Understanding Dynamics of Polarization via Multiagent Social Simulation

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ABSTRACT

It is widely recognized that the Web contributes to political polarization and, moreover, such polarization affects not just politics but also attitudes about public health, such as about vaccination. Polarization in social networks is challenging because it depends not only on user attitudes but also on their interactions and exposures to information. We adopt Social Judgment Theory and model user behavior based on empirical evidence from past studies and analyze how the sharing of content affects user satisfaction and political inclination. We design a social simulation to investigate three questions on what influences polarization. We find that (1) the extent of selective exposure has no effect on polarization; (2) balanced discussions increase polarization over when one issue dominates; and (3) having more tolerant users slows polarization down. Moreover, user satisfaction is lowest in networks with low selective exposure, imbalanced discussions, and intolerant users.

CCS CONCEPTS

• Computing methodologies → Modeling and simulation; **• Social and professional topics → User characteristics**.

KEYWORDS

The new normal; Information diffusion; Social judgment theory; Selective exposure; Social media platforms

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1 INTRODUCTION

As the COVID-19 pandemic crosses the two-year mark, we can see that it has established a new normal, not only in the objective challenges it poses to society and business but also in terms of attitudes and behaviors that are antivax, antimask, and antiscience. Political polarization is a societal problem since it makes rational decision making and resource allocation difficult. The Web enables fast information diffusion across traditional boundaries, which unfortunately has contributed to polarization. Social media influences users in subtle ways, especially regarding politics [32]; moreover, online and offline political participation are correlated [3, 15].

Three factors influence polarization. First, selective exposure to attitude-conforming information exacerbates confirmation bias, polarizing opinions further [9, 17, 38, 41]. Conversely, cross-cutting exposure (i.e., to attitude-disconfirming information) has a depolarizing effect [17], though with caveats [9, 18]. Selective exposure arises in and strengthens echo chambers, wherein a person encounters only beliefs or opinions that coincide with their own so that their existing views are reinforced and alternative ideas are suppressed. Second, politicians use social media to set the agenda for discussion that favors their political interests [42]. Agenda-setting refers to influencing the perceived salience of topics, drawing attention to certain topics by discussing them disproportionately over other topics [28]. Agenda-setting biases the discussion toward an issue and can accelerate polarization. Third, user tolerance for ideas that contradict their own stance lowers polarization [6].

Understanding the dynamics of polarization based on information sharing on social media can help us identify the factors that contribute to polarization and in finding potential interventions. We analyze the effects of selective exposure, imbalanced discussion on topics, and tolerant users on polarization among users. Specifically, we investigate the following research questions.

$\text{RQ}_{\text{exposure}}$. *Does selective exposure to attitude-conforming information contribute to polarization?*

$\text{RQ}_{\text{balanced}}$. *Do balanced discussions on issues reduce polarization?*

$\text{RQ}_{\text{tolerance}}$. *Does having more tolerant users in the social network help reduce polarization?*

We develop a multiagent social simulation to address these research questions. To address $\text{RQ}_{\text{exposure}}$, we emulate selective exposure by filtering posts based on the receiving user's stance toward a given issue. To address $\text{RQ}_{\text{balanced}}$, we experiment by varying the imbalance of the discussion on one issue while keeping the other issues balanced. For $\text{RQ}_{\text{tolerance}}$, we model tolerant users by having a higher level of tolerance toward both opposing and congenial views. We operationalize tolerant users using Social Judgment Theory [36], which defines tolerant people as ones having wider latitude of non-commitment.

For $\text{RQ}_{\text{exposure}}$, we find that selectivity of exposure has little effect on polarization. For $\text{RQ}_{\text{balanced}}$, we find that balance doesn't necessarily reduce polarization. For $\text{RQ}_{\text{tolerance}}$, we find that tolerant users do reduce polarization. Our findings on $\text{RQ}_{\text{tolerance}}$ agree with the existing literature, whereas our findings on $\text{RQ}_{\text{balanced}}$ conflict with the existing literature. Some but not all prior work has shown a correlation between selective exposure and increased

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polarization. These findings suggest avenues for further theoretical development in tandem with consideration of interventions to reduce polarization.

Organization. Section 2 describes the background and discusses the related works. Section 3 explains the methodology, including definitions and the simulation design. Section 4 details the experimental setup and the results of our experimentation. Section 5 includes a discussion and underlines the limitations and threats to validity of this work. Section 6 concludes with future directions.

2 BACKGROUND AND RELATED WORK

Theory of Cognitive dissonance [7] asserts that when a person is confronted with contrasting ideas, it causes psychological discomfort. This makes people more selective in their information consumption and can lead to confirmation bias. *Confirmation bias* is the tendency of people to accept "confirming" evidence at face value while subjecting "dis-confirming" evidence to critical evaluation [27], resulting in people gravitating toward information that aligns (confirms) their existing views. Bias exists in the selection and sharing of information, especially news [12, 22].

Selective exposure is a tendency of people to choose and spend more time on information that is consistent with their existing opinions and beliefs. Individuals tend to choose the information that is consistent with their existing beliefs [21, 35, 39], though this may not always be true. Some prior works suggest that partisan selective exposure may be a myth [20, 43]. Freedman and Sears [8] argue against voluntary selective exposure in favor of *de facto selectivity*, claiming that most examples of selectivity in mass communication can be attributed to complex factors such as demography, education, social connections, and occupation, which are incidental to the supportiveness of the information. People prefer supportive information in some situations while dissonant information in other situations. Individuals with strong preferences are more likely to spend more time reading negative (unfavorable) information about their choice [29], perhaps to critique it [11].

