# 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 such polarization affects not just politics but also attitudes about public health, such as 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 the Social Judgment Theory and model user behavior based on empirical evidence from past studies and analyze how content sharing affects user satisfaction and political inclination. We design a social simulation to investigate three questions on what influences polarization. We find that (1) higher selective exposure leads to lower and early saturation of polarization; (2) imbalanced discussions lead to the same levels of polarization as balanced discussions; and (3) having more tolerant users slows down polarization. Moreover, user satisfaction is highest in networks with high selective exposure.

## 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 find 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?*

**$\text{RQ}_{\text{imbalanced}}$.** *Does imbalanced discussions on issues increase 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 towards a given issue. To address $\text{RQ}_{\text{imbalanced}}$, we experiment by varying the weights for different issues. 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 higher selective exposure leads to lower polarization and early saturation of polarization than lower levels of selective exposure. For $\text{RQ}_{\text{imbalanced}}$, we find that imbalance doesn't necessarily increase 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 $\text{RQ}_{\text{exposure}}$ conflicts with some of the existing literature while it agrees with a few. Some but not all prior work has shown a correlation between selective exposure and increased polarization, while some have raised doubts on the validity of such results which are based on self-reported data that may be biased. 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

The 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 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 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 has 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] investigate the causal relationship between partisan selective exposure and polarization and find 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 makes individuals aware of legitimate rationales for oppositional viewpoints [31]. Exposure to disagreeing viewpoints 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 in 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 the 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 the 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-world 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] study the effects of selective exposure using empirical evidence but 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 multiagent 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* = $\{(a_1, a_2), (a_4, a_9), \ldots, (a_x, a_y)\}$ represent 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, *i* is the issue mentioned in (or discussed in) the post, and *s* is the stance of the post towards the issue (continuous value in [−1, 1], where −1 is extremely critical, and 1 is extremely supportive).

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. Updates to the social network and agent's attributes are made after each post is diffused in the social network.

*Definition 3.3 (Agent).* An agent represents a user in the social network. An agent is a tuple *(S, P, A)* where *S* holds the social network information *(user_activity, privacy_preference, friend_list, sanctions)*, *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}.*

*User_activity* captures how actively an agent visits the platform, and *privacy_preference* captures how willing the agent is to share posts. Both range between [0, 1] (0 represents most inactive/unwilling and 1 most active/willing). *Friend_list* is a list of directly connected nodes (friends) in the social network. A *sanction* captures the reaction of other users to a post (analogous to likes and comments). Each agent has a stance towards an issue represented as a continuous value between [-1,1], -1 indicating extreme opposition, and 1 extreme support for the issue. *Political_inclination* of an agent depends on its stance towards different issues and is computed as the difference of the mean stance of issues favoring and opposing a political party. *Political_inclination* ranges between [−1, 1], −1 extreme supporter of party1 (<0), 0 non-partisan, and 1 extreme supporter of party2 (>0).

*Definition 3.4 (Sanctions).* Sanctions are reactions that each agent provides to the posts they receive. 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 supporting it and the other opposing it. Issues are predefined, and each agent holds a stance on each issue. An agent's political inclination is constituted by its stance toward different issues.

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 neighboring agents can then choose to share it further with a probability of sharing that depends on the content of the post and the neighboring agent's preference. An agent's preferences involve how active the agent is on the social networking platform, its stance towards the issue (support vs. opposing), and its privacy preference. The content of a post includes the issue mentioned in the post and its stance toward it. Equation 1 describes the computation for sharing probability $sP(a_\mathrm{x}, p_\mathrm{k})$ for the agent $a_\mathrm{x}$ to share the post $p_\mathrm{k}$.

$$\begin{aligned} sP(a_x, p_k) = c &\times uA(a_x, p_k) \\ &\times |uS(a_x, i) \times pS(p_k, i)| \\ &\times pP(a_x, p_k) \end{aligned} \tag{1}$$

where $c$ is a constant, $a_x$ is an agent, $p_k$ is the $k^{\text{th}}$ post being shared in the network, and $i$ is the issue being discussed in the shared post. $uA(a_x, p_k)$ is the user activity of user $a_x$ when post $p_k$ is being shared, $uS(a_x, i)$ is the user $a_x$'s stance towards issue $i$, $pS(p_k, i)$ is the stance of the post towards issue $i$, and $pP(a_x, p_k)$ is the privacy preference of user $a_x$ while post $p_k$ is being shared in the network. An agent with low $sP(a_x, p_k)$ is more likely not to share a post further and may enter the state *Disinterested*. Disinterested agents are not a candidate for sharing the post ($p_k$) further.

