In the Dark: Agent-Based Modeling of Uninformed Individuals within Polarized Groups

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Abstract

Intuitively, adding uninformed individuals to a group should undermine group efficiency, as they create coordination costs while lacking the expertise to meaningfully contribute. However, uninformed individuals may be able to overcome deadlocks in otherwise polarized groups by heightening conformity pressures. Modeling group members' decision making using a sequential sampling model based on Decision Field Theory (DFT: Busemeyer & Townsend, 1993), we present an existence proof of how ignorance can, in contrast to intuition and prominent economic accounts, facilitate improved group decision making. The implications of these findings for cognitive science, organizational behavior, and social impact are discussed.

Keywords: agent-based modeling; group decision-making; ignorance; individual preferences; group conformity

Background

"Two Heads are Better Than One"

Courtroom juries, executive boards, congressional committees – group decision-making is common across societal domains. While facilitating group decisions is often money and time-intensive, it is usually thought worthwhile due to improved performance by groups compared to even the best individuals (Laughlin 2006; Hastie, 1986). Groups display increased transactive memory (Forsyth, 2010), improved identification of mistakes (Ziller, 1957), and creation of alternatives that wouldn't be identified individually (Watson, 1931).

One mechanism behind this improved collective performance, often utilized by organizational behaviorists, is diversity of both expertise and experience (Milliken & Martins, 1996; Williams & O'Reilly, 1998, Simons, 1999). Give a manager a team of two engineers, an accountant, and a marketing specialist and they'll end up with a product more developed and profitable than a team of 4 engineers alone. Create a workgroup of individuals from different cultural backgrounds and they'll utilize broader problem-solving methods than a homogeneous group. This is consistent with the traditional economic belief that decisions are improved by providing additional information or experience to the decision-maker, to be rationally factored into their decision process.

Knowledge-Level Diversity

Another less-studied form of group diversity lies in the depth of knowledge that individuals have relating to the task at hand. Traditional theory generally posits that a more informed group should be best positioned to optimize cooperative performance, and that withholding information about the task or potential outcomes from group members should hamper performance[1]. However, evidence shows that this might not always be the case.

A recent collective social learning study (Goldstone et al., 2013) found that groups able to share less information sometimes had more optimal outcomes in a 15-round minimal search task than a fully connected group. When the group's hidden payoff function was multimodal or "needle"-shaped, a less-connected group form (the small-world and regular lattice structure, respectively) more quickly found the maximum payoff strategy; when individuals had less knowledge about each other's decisions, they were driven to continue exploring new options rather than to imitate decisions which might have found only a local maximum payoff rather than the global peak.

Uninformed individuals were also shown to improve a polarized group's decision making in a study on schooling fish by Couzin et al. (2011), which serves as the primary inspiration for our own modeling. Couzin et al. trained fish to have preference for different locations in a food tank (through classical conditioning with food placement), then released 6 fish with a weak preference for location A and 5 fish with a strong preference for location B together in the tank. The fish had to balance the desire to reach their trained food target with their biological need to school together as one group; in many cases, the 5 strong-willed B fish were able to win over the 6 weakly incentivized A fish. However, adding 5+ unincentivized fish to the school returned control to A fish, and thus resulted in a more "democratic" path choice for the school. While this precise result is surely interesting to researchers of collective animal dynamics, it also begs the question of collaborative human behavior: **under what conditions can uninformed individuals improve group decision-making, making knowledge-level diversity advantageous in group scenarios?**

[1] This trend does not always apply in non-cooperative group situations, where effects like the wisdom of crowds can be weakened by socialization (Lorenz, 2011), but otherwise holds.

