# ODD Protocol for ”Who gets to be good? Biased evaluations, informal networks, and emergent capability inequality in organizations”

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## 1. Overview

### 1.1 Purpose

The purpose of this agent-based simulation model is to investigate the emergence of inequalities in organizations resulting from the interaction of formal hierarchical structures and informal, similarity-based networks. The model explores how subjective performance evaluations, informal knowledge sharing, and resource allocation mechanisms jointly affect the distribution of resources, effort, motivation, capability, and performance among employees over time.

A particular focus is placed on the role of demographic similarity in shaping informal ties, and how these ties affect both access to resources and the propagation of (dis)advantages through feedback loops. Informal connections are formed based on shared demographic characteristics, influencing agents' access to information and their social position within the network.

The model enables the analysis of:

- subjective performance evaluations shaped by demographic biases,
- dynamic effort and capability updates based on motivation, utility, and informal learning,
- the influence of informal resource flows and reciprocity in similarity-based networks,
- feedback mechanisms leading to path-dependent outcomes and systemic disparities.

The model is intended for exploratory simulation and scenario analysis, particularly to assess how inequality patterns may emerge or be amplified in demographically diverse organizations.

### 1.2 Entities, State Variables, and Scales

#### 1.2.1 Entities

The model consists of two main types of entities (see Tab. 1)

| Entity | Description |
|---|---|
| `EmployeeAgent` | Individual member of the organization with demographic attributes, behavioral states, and connections in formal and informal networks. |
| `Organization` | The simulated environment, composed of a formal hierarchy and a dynamic informal network based on demographic similarity. |

Table 1: Entities in the model

#### 1.2.2 State Variables and Attributes

Each instance of an **EmployeeAgent** is characterized by the following state variables:

| Variable | Description | Range / Type |
|---|---|---|
| `capability` | Inherent ability level; evolves with learning and decays over time | [0.01, 1.0] |
| `effort` | Chosen exertion level based on motivation, incentives, and social influence | [0.01, 1.0] |
| `formal_resources` | Resources allocated through the formal hierarchy (e.g., budget, authority) | $\geq 0.05$ |
| `informal_resources` | Informal resources such as support, information, or guidance from peers | $\geq 0.05$ |
| `performance` | Normalized output based on capability, effort, and resources | [0, 1] |
| `evaluation` | Subjective evaluation of performance, possibly biased | Real number |
| `motivation` | Internal drive to exert effort; influenced by feedback and deprivation | [0.01, 1.0] |
| `utility` | Net benefit from effort, considering evaluation and effort cost | Real number |
| `deprivation` | Relative deprivation compared to peers' utilities | [0, 1] |
| `centrality` | Normalized eigenvector centrality in informal network | [0, 1] |
| `cost_of_effort` | Cost to exert effort, inversely related to motivation | [0, 1] |
| `incentive_parameter` | Weighting of evaluation in utility calculation | [0.01, 1.0] |

Table 2: Core state variables of `EmployeeAgent` and their computational domains

In addition, each instance of **EmployeeAgent** is characterized by demographic attributes, including `age`, `gender`, `race`, `sexual orientation`, and `education`.

The instance of the `Organzation` is represented through the following core variables:

| Variable | Description | Range / Type |
|---|---|---|
| informal_network | Directed graph encoding informal (e.g., similarity-based) ties | networkx.DiGraph |
| estimated_cost_of_effort | Model-wide estimate of agents' cost of exerting effort | Float |
| estimated_motivation | Model-wide average motivation estimate | Float |
| estimated_formal_resources | Estimated average formal resources among agents | Float |
| estimated_informal_resources | Estimated average informal resources among agents | Float |
| estimated_optimal_effort | Theoretical optimal effort under current conditions | Float |
| estimated_optimal_incentive | Theoretical optimal incentive parameter | Float |

Table 3: Core variables of Organization and their computational domains

In addition, the instance of Organization has the following characteristics:

| Variable | Description | Range / Type |
|---|---|---|
| formal_network | Directed graph encoding hierarchical structure | networkx.DiGraph |
| bias_distributions | Bias distributions by demographic group and trait | Dict |
| hierarchical_levels | Mapping of agents to levels in the formal hierarchy | Dict[int, int] |
| num_agents | Total number of agents in the model | Integer |
| alpha | Share of formal resources allocated equally (vs. performance-based) | [0, 1] |
| lambda | Fraction of superior's resources redistributed to subordinates | [0, 1] |
| incentive_update_interval | Number of steps between incentive updates | Integer |

Table 4: Additional characteristics of the Organizational

#### 1.2.3 Scales

The following scales are relevant for the model (see Tab. 5):

### 1.3 Process Overview and Scheduling

The model proceeds in discrete time steps. Each step involves a agent evaluation and top-down allocation of formal resources followed by individual agent updates. Agents are updated in randomized

| Scale | Description |
|---|---|
| Temporal scale | Discrete time steps representing organizational decision cycles (e.g., weekly or monthly). |
| Organizational scale | Fixed population of 50 agents, representing a mid-sized organization. |
| Spatial scale | No physical space; interaction is defined by network topology. |

Table 5: Scales

order. The process is summarized in the pseudocode below.