2.1 Social Media and Politics

The number of users on social media platforms has increased rapidly over the years. Only 8% of internet users in the US used some kind of social networking platform in 2005 [24], whereas, in 2021, 69% use Facebook, and 40% use Instagram [2]. The use of social networking sites for political discussions have also increased over the years. Social media is now among the most common ways people, particularly young adults, get their political news [13]. A meta-analysis from 36 past studies assessing the relationship between social media use and participation in civic and political life found a positive correlation between the two with more than 80% of the coefficients as positive [4]. Adults who use social networking sites as a political tool are more likely to participate in politics [3]. This is true across various cultural and geographical boundaries, including empirical evidence from the US [13], Pakistan [1], and Taiwan [44].

Selective exposure to political information is correlated with polarizing people's opinions to align with the values of the political party they support [9, 17, 38, 41]. Though the causal direction, i.e., whether selective exposure leads to polarization or the other way around, is less obvious [38]. Habitual online news users are less likely to exercise selectivity to get attitude-consistent exposure, which reduces their likelihood of participating in the political system [23]. The longer individuals spend on attitude-consistent content associated with slanted sources, the more immediate attitude reinforcement occurs, and its impact can be detected even after a couple of days of exposure [41]. Stroud et al. [38] investigated the causal relationship between partisan selective exposure and polarization and found strong evidence suggesting selective exposure leads to polarization while also finding limited evidence suggesting reverse causal direction.

Cross-cutting exposure in social networks contributes in fostering political tolerance and make individuals aware of legitimate rationales for oppositional viewpoints [31]. Exposure to disagreeing viewpoint contributes to people's ability to generate reasons, particularly why others might disagree with their view [34]. Kim and Chen [19] found that exposure to cross-cutting perspectives results in a higher level of political engagement, though this may depend on the type of social media platform used. Cross-cutting exposure, widely assumed to encourage an open and tolerant society, is not necessarily the kind of environment that produces enthusiastically participatory individuals. People belonging to social networks involving greater political disagreement are less likely to participate in politics [30, 31]. Constant exposure to disagreement may necessitate trade-offs in other social network characteristics such as relationship intimacy and frequency of communication [31]. Conflict-avoiding individuals, in particular, are more likely to respond negatively to cross-cutting exposure by limiting their political participation to avoid confrontations and putting their social relationships at risk [30].

Garrett et al. [9] examined survey data following elections from the US and Israel and found consistent results despite cultural differences. They found that pro and counter-attitudinal information exposure has a distinct influence on perceptions of and attitudes toward members of opposing political parties.

Mutz [30] analyzed the consequences of cross-cutting exposure on political participation and found that people whose social networks involve greater political disagreement are less likely to participate in politics and are more likely to hold politically ambivalent views.

2.2 Multiagent Social Simulation

Many earlier models on opinion and influence propagation are based on a centralized diffusion process, overlooking the decentralized nature of information diffusion in social networks.

Kempe et al. [16] design two fundamental diffusion models for influence maximization, namely, the Independent Cascade Model (ICM) and the Linear Threshold Model (LTM). Influence in these models is transferred through the correlation graph starting from a set of seed nodes (activated nodes) and its strength decreased when hopping further away from the activated node.

Jiang et al. [14] design a preference-aware and trust-based influence maximization model called Preference-based Trust Independent Cascade Model (PTICM) that takes into account user preferences and trust between users in computing influence propagation.

Li et al. [26] design a novel agent-based seeding algorithm for influence maximization, named Enhanced Evolution-Based Backward selection that models individual user preferences and social context based on social influence and homophily effect. Their results suggest that individuals are influenced by their social context much more than retaining their own opinions, and though the Prior Commitment Level (PCL) of a user is an essential factor for influence propagation, users tend to revise their PCL over time.

Chen et al. [5] propose a group polarization model based on SIRS epidemic model and factor in the relationship strength based on the J-A (Jager and Amblard) model. They use a BA network model due to its closeness to the real social network structure and a Monte Carlo method to conduct simulation experiments.

Though many studies have investigated polarization in the past, a common limitation has been that past studies either look at one time exposure or study these effects in isolation. For instance, Stroud [37] studied the effects of selective exposure using empirical evidence but they rely on data from one-time exposure and study the immediate effects without differentiating the long-term effects. However, the evidence from past studies suggests that political participation and its effects is a long-term process that unfolds over time based on multiple exposures [10, 40]. Further, existing research has mostly focused on effects at an individual level, i.e., relying on self reported data of how an individual is impacted by exposure to potentially polarizing content. However, this may contain user bias and overlook how changes in one part of the social network can impact other parts.

To address these limitations of existing work we design a multi-agent social simulation that can emulate information diffusion on social networks. We model user behavior based on existing social science theories and empirical evidence from prior studies.

3 METHODOLOGY

3.1 Definitions

Definition 3.1 (Social Network). Social Network is an undirected graph with nodes representing agents and the links connecting the nodes representing a relationship between two agents. A social network can be represented as *G= (nodes, edges)*, where *nodes* = $\{a_1, \ldots, a_n\}$ are agents and *edges* = $\{(a_1, a_2), (a_4, a_9), \ldots, (a_x, a_y)\}$ represents a direct connection between pair of agents in the social network (i.e., friends).