In J. Culbertson, A. Perfors, H. Rabagliati & V. Ramenzoni (Eds.), *Proceedings of the 44th Annual Conference of the Cognitive Science Society.*

While humans aren't intrinsically pulled toward homogenous group behavior as strongly as fish, a core component when applying this decision task to a polarized human group is the tension between a decision maker's individual preferences and the group norms that they observe. If I initially strongly prefer one outcome, but the rest of my group prefers another, which outcome will I endorse? How much "peer pressure" can my internal preference withstand? This previously studied tradeoff between conformity and individualism (Golman et al., 2021) doesn't impact uninformed individuals lacking an individual preference, who only have a group cohesion motive to follow. Pressures toward group cohesion can be so powerful that groups sometimes unanimously endorse outcomes that no individual member supports, as in cases of pluralistic ignorance (Kats & Allport, 1931), or succumb to other unhealthy group dynamics such as groupthink (Baron, 2005). The inclusion of uninformed individuals can create pressures toward cohesion rather than individual preference, allowing a polarized group to both more often and more quickly come to a consensus but perhaps also inviting in these group performance errors.

Modeling

We developed an interactive NetLogo agent-based model where uninformed individuals are added into a polarized group choosing between two outcomes in a decision space.

Model Setup

Figure 1 shows this simulation option space, represented by a 2-dimensional area of size 32 units x 32 units and centered on (0,16). At (-8,16) and (8,16) lie two square outcome targets, A (red) and B (blue) respectively. At any point in time, an agent's location (ρ_{xi}, ρ_{yi}) represents their preference between outcomes A and B; an agent directly on top of target A at (-8,16) prefers A with 100% certainty, while an agent located halfway between the targets is indifferent to the outcomes. The agents begin the simulation at a random location in this decision space.

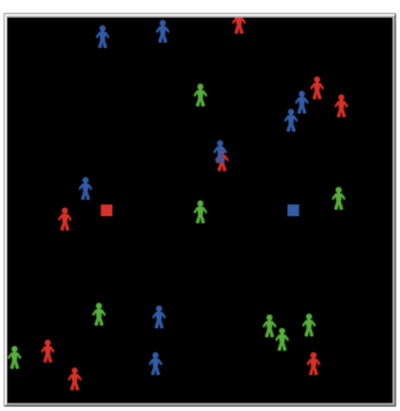

Figure 1: the simulation decision space, centered on (0,16) with red outcome target A at (-8,16) and blue outcome target B at (8,16). Displayed is a trial with 24 agents.

The agents' location over time is impacted by two factors: their initial bias, and the current information they hold. The agent group is composed of N_A agents initially biased toward target outcome A (and colored a corresponding red), N_B agents initially biased toward target outcome B (colored blue), and N_Z "uninformed" agents unbiased toward either target (green). Figure 1 displays a trial in which all 3 groups have 8 agents. The agents hold their initial bias with strength λ, which signifies the proportion of their decisions that are driven by the initial bias. In this model, all agents biased toward the same outcome target also share the same bias strength, called λ_A for A-biased individuals and λ_B for B-biased individuals (note that $\lambda_Z = 0$ because the uninformed individuals don't have any bias upon which to designate a strength).

The current information γ that an agent holds exists within 5 stepwise options, ranging from -1 (providing strong support for outcome A) to 1 (providing strong support for outcome B). An agent's γ changes over time through a sequential sampling method explained further in Model Process, but its initial value corresponds with the agent's initial bias: N_A agents start with $\gamma = -1$, N_B have $\gamma = 1$, and N_Z have $\gamma = 0$[2].

While not necessarily true for all analyses that could be done with this model, in our explored base case $N_A = N_B$ and $\lambda_A = \lambda_B$; that is, our polarized group is evenly split between individuals preferring outcome A and outcome B, and all informed individuals hold the same strength of initial preference (model adaptations where these assumptions do not apply are discussed in Future Work).

Model Process

Each time period in the model involves two steps enacted by all agents in unison: information updating, and moving.

Information Updating In this step, an agent's current information γ is updated either through reinforcement of their initial bias or through weighted random sampling of another individual in the group. This step signifies the aforementioned tension between individual preferences and pressures to conform to social norms, and the unknown or stochastic process used to reconcile this tension is represented through sequential sampling based on Decision Field Theory (Busemeyer & Townsend, 1993). With probability lambda, the agents reinforce their own initial bias by changing their current information γ by one step of 0.5 toward their biased target, if possible. For example an A-bias individual would update their γ from 0 to -0.5, but a B-biased individual with a γ at the maximum of 1 would keep $\gamma = 1$. Note that uninformed individuals with $\gamma_Z = 0$ will never follow an initial bias, thus relying solely on group cues to update their preference.

