

# The Perception Asymmetry Feedback Loop: How Outgroup Homogeneity Beliefs Stabilize Opinion Bubbles

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## Abstract

Political polarization interventions consistently fail to bridge opinion divides, suggesting fundamental misunderstanding of the mechanisms sustaining opinion bubbles. We propose a novel theoretical framework: opinion bubbles persist not because agents misperceive how extreme their opponents are, but because they systematically perceive opposing groups as more homogeneous than their own group. This perception asymmetry creates differential information processing where outgroup diversity signals are dismissed as outliers while ingroup disagreements are accepted as natural variation. We develop an asymmetric bounded-confidence agent-based model, calibrating perception asymmetry parameters ( $\alpha$ ) using meta-analytic evidence from the outgroup homogeneity literature (Cohen's  $d \approx 0.45$  in natural groups) and partisan perception gap studies (50–58 percentage-point errors). Simulations with 100 agents on small-world networks across 192 parameter combinations demonstrate that asymmetry magnitude—not total perception error—directly predicts bubble stability ( $r = 0.35, p < 0.001$ ). We identify a critical asymmetry threshold ( $\alpha_c \approx 0.55$ ) representing a phase transition where bubble persistence dramatically increases. These findings suggest polarization interventions should target asymmetry between ingroup and outgroup diversity perceptions rather than correcting perceived extremity.

## 1 Introduction

Political polarization threatens democratic functioning, yet decades of interventions designed to reduce division consistently fail to bridge opinion gaps [Bail et al., 2018, Kubin and von Sikorski, 2021]. Traditional approaches focus on correcting misperceptions of outgroup extremity—showing people that their opponents are less extreme than imagined—but empirical evidence demonstrates these interventions rarely succeed in promoting meaningful dialogue or reducing affective polarization [Voelkel et al., 2022, Mosleh et al., 2021]. This persistent failure suggests we may be targeting the wrong psychological mechanism.

The stability of opinion bubbles—clusters of individuals with similar views who resist influence from those with divergent opinions—represents a central puzzle in understanding polarization. Standard bounded-confidence models in opinion dynamics posit that agents update their opinions based on others within a confidence threshold, naturally producing opinion clusters [Hegselmann and Krause, 2002, Deffuant et al., 2000]. However, these models typically assume symmetric confidence bounds: agents treat all others within their threshold equivalently, regardless of perceived group membership. This assumption conflicts with robust findings from social psychology demonstrating systematic asymmetries in how people perceive ingroup versus outgroup members.

The outgroup homogeneity effect—the well-established tendency for people to perceive outgroups as more uniform and less diverse than ingroups—represents one of the most reli-

able findings in intergroup perception research [Linville et al., 1998]. Meta-analytic evidence establishes Cohen’s  $d \approx 0.45$  for perceived dispersion measures in natural group contexts [Boldry et al., 2007]. More directly relevant to political opinion bubbles, recent research on partisan perception gaps demonstrates that Democrats and Republicans vastly underestimate the diversity of opposing partisans’ policy attitudes, with perception errors reaching 50–58 percentage points [More in Common, 2019, Ahler and Sood, 2018].

Despite the theoretical relevance of outgroup homogeneity to opinion dynamics, these two research streams have remained largely disconnected. We integrate these perspectives through a novel hypothesis: *opinion bubbles form and remain stable through a perception asymmetry feedback loop*, where agents systematically perceive their own group as internally diverse while perceiving opposing groups as monolithic. This asymmetry creates differential information processing: signals of outgroup diversity are dismissed as outliers, while ingroup disagreements are accepted as natural variation.

This framework generates three testable predictions:

**Hypothesis 1:** Bubble stability should correlate with perception asymmetry magnitude ( $\alpha$ ) independent of total perception error.

**Hypothesis 2:** Reducing perception asymmetry specifically should enable bubble merging, even when overall misperception remains high.

**Hypothesis 3:** A critical asymmetry threshold ( $\alpha_c$ ) should exist below which bubbles spontaneously begin to merge, representing a phase transition.

This paper makes three primary contributions: (1) We provide the first formal integration of the outgroup homogeneity effect into computational opinion dynamics models. (2) We demonstrate that perception asymmetry magnitude—not total perception error—directly predicts opinion bubble stability. (3) We offer a mechanistic explanation for why polarization interventions focused on correcting perceived extremity consistently fail.