Definition 3.2 (Post). Agents in a social network interact by sharing posts that can be represented as *Post = (a, i, s)*, where *a* is the author and *i* is the issue mentioned in (or discussed in) the post, and *s* is the stance of the post toward the issue (continuous value in $[-1, 1]$, where -1 is extremely critical and 1 is extremely supportive).

Update to the social network and agent's attributes are made after each post is diffused in the social network. A post serves as a timestep in this simulation and is used to track changes in the social network as more and more posts are shared.

Definition 3.3 (Agent). An agent represents a user in the social network. An agent is a tuple *(S, P, A)* where *S* holds social network information *(user_activity, friend_list, sanctions, privacy_preference)*, *P* holds information on political predisposition *(stance toward issues, political_inclination)*, and *A* holds information about the agent's actions. An agent is capable of taking two actions: *{share_post, provide_sanction}*.

$userAct(a_x, p_k)$ represents user activity and captures how active an agent is on the platform and ranges in $[0, 1]$ (0 represents most inactive and 1 most active). *Friend_list* is a list of directly connected nodes (friends) in the social network (G). *Sanctions* capture the reaction of other users to a post (analogous to likes and comments) and are represented as $sancScore(a_x, p_k)$. $stance(a_x, i)$ represents the stance of an agent (a_x) toward an issue (i). *Political inclination* is captured by a continuous value in $[-1, 1]$, -1 extreme supporter of party1 (<0), 0 non-partisan and 1 extreme supporter of party2 (>0), this is captured as $polIncl(a_x, p_k)$.

Definition 3.4 (Sanctions). Sanctions are reactions that each agent provides to the posts they receive. Sanction scores can be positive or negative and depend on the content of the post (party mentioned and stance toward it), user's activity, and stance on an issue. Users provide positive sanctions to more congenial posts and negative to more disagreeable posts based on their stance on an issue.

Definition 3.5 (Issues). Issues refer to the topics being discussed. Each issue has one political party in support of it and the other opposing it. Issues are predefined and each agent holds a stance toward each of the issues. An agent's political inclination is constituted by its stance toward different issues and is computed as the mean of all issues supported (or opposed) by a political party.

With respect to a post an agent can be in one of the four states: (1) *Not-received (susceptible):* Agents who haven't yet received the post (all agents other than the author are in this state at the start of the simulation); (2) *Received (contacted):* Agents who have received the post (but not yet shared it); (3) *Spreader (infector):* Agents who have shared the post with their friends; and (4) *Disinterested (refractory):* Agents who received the post but chose not to share it further and lost interest in the post over time.

The simulation starts with an agent (a_x) sharing a post (p_k) with its neighbors in the social network. The agent's neighbors can then choose to share it further with a probability of sharing (Equation 1) that depends on the *content* of the post and the agent's *preferences*. Agent's preferences involve how *active* the agent is on the social networking platform, its *stance* toward the issue (support vs oppose) and its privacy preference. The content of a post includes *issue mentioned* in the post and its *stance* toward it.

$$\begin{aligned} sharingProb(a_x, p_k) = c \times userAct(a_x, p_k) \times \\ |stance(a_x, i) \times pStance(p_k, i)| \times \\ privPref(a_x, p_k) \end{aligned} \tag{1}$$

where c is a constant. An agent with low $sharingProb(a_x, p_k)$ is more likely to not share a post further and may enter the state *Disinterested*. Disinterested agents are not a candidate for sharing the post (p_k) further in the social network.

The agents who receive the post provide a sanction. Sanctions can be positive or negative (analogous to likes and comments). Sanction scores (Equation 2) depend on how *active* the receiving agent is, the receiving agent's *stance* toward the issue at hand and the *stance* of the post toward the issue.

$$\begin{aligned} sancScore(a_x, p_k) = c \times userActivity(a_x, p_k) \times \\ |stance(a_x, i) \times pStance(p_k, i)| \end{aligned} \tag{2}$$

Sanction scores affect user activity and stance of each agent toward an issue. Agents prefer positive sanctions (social acceptance) and this, in turn, increases their activity on the platform, while negative sanctions discourage agents from sharing their views in the future, hence reducing their participation (user activity). The update in user activity depends on the sanction scores received by an agent for the post it shares. User activity of an agent is computed using Equation 3 and is updated after every new post.

$$\begin{aligned} userAct(a_x, p_k) = \\ userActivity(a_x, p_{k-1}) + c \times \\ \sum_{p_i \in pshared(a_x, p_{k-1})} \sum_{a_i \in neighbor(G, a_x)} sanction\_score(a_i, p_i) \end{aligned} \tag{3}$$

where c is a constant, $pshared(a_x, p_{k-1})$ refers to all the posts shared by agent a_x before it shares post p_k and $neighbor(G, a_x)$ refers to all neighboring agents to agent a_x in G.

The stance of an agent towards an issue is impacted by the sanctions it receives from other agents. We model this shift in the position of an agent using Social Judgment Theory (SJT) [36], which describes how individuals change their position when confronted with another position. According to SJT, an individual will shift its position in the direction of the other position if it falls within its *latitude of acceptance* (assimilation), whereas it will shift away from the other position if it falls beyond its *latitude of rejectance* (contrast). This shift is proportional to the strength of the ties and is given by μ, for instance, for an agent a_i, a threshold determining the latitude of acceptance u_i and a threshold determining the latitude of rejection t_i with $t_i > u_i$. When this agent a_i interacts with another agent a_j the following rules are applied to compute the shift in position (da_i) of agent a_i,

$$\begin{aligned} If |a_i - a_j| < u_i, \qquad da_i = \mu \times (a_j - a_i) \\ If |a_i - a_j| > t_i, \qquad da_i = \mu \times (a_i - a_j) \end{aligned} \tag{4}$$

where μ controls the strength of the influence.