The second preference updating method, through group sampling, represents an individual's willingness to conform

[2] These neutral agents have both no current information and no initial bias, hence their label as "uninformed" rather than simply "unbiased" (the agents still exhibit biases in social sampling, elaborated in Model Process).

or be swayed by other group members' views. With probability (1- γ), agents use a weighted random sampling method to choose one other individual and adapt by 1 step toward that individual's current information γ; consider this analogous to holding a conversation with another group member and being swayed by some of the evidence they have. The sampling weight corresponds to each agent's "neighbor count", or the number of other agents within 3 units of their preference location[3]. This weighting represents information amplification through social networks, or placing more trust in an individual's credibility due to the commonality of their opinion[4].

Thus each time period, an agent's γ is either updated through their own initial preference or the influence of another group member. Figure 2 shows an example path of three agents' γ over time: one initially A-biased individual who starts at γ = -1, one B-biased individual who starts at γ = 1, and one uninformed individual at γ = 0.

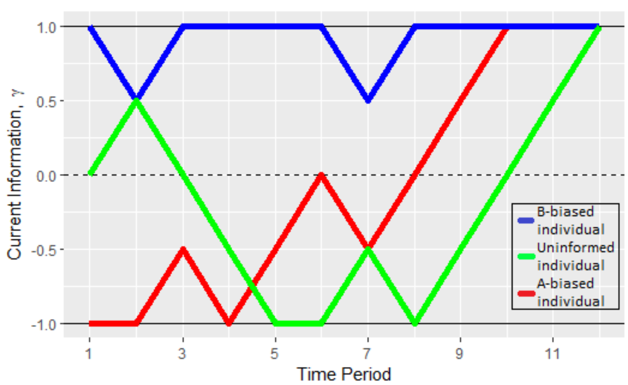

Figure 2: Each time period, the agents' γ values are updated by a step of 0.5 either toward their initial bias (Target A = -1, Target B = 1) or through influence from another individual. When an agent has γ <0 for a certain time period they will move toward target A, or target B if γ >0.

Moving Once all agents have updated their current information variable γ, they all take a movement step in unison based on that value. If $\gamma_i < 0$ then agent *i* will turn to face target A, and if $\gamma_j > 0$ then agent *j* will turn to face target B; both agents will then move forward 1 unit. If an agent has γ = 0, they will not move at all during that time period. With a now-updated location in the decision space (representing the agent's current outcome preference), the agents return to the information updating step and repeat the process until consensus is reached.

Consensus Conditions This model utilizes a strict definition of consensus where all agents must cluster within a 5x5 area on the 32x32 unit decision space. If this occurs with the average agent location to the left of x=-6, this is considered a win for option A and if the average agent location is to the right of x = 6, it is a win for option B; agents can hypothetically come to a "no win" consensus between the two areas, but this was extremely uncommon and likely due to noise. If agents don't achieve consensus within 200 time periods, the trial is ruled "no consensus".

Model Outcomes

Testing of this model was replicated with two group sizes: a "small group" with $N_A = N_B = 6$ agents, and a "large group" with $N_A = N_B = 20$ agents[5]. For each group size, 500 simulation trials were completed at every combination level[6] of $20 <= \lambda <= 50$ and $0 <= N_Z <= 3N_A$. Outcomes of interest include the proportion of trials at a given λ and N_Z which resulted in a consensus outcome[7], and the average speed of consensus (measured in number of time periods) in those cases. The latter excludes "non-consensus" cases, which the data coded as speed = 200 time periods, to partially control for interactions between ability to reach consensus and consensus speed. We will first display results for the small group, then explore differences between small and large groups at the end of the Outcomes section.