**Algorithm 1:** Simulation schedule

```
Initialization:
    Load parameters
    Create agents with demographic traits and initial state (Sec. 3.1)
    Generate formal hierarchy (Sec. 3.3.1)
    Generate similarity-based informal network (Sec. 3.3.2)
foreach timestep t = 1 to T do
    Processes of Organization:
        Assign root resources to top-level manager
        foreach agent i in the formal hierarchy do
            Evaluate agent performance (Sec. 3.3.3)
        end
        foreach manager i in the formal hierarchy do
            Allocate resources to subordinates j ∈ S_i (Sec. 3.3.4)
        end
        if t mod incentive_update_interval = 0 then
            Update incentive parameter for all agents (Sec. 3.3.5)
        end
    Processes of EmployeeAgent:
        foreach agent do
            Update motivation (Sec. 3.3.6)
            Update cost of effort (Sec. 3.3.7)
            Update effort (Sec. 3.3.8)
            Update capability (Sec. 3.3.9)
            Update performance (Sec. 3.3.10)
            Share informal resources with neighbors (Sec. 3.3.11)
            Deplete formal and informal resources (Sec. 3.3.12)
            Decay reciprocity scores (Sec. 3.3.13)
            Update utility and compute relative deprivation (Sec. 3.3.14)
            Store evaluation history
        end
    Data Collection:
    Store model-level and agent-level metrics
end
End simulation and export results
```

## 2. Design Concepts

### 2.1 Basic Principles

The model integrates theories from organization theory, sociology, and network analysis to explore how formal hierarchies and informal similarity-based networks jointly shape outcomes within organizations. It assumes that informal ties emerge through demographic similarity (homophily), which affects agents' access to informal resources such as knowledge or guidance. These informal dynamics interact with formal resource allocation and subjective evaluations, creating feedback loops that can reinforce early advantages or disadvantages. This framework enables the analysis of emergent inequality as a systemic outcome of local interactions and structural embeddedness.

### 2.2 Emergence

The model produces several emergent outcomes that arise from the interaction of formal structure, informal similarity-based ties, and individual behavioral adaptations. These emergent properties are not explicitly coded but result from the accumulation of micro-level processes such as resource exchanges, feedback effects, and motivational dynamics.

- **Inequalities in effort, performance, motivation, and capabilities** emerge as agents respond to subjective evaluations, varying access to resources, and the influence of their informal network position.
- **Unequal access to informal resources** is shaped by demographic similarity and reciprocity-based sharing, affecting centrality and resource accumulation.

Table 6 summarizes how key emergent patterns are computed or composed in the model.

| **Emergent property** | **Description and computational basis** |
|---|---|
| Effort inequality | Arises from utility maximization, heterogenous capabilities, relative deprivation, and social influence from informal network neighbours. |
| Performance | Based on a nonlinear function of effort, capability, and log-scaled access to resources. Amplified through feedback loops and differential access to informal knowledge. |
| Motivation | Motivation depends on subjective feedback (evaluation vs. performance), deprivation, and baseline drift. |
| Resource access | Formal resources flow top-down via hierarchical allocation; informal resources are shared probabilistically based on reciprocity, similarity, and relative deprivation. Asymmetric flows can cause cumulative advantages. |
| Network centrality | Informal network positions evolve endogenously through reciprocal sharing. Centrality determines informal influence and indirectly affects evaluation and performance. In addition, there is random network rewiring with a small probability to capture randomness in social connections. |

Table 6: Emergent properties and their computational basis

### 2.3 Adaptation

Agents in the model adapt their behavior based on internal states, performance feedback, social context, and further local information. Table 7 summarizes the key adaptive mechanisms and how they influence agent decisions and interactions over time.

| Adaptation Type | Description |
|---|---|
| Effort | Agents adjust their effort by optimizing utility, which balances expected performance benefits (based on capability, effort, resources) against the cost of exertion. This is influenced by informal peer behavior (social influence) and by relative deprivation compared to neighbors. |
| Motivation | Motivation is updated based on feedback (difference between evaluation and performance), relative deprivation, and a drift toward baseline motivation. Moderate deprivation may increase motivation, while high deprivation leads to withdrawal. Random noise is considered to capture idiosyncratic effects on motivation. |
| Capability | Agents' capabilities evolve based on formal and informal resources received. Learning efficiency declines as capability increases, and a decay factor prevents unbounded growth. |
| Informal Resource | Agents probabilistically share informal resources with neighbors depending on deprivation, cost of sharing, and reciprocity. Stronger or more reciprocal ties increase the likelihood of sharing. |
| Informal network ties | Agents remove ties in the informal network when reciprocity falls below a threshold, effectively pruning weak or unreciprocated connections. This allows the network to evolve endogenously. |

Table 7: Overview of adaptive behaviors in the agent-based model.

### 2.4 Objectives

Agents in the model are designed as boundedly rational utility maximizers.

### 2.5 Learning

Agents improve their capabilities over time based on access to resources and social learning. Specifically, capability growth is driven by:

- Access to formal and informal resources.
- A learning efficiency function that decreases as an agent's capability increases, preventing unlimited growth and introducing heterogeneity.
- Stochastic variation simulating idiosyncratic learning success or failure.

Capability is updated as a balance between resource-driven learning and decay, ensuring both improvement and degradation are possible. No centralized or global learning occurs; all adaptation is local and based on an agent's resources.