In this simulation, the attitude shift is computed using the sanction score received and the difference in attitude (for the issue at hand) between the author of the post and the receiving agent. In this simulation, the strength of ties is the same between all pairs of connected agents, hence a value of 1 is used for μ. The difference in attitude is computed as described in Equation 5.

$$attDiff(a_x, a_y, i) = |stance(a_x, i) - stance(a_y, i)| \tag{5}$$

where i is the issue. Equation 6 shows how to compute the shift in the attitude of an agent after it receives sanctions for a post it shared. This shift in the agent's attitude depends on the difference in stance between the author and the receiving agent (toward the issue discussed in the post) and the sanctions it receives.

$$\begin{aligned} attShift(a_x, p_k) = \\ \sum_{a_n \in neighbor(G, a_x)} \sum_{p_i \in pShared(a_x, p_{k-1})} sancScore(a_n, p_i) \\ \times attDiff(a_x, a_n, i) \end{aligned} \tag{6}$$

The simulation progresses with agents sharing posts with other agents, causing each post to diffuse further in the social network. Each post receives sanction scores from all agents that receive it and these sanction scores, in turn, impact the author agent's activity score and stance toward various issues. The political inclination of each agent is determined based on its stance toward different issues and is computed as the mean of all stance weighted equally. An agent supports a political party with which its mean stance toward issues is in agreement with. The political inclination of an agent is updated based on the shift in stance toward different issues as more and more posts are shared in the social network.

3.2 Agent Goals

Agents in this simulation are capable of two actions, sharing a post, and providing sanctions to the posts they have received. Each agent in the simulation tries to maximize its influence and popularity in the network by sharing relevant content and providing appropriate sanctions. Accordingly, we define two goals for each agent—*Promoting Views* and *User Satisfaction*.

Promoting Views. All agents try to promote their own political views on different issues by sharing relevant posts with their friends (neighbors in the social network). Agents also achieve this by providing positive and negative sanctions to each post they receive, positive sanctions to what agrees with their political predisposition, and negative to what doesn't.

User Satisfaction. All agents in the simulation try to maximize their satisfaction. User satisfaction is computed based on the sanctions received from other agents. Positive sanctions are desirable while negative sanctions are undesirable. Agents change their stance toward issues to ensure getting more aggregate positive sanctions over time.

4 EXPERIMENTS AND RESULTS

We use the Facebook social network from Leskovec et al. [25] to seed the simulation. The social network consists of 4,039 nodes (agents) and 88,234 edges (friendships) and an average clustering coefficient of 0.605,5. Stance toward different issues for each agent is initialized based on a random bounded normal distribution in [−1, 1], −1 implying extreme supporter of party1 while +1 implying extreme supporter of party2, a value of 0 means neutral (non-partisan) agent. Privacy preference and user activity are also initialized based on a random bounded normal distribution in [0,1], 0 implying least and 1 implying most.

We generate an equal number of posts for each issue with the same bounded normal distribution of stance toward various issues. This ensures the same amount of criticism and praise for all issues being discussed to ensure balance across topics. We also ensure consistency between the stance of the agent who starts sharing the post (original author) and the stance of the post by choosing the author agents accordingly. If an agent supports issue A, it will only start a supportive post on issue A, while an agent who opposes it only starts a critical one on that issue. Authors are selected at random to start sharing a post half of the time and based on their activity score and privacy preference for the other half of the time.

Metrics. Following are the metrics we use to measure polarization in the social network and user satisfaction.

Polarization. Polarization measures how far agents are from the center in either direction (i.e., in favor of either party). Polarization is measured as the aggregate root mean square distance of all agents from the center (0 being the non-partisan point-of-view) and can range over [0, 1], from none to most polarization. Polarization is computed for the entire social network as described in Equation 7.

$$Polarization(G, p_k) = \sum_{a_i \in agents} \sqrt{\frac{polIncl(a_i, p_k)^2}{num(G, agents)}} \tag{7}$$

where $polIncl(a_i, p_k)$ refers to the political inclination of agent a_i after sharing posts p_k and $num(G, agents)$ is the total number of agents in the overall social network.

Polarity. Polarity is indicative of the political side that has more aggregate support in the network. We measure polarity as the mean of political inclination of all agents. Polarity can range over $[-1, 1]$, with -1 indicating absolute support (by all agents) for one political party and +1 for the other, and 0 being neutral. Polarity is computed as described in Equation 8.

$$Polarity(G, p_k) = \sum_{a_i \in agents} \frac{polIncl(a_i, p_k)}{num(agents)} \tag{8}$$

Homophily. Homophily measures the homogeneity of a network structure based on the political inclination of agents. Higher homophily is indicative of more segregation in the social network. We use the assortativity of the social network [33] to measure homophily. The value of homophily ranges over [-1,1], with 1 indicating a perfectly assortative network and values between [-1,0] indicating a perfectly disassortative network. Homophily is computed using Equation 9.

$$Homophily(G, p_k) = \frac{\sum_i e_{\mathrm{ij}} - \sum_i a_{\mathrm{i}} b_{\mathrm{j}}}{1 - \sum_i a_{\mathrm{i}} b_{\mathrm{j}}} \tag{9}$$

where e_{ij} is the fraction of edges in a network that connect a vertex of type i to one of type j, and a_i and b_j are the fractions of each type of end of an edge that is attached to vertices of type i, and type j respectively. The type depends on the agent's political inclination and we use 20 equally spaced groups based on the political inclination to compute homophily of the network. We use the networkx [1] implementation of assortativity to compute homophily.