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

$$\begin{aligned} sS(a_x, p_k) = c \times uA(a_x, p_k) \\ \times |uS(a_x, i) \times pS(p_k, i)| \end{aligned} \tag{2}$$

where $sS(a_x, p_k)$ is a sanction score provided by agent $a_x$ for the post $p_k$ it received. Sanction scores affect user activity and the stance of each agent towards an issue. Agents prefer positive sanctions (social acceptance), which 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. An agent's user activity ($uA(a_x, p_k)$) is computed using Equation 3.

$$\begin{aligned} uA(a_x, p_k) = uA(a_x, p_{k-1}) + c\times \\ \sum_{p_i \in sP(a_x, p_{k-1})} \sum_{a_i \in N(G, a_x)} sS(a_i, p_i) \end{aligned} \tag{3}$$

where c is a constant, $uA(a_x, p_{k-1})$ represents the user activity of agent $a_x$ before post $p_k$ is shared, $sP(a_x, p_{k-1})$ refers to all the posts shared by agent $a_x$ before it shares post $p_k$ and $N(G, a_x)$ refers to all neighboring agents to agent $a_x$ in $G$.

An agent's stance 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 $\mu$, 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 $\mu$ is a constant that controls the strength of the influence.

In this simulation, the attitude shift is computed using the sanction scores received and the difference in attitude (towards 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 $\mu$ is 1. The attitude difference is computed as the difference in stance between agents (Equation 5).

$$aD(a_x, a_y, i) = |uS(a_x, i) - uS(a_y, i)| \tag{5}$$

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

$$\begin{aligned} aS(a_x, p_k, i) = \sum_{a_n \in N(G, a_x)} \sum_{p_i \in sP(a_x, p_{k-1})} sS(a_n, p_i) \\ \times aD(a_x, a_n, i) \end{aligned} \tag{6}$$

where $aS(a_x, p_k, i)$ is the attitude shift in the agent $a_x$ on the issue $i$ based on the sanctions it receives as $p_k$ is shared.

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. An agent supports a political party with which its mean stance toward issues is in agreement.

### 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 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. We predefine six issues, three favoring each political party, and each agent's stance towards different issues is initialized based on a random bounded normal distribution in $[-1, 1]$, $-1$ implying extreme criticism while $+1$ implying extreme support. 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 artificially 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 discussed issues to ensure balance across topics. We generate 5,000 posts that are shared in each experimental setup between agents. We also ensure consistency between an agent's stance 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. Agents are chosen to be authors of a post based on their activity score and privacy preference half of the time and at random for the other half.

**Metrics.** Following are the primary 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 ranges between [0,1] and is measured as the aggregate root mean square distance of all agents from the center (0 being the non-partisan point-of-view).

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

where $polIncl(a_i, p_k)$ refers to the political inclination of agent $a_i$ after sharing post $p_k$ and $num(G, agents)$ is the total number of agents in the 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 between $[-1, 1]$, with $-1$ indicating absolute support (by all agents) for one political party and +1 for the other, and 0 neutral.

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

**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.

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

where $e_{ij}$ is the fraction of edges in a network that connects 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 attached to vertices of type $i$, and type $j$ respectively. The type depends on the agent's political inclination and we group agents into 20 equally spaced groups based on their political inclination to compute homophily. We use the networkx [1] implementation of assortativity to compute network homophily.

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

$$uSat(a_x, p_k) = c \times \sum_{a_i \in N(G, a_x)} \sum_{p_i \in sP(a_x, p_{k-1})} sS(a_i, p_i) \tag{10}$$

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

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

**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. To address $\mathrm{RQ}_{\mathrm{imbalanced}}$ (*Do imbalanced discussions on various issues increase polarization?*), we vary the weights of the discussed issues. To address $\mathrm{RQ}_{\mathrm{tolerance}}$ (*Does having more tolerant users in the social network help reduce polarization?*), we vary agents' tolerance levels. We analyze the impact of changing these configurations on polarization and user satisfaction.