Visualizing Main Effects: Bias Strength

Unsurprisingly, both a group's ability to come to a consensus and speed of reaching consensus are highly reliant on the strength of initial bias the informed members hold. Figures 3 and 4 on the following page show this reliance, with higher strengths of initial bias λ generally correlating with a lower likelihood of coming to a consensus and slower speed of consensus. Interestingly, these effects occur at different places along the λ scale – speed of consensus shows a smooth logistic trend from 20 to 50, while likelihood of reaching consensus doesn't begin to diverge from 100% until λ > 35.

[3] Increasing the neighbor radius (values up to 6 were tested) did not significantly impact outcomes.

[4] Replacement of "popularity weighting" in the model with democratic random sampling caused no significant change in the group's ability to come to a consensus, but slightly slowed the speed of consensus-making. The weighting method calls on social opinion modeling (Castellano, 2009).

[5] Additional group sizes were explored and showed little variability in outcomes (with incremental impacts on effect sizes when adding/subtracting agents), resulting in the authors' choice to fully test and analyze the two listed group sizes.

[6] Early testing found that quick consensus was always reached when λ < 20 and never reached within 200 time periods when λ > 50, regardless of incorporation of uninformed individuals.

[7] The model defines success as a trial reaching any option consensus for proof of concept, but the model can be altered to define success as a particular outcome (elaborated in Discussion).

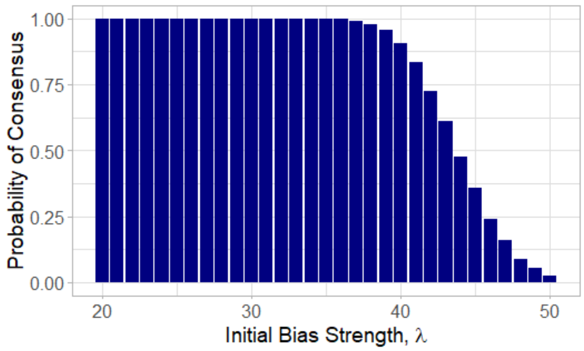

Figure 3: Controlling for number of uninformed individuals, increasing the informed individuals' initial bias strength decreases the group's ability to reach a consensus.

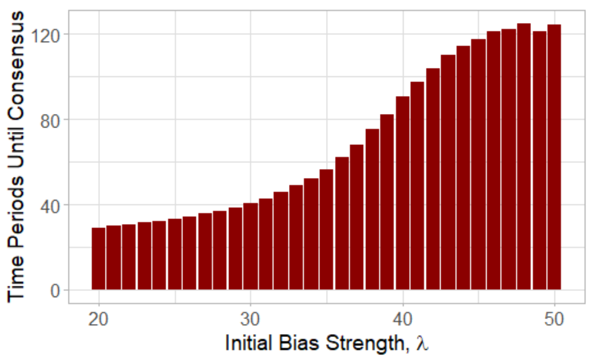

Figure 4: Controlling for number of uninformed individuals, increasing the informed individuals' initial bias strength increases the time needed to reach consensus.

Visualizing Main Effects: Uninformed Individuals

The true manipulation of interest with this data controls for bias strength and varies the number of uninformed agents in a group. The impact of manipulating N_Z seen in Figure 5 and 6 is less strong but still evident; ***Increasing the number of uninformed agents in the group makes the group both more likely to reach consensus and decreases the number of time periods needed to reach that consensus***.

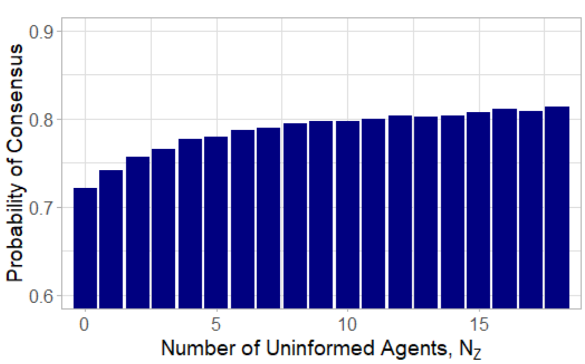

Figure 5: Controlling for strength of initial bias, increasing the number of uninformed agents added to a group of 12 informed agents, split evenly between a bias for Target A and Target B, increased the group's likelihood of coming to a consensus within 200 time periods.