User Satisfaction. User satisfaction measures how satisfied a user is based on the outcome of its actions on the social network. We operationalize this using the sanction scores that each agent gets for sharing the content with other agents in the social network.

$$userSat(a_x, p_k) = c \times \sum_{a_i \in neighbor(G, a_x)} \sum_{p_i \in pShared(a_x, p_{k-1})} sancScore(a_i, p_i) \tag{10}$$

where $userSat(a_x, p_k)$ refers to the user satisfaction of agent a_x after the post p_k has diffused in the social network.

List of Experiments. To address $\mathrm{RQ}_{\mathrm{exposure}}$ (*Does selective exposure to attitude-conforming political information contribute to polarization?*), we vary the levels of selective exposure in our simulation and analyze its impact on polarization and user satisfaction. To address $\mathrm{RQ}_{\mathrm{balanced}}$ (*Do balanced discussions on various issues reduce polarization?*), we vary the proportion of an issue based on the frequency of discussion (while keeping other issues balanced) and analyze its impact on polarization and user satisfaction. To address $\mathrm{RQ}_{\mathrm{tolerance}}$ (*Does having more tolerant users in the social network help reduce polarization?*), we vary agents' tolerance levels and analyze its impact on polarization and user satisfaction.

We use the same social network and seed data within each experimental setup to ensure a fair comparison. For each experiment, we compute our metrics, including polarization, polarity, homophily, and user satisfaction. In addition to these metrics, we compute other metrics that compare the change in initial and final states of users on their levels of satisfaction (negative, zero-satisfaction, or positive), activity (low, medium, or high), and polarization (less or high). Table A.2 describes these metrics and lists their thresholds.

Figures 1, 2 and 3 compare how polarization, polarity, homophily, and user satisfaction changes with more posts being shared in the social network under different experimental setups. Tables 1 and 2 summarize our findings for the three experiments on our metrics, and Table A.1 includes a description for notations used to explain the simulation design. Sections 4.1, 4.2, and 4.3 describe the results of the three experiments in detail.

4.1 Experiment 1: Selective Exposure

We emulate selective exposure in our simulation by only exposing each agent to posts from other agents who have a similar stance (within a specified threshold) pertaining to the issue being discussed in the post. To operationalize selective exposure, we use a threshold value of the difference in the stance between two agents beyond which they stop seeing each other's post. An agent only sees posts from other agents whose stances differ on a given issue within a threshold value. We experiment with three threshold values for selective exposure, Low (allows a difference of 80% in stance toward the issue in the post), Medium (allows 50% difference), and High (allows 20% difference). The stance of an agent itself depends on the sanctions it receives (over time) from other agents who see its post, making the selective exposure more dynamic.

Table 1 includes results for Experiment 1. High selective exposure leads to less activity (i.e., sharing of posts) in the social network. This is evident in lower counts for unique authors (agents who start the post), spreader agents (agents who shared a post further in the social network), and disinterested agents (agents who receive the post but did not share it further). Table 2 compares the initial and final distribution for different agent attributes. The number of users with low activity (Activity score <0.33) increased substantially for all the three levels of selective exposure (around 6x for high and 8x for medium and low selective exposure) as more posts were shared in the social network. We also notice a decline in low polarized users (with political inclination in $[-0.5, 0.5]$) by about 22%—24% for different levels of selective exposure. However, the increment in highly polarized users (political inclination either >0.5 or <$-$0.50) is around 10x for all three settings of selective exposure.

High selective exposure consistently achieves (marginally) better user satisfaction than medium and low (Figure 1). Mean user satisfaction for high selective exposure (-0.0023) is marginally better compared to medium (-0.0168) and low (-0.0288) selective exposure, though all have a negative user satisfaction (Table 1). The number

[1] https://networkx.org/documentation/stable/reference/algorithms/assortativity.html

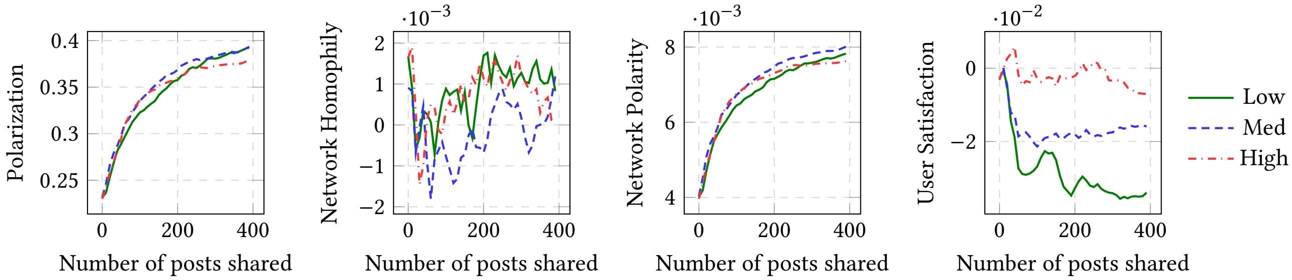

Figure 1: Experiment 1 (Selective Exposure): Comparing polarization, homophily, network polarity, and user satisfaction of agents in the social network with different levels of selective exposure.

of users with negative user satisfaction is higher than positive for all three levels of selective exposure (Table 2).