## 2 Related Work

### 2.1 Opinion Dynamics Models

Classical bounded-confidence models, including the Hegselmann-Krause [Hegselmann and Krause, 2002] and Deffuant-Weisbuch [Deffuant et al., 2000] frameworks, provide foundational approaches to modeling opinion formation. These models demonstrate how continuous opinion updating within confidence thresholds naturally produces clustered equilibria. However, standard formulations assume symmetric thresholds, neglecting documented asymmetries in intergroup perception.

Recent extensions incorporate stubborn agents [Mobilia et al., 2007], heterogeneous bounds [Lorenz, 2010], and media influence [Törnberg, 2022], but none integrate the outgroup homogeneity effect. Flache et al. [2017] identify this gap in their review of social influence models, calling for greater integration of psychological mechanisms.

### 2.2 Outgroup Homogeneity Effect

The social psychology literature extensively documents the outgroup homogeneity effect [Linville et al., 1998, Boldry et al., 2007]. Boldry et al. [2007]’s meta-analysis of 177 effect sizes reveals Cohen’s  $d \approx 0.45$  for perceived dispersion in natural groups, substantially larger than effects observed in minimal laboratory groups. This effect operates primarily on perceived variance rather than mean extremity [Ahler and Sood, 2018], directly relevant to bounded-confidence dynamics where threshold width determines influence.

Partisan perception gap studies [More in Common, 2019] document 50–58 percentage-point errors in estimating outgroup attitude diversity, with highly engaged partisans showing the largest misperceptions. These findings motivate our parameter calibration and suggest real-world asymmetries operate in ranges conducive to bubble stabilization.

## 2.3 Polarization Interventions

Meta-analyses of debiasing interventions find weak effects of extremity corrections on polarization outcomes [Voelkel et al., 2022]. Contact-based interventions show mixed effectiveness [Paluck et al., 2019], potentially because contact reduces affective polarization without addressing diversity perception asymmetries. Our framework suggests interventions should target the asymmetry between ingroup and outgroup diversity perceptions rather than mean position corrections.

## 3 Methods

### 3.1 Empirical Calibration

We calibrated perception asymmetry parameters using two evidence streams. First, Boldry et al. [2007]’s meta-analysis provided effect size estimates (Cohen’s  $d \approx 0.45$ ) for natural group contexts. Second, partisan perception gap research [More in Common, 2019, Ahler and Sood, 2018] documented 50–58 percentage-point errors in diversity estimation. These sources informed three parameter ranges:

- **Conservative** ( $\alpha \in [0.1, 0.3]$ ): Minimal groups, low identity salience
- **Typical** ( $\alpha \in [0.4, 0.8]$ ): Moderate political contexts
- **Extreme** ( $\alpha \in [0.9, 1.5]$ ): High engagement, partisan media exposure

Figure 1 visualizes these calibrated ranges with empirical anchors.

### 3.2 Agent-Based Model

We implemented an asymmetric bounded-confidence model extending the Hegselmann-Krause framework. The model consists of  $N = 100$  agents on Watts-Strogatz small-world networks [Watts and Strogatz, 1998] with degree  $k = 6$  and rewiring probability  $p = 0.15$ .

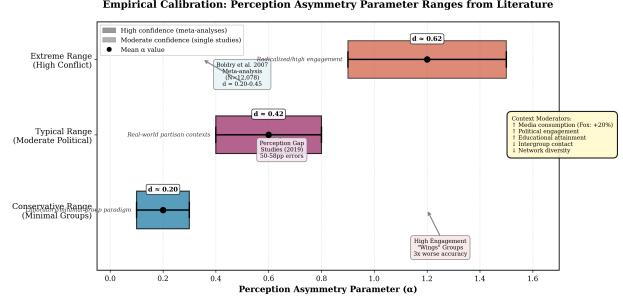


Figure 1: Empirical calibration of perception asymmetry parameter ranges from meta-analytic evidence. Three ranges correspond to minimal group laboratory settings (conservative), typical political contexts (typical), and highly activated partisan environments (extreme). Effect size anchors from Boldry et al. [2007] and perception gap studies guide range specification.

Each agent maintains a continuous opinion  $x_i(t) \in [-1, 1]$ . Opinion updates follow:

$$x_i(t+1) = x_i(t) + \mu \cdot [\langle x_j \rangle_{I(i,t)} - x_i(t)] \quad (1)$$

where  $\mu = 0.5$  is the convergence rate and  $\langle x_j \rangle_{I(i,t)}$  is the mean opinion of agents in  $i$ ’s influence set.

