context, $x_{min} \geqslant 0$.

Contributor Incentive

The cognitive load for voting tasks and the time costs involved can prevent many members from participating in voting. For example, at its worst, only 1% of MakerDAO token holders participated in voting activities, with most holding the governance token as an investment tool and staying silent about organizational governance (Zhao et al. 2022). Incentives are thus introduced to increase the engagement of individuals and align their interests with organizational performance. For simplification, γ tokens will be awarded to those who contribute to the newly formed consensus. Let p_i be the inactive probability, the incentive also triggers the re-activation of those inactive individuals. Thus, γ also represents the probability of reactivation.

Simulation Results and Theoretical Propositions

Baseline Model

In the baseline mode, we present the performance of 1) the most efficient hierarchy (i.e., $p_1 = 0.1, p_2 = 0.9$), 2) naïve DAO based on plurality voting (i.e., $\theta = 0.5$), and 3) autonomy. As shown in Figure 2a, in static environments, hierarchies (the orange dashed line) outperform DAOs (the orange solid line), which outperform autonomies (the orange dotted line). Conversely, regarding solution diversity, hierarchies maintain the lowest level of diversity (the blue dashed line in Figure 2a), while DAOs maintain a middle level of diversity (the blue solid line), with autonomies maintaining the highest level of diversity (the blue dotted line). In sum, hierarchies perform well in static environments.

There is a long-established literature on the wisdom of crowds that is based on two fundamental assumptions: small individual errors and diversity of judgments (Keuschnigg and Ganser 2017). However, in our model, individuals' beliefs are randomly initialized, and thus they are "fooled" to make a large error (the initial performance is below 0.5 in Figure 2a). Our results basically describe the wisdom of crowds from a reinforcement perspective. The wisdom of crowds relies on small positive disturbances and diverse judgments. Outperforming peers in the same group provide small positive disturbances and cancel out individual errors, whereas digital consensus provides another disturbance and cancels out local group errors. In sum, drawing on the comparison tradition of performance and diversity, the baseline model closely reproduces the "diversity prediction theorem" (Page 2008). This further validates our computational representation.

However, solution diversity always decreases once agents learn from each other. It is highly likely that some procedure nuances will be lost if we stop at the traditional comparison. Therefore, we introduce another metric, performance variance, to shed light on the learning process. Figure 2b depicts three distinct processes. The performance variance of the hierarchy generally declines and converges at a low level, while the performance variance of the autonomy generally increases and converges at a high level. The performance variance of the DAO, however, shows a wave pattern – variance accumulates and then declines. The decreasing performance variance of hierarchies suggests an institutional advantage of unification and centralized control. By contrast, the increasing variance of autonomies suggests that extreme behaviors are more likely to occur when there is no cross-group coordination. DAOs learn through a much more complex mechanism. Supplementary evidence is provided in Figure 4b for elaboration. Figure 4b shows one typical simulation run (Figure 2b displays integration results for 500 runs) in which individual performance is plotted on a 3D surface, along with the ruggedness of the surface calculated by Laplacian-filtered curvature. It is worth noting that before digital consensus is established, only "lucky" groups may come across promising solutions. Therefore, as promising solutions accumulate, the performance variance naturally rises (see the first peak in Figure 2b). Just before the first consensus is reached, the ruggedness of the performance surface reaches its peak (see upper-left sub-figure in Figure 4b). However, once a consensus is reached, the inherent luck difference will be eliminated due to cross-group learning. Thus, the performance surface becomes smoother, and performance variance decreases. Iteratively, another consensus will be established in another round. Taken together, the wave pattern in DAO's performance variance/ruggedness suggests another organizing philosophy for coordination across groups – DAOs evolve through a staggered process of polarization and homogenization, as opposed to autonomies' continuous polarization and hierarchies' continuous homogenization.