We use the same social network and seed data in all experiments to ensure a fair comparison. For each experiment, we compute our metrics, including polarization, polarity, homophily, and user satisfaction. In addition to these primary metrics, we compute secondary metrics that compare the change in each agent's initial and final states. Table A.2 describes the secondary metrics and lists their thresholds.

Figures 1, 2, and 3 compare how polarization, polarity, homophily, and user satisfaction change with more posts being shared under different experimental setups. Tables 1 and 2 summarize our findings for the three experiments, and Tables A.1 and A.2 include a description of notations used to explain the simulation design and metrics respectively. Sections 4.1, 4.2, and 4.3 describe the experimental setup and 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 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 stance differs on a given issue within a threshold value. We experiment with four threshold values for selective exposure, *None* (allow all agents to see all content shared by neighboring agents without any content filtering, i.e., no selective exposure), *Low* (allows a difference of 80% in the stance between sharing and receiving agent towards the issue in the post), *Medium* (allows 50% difference), and *High* (allows 20% difference). An agent's stance changes based on the sanctions it receives (over time) from other agents who see its post, making the selective exposure dynamic.

Figure 1 compares the impact of different levels of selective exposure on all the primary metrics. High selective exposure leads to early saturation and lower levels of polarization compared to low/medium levels or no selective exposure. Low and medium levels of selective exposure lead to marginally higher polarization than to no selective exposure. Mean polarization is highest (0.4914) under low selective exposure and lowest (0.4463) under high selective exposure (Table 1). The number of highly polarized agents increases most when no selective exposure is applied (7.3% of all agents, up from 3.29% at the start of the simulation, Table 1).

Network homophily shows little variations across different levels of selective exposure. Mean network homophily is highest (0.0184) with no selective exposure and the lowest (0.0112) for medium selective exposure (Table 1). Network polarity shows more variation when no selective exposure is applied than when selective exposure is applied (Figure 1). Mean polarity is highest (0.1541) for no

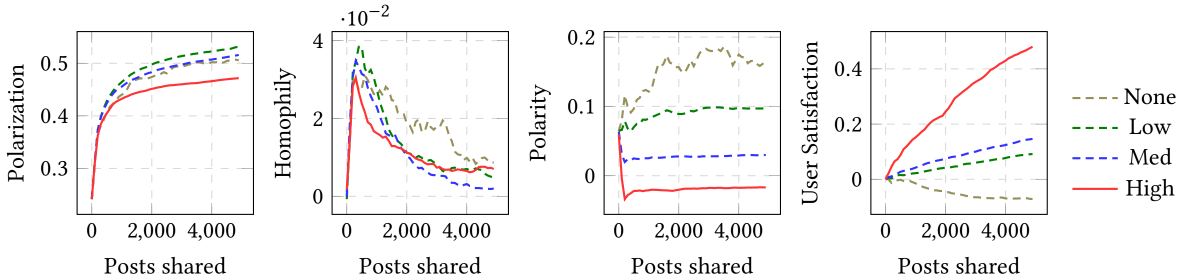


**Figure 1: Experiment 1 (Selective Exposure): Comparing polarization, homophily, network polarity, and user satisfaction of agents in the social network with different levels of selective exposure.**

selective exposure and lowest (-0.0192) for high selective exposure (Table 1).

All levels of selective exposure achieve better user satisfaction than when no content filtering (no selective exposure) is applied. User satisfaction increases with the increase in the level of selective exposure. High selective exposure consistently maintains a higher user satisfaction than when selective exposure is low, medium or none as shown in Figure 1. Mean user satisfaction is lowest (-0.0473) for no selective exposure and highest (0.2934) for high selective exposure. The proportion of satisfied users is highest when selective exposure is high, followed by medium, low and no selective exposure in that order (Table 2).

The number of highly active users reduce for all settings, most when selective exposure is low (from 82.07% at the start of the simulation to 28.13% when the simulation completed sharing 5k posts) and least for high selective exposure (from 82.07% to 51.52%). High selective exposure leads to a lower proportion of spreading and receiving agents compared to lower levels of selective exposure (Table 2).

***Takeaway (selective exposure).*** *High levels of selective exposure leads to lower levels of polarization and a higher user satisfaction than when selective exposure is low or none.*

## 4.2 Experiment 2: Imbalanced Discussion

We experiment by varying weights for different issues such that issues with higher weight fetch more intense sanctions and have a higher probability of being shared. We simulate four configurations, *config A:* all issues have the same weights; *config B:* issues are assigned weight randomly (with weights varying between 0.5x-3.0x); *config C:* weights of all issues favoring party1 are double (2x) of the weights of all issues favoring party2; *config D:* weights of all issues favoring party2 are double (2x) of the weights of all issues favoring party1. In each case, the issues are balanced in frequency and stance distribution for both sides, and we use the same posts for all the runs.