Table 1 shows the results of the simulation run for all three levels of selective exposure. Mean polarization is highest when selective exposure is medium, with high and low exposure slightly behind. Mean polarity has similar values for all three levels of selective exposure, showing little to no difference. Homophily is lower for a medium level of selective exposure throughout the simulation run compared to high and low selective exposures. The number of unique authors, agents who received a post, spreader agents, and disinterested agents are highest when selective exposure is low.

> ***Takeaway (exposure).*** *Different levels of selective exposure lead to similar levels of polarization in the network, and mean user satisfaction is highest for high selective exposure.*

4.2 Experiment 2: Balanced Discussion

We experiment with different proportions of one issue while maintaining balance on the other issues being discussed. We experiment with three scenarios: (1) all issues have the same count; (2) when the most popular issue is one-third (33%) of all discussions; and (3) when it is two-thirds (67%) of all the issues being discussed. In each case, the issues are balanced in frequency and stance distribution for both sides, and the total number of posts shared remains the same for all the runs.

As Figure 2 shows, polarization and polarity increase in the social network for all three distributions of issues. Surprisingly, polarization is slow when a single issue dominates the discussions compared to when the issues are balanced. Network homophily and user satisfaction are marginally higher when one issue dominates compared to a balanced discussion, though all three cases achieve a negative mean user satisfaction score.

Table 2 compares the initial and final user states for all three experimental setups. The numbers of agents who received a post and of spreader agents are higher for all three cases in this experiment than with any level of selective exposure in experiment 1. The number of users who have negative user satisfaction is highest for the most imbalanced case (when two-third of the discussion is dominated by just one issue). Surprisingly, the number of highly polarized users is higher when issues are balanced compared to when one issue dominates the discussion.

> ***Takeaway (balanced).*** *Polarization is slower and user satisfaction is higher when one issue dominates the discussion.*

4.3 Experiment 3: Tolerant Users

Tolerance of an agent is defined based on its latitude of non-commitment [36], i.e., the difference between the latitude of acceptance and latitude of rejectance, higher difference implies more tolerance. We run our simulation model with three levels for tolerance, namely, *low*, *medium*, and *high*. High tolerant users only react to posts from agents within 30% of difference in stance towards an issue (latitude of non-commitment is 70%), 60% for medium tolerance (latitude of non-commitment is 40%), and 90% for low tolerance (latitude of non-commitment is 10%). A low tolerant agent is more likely to accept or reject an opinion (i.e., provide sanction to a post), while a high tolerant agent is less likely to do so.

Figure 3 shows that when agents are more tolerant, both polarization and polarity grow noticeably slower than with medium and less tolerant agents under the same conditions. Surprisingly, low levels of tolerance lead to less polarization than the medium level of tolerance. The user satisfaction is lowest in case of high tolerance and highest for low tolerance. Homophily is consistently lower for a high tolerance compared to medium and low, concurring that when users have high tolerance the network structure is less homogeneous. The numbers of unique author agents, receiving agents, and spreader agents are among the highest compared to other experimental setups (Table 2), showing that the user activity (sharing of posts) in the network is highest in this setting. High tolerance in agents produces the least highly polarized users (agents with political inclination either <-0.5 or >0.5) and mid level of tolerance produces the highest.

> ***Takeaway (tolerance).*** *High tolerance in agents slows down polarization but also leads to lower levels of user satisfaction.*

5 DISCUSSION

The results from the simulation runs with selective exposure do not provide a conclusive picture as to which setting leads to more polarization. The difference in polarization is marginal when different levels of selective exposures are compared. As expected, high levels of selective exposure lead to more user satisfaction compared to low and medium levels of selective exposure (Figure 1). Selective exposure also produces the most of users with a extreme political stance.

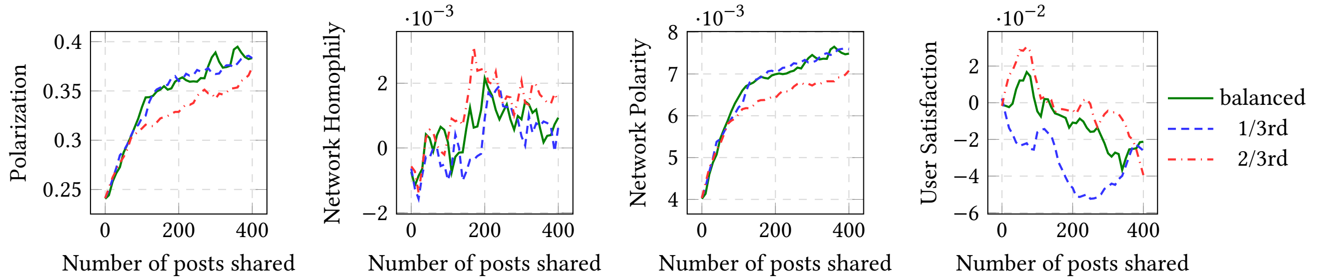

Figure 2: Experiment 2 (Balanced Discussion): Comparing polarization, homophily, network polarity, and user satisfaction of agents with different proportions of issues being discussed. Only one issue is discussed disproportionately while all other issues are balanced (i.e., same number and distribution for stance supporting and opposing each party's favoring issues)