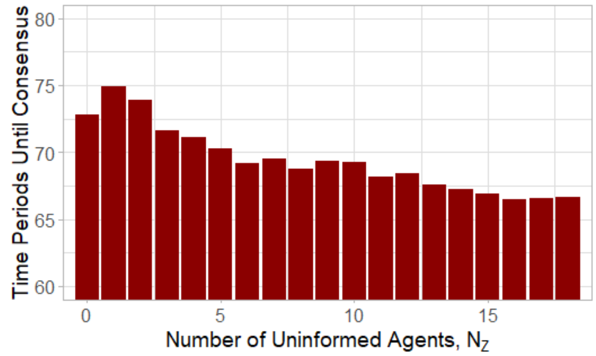

Figure 6: Controlling for initial bias strength, increasing the number of uninformed individuals added to a group of 12 polarized informed agents decreased the time needed for the group to reach consensus (among trials where consensus was reached in less than 200 time periods).

An interesting feature of Figure 6 is the slowing of consensus speed with just one or two uninformed individuals compared to zero, followed by an increase in efficiency with 3 or more uninformed compared to a purely polarized group, which will be elaborated in the Discussion section.

Both data trends fit well to a quadratic function of N_Z, regression information for which is below in Tables 1 and 2.

Table 1: Quadratic Model of Probability of Consensus based on Number of Uninformed Agents (adj R^2 = 0.9546)

<table>
<tr><th>Coeff</th><th>Estimate</th><th>Std. Error</th><th>t value</th><th>Pr(>|t|)</th></tr>
<tr><td>Intercept</td><td>0.733</td><td>-3.321e-03</td><td>220.852</td><td><2e-16</td></tr>
<tr><td>N_Z^2</td><td>-3.423e-04</td><td>4.587e-05</td><td>-7.462</td><td>1.35e-06</td></tr>
<tr><td>N_Z</td><td>1.019e-02</td><td>8.554e-04</td><td>11.917</td><td>2.27e-09</td></tr>
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Table 2: Quadratic Model of Time Periods Until Consensus based on Number of Uninformed Agents (adj R^2 = 0.9098)

<table>
<tr><th>Coeff</th><th>Estimate</th><th>Std. Error</th><th>t value</th><th>Pr(>|t|)</th></tr>
<tr><td>Intercept</td><td>74.067</td><td>0.465</td><td>159.212</td><td><2e-16</td></tr>
<tr><td>N_Z^2</td><td>0.018</td><td>0.006</td><td>2.828</td><td>0.0121</td></tr>
<tr><td>N_Z</td><td>-0.742</td><td>0.120</td><td>-6.195</td><td>1.28e-05</td></tr>
</table>

A helpful point comparison from this data is between the purely polarized group with zero uninformed individuals and a group with 6 uninformed individuals (equivalent to one polarized subgroup, thus consisting 33% of total group size). In this model, adding 6 uninformed agents increases the group's probability of consensus by 6.5% (from 72.2% to 78.7%) and decreases the number of time periods needed for consensus by 2.5 (from 72.8 to 70.3). With 15,500 total trials run at each N_Z level, these differences are both statistically significant at the 0.001 level.

Interactions of Bias and Group Size

Combining these two manipulated variables was also explored for interaction effects on probability and speed of consensus. For both outcomes, we conducted an Akaike Information Criterion comparison of fit between first- and second-degree polynomial functions based on N_Z and λ. Both AIC analyses show that a quadratic function is best fit to the data. The chosen quadratic models are elaborated in Tables 3 and 4, both showing significance of the interaction term[8].