Results across different configurations for experiments with different issue weights show minor variations as shown in Figure 2. The experiments show little difference for all metrics across the four configurations we experiment.

***Takeaway (imbalanced).*** *Imbalanced discussion leads to similar levels of polarization as balanced discussions.*

## 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. The 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 the 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. The mean polarization is lowest (0.3647) when the tolerance level is high and the highest (0.4935) when tolerance is low (Table 1). Mean polarity is the lowest (0.1083) for high tolerance and highest (0.1817) for medium tolerant users. Mean user satisfaction is highest when tolerance is high among agents and lowest when tolerance is low.

The proportion of unsatisfied users is highest (73.53%) when tolerance is low and lowest (56.33%) when tolerance is high. The proportion of highly polarized agents is lowest (3.62%) when tolerance is high and highest (10.00%) when tolerance is low. The number of highly active users declines more when agents are less tolerant than when agents are tolerant (Table 2).

***Takeaway (tolerance).*** *High tolerance in agents slows down polarization and leads to less number of highly polarized agents and better user satisfaction.*

# 5 DISCUSSION

Surprisingly, selective exposure leads to early saturation and less polarization compared to lower levels and no selective exposure. This may be caused due to less content sharing among agents with a vastly different stances on an issue. This is evident in the lower number of spreader and receiving agents when selective exposure is high compared to low/medium or no selective exposure. As expected, user satisfaction is higher for higher levels of selective exposure. High selective exposure leads to most user satisfaction and no selective exposure leads to least.

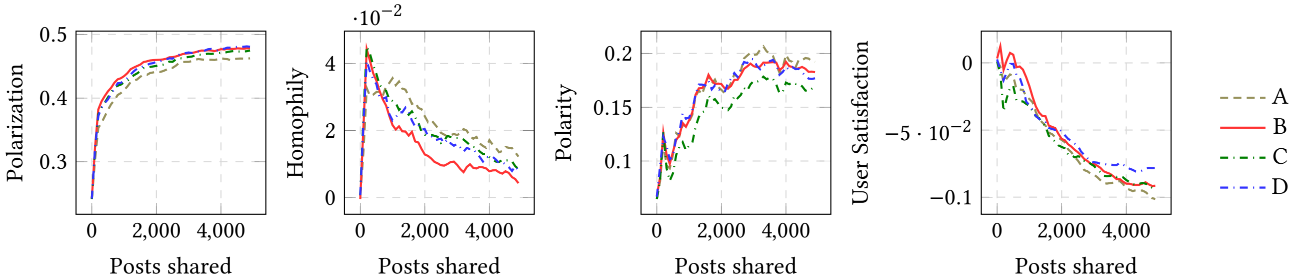


**Figure 2: Experiment 2 (Imbalanced Discussion): Comparing polarization, homophily, polarity, and user satisfaction of agents with different weights of issues being discussed. Configuration A corresponds to a balanced discussion (all issues weighed equally), B corresponds to a random imbalanced discussion, C corresponds to all issues favoring partyA weighed higher, and D corresponds to all issues favoring partyB weighed higher.**

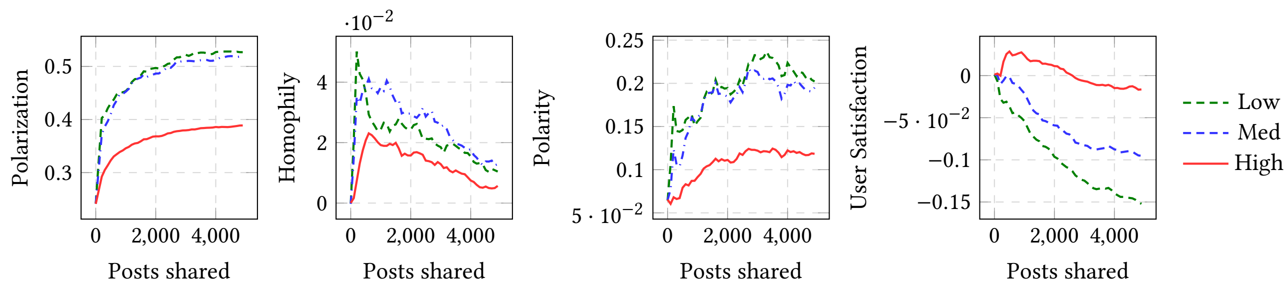


**Figure 3: Experiment 3 (Tolerance): Comparing polarization, homophily, network polarity, and user satisfaction of agents in the social network with different tolerance levels.**