### 2.6 Prediction

Agents in the model do not engage in explicit prediction of future states or outcomes. All behavioral updates are reactive and based on current or recent experiences. Although agents optimize their effort based on a utility function that includes performance incentives and effort costs, this is a static optimization rather than a forward-looking prediction.

### 2.7 Sensing

Agents have limited local information about their environment. They base their decisions on individual characteristics, received feedback, and the behavior of peers in their informal network. Table 8 summarizes what agents can sense and how it affects their behavior.

| **Sensed variable** | **Description and impact on behavior** |
|---|---|
| Subjective evaluation | Each agent receives an evaluation of their performance. The difference between evaluation and true performance is used as feedback to update motivation. |
| Own performance | Agents are aware of their actual performance and use it for internal comparison. |
| Informal neighbor utilities | Agents compare their own utility to that of their neighbors to compute relative deprivation. This influences motivation and effort. |
| Reciprocity scores | Agents sense the reciprocity scores on outgoing ties to neighbors, which determines the probability of sharing informal resources. |
| Neighbor effort levels | Agents observe the average effort of their neighbors and adjust their own effort through social influence. |
| Own motivation and utility | Agents use their current motivation to compute effort cost and update utility based on performance and evaluation. |
| Mean motivation, cost of effort, formal and informal resources | The organization senses these mean values (across the entire agent population) to update the incentive parameter. |

Table 8: Sensed variables and their influence on agent behavior

### 2.8 Interaction

Agents interact with their peers in the informal network through resource sharing and social comparison. Interactions are shaped by demographic similarity, reciprocity, and relative deprivation. The table below summarizes the forms of agent interaction and their computational basis.

| Interaction type | Description and computational mechanism |
|---|---|
| Informal resource sharing | Agents probabilistically share informal resources with neighbors based on reciprocity scores, deprivation, and the strength of similarity-based ties. |
| Reciprocity dynamics | Sharing informal resources increases reciprocity scores on the reverse edge (receiver to sender), strengthening the likelihood of future returns. Reciprocity decays over time. |
| Effort imitation | Agents observe the average effort of their informal neighbors and partially adjust their own effort via weighted averaging. This captures social influence and peer effects. |
| Relative deprivation | Agents compare their own utility to the utility of their informal neighbors. If neighbors perform better, this creates deprivation effects, which influence motivation and effort. |
| Tie formation | If no existing tie exists in the informal network, agents may create a new one after receiving resources, initializing reciprocity and strength values. |

Table 9: Agent interactions and their computational basis

### 2.9 Stochasticity

Stochastic elements are introduced at various stages of the simulation to reflect heterogeneity, uncertainty, and behavioral variability. These stochastic processes influence both agent attributes and dynamic behaviors throughout the simulation.

| **Stochastic element** | **Description** | **Distribution** |
|---|---|---|
| Informal network | Informal links are formed probabilistically based on demographic similarity and a logistic linking function. | Bernoulli (via sigmoid function) |
| Noise term | Noise term added to effort, motivation, learning. | $\mathcal{N}(0, 0.02)$ |
| Resource sharing | Whether to share informal resources with a neighbor is drawn from a probability defined by a sigmoid function over reciprocity, deprivation, and sharing cost. | Bernoulli (via sigmoid function) |
| Ties in informal network | When a new informal tie is formed, its strength is sampled from a clipped normal distribution. | $\mathcal{N}(0.75, 0.1)$, clipped to [0.01, 1] |
| Initial capability | Agent capabilities at initialization are drawn from a normal distribution. | $\mathcal{N}(0.5, 0.1)$, clipped to [0.01, 1] |
| Initial demographics | Agents' demographic traits (e.g., gender, race, education, age, orientation) are sampled from predefined categorical distributions. | Categorical (empirical distributions) |
| Network rewiring | With a certrain probability, agents update the connections in their informal network. | Bernoulli |

Table 10: Stochastic elements in the model, their implementation, and underlying distributions

### 2.10 Collectives

Agents do not belong to fixed collectives in a strict sense. However, the model exhibits several forms of emergent and structural collectivity:

- **Informal clusters:** Agents form informal clusters based on demographic similarity (e.g., age, gender, race, education, sexual orientation). These clusters emerge through similarity-based network formation and influence the flow of informal resources.

- **Reciprocity-based subnetworks:** Informal ties evolve dynamically based on reciprocity. Agents that repeatedly exchange information with each other may form stable, cooperative subnetworks that serve as localized collectives.

- **Hierarchical units:** Agents are embedded within a formal organizational hierarchy, which defines supervisor–subordinate relationships. While these units do not interact as collectives, they determine resource flows and evaluation structures.

### 2.11 Observation

#### Observations

The model collects data at both the agent and system levels to analyze the emergence and evolution of inequality dynamics over time. The following key metrics are recorded:

- **Agent-level variables:** Effort, capability, evaluation, performance, formal and informal resources, motivation, utility, relative deprivation, and social position (centrality) are tracked for each agent at every time step.
- **Model-level aggregates:** The model records average and distributional statistics across the agent population, such as mean effort, capability, evaluation, performance, and resource access.
- **Scenario metadata:** All scenario-specific parameters are stored alongside the output to allow systematic comparison across runs.