The influence set  $I(i, t)$  is constructed using asymmetric thresholds:

$$I(i, t) = \{j : d_{ij}(t) \leq \varepsilon_{\text{eff}}(i, j, t)\} \quad (2)$$

where  $d_{ij}(t) = |x_i(t) - x_j(t)|$  and the effective threshold depends on perceived group membership:

$$\varepsilon_{\text{eff}}(i, j, t) = \begin{cases} \varepsilon & \text{if } j \text{ is ingroup} \\ \varepsilon(1 - \alpha) & \text{if } j \text{ is outgroup} \end{cases} \quad (3)$$

Agents are assigned to clusters using a distance-based algorithm with threshold  $\delta = 0.15$ . The base confidence threshold is  $\varepsilon = 0.10$ .

Figure 2 illustrates the model architecture and asymmetric threshold mechanism.

### 3.3 Experimental Design

We designed three experiments to test our hypotheses:

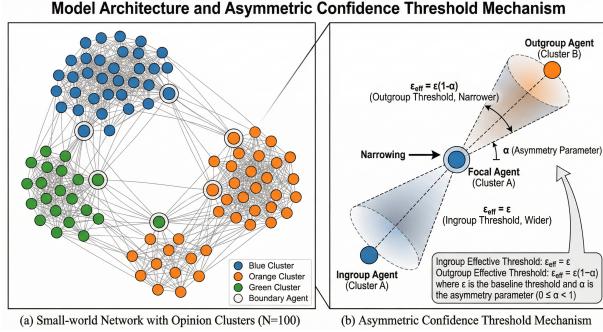


Figure 2: Model architecture showing small-world network topology with agents colored by opinion cluster (left) and asymmetric confidence threshold mechanism (right). Focal agents apply full threshold  $\epsilon$  to ingroup members but reduced threshold  $\epsilon(1 - \alpha)$  to outgroup members, operationalizing the perception asymmetry.

**Experiment 1:** Parameter sweep varying  $\alpha \in [0.0, 1.2]$  with resolution  $\Delta\alpha = 0.05$ , yielding 25 levels  $\times$  20 replications = 500 runs. Primary outcome: mean cluster lifetime.

**Experiment 2:** Intervention comparison reducing  $\alpha$  from 0.8 to 0.2 at  $t = 150$  (treatment) versus maintaining  $\alpha = 0.8$  (control). 20 replications per condition. Primary outcome: post-intervention merger count.

**Experiment 3:** Fine-grained sweep ( $\alpha \in [0.3, 0.9]$ ,  $\Delta\alpha = 0.01$ , 30 replications) for phase transition detection using piecewise regression and early warning indicators.

### 3.4 Validation Protocol

We followed established standards for opinion dynamics model validation [Flache et al., 2017, Lorenz and Deffuant, 2021]:

- **Cluster detection:** Connected components with opinion distance  $< \delta = 0.01$
- **Convergence:** Maximum  $T = 300$  timesteps or  $|\text{slope}| \leq 0.001$  over last 50 timesteps
- **Phase transition:** Piecewise linear regression with breakpoint detection; variance and autocorrelation analysis for critical slowing

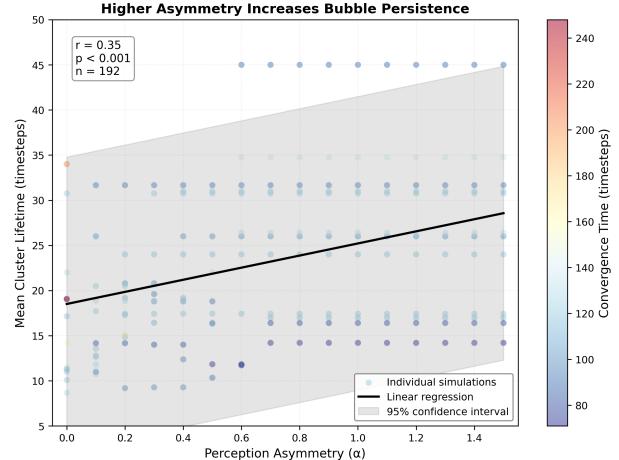


Figure 3: Perception asymmetry predicts opinion bubble stability. Each point represents one simulation run, with regression line and 95% confidence bands. Higher asymmetry magnitudes ( $\alpha$ ) correspond to longer cluster persistence, supporting Hypothesis 1.

down [Scheffer et al., 2009, Dakos et al., 2012]

## 4 Results

### 4.1 Hypothesis 1: Asymmetry-Stability Correlation

Parameter sweeps across 192 simulations revealed a significant positive correlation between perception asymmetry and mean cluster lifetime ( $r