| Experiments | Config | Receiving Agents | Spreader Agents | Disinterested Agents | Mean Polarization | Mean Homophily | Mean Polarity | Mean User Satisfaction |
|---|---|---|---|---|---|---|---|---|
| Selective Exposure | None | 9.381 | 4.2479 | 5.1331 | 0.4709 | 0.0184 | 0.1541 | -0.0473 |
| | High | 3.0078 | 1.5730 | 1.4347 | 0.4463 | 0.0116 | -0.0192 | 0.2934 |
| | Med | 6.1845 | 2.4949 | 3.6895 | 0.4791 | 0.0112 | 0.0274 | 0.0858 |
| | Low | 8.2600 | 3.3831 | 4.8769 | 0.4914 | 0.0141 | 0.0905 | 0.0511 |
| Imbalanced Discussions | Config A | 9.0541 | 4.0773 | 4.9768 | 0.4366 | 0.0224 | 0.1708 | -0.0645 |
| | Config B | 5.6732 | 2.6799 | 2.9933 | 0.4549 | 0.0150 | 0.1678 | -0.0571 |
| | Config C | 6.7032 | 3.1570 | 3.5462 | 0.4478 | 0.0204 | 0.1504 | -0.0642 |
| | Config D | 6.6865 | 3.1435 | 3.5430 | 0.4525 | 0.0188 | 0.1680 | -0.0553 |
| Tolerant Users | High | 12.6243 | 5.5522 | 7.0721 | 0.3647 | 0.0129 | 0.1083 | 0.0022 |
| | Med | 9.2966 | 4.1867 | 5.1099 | 0.4832 | 0.0263 | 0.1817 | -0.0612 |
| | Low | 8.1014 | 3.5293 | 4.5721 | 0.4935 | 0.0218 | 0.1964 | -0.1020 |

**Table 1: Summary from average of 10 independent simulation runs for different setups and configurations. Values for receiving agents, spreader agents, and disinterested agents are all in %. Config A: all issues weigh equal, config B: random weights for issues, config C: all party1 favoring issues weigh higher, and config D: All party2 favoring issues weigh higher.**

Varying the weights of issues didn't seem to have much impact on polarization, and different configurations show little variations. This could be because a higher weight for an issue fetches more intense sanctions, both positive and negative but do not bias the opinion in either direction, leading to the same levels of polarization.

Polarization is slowed down substantially when tolerance in users is high. Simulation setup with most tolerant users experience least network polarization and end up with least network polarity than when agents are less tolerant. 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 a higher number of

| Experiments | Config | Neutral Satisfied | Satisfied Users | Unsatisfied Users | Low Activity | Medium Activity | High Activity | Low Polarized | Highly Polarized |
|---|---|---|---|---|---|---|---|---|---|
| Initial User Distribution | | 100 | 0 | 0 | 1.2627 | 16.6625 | 82.0748 | 96.7071 | 3.2929 |
| Selective Exposure | None | 1.6588 | 36.2218 | 62.1193 | 29.0171 | 32.8547 | 38.1282 | 92.6962 | 7.3038 |
| | High | 1.8321 | 73.4588 | 24.7091 | 18.5442 | 29.9332 | 51.5226 | 96.0634 | 3.9366 |
| | Med | 1.7826 | 57.2667 | 40.9507 | 37.6083 | 31.4682 | 30.9235 | 96.5090 | 3.4910 |
| | Low | 1.7331 | 53.9738 | 44.2931 | 38.772 | 33.1023 | 28.1258 | 94.2560 | 5.7440 |
| Imbalanced Discussion | Config A | 1.6588 | 32.7309 | 65.6103 | 30.6512 | 31.8148 | 37.5340 | 92.5229 | 7.4771 |
| | Config B | 2.0550 | 34.5878 | 63.3573 | 46.2986 | 29.2399 | 24.4615 | 93.3399 | 6.6601 |
| | Config C | 1.8074 | 35.3553 | 62.8373 | 41.1983 | 30.0569 | 28.74478 | 93.8103 | 6.1897 |
| | Config D | 2.0054 | 36.9894 | 61.0052 | 39.7128 | 30.7749 | 29.5123 | 92.8200 | 7.1800 |
| Tolerant Users | High | 1.5350 | 42.1391 | 56.3258 | 24.4862 | 34.1174 | 41.3964 | 96.3852 | 3.6148 |
| | Med | 1.7331 | 33.4736 | 64.7933 | 30.8493 | 32.6318 | 36.5189 | 89.8242 | 10.1758 |
| | Low | 1.6836 | 24.7834 | 73.5331 | 34.7363 | 31.4187 | 33.8450 | 89.9975 | 10.0025 |