## 3. Details

### 3.1 Initialization

During model initialization, a fixed number of agents are created and assigned individual attributes. Each agent is instantiated with the elements summarized in Tab. 11.

| **Variable** | **Type** | **Initialization** |
|---|---|---|
| Gender | Categorical | Sampled from weighted distribution |
| Age | Continuous | Sampled from truncated normal distribution |
| Race | Categorical | Sampled from weighted distribution |
| Sexual Orientation | Categorical | Sampled from weighted distribution |
| Education Level | Categorical | Sampled from weighted distribution |
| Capability | Continuous | Sampled from normal distribution |
| Effort | Continuous | Initialized to 0.5 |
| Motivation | Continuous | Initialized to 0.5 |
| Formal Resources | Continuous | Initialized to 0.5 |
| Informal Resources | Continuous | Initialized to 0.5 |
| Performance | Continuous | Initialized to 0.0 |
| Evaluation | Continuous | Initialized to 0.0 |
| Utility | Continuous | Initialized to 0.0 |
| Relative Deprivation | Continuous | Initialized to 0.0 |
| Network Centrality | Continuous | Initialized to 0.0 |

Table 11: Initial agent states

### 3.2 Input Data

#### Input Data

The model uses predefined probabilistic distributions to assign demographic characteristics to each agent at initialization. These characteristics are sampled independently and remain fixed throughout the simulation. The data reflect stylized population-level distributions.

The following demographic attributes are initialized:

- **Gender:** Categorical distribution over `["Male", "Female", "Diverse"]` with respective weights `[0.51, 0.44, 0.05]`. The data is taken from U.S. Bureau of Labor Statistics [2024].
- **Race:** Categorical distribution over `["White", "Black", "Asian", "Other"]` with weights `[0.75, 0.14, 0.06, 0.05]`. The data is taken from U.S. Census Bureau [2024].
- **Sexual Orientation:** Categorical distribution over `["Heterosexual", "Homosexual", "Bisexual", "Other"]` with weights `[0.91, 0.03, 0.04, 0.02]`. The data is taken from Ipsos [2023].
- **Education Level:** Categorical distribution over `["below High School", "High School", "College", "Bachelor", "Advanced"]` with weights `[0.09, 0.28, 0.25, 0.23, 0.15]`. The data is taken from U.S. Bureau of Labor Statistics [2024].
- **Age:** Sampled from a truncated normal distribution with mean 39, standard deviation 10, and bounded within $[16, 65]$ years. The data is taken from U.S. Census Bureau [2023].

To reduce complexity and isolate first-order effects, intersectionality (i.e., interaction effects across demographic attributes) is disabled in this model version.

### 3.3 Submodels

Tables 12 and 13 provides an overview of the notation employed in the following sections outlining the submodels of the simulation model.

| Notation | Description |
|---|---|
| $\alpha$ | Proportion of formal resources distributed based on evaluation (vs. equal sharing among subordinates) |
| $\beta_c$ | Slope parameter in the logistic function linking motivation to cost of effort |
| $\beta^{\text{cap}}$ | Weight placed on formal (vs. informal) resources in the learning process affecting capability growth |
| $c_i^{\text{sharing}}$ | Fixed cost for agent $i$ when sharing informal resources with others |
| $\delta^{\text{centrality}}$ | Scaling parameter controlling the influence of network centrality in evaluation bias |
| $\delta^{\text{informal}}$ | Fraction of informal resources an agent is willing to share in each time step |
| $\delta_I$ | Depletion rate for informal resources |
| $\delta_F$ | Depletion rate for formal resources |
| $\gamma^{\text{cap}}$ | Rate at which an agent's capability decays over time i |
| $\kappa^{\text{cap}}$ | Parameter determining how rapidly learning efficiency declines with increasing capability |
| $\kappa^{\text{RS}}$ | Decay factor for reciprocity scores over time |
| $\lambda_{RD}$ | Sensitivity parameter for the effect of relative deprivation on motivation and effort |
| $\lambda_f$ | Share of an agent's formal resources allocated to subordinates in the formal hierarchy |
| $\lambda_{\text{cap}}$ | Base learning rate determining how quickly capability increases given available resources |
| $N$ | Number of employee agents |
| $N_{\text{sub}}$ | Number of subordinates per manager |
| $\omega$ | Weight placed on peers' effort levels in the social influence component of effort updates |
| $\rho$ | Decay factor for reciprocity scores |
| $R_{\text{root}}$ | Resources of root agent that are further allocated to subordinates |
| $T_{\mathcal{I}}$ | Time steps between incentive updates |
| $\theta^{\text{similarity}}$ | Scaling factor for Jaccard similarity in informal network creation |
| $\theta_{RD}$ | Threshold beyond which relative deprivation significantly reduces motivation |

Table 12: Model notation used in submodel equations (exogenous variables)