Table 3: Quadratic Regression Model for Probability of Consensus

Coeff	Estimate	Std. Error	t value	Pr(>|t|)	
Intercept	-0.932	5.98e-02	-15.6	<2e-16	***
N_Z^2	-3.423e-04	1.250e-04	-2.7	0.006	**
λ^2	-2.513e-03	4.676e-05	-53.7	<2e-16	***
N_Z	-5.261e-03	3.337e-03	-1.6	0.115	
λ	0.141	3.351e-03	42.2	<2e-16	***
$N_Z*\lambda$	4.416e-04	6.820e-05	6.5	2.01e-10	***

Table 4: Quadratic Regression Model for Consensus Speed, Measured in Number of Trials Needed for Consensus

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)	
Intercept	37.413	5.954	6.283	6.49e-10	***
N_Z^2	0.027	0.012	2.187	0.029	*
λ^2	0.089	0.005	19.140	<2e-16	***
N_Z	-0.381	0.332	-1.148	0.251	
λ	-2.256	0.334	-6.761	3.34e-11	***
$N_Z*\lambda$	-0.016	0.007	-2.358	0.019	*

Effects of Group Size

Data gathered from the large group, with $N_A = N_B = 20$ individuals and N_Z ranging from 0 to 60, diverges in a couple meaningful ways from the small group. The large group's probability of consensus based on number of uninformed agents, seen in Figure 7, follows a similar shape as the small group but the impacts of each additional uninformed individual are diminished, and adding N_A uninformed individuals (now 20) only increases the group's likelihood of consensus by 3% compared to the small group's 6.5% from the inclusion of 6 uninformed individuals.

[8] While we find statistical significance, significance is a function of sample size (here 589 simulated combinations of N_Z and λ) thus the effect size, particularly in applied environments, is uncertain and relies heavily on group size and operationalization of bias strength.

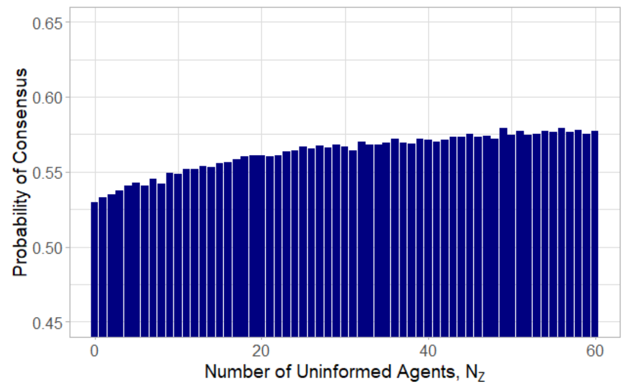

Figure 7: Increasing the number of uninformed agents to a group of 40 polarized agents increases the group's probability of consensus in a model fit by a quadratic curve (adj $R^2 = 0.9753$).

Figure 8 shows the biggest departure from small-group trends, as the negative correlation between number of uninformed agents and time periods needed for consensus has nearly vanished. A quadratic model fit to this data only has an R^2 of 0.2274.

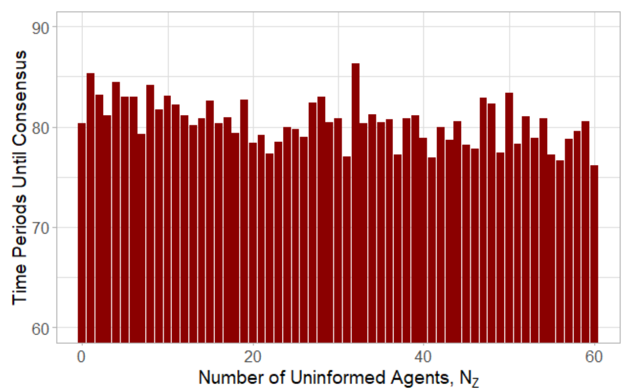

Figure 8: Increasing the number of uninformed agents to a group of 40 polarized agents shows a weakly decreasing trend in number of time periods needed to reach consensus.

Discussion & Future Work

This data offers preliminary support for the existence of *positive* utility of uninformed individuals in polarized group scenarios, contrary to common belief and practice. Intuitively, adding many uninformed individuals to a polarized group should introduce additional noise into the group's decision making and decrease their likelihood and speed of consensus. This model definitively shows the opposite: **adding uninformed individuals to a group *increases* their likelihood and speed of overcoming polarization to reach a consensus**. Figures 5 and 6 illustrate the main effect of uninformed member inclusion toward these outcomes when added to a group of 12 polarized agents.