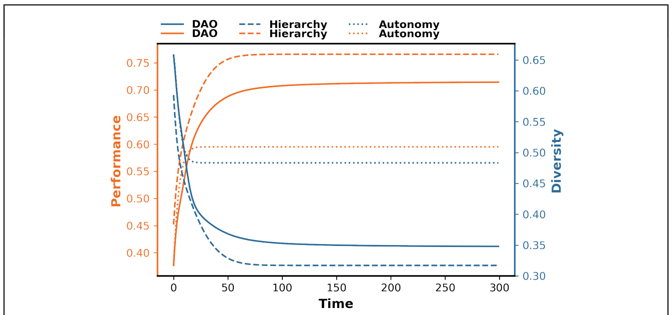

Figure 2a. Performance-Diversity Synthese across Time

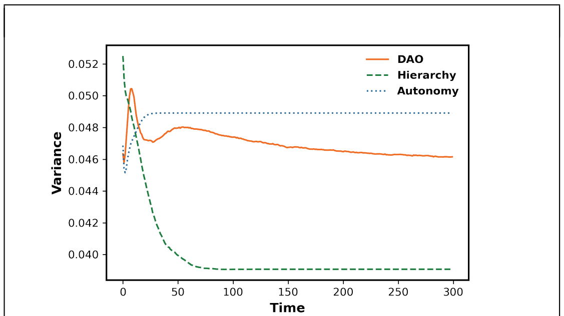

Figure 2b. Performance Variance across Time

Extension 1: Environmental Turbulence

Since DAOs can maintain solution diversity to a certain extent, a turbulent environment might magnify such an advantage. Figure 3 shows that under turbulence, the original outperforming hierarchy will degrade rapidly. In contrast, DAOs degrade more slowly. DAOs typically degrade in a similar manner to autonomies (see the orange and blue lines in Figure 3), suggesting that digital consensus facilitates cross-group coordination without sacrificing flexibility. We also calculate the intersection of DAOs' and hierarchies' performance curves. The intersection delays as the turbulence period increases (i.e., less frequent turbulence) and intensity decreases. This suggests that hierarchies can hold a competitive advantage longer in a less turbulent environment. This conclusion resonates with the baseline finding that hierarchies are better suited to static environments. One may question the magnitude of the performance gap between hierarchies and DAOs. Yet, even a small performance reversal between naïve DAOs and the most efficient hierarchies is notable. In fact, by slightly raising the voting threshold for DAOs or reducing the efficiency of top-down supervision, DAOs' outperformance will increase quantitatively. There are no qualitative differences in the results for different values of T_{tb} and I_{tb}. Based on the results of the baseline and extension 1, we propose:

> **Proposition 1a:** *In static environments, hierarchies outperform DAOs, and DAOs outperform autonomies.*
> **Proposition 1b:** *In turbulent environments, DAOs tend to outperform hierarchies and autonomies.*