| Notation | Description |
|---|---|
| $c_i^{\text{effort}}$ | Internal cost per unit of effort for agent $i$ |
| $C_i$ | Agent $i$'s capability |
| $\mathbf{d}_i$ | Demographic attribute vector of agent $i$ (e.g., age, gender, education) |
| $\Delta_{\text{fb}}$ | Feedback discrepancy between actual performance and subjective evaluation |
| $E_i$ | Effort level chosen by agent $i$ |
| $G_I(V, E_I)$ | Informal network defined over set of agents $V$ with informal edges $E_I$ |
| $G_F(V, E_F)$ | Formal hierarchical network over agents $V$ with directed edges $E_F$ |
| $\mathcal{I}_i$ | Incentive multiplier influencing how much utility agent $i$ gains from evaluation |
| $M_i$ | Motivation level of agent $i$ |
| $\mathcal{N}_i$ | Informal network neighbors of agent $i$ |
| $P_i$ | True performance of agent $i$, computed from effort, capability, and resource access |
| $P_i^{\text{eval}}$ | Subjective evaluation received by agent $i$ (possibly biased) |
| $R_{Fi}$ | Total formal resources available to agent $i$ at a given time step |
| $R_{Ii}$ | Total resources available to agent $i$ at a given time step |
| $RD_i$ | Relative deprivation of agent $i$ based on utility comparisons with informal neighbors |
| $RS_{ij}$ | Reciprocity score representing agent $j$'s past support to agent $i$ |
| $S_i$ | Set of subordinates reporting formally to agent $i$ |
| $s_{ij}$ | Strength of the informal network tie from agent $i$ to agent $j$ |
| $U_i$ | Agent $i$'s utility, combining incentive-based gains and effort costs |

Table 13: Model notation used in submodel equations (endogenous variables)

### 3.3.1 Create formal structure

The formal organizational structure is generated as a directed tree graph $G_F = (V, E_F)$, where nodes represent agents and edges indicate reporting lines from superiors to subordinates. The tree is constructed top-down, beginning with a single root node (the top-level manager) and expanding until the total number of agents reaches the predefined size $N$.

Each manager is assigned an exogenously fixed number of subordinates $N^{\text{sub}}$. The construction proceeds as follows:

1. Initialize the root agent at hierarchical level $L = 0$.
2. Maintain a queue of agents eligible to receive subordinates.
3. Iteratively:
   - Pop the next manager $v_i$ from the queue.
   - Assign up to $n_s$ subordinates, subject to the remaining available agent slots.
   - For each subordinate $v_j$, add a directed edge $(v_i \to v_j)$, assign level $L + 1$, and enqueue $v_j$ for possible further expansion.

### 3.3.2 Create informal network

At initialization, the informal network is constructed as a directed graph $G_I = (V, E_I)$, where each edge $(i, j) \in E$ represents a potential channel for informal resource sharing from agent $i$ to agent $j$.

Each agent $i \in V$ is characterized by a set of categorical demographic attributes:

$$\mathbf{d}_i = \{\text{gender}_i, \text{race}_i, \text{education}_i, \text{sexual orientation}_i, \text{age group}_i\}$$

To determine the probability of forming an informal tie, a *Jaccard similarity* is computed between each unique agent pair $(i, j)$. Each agent's characteristics are represented as a multiset of attribute values. The Jaccard similarity is defined as:

$$\text{Jaccard}(i, j) = \frac{|\mathbf{d}_i \cap \mathbf{d}_j|}{|\mathbf{d}_i \cup \mathbf{d}_j|}$$

where intersection and union are computed over the frequency counts of each attribute category.

This similarity value is scaled by a parameter $\theta^{\text{similarity}}$ (the similarity scaling factor) to compute the probability of a directed tie:

$$P(i \to j) = \theta^{\text{similarity}} \cdot \text{Jaccard}(i, j)$$

A random draw $u \sim \mathcal{U}(0, 1)$ determines whether the edge is instantiated. If $u < P(i \to j)$, an edge is created from $i$ to $j$. Each edge is initialized with: (i) A *reciprocity score* of zero and (ii) a *tie strength* sampled from the truncated normal distribution: $s_{ij} \sim \text{clip}\left(\mathcal{N}(0.75, 0.1), 0.01, 1\right)$.

### 3.3.3 Evaluate agents

The model assumes that each agent's actual performance $P_i$ is observable and computed during the simulation step (see Sec. 3.3.10). This raw performance is normalized using the theoretical maximum performance:

$$P_i^{\text{norm}} = \frac{P_i}{P_{\text{max}}} \quad .$$

**Subjective evaluations** are based on normalized performance but may be biased, meaning that the evaluation score $P_i^{\text{eval}}$ includes both performance and social/demographic distortions:

$$P_i^{\text{eval}} = P_i^{\text{norm}} + \text{bias}_i + \delta^{\text{centrality}} \cdot \text{centrality}_i$$

- $\text{bias}_i$ is derived from probabilistic bias distributions related to agent attributes such as gender, race, age, sexual orientation, and education.
- $\text{centrality}_i$ is the agent's normalized centrality in the informal network, scaled by parameter $\delta^{\text{centrality}}$.
- The evaluation score is clipped to the interval $[0, 1]$.

### 3.3.4 Allocate formal resources

Formal resources are allocated through the formal organizational hierarchy, modeled as a directed graph $G_F = (V, E_F)$, where edges point from managers to subordinates. The allocation process follows a top-down approach, starting from a root node (e.g., the CEO) that receives an exogenous resource endowment $R_{\text{root}}$.

Each agent $i$ receives a resource amount $R_{Fi}$ which is partially redistributed to their direct subordinates $S_i \subset V$ according to the following rule.

The fraction $\lambda_f \in [0, 1]$ determines how much of $R_{Fi}$ is passed on to subordinates $(\lambda_f \cdot R_{Fi})$. The remaining portion $(1 - \lambda_f) \cdot R_{Fi}$ is retained by agent $i$.