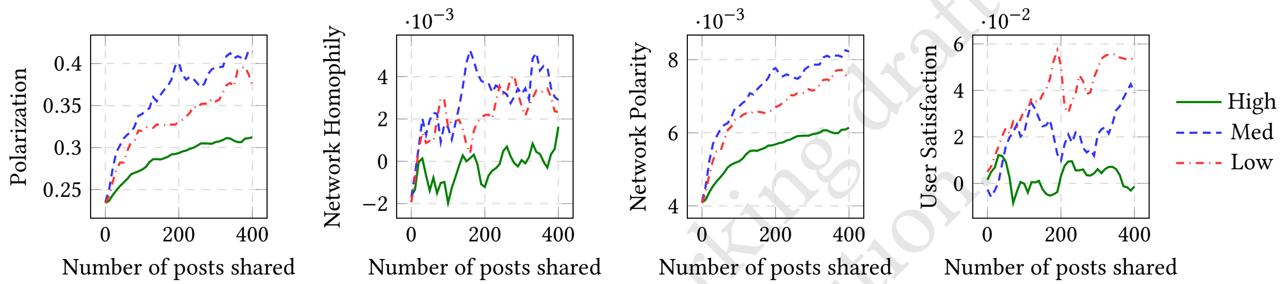

Figure 3: Experiment 3 (Tolerance): Comparing polarization, homophily, network polarity, and user satisfaction of agents in the social network with different tolerance levels.

Table 1: Summary of simulation runs for different simulation setups and configurations. Values for Unique authors, Agents received, Spreader agent, and Disinterested agents are all in %.

Experiments	Config	Unique Authors	Agents Received	Spreader Agents	Disinterested Agents	Mean Polarization	Mean Homophily	Mean Polarity	Mean User Satisfaction
1. Selective Exposure	High	4.78	10.77	5.17	5.6	0.347,4	0.000,7	0.007	−0.002,3
	Med	4.9	18.51	8.45	10.07	0.354,8	−0.000,2	0.007,1	−0.016,8
	Low	5.37	24.81	11.56	13.26	0.347	0.000,8	0.006,9	−0.028,8
2. Balanced Discussion	Balanced	5.55	26.72	12.8	13.92	0.348,2	0.000,6	0.006,7	−0.010,9
	1/3rd	5.77	30.71	14.4	16.31	0.347,3	0.000,3	0.006,8	−0.032,7
	2/3rd	5.79	31.64	15.09	16.55	0.327,4	0.001,2	0.006,3	−0.001,5
3. Tolerant Users	High	5.45	42.5	19.35	23.15	0.289,5	−0.000,2	0.005,6	0.002,5
	Med	6.04	45.51	23.82	21.7	0.366,8	0.003	0.007,2	0.021,6
	Low	5.64	32.04	16.79	15.24	0.336	0.002,2	0.006,7	0.039,5

Selective exposure experiences the largest decline in user activity as more and more posts are shared compared to other experimental setups. Highly active users (activity score >0.67) decline by about 13% for high, 19% for medium, and 20% for low levels of selective exposure while less active users (activity score <0.33) increased, around 6x for high and 8x for medium and low (Table 2). This is consistent with findings from prior studies on selective exposure and political participation, which have found selective exposure over time reduces user's participation in political discussion, though this effect may be due to reduced selective bias in media choice as users become more habituated with online news consumption and not because of selective exposure [23].

Varying the distribution of issues being discussed based on frequency has some effect on polarization and user activity. Surprisingly, a balanced discussion on issues polarizes agents faster compared to when one issue dominates and also produces higher number of highly polarized users. The overall user satisfaction is highest when one issue dominates compared to more balanced discussions.

Polarization is slowed down substantially when tolerance in users is high (Figure 3). Simulation setup with most tolerant users experience least network polarization as more posts are shared and

Table 2: Comparison of user distribution (based on frequency) between initial and final states of the agent for each simulation setup and configuration (Values are in %).

Experiments	Config	User Details	Zero User Satisfaction	Positive User Satisfaction	Negative User Satisfaction	Low User Activity	Medium User Activity	High User Activity	Low Polarized Users	Highly Polarized Users
1. Selective Exposure	Initial		100	0	0	2.01	14.04	83.96	97.45	2.55
	High	Final	14.73	41.84	43.43	11.44	18.37	70.19	75.37	24.71
	Med	Final	10.82	40.31	48.87	15.45	20.92	63.63	73.95	26.24
	Low	Final	13.52	38.08	48.4	15.97	19.04	64.99	75.22	25.03
2. Balanced Discussions	Initial		100	0	0	0.94	12.8	86.26	97.05	2.95
	Balanced	Final	16.09	38.7	45.21	9.58	18.1	72.32	76.5	23.77
	One-third	Final	15.6	38.43	45.98	9.16	18.49	72.34	75.04	25.15
	Two-third	Final	15.75	37.66	46.6	13.44	18.89	67.67	77.69	22.31
3. Tolerant Users	Initial		100	0	0	0.72	11.83	87.45	97.52	2.48
	High	Final	13.77	41.4	44.84	6.93	17.63	75.44	85.14	14.86
	Mid	Final	14.53	43.33	42.14	12.38	16.66	70.96	73.76	26.81
	Low	Final	16.98	44.05	38.97	9.19	17.65	73.16	76.55	23.5

end up with least network polarity compared with all other experimental setups. This is consistent with earlier findings from Coscia et al. [6], who also found lower levels of network polarization with high user tolerance in a social network. A more tolerant social network also witnesses the most agents who received a post, spreader agents, and disinterested agents. User satisfaction is lowest when tolerance is high but shows low fluctuations, whereas low tolerance produced the highest user satisfaction.