**Table 2: Summary from an average of 10 simulation runs comparing user distribution (based on frequency) between initial and final states of the agent for different simulation setups and configurations (Values are in %). Config A-D are the same as described in Table1 description.**

receiving and spreader agents, demonstrating that more sharing happens when agents are more tolerant. This also leads to the highest proportion of disinterested agents, demonstrating that many agents chose not to share posts further in their network. The proportion of disinterested agents is highest when agents have a high tolerance.

Across all experimental settings, high selective exposure achieves the highest mean user satisfaction and one of the lowest proportions of highly polarized users. Also, high tolerance in agents leads to the lowest levels of polarization and most disinterested agents across all experiments.

## 5.1 Limitations

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

*First*, sharing of posts and opinion shifts are 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 (i.e., has reached all agents it could have). This limits our simulation to not factor in the 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 and 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 incur some threats to validity.

*First*, we assume equal strength of ties between each pair of connected agents. In reality, people have varying strengths of ties, affecting how they react to posts from others and how it influences them. *Second*, we do not consider offline events that may influence an agent's inclination towards 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 of factors that affect such decisions.

# 6 CONCLUSION

We develop a multiagent social simulation to investigate the dynamics of polarization in social networks. Via simulation experiments, we find that higher selective exposure to congenial content leads to early saturation and lower polarization along with higher user satisfaction than when selective exposure is low or none. Also, higher user tolerance substantially slows down polarization in a social network and achieves a better user satisfaction. Imbalanced discussions on an issue show minor variations in network polarization and homophily across different experimental setups.

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 this analysis. Further, 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 |
|---|---|
| $c$ | A constant (scale factor) to scale up smaller values. We use the value of 10. |
| $a_x$ | Agent $x$ |
| $p_k$ | $k^{\text{th}}$ post shared in the network |
| $uS(a_x, i)$ | Stance of $a_x$ toward issue $i$ |
| $pS(p_k, i)$ | Stance of $p_k$ toward issue $i$ |
| $uA(a_x, p_k)$ | Activity score for $a_x$ while $p_k$ is being shared |
| $pP(a_x, p_k)$ | Privacy preference of $a_x$ as $p_k$ is being shared |
| $sP(a_x, p_k)$ | Probability of agent $a_x$ to share post $p_k$ |
| $sS(a_x, p_k)$ | Sanction score $a_x$ provides on receiving $p_k$ |
| $aD(a_x, a_y, i)$ | Difference in attitude between $a_x$ and $a_y$ toward the issue $i$ |
| $aS(a_x, p_k)$ | 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 |
| $pS(a_x, p_{k\text{-}1})$ | All the posts shared by $a_x$ prior to $p_k$ |
| $N(G, a_x)$ | all agents directly connected to agent $a_x$ in the social network $G$ |
| $num(G, agents)$ | Total number of agents in the social network $G$ |

**A.2: Secondary metrics to compare the change in initial and final states of users.**

| Metric | Description |
|---|---|
| Neutral Satisfied | Agents with user satisfaction equal to zero |
| Satisfied Users | Agents with user satisfaction greater than zero |
| Unsatisfied Users | Agents with user satisfaction less than zero |
| Low Activity | Agents with user activity score equal to or lower than 0.33 |
| Medium Activity | Agents with user activity score greater than 0.33 and lower than 0.67 |
| High Activity | Agents with user activity score equal to or more than 0.67 |
| Low Polarized | Agents with Political inclination over $[-0.5, 0.5]$ |
| Highly Polarized | Agents with Political inclination greater than 0.5 or lower than $-0.5$ |