The allocation to each subordinate $j \in S_i$ is a convex combination of (i) *equal distribution* (uniform among all subordinates of an agent) and (ii) *performance-based allocation* using subjective evaluations. Let $\alpha \in [0, 1]$ control the weight of performance-based allocation versus equal split. The share of $\lambda_f \cdot R_{Fi}$ allocated to agent $j \in S_i$ is given by:

$$R_{Fi \to j} = \left( \frac{1 - \alpha}{|S_i|} + \alpha \cdot \frac{P_j^{\text{eval}}}{\sum_{k \in S_i} P_k^{\text{eval}}} \right) \cdot \lambda_f \cdot R_{Fi}$$

where $P_j^{\text{eval}}$ is the *subjective evaluation* of agent $j$.

The resource allocation process is recursively applied from top to bottom in the formal hierarchy until all agents have received their resources.

#### 3.3.5 Update of incentive parameter

The incentive parameter $\mathcal{I}_i(t)$ determines how strongly an agent is rewarded for their evaluation when computing utility. Rather than remaining fixed, this parameter is periodically updated to align agent behavior with organizational goals.

At fixed intervals of $T_{\mathcal{I}}$ steps, the model estimates the following global averages across all agents:

- $\hat{M}(t)$: average motivation,
- $\hat{R}_F(t) + \hat{R}_I(t)$: average total resources (formal + informal),
- $\hat{c}(t)$: average cost of effort.

Using these estimates, the model derives the incentive level that would balance effort benefits with effort costs:

$$\mathcal{I}^*(t) = \frac{\hat{c}(t)}{\hat{M}(t) \cdot (\hat{R}_F(t) + \hat{R}_I(t))}$$

This optimal incentive $\mathcal{I}^*(t)$ is then broadcast to all agents as their new incentive parameter:

$$\mathcal{I}_i(t) \leftarrow \mathcal{I}^*(t) \quad \forall i$$

#### 3.3.6 Update of motivation

Agents update their motivation at each time step based on three interacting components: (i) Feedback from subjective evaluations, (ii) relative deprivation, (iii) baseline drift and noise. Let us use the following formal representation of the elements determining motivation:

- $M_i(t)$: motivation of agent $i$ at time $t$
- $\Delta_{\text{fb}} = \text{evaluation}_i - \text{performance}_i$: difference between perceived and actual performance (feedback delta)

- $RD_i$: relative deprivation (how disadvantaged the agent feels relative to peers)
- $\eta \sim \mathcal{N}(0, 0.02)$: Gaussian noise
- $M_0 = 0.5$: baseline motivation
- $\tau = 0.05$: rate of drift toward the baseline

The components are combined as follows:

$$
\begin{aligned}
\text{NormalizedFeedback}_i &= \frac{1}{1 + e^{-\Delta_{\text{fb}}}} \\
\text{DeprivationEffect}_i &= \frac{1}{1 + \exp(-\lambda_{\text{RD}} \cdot (RD_i - \theta_{\text{RD}}))} \\
\Delta M_i &= (\text{NormalizedFeedback}_i - 0.5) \cdot 0.1 \\
&\quad - \ \text{DeprivationEffect}_i \cdot 0.1 \\
&\quad + \ \tau(M_0 - M_i(t)) + \eta \\
M_i(t+1) &= \text{clip}(M_i(t) + \Delta M_i, \ 0.01, \ 1.0)
\end{aligned}
$$

The motivation update mechanism captures the interplay between perceived performance feedback, social comparison, and internal regulation. When an agent receives positive feedback (i.e., when the subjective evaluation exceeds actual performance ) its motivation increases, and vice versa. This feedback effect is smoothly scaled using a sigmoid function to ensure realistic, bounded changes. At the same time, motivation is shaped by relative deprivation: agents who perceive themselves as worse off compared to their peers experience a motivational penalty. This penalty is modeled via another sigmoid function, which ensures that only moderate to high levels of deprivation meaningfully reduce motivation, reflecting the psychological phenomenon of disengagement or burnout. In addition to these influences, each agent's motivation drifts toward a neutral baseline over time, mimicking a natural psychological tendency to return to equilibrium. Finally, Gaussian noise introduces stochastic variability, capturing unobserved factors and idiosyncrasies in agents' responses.

### 3.3.7 Update of cost of effort

Agents adjust their internal *cost of effort* dynamically depending on their current level of motivation. The function captures the intuition that motivated employees perceive effort as less costly, while demotivated employees perceive a higher effort burden.

The cost **per unit of effort** is modeled as a decreasing logistic function:

$$
c_i^{\text{effort}}(t) = \frac{1}{1 + \exp\left(\beta_c \cdot (M_i(t) - 0.5)\right)}
$$

- $c_i^{\text{effort}}(t)$: cost per unit of effort for agent $i$ at time $t$
- $M_i(t)$: motivation of agent $i$ at time $t$
- $\beta_c$: sensitivity of cost to motivation

The function ensures:

- When motivation is low ($M_i \ll 0.5$), $c_i^{\text{effort}}(t) \to 1$ (effort feels costly)
- When motivation is high ($M_i \gg 0.5$), $c_i^{\text{effort}}(t) \to 0$ (effort feels cheap)

### 3.3.8 Update of effort

Agents choose their effort level $E_i(t)$ in each step to maximize their expected utility, influenced by:

- their own capability and resources,
- cost of effort (which depends on motivation),
- the effort level of informal network neighbors (social influence),
- and perceived relative deprivation (psychosocial effect).