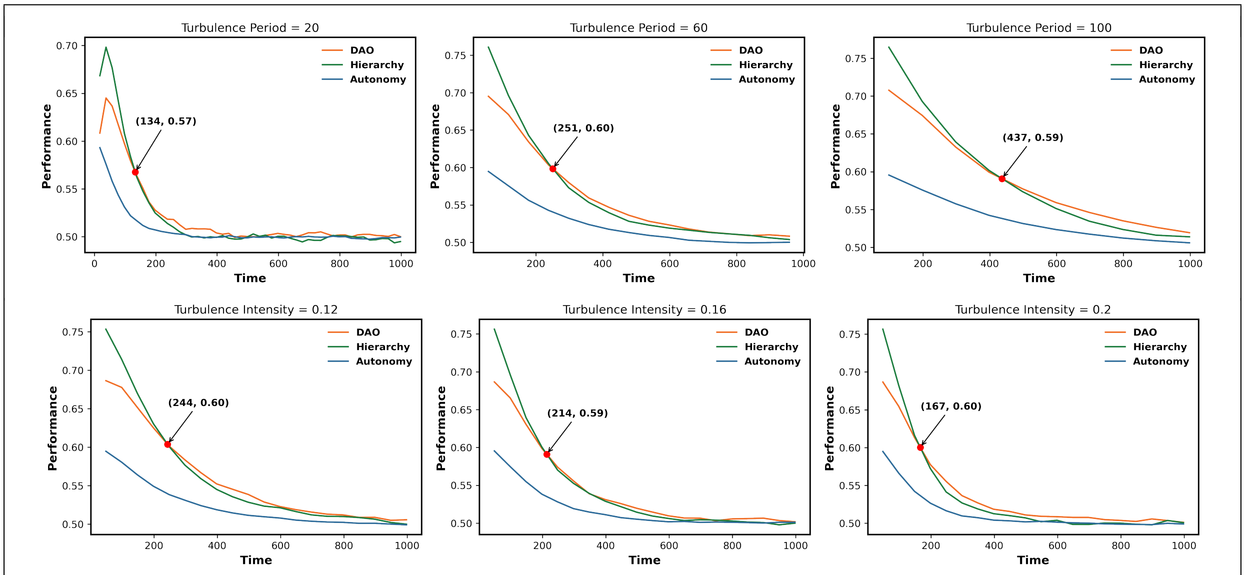

Figure 3. The Performance of Autonomy, DAO, and Hierarchy in Turbulent Environments across T_{tb}, I_{tb}

Extension 2: Voting Threshold

This extension relaxes the common assumption that digital consensus follows the simple majority rule (i.e., $\theta = 0.5$). Figure 4a shows an inverted U-shaped relationship between θ and DAO performance (and a U-shaped relationship between θ and DAO solution diversity), suggesting that both overly relaxed and tightly restricted voting are ineffective. The optimal voting threshold situates between 0.55 and 0.60. The reason is that overly relaxed thresholds make DAOs quickly settle on a premature consensus, leading to a shortsighted or even an incorrect direction for the whole organization. Recent analysis also suggests that an insufficiently high threshold makes the community vulnerable to malicious attacks (e.g., Zhang et al. (2018)). An increasing threshold between 0.55 and 0.60 does improve DAOs' performance, but at the expense of slower improvement rates. In our simulation, it takes about 100 iterations for DAOs with $\theta = 0.5$ to converge, about 125 iterations for DAOs with $\theta = 0.55$, and more than 1000 iterations for DAOs with $\theta = 0.6$. Thus, given the minor improvement from 0.55 to 0.60, the optimal voting threshold θ is ideally near 0.55. Although supplementary experiments are not reported here, we find that tiny increases in voting thresholds ensure that most disturbances are positive.

This experiment basically reveals that the voting threshold can be used to manipulate the efficiency of meta-organizational learning. One may intuit that the threshold in this study can adjust the trade-off between consensus maturity and speed of cross-group idea exchange. However, the spread of idea exchange slightly changes from $\theta = 0.5$ (convergence time = 100) to $\theta = 0.55$ (convergence time = 125), but the quality of consensus significantly increases from 0.67 to 0.89 (see the orange dashed line in Figure 4a). In addition, when $\theta > 0.60$, the idea spread is severely inhibited, but we do not observe any improvement in consensus quality. Thus, this intuition cannot explain these critical points or edges in such self-organizing complex systems. According to our investigation on variance dynamics across θ, although supplementary results are not reported here, voting thresholds control the stress that holds good solutions within "lucky" groups. With overly low thresholds, arbitrary elements can pass as consensus. Once individuals learn from such arbitrary consensuses, the community converges prematurely at local optima. On the other hand, overly high thresholds block the opportunity for other groups to learn from the "lucky" ones. The variance in performance accumulates easily, but is difficult to release. Therefore, more than the intuitive trade-off between consensus maturity and idea exchange speed, the voting threshold typically adjusts the wave peak, a necessary degree of performance polarization before homogenization. Therefore, we propose:

> **Proposition 2:** *Voting threshold has an inverted U-shaped impact on DAOs' performance.*