Figure 6 also offers a potential explanation to why these results seen unintuitive; indeed, most people can recount an experience where bringing an uninformed individual into a group task at work or school seemed to hinder the decision-making process. This data lends support to that experience, as adding the first and second uninformed individual to a group of 12 slowed the group's consensus-gathering ability, while the addition of 3+ uninformed individuals (25% of the informed group) speeds up consensus-gathering relative to a group with no uninformed individuals. Finding the real-world threshold for this flipped directional effect could be critical in further supporting this theory of decision-making and its broad applicability.

The effect of group size on the utility of these uninformed individuals is another result of interest – the large group sees a dampened impact of uninformed individuals in increasing consensus likelihood, and almost completely loses the impact on consensus speed found with the small group (which is reasonable considering a larger group's increased number of possible connections and conversations for sharing information). Extending this trend in the other direction might imply that a smaller group (say, with only 3 individuals on each side of a polarized issue) would benefit even further from the addition of uninformed members.

Of course, as useful as simulations can be to map out the space of possible outcomes and generate hypotheses, all findings suggested by these simulations will need to be confirmed with empirical testing of human participants[9]. The model's basis in proven cognitive mechanisms such as sequential sampling for preference updating and tradeoffs between individual biases and group conformity desires (Golman et al., 2021; Kats & Allport, 1931) solidify our confidence in its plausibility of application across domains. For example, one possible application of this model is in the optimal composition of productive workgroups. If a firm budgets for 20 individuals in a focus group, should that group be made up of solely informed and biased individuals or would results be improved by the inclusion of 2, 5, or 10 uninformed individuals?

Another application of these results that can't escape our attention is in the realm of political polarization. Thomas Jefferson once said "a properly functioning democracy depends on an informed electorate", and this sentiment has persisted into the modern political landscape. Yet despite the immense amount of information and educational materials now at our fingertips, America is the most polarized it's been in decades (Carothers & O'Donohue, 2019). This polarization leads to inconsistent policy with often worse outcomes than any individual choice (Baker, Bloom, & Davis, 2016). Thus, although many proposed interventions to overcome the 'polarization crisis' in modern politics involve voter education, our preliminary results suggest that the boundary conditions and assumptions underlying these efforts should be explored, as situations may exist where the presence of less informed individuals serves to lubricate the gears of consensus building in groups and society. While uninformed individuals might not be able to overcome the most extreme polarization (in our model, no number of uninformed agents could overcome an initial bias strength of $\lambda = 50$) or extremely loud or noisy groups, in more mild or smaller cases of polarization uninformed agents could potentially promote consistency and consensus. Of course, there are many obvious benefits to voter education, and we do not mean to suggest that such initiatives are inherently problematic; rather our results suggest a nuanced approach to designing voter education initiatives so as to avoid negative externalities.

Beyond the existence proof of the benefits of adding uninformed individuals to a group, this NetLogo model was built with a modular framework to facilitate adaptation to scenarios of varying group parameters, upon which similar data analysis can be completed and confirmed with human subjects. One promising application involves defining utility values for outcomes such that there exists an optimal outcome choice (rather than success being defined simply as coming to any consensus). We believe that results will be largely similar, as model mechanisms facilitate choosing an optimal outcome in the likely case where a majority of agents do have accurate information with which to sway the uninformed agents; of course there may also be opposite situations where a misinformed majority (through perceptual or media biases) leads to a suboptimal outcome choice. Additionally, informed subgroups could have unbalanced group sizes N_A and N_B, or differences in initial preference strength. The model can be adapted to environments with more than 2 outcome targets, or many different groups of informed individuals with varying preference strength. Expansion upon these alternative decision frameworks could cement the domain of knowledge-level diversity and the utility of uninformed individuals in group decision making as one of immense opportunity for future exploration.

[9] The primary author can be contacted for more information regarding empirical application of this model.

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