**Utility-based optimal effort** Agents first determine the effort level that maximizes their expected utility:

$$U_i(E) = \underbrace{E \cdot C_i \cdot (R_{Fi} + R_{Ii})}_{\text{expected performance}} \cdot \mathcal{I}_i - \underbrace{E \cdot c_i^{\text{effort}}}_{\text{effort cost}}$$

where:

- $E$: effort level
- $C_i$: capability
- $R_{Fi}, R_{Ii}$: formal and informal resources
- $\mathcal{I}_i$: incentive parameter
- $c_i^{\text{effort}}$: current cost of effort

The optimal effort $E_i^{\text{opt}}$ is found numerically.

**Social influence adjustment** Effort is adjusted based on the average effort of neighbors in the informal network:

$$\bar{E}_N = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} E_j(t)$$

$$E_i^{\text{adj}} = (1 - \omega) \cdot E_i^{\text{opt}} + \omega \cdot \bar{E}_N$$

where $\omega$ is the social influence weight.

**Relative deprivation effect** Effort is further modulated by perceived relative deprivation $RD_i(t)$, using a sigmoid function:

$$\text{DeprivationEffect}_i = \frac{1}{1 + \exp(-\lambda_{\text{RD}}(RD_i(t) - \theta_{\text{RD}}))}$$

$$E_i^{\text{final}}(t) = \max\left(0.01, \min\left(1.0, E_i^{\text{adj}} - 0.1 \cdot \text{DeprivationEffect}_i + \eta\right)\right)$$

where:

- $\lambda_{\text{RD}}$: sensitivity to deprivation
- $\theta_{\text{RD}}$: threshold for deprivation effect
- $\eta \sim \mathcal{N}(0, 0.02)$: decision noise

#### 3.3.9 Update capability

Agents' capability $C_i(t)$ evolves based on informal and formal resource inputs, modulated by a learning efficiency function that declines as capability increases. A decay term prevents runaway growth.

**Learning Input** Each agent learns from their own resource intake, normalized relative to the current maximum across agents:

$$r_{Fi} = \frac{R_{Fi}}{\max_j R_{Fj} + \varepsilon}, \quad r_{Ii} = \frac{R_{Ii}}{\max_j R_{Ij} + \varepsilon}$$

where $\varepsilon$ is a small constant to avoid division by zero.

**Resource-weighted learning effect**

$$L_i = (\beta^{\text{cap}} \cdot r_{Fi} + (1 - \beta^{\text{cap}}) \cdot r_{Ii}) \cdot \lambda_{\text{cap}}$$

where:

- $\beta^{\text{cap}}$: weight on formal vs. informal learning resources
- $\lambda^{\text{cap}}$: base learning rate

**Learning eficiency** Learning becomes harder as capability increases. A Gaussian-like decay is applied:

$$\text{Efficiency}_i = \exp\left(-\kappa^{\text{cap}} \cdot (C_i(t) - C_0)^2\right)$$

with:

- $C_0$: target mid-level capability
- $\kappa^{\text{cap}}$: learning difficulty growth parameter

**Capability decay** A linear decay term is subtracted:

$$D_i = \gamma^{\text{cap}} \cdot C_i(t)\ .$$

**Capability update equation**

$$C_i(t+1) = \text{clip}\left(C_i(t) + L_i \cdot \text{Efficiency}_i - D_i + \eta,\ 0.01, 1\right)$$

where $\eta \sim \mathcal{N}(0, 0.02)$ indicates learning noise.

#### 3.3.10 Update of performance

The performance of agent $i$ at time $t$, denoted $P_i(t)$, is a nonlinear function of the agent's current *capability*, *effort*, and *resources* (both formal and informal). It is calculated as:

$$P_i(t) = \frac{C_i(t) \cdot E_i(t) \cdot \log_2\left(1 + R_{Fi}(t) + R_{Ii}(t)\right)}{C_{\max} \cdot E_{\max} \cdot \log_2(1 + R_{\max})} \tag{1}$$

Where:

- $C_i(t)$: Capability of agent $i$
- $E_i(t)$: Effort of agent $i$
- $R_{Fi}(t)$: Formal resources available to agent $i$
- $R_{Ii}(t)$: Informal resources available to agent $i$
- $C_{\max}$, $E_{\max}$, $R_{\max}$: Maximum values used for normalization

Performance emerges from the interaction between individual characteristics (effort and capability) and resource access. The use of a logarithmic function ensures that additional resources contribute to performance with diminishing returns, preventing unbounded growth.

#### 3.3.11 Share informal resources and update reciprocity

At each time step, agents decide whether to share informal resources (e.g., knowledge, support) with their neighbors in the informal network. This process is probabilistic and depends on three key factors: the agent's current level of relative deprivation, the reciprocity score of the tie, and the cost of sharing. The decision mechanism is inspired by logistic (sigmoid) functions, allowing for smooth and bounded probabilities.

**Sharing probability** The probability that an agent shares informal resources with a neighbor is modeled using a sigmoid function based on three elements: relative deprivation, the reciprocity score of the tie, and the agent's cost of sharing. Higher deprivation increases the agent's likelihood to share, reflecting a behavioral tendency to seek connection when feeling disadvantaged. Reciprocity reflects past cooperative behavior from the neighbor, reinforcing mutual exchange. The cost of sharing acts as a deterrent, reducing the likelihood of resource transfer when burdens are high. Together, these components capture a boundedly rational decision process underlying informal cooperation in similarity-based networks.