In all simulation runs, the user activity decreases as the polarization in the network increase. This likely happens because agents seek an aggregate positive sanction which becomes more challenging to achieve as the social network gets more polarized.

5.1 Limitations

Our simulation models user preferences and emulates user behavior on social networking platforms to investigate polarization. However, there are a few limitations of our model that stems from the simplifications (of user behavior and its impacts).

First, sharing of posts and opinion shift is sequential in this simulation, i.e., only one post is being shared in the network at any given time. Another post starts diffusing in the network only when the previous post has completely diffused into the network (i.e., has reached all agents it could have, and the only agents who have received the post and not yet shared ahead are in the Disinterested state). This limits our simulation to not factor in effects of parallel exposure to different (maybe conflicting) information, i.e., being exposed to several posts relating to an issue before forming (shifting) an opinion pertaining to an issue.

Second, the social network in this simulation is static, i.e., neither a new link is formed nor an existing one severed at any time. Though, selective exposure does partially make the network dynamic by filtering posts based on the difference in stance between two agents towards an issue. A dynamic social network demands far more computational resources as well as some knowledge of the offline world to appropriately link or delink agents over time.

5.2 Threats to Validity

Modeling user behavior is a challenging task that demands an intricate understanding of human psychology and an extensive operationalization of human traits. Though we model each agent based on theories from social science and relevant observations from previous related works, the simplifications done to formalize the setup incurs some threats to validity.

First, we assume equal strength of ties between each pair of connected agents. In reality, people have varying strength of ties, which affects how they react to posts from others and how they are influenced by those posts. *Second*, we do not consider offline events that may influence an agent's inclination toward an issue. In our simulation model, an agent's stance changes only as a consequence of sanctions it receives from other agents when it shares a post. *Third*, we only consider a user's own preferences and content of the post when deciding to share a post and provide sanctions. In reality, there may be a myriad factors that affect such decisions. *Forth*, the computational needs are high for running the simulation several times to aggregate results to get more robust and reliable results. Our results are based on a single run.

6 CONCLUSION

We develop a multiagent social simulation to investigate the dynamics of polarization in social networks. Via simulation experiments, we find that varying the levels of selective exposure to attitude-confirming political information has little or no effect on the magnitude of polarization and network polarity. However, higher tolerance among users substantially slows down polarization in a social network. Surprisingly, disproportionate discussion on an issue achieves lower polarization under the same conditions and slightly higher user satisfaction than balanced discussion.

These results, however, should be taken with caution. Although our model is based on assumptions grounded in prior studies on polarization on social media, we use artificially generated data for our analysis. Reliably modeling user behavior is non-trivial and requires a fine-grained understanding of user behavior. We make simplifying assumptions in our model.

A direction for future work is to develop richer simulation models that capture dynamics of social networks, such as forming and severing ties between agents and diffusing several posts simultaneously in the network. Another direction is to seed the simulation with data collected from real users via a human-subject study.

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APPENDIX

A.1: Notations used to describe the simulation design.

Notation	Description
a_x	Agent x
p_k	k^{th} post shared in the network
$stance(a_x, i)$	Stance of a_x toward issue i
$pStance(p_k, i)$	Stance of p_k toward issue i
$userActivity(a_x, p_k)$	Activity score for a_x while p_k is being shared
$privPref(a_x, p_k)$	Privacy preference of a_x as p_k is being shared
$sharingProb(a_x, p_k)$	Probability of agent a_x to share p_k
$sancScore(a_x, p_k)$	Sanction score a_x provides on receiving p_k
$attDiff(a_x, a_y, i)$	Difference in attitude between a_x and a_y toward the issue i
$attShift(a_x, p_k)$	Shift in attitude of a_x after receiving sanctions for sharing the post p_k
$polIncl(a_x, p_k)$	Political inclination of a_x after the post p_k has diffused in the social network
$userSat(a_x, p_k)$	Satisfaction score for agent a_x after the post p_k has diffused in the network
$num(G, agents)$	Total number of agents in the social network G
$Polarization(G, p_k)$	Root mean square distance of each agent from neutral point of view for the social network G after p_k has diffused the network
$Polarity(G, p_k)$	Mean political inclination of the overall social network G after p_k has diffused the network
$Homophily(G, p_k)$	Homophily of the social network G based on political inclination of agents after p_k has diffused the network
$neighbor(G, a_x)$	all agents directly connected to agent a_x in the social network G
$pShared(a_x, p_{k-1})$	All the posts shared by a_x prior to p_k

A.2: Metrics to compare the change in initial and final states of users.

Metric	Description
Zero User Satisfaction	Agents with user satisfaction equal to zero
Positive User Satisfaction	Agents with user satisfaction greater than zero
Negative User Satisfaction	Agents with user satisfaction less than zero
Low User Activity	Agents with user activity score equal to or lower than 0.33
Medium User Activity	Agents with user activity score greater than 0.33 and lower than 0.67
High User Activity	Agents with user activity score equal to or more than 0.67
Less Polarized User	Agents with Political inclination over $[-0.5, 0.5]$
Highly Polarized User	Agents with Political inclination greater than 0.5 or lower than -0.5