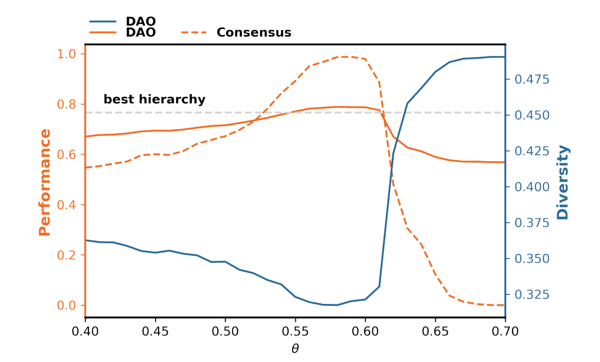

Figure 4a. Performance-Diversity Synthese across θ

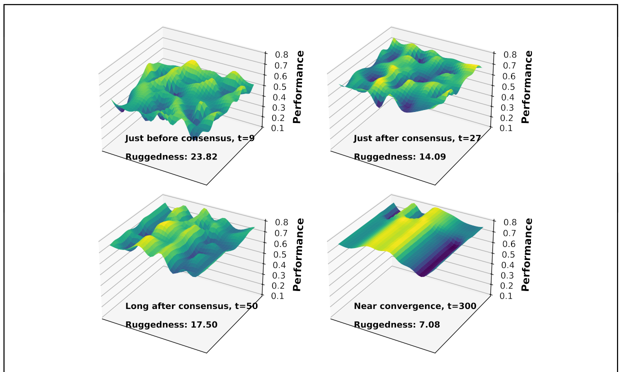

Figure 4b. The Ruggedness Metric in a Typical Run

Extension 3: Token Asymmetry

We directly manipulate the degree of inequality using the shape parameter ρ of the Pareto distribution. Roughly, $\rho = 1$ corresponds to a Gini coefficient of 0.9, $\rho = 2$ corresponds to a Gini coefficient of 0.7, and $\rho = 3$ corresponds to a Gini of 0.6. Thus, larger ρ indicates greater equality. Figure 5a shows that greater token asymmetry (i.e., inequality; low ρ) will inhibit DAOs' performance. This is because higher asymmetry typically suppresses the variance peak (see red and blue lines Figure 5b) such that minority views from a smaller number of influential individuals pre-emptively assimilate the community. Yet, when we look at diversity dynamics in Figure 5a, such nuance is hard to discern. Homogenization into minority views and homogenization into broad-based views occurs similarly. In sum, asymmetry concentrates consensus toward a narrow range of viewpoints, resulting in insufficient polarization before homogenization. Therefore, we propose:

Proposition 3: *Token asymmetry has a negative impact on DAOs' performance.*

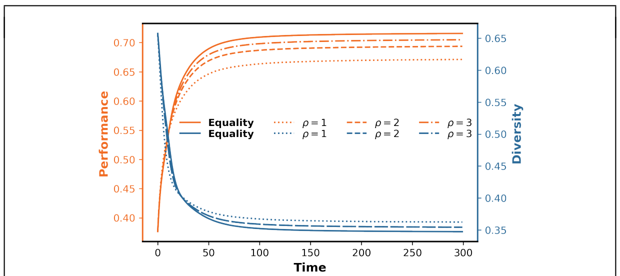

Figure 5a. Performance-Diversity Synthese across ρ

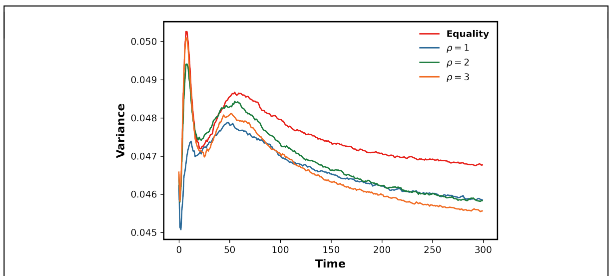

Figure 5b. Performance Variance of DAOs across ρ

Extension 4: Contributor Incentive

We conduct a two-by-two experiment ($\theta = 0.5$) with engagement ($p_i = 0.1$ for high engagement and $p_i = 0.4$ for low engagement) and incentive ($\gamma = 0.9$ for strong incentive and $\gamma = 0.1$ for weak incentive). We find that providing stronger incentives negatively affects DAOs' performance when individuals are highly engaged in voting (see solid and dashed orange lines in Figure 6a). This is because the large rewards will create additional asymmetry. Such asymmetry is small as per our analysis, albeit not reported herein, as it is a wide-range reward. By contrast, incentives are beneficial when individuals rarely vote (see solid and dashed yellow lines in Figure 6a). This is because reactivating inactive individuals, instead of making them autonomous and polarized, provides more benefits than the damage caused by asymmetry (see blue and green lines in Figure 6b). Overall, the inactive rate and incentive degree adjust the wave pattern jointly, with the incentive degree suppressing (similar to asymmetry) and the inactive rate amplifying the wave. Qualitative results remain unchanged across values of γ ($0.1 \sim 0.9$) and p_i ($0 \sim 0.40$). Therefore, we propose:

> **Proposition 4a:** *When inactivity rates are high, the contributor incentive has a positive impact on DAOs' performance.*
> **Proposition 4b:** *When inactivity rates are low, the contributor incentive has a negative impact on DAOs' performance.*

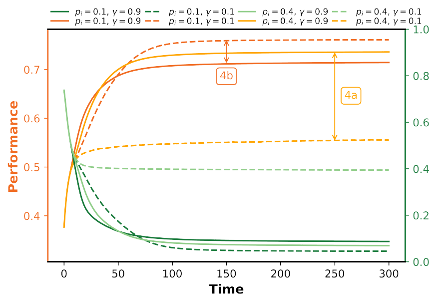

Figure 6a. Performance-Diversity Synthese across p_i, γ

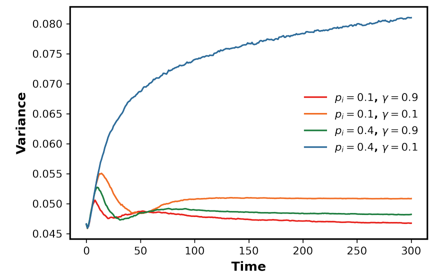

Figure 6b. Performance Variance across p_i, γ

Sensitivity Analysis

Recalling that many parameters that are not of direct interest in this study are initially aligned with the prior literature, we conduct sensitivity analyses of these parameters, including the group size z ($\underline{7}$, 14, 28), the number of individuals n (280, $\underline{350}$, 420, 490), the number of managers n' (40, $\underline{50}$, 60, 70), the aggregation level α (1, $\underline{3}$, 5), the learning rate η ($0.1 \sim 0.9$, $\underline{0.3}$), and the size of the reality m (60, $\underline{90}$, 120, 150). Default values are underlined. Qualitative results are consistent across these parameter values. Hierarchies with varying supervision efficiencies are also examined (i.e., across p_1 and p_2). Results show that naïve DAOs can outperform relatively deficient hierarchies (e.g., $p_1 > 0.3$, $p_2 = 0.9$). Lastly, the induced asymmetry is insensitive to the magnitude of γ (e.g., $1, 10, 100$) in the wide-range incentive. Thus, the probability of reactivation γ can stay within $(0, 1)$ for simplification.

One may also question the impact of personnel turnover on performance outcomes. Once individuals are willing to reset their beliefs with probability p_3 (e.g., individual reconfiguration (Sturm et al. 2021)), sensitivity experiments show that experimenting with new ideas can mitigate performance decline arising from environmental turbulence, consistent with prior literature (e.g., Fang et al. (2010) and March (1991)). Performance is largely restored to the static level. Thus, in line with the baseline model, hierarchies will outperform DAOs. Yet, with additional experimentation, autonomies may perform better than DAOs and hierarchies if the reconfiguration rate p_3 is sufficiently large (e.g., $p_3 > 0.20$, $p_3 \in (0, 0.5)$ as in Sturm et al. (2021)), resonating with the literature that autonomous teams excel in intensive organizational experimentation (e.g., Patanakul et al. (2012) and Puranam et al. (2006)).

Discussions and Conclusion

Organizing in the absence of authority while integrating individual agents' choices has remained one of the most fundamental and pressing issues in organizational design (Beck et al. 2018; Piezunka and Schilke 2023). We propose digital consensus as the vehicle facilitating across-group coordination while respecting diversity. Coordination based on digital consensus can maintain a certain level of intellectual diversity. By contrast, even the most efficient hierarchy tends to maintain a low level of knowledge diversity. As a result, naïve DAOs cannot outperform the most efficient hierarchy in a static environment. However, DAOs tend to outperform hierarchies in a turbulent environment. Autonomies perform poorly and only excel in intensive experimentation.

Our first contribution relates to DAO governance, by theorizing digital consensus and its mechanism (i.e., *what is* & *how*). Our results indicate that digital consensus can be used to enable the wisdom of crowds. We propose that DAOs represent a new organizing philosophy of staggered polarization and homogenization. By contrast, hierarchies represent continuous homogenization, while autonomies represent continuous polarization. These arguments are more of an institutional perspective than a learning perspective, for two reasons. First, a learning perspective emphasizes the exploitation-exploration trade-off. For example, a certain degree of exploration is controlled by the p_1 or η. In fact, we can always restrain these learning parameters to enhance exploration. Yet, even the most efficient hierarchies cannot resist the force of institutional homogenization. Second, if comparable, polarization includes the pursuit of diverse refinements, which is exploratory, and the localization of inherent "luck," which is exploitative. Homogenization involves globalizing what is known, which is exploitative, and releasing local luck constraints, which is explorative. Thus, we prefer a separate institutional perspective to streamline logical reasoning. We also point out that certain design elements can adjust/distort this staggered process when organizing through digital consensus (i.e., *what might be*). Several propositions based on the proposed evolution mechanism can inform further empirical studies on DAO governance and digital consensus design in practice.

The second contribution relates to organizational design literature, with an extended theory of meta-organizations (i.e., *how*). We need to revisit the organizational code design in March's (1991) seminal work. It is worth noting that there is a "magic hand" adjusting the organizational code toward the superior majority view, representing the institutional advantage of hierarchies (e.g., promotion via elitism). In such wisdom of elitism, quickly forming a centralized and unified code is desirable. Hierarchical power will correct inferior organizational codes by promoting elitists. However, in the wisdom of crowds, there are no formal roles accounting for the purity of such wisdom – no one can turn the tide. Thus, we propose that the wisdom of crowds strongly relies on "*socialization tensions*", namely the self-confined difficulty of accepting any local belief as a global consensus (see a tug-of-war between two insects in Figure 7a). Socialization tension is then assembled into a net as individuals self-organize, with every node defending its beliefs. Such a tension net can be tensed to approach an edge of chaos by slightly increasing the voting threshold (see the horizontal stretching in Figure 7c). Yet, once voting thresholds grow much larger, the self-organizing system may be torn into pieces – DAOs approach autonomies and socialization across groups ceases. Besides being tensed, the net of socialization tension may also be distorted. Asymmetries concentrate tensions in local areas, impairing consensus representativeness and polarization (see the vertical stretching in Figure 7d). Conversely, inactivity releases tension in certain areas, impairing consensus representativeness and homogenization. The distortions could be more detrimental than tearing apart in that the latter only produces autonomy, while the former produces privilegism and/or dictatorship. In sum, a fair socialization tension with sufficient strength ensures the efficiency of meta-organizational learning through digital consensus.

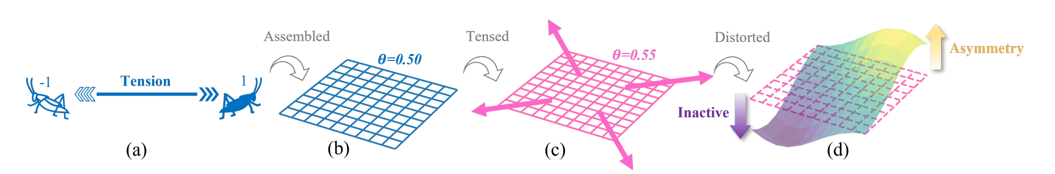

Figure 7. The Socialization Tension as Another Magic Hand in Meta-Organizational Learning

This study has limitations that suggest potential directions for future research. One avenue is to incorporate more group topologies than our regular ones. It is likely that centralization may not naturally disappear as a result of DAOs, but take on different forms. Inspired by Fang et al. (2010), complex topologies (e.g., by involving opinion leaders, the community can be expanded) may further affect consensus formation and thus organizational performance. Second, ongoing DAOs use a variety of governance tools and voting designs. For example, a typical solution to low engagement is to introduce delegation. One interesting question here is how to design delegation holistically without excessively distorting the socialization tension net given a smaller group of delegates. Extensions derived from such socialized voting designs may provide insights into recent trial-and-error practices. In sum, many common designs/tactics may induce unintended consequences through the lens of socialization tension, begging our careful consideration.

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