For each neighbor $j$ of agent $i$, the probability of sharing informal resources is computed as:

$$P_{i\to j} = \frac{1}{1+\exp\left(-\left(-\frac{RD_i}{2} + RS_{ij} - c_i^{\text{sharing}}\right)\right)} \tag{2}$$

Where:

- $RD_i$ is the relative deprivation of agent $i$,
- $RS_{ij} \in [0,1]$ is the current reciprocity score on the edge from $i$ to $j$,
- $c_i^{\text{sharing}}$ is the cost of sharing for agent $i$ (fixed at 0.1 by default).

**Resource allocation:** If agent $i$ decides to share, the total shared amount is a fixed fraction $\delta^{\text{informal}}$ of its current informal resources $R_{Ii}$. The amount shared with each neighbor is distributed proportionally to the strength $s_{ij}$ of the edge, relative to the total outgoing edge strength:

$$IR_{i\to j} = \left(\delta^{\text{informal}} \cdot R_{Ii}\right) \cdot \frac{s_{ij}}{\sum_{k\in\mathcal{N}_i} s_{ik}} \tag{3}$$

Where:

- $\delta^{\text{informal}}$ is the informal resource sharing fraction,
- $s_{ij}$ is the strength of the tie from $i$ to $j$,
- $\mathcal{N}_i$ is the set of neighbors of $i$ in the informal network.

**Reciprocity update:** If sharing occurs, the reciprocity score on the reverse edge $RS_{ji}$ is incremented proportionally to the amount received:

$$RS_{ji} \leftarrow RS_{ji} + \kappa^{\text{RS}} \cdot IR_{i \to j} \tag{4}$$

Where $\kappa^{\text{RS}}$ is a small scaling factor controlling how quickly reciprocity evolves. If the reverse edge does not yet exist, it is created.

This mechanism leads to dynamic changes in the informal network structure over time. Stronger and more reciprocal ties are reinforced, while unreciprocated or weak ties may decay and eventually be removed if reciprocity scores fall below a threshold.

#### 3.3.12 Deplete formal and informal resources

Agents' formal and informal resources are gradually depleted over time, reflecting the consumption and natural decay of both tangible (e.g., funding, support) and intangible (e.g., guidance, attention) resources.

**Formal resource depletion** Formal resources $R_{Fi}(t)$ are updated at each time step using a fixed depletion rate $\delta_f$. The update rule is:

$$R_{Fi}(t+1) = \max(\epsilon, R_{Fi}(t) \cdot (1 - \delta_f))$$

where $\epsilon$ is a minimum threshold to avoid complete depletion and ensure agents retain some formal functionality.

**Informal resource depletion** Informal resources $R_{Ii}(t)$ are also depleted based on a depletion rate $\delta_I$. The depletion rule is:

$$R_{Ii}(t+1) = \max\left(\epsilon, R_{Ii}(t) \cdot (1 - \delta_I)\right)$$

The depletion rate is scaled by the current level of informal resources, introducing nonlinearity and reflecting diminishing marginal retention of informal knowledge. This design choice ensures that highly connected or active agents cannot accumulate informal power indefinitely.

#### 3.3.13 Decay of reciprocity scores

To prevent the accumulation of indefinitely high reciprocity in the informal network, agents apply exponential decay to the reciprocity score of each outgoing tie at every time step.

Let $RS_{ij}(t)$ denote the reciprocity score from agent $i$ to agent $j$ at time $t$. The score is updated using a decay factor $\rho \in (0, 1)$ as follows:

$$RS_{ij}(t+1) = RS_{ij}(t) \cdot \rho$$

This rule is applied to all outgoing edges in the agent's informal network neighborhood. The decay ensures that previously strong informal ties weaken over time unless maintained through ongoing resource sharing. If the decayed reciprocity score between agent $i$ and agent $j$ falls below a predefined threshold of 0.01, the edge $(i \to j)$ is removed from the informal network.

### 3.3.14 Update utility and compute relative deprivation

At each time step, agents update their utility based on their subjective evaluation, the incentive they receive, and the effort they exert. The utility function is defined as:

$$U_i(t) = \mathcal{I}_i(t) \cdot P_i^{\text{eval}}(t) - c_i(t) \cdot E_i(t)$$

where:

- $\mathcal{I}_i(t)$: incentive parameter at time $t$,
- $P_i^{\text{eval}}(t)$: subjective evaluation at time $t$,
- $c_i(t)$: cost per unit of effort at time $t$,
- $E_i(t)$: effort exerted by agent $i$ at time $t$.

Agents also evaluate their standing in the informal network by computing their **relative deprivation**. For agent $i$, relative deprivation is defined as:

$$RD_i(t) = \frac{1}{\sum_{j \in N_i} U_j(t)} \sum_{j \in N_i} \max(0, U_j(t) - U_i(t))$$

where:

- $N_i$: set of neighbors of agent $i$ in the informal network,
- $U_j(t)$: utility of neighbor $j$ at time $t$.

This expression captures how much better off an agent's peers are, on average, compared to themselves. The higher the relative deprivation $RD_i(t)$, the stronger the agent's perception of disadvantage, which subsequently influences their motivation, effort, and willingness to share informal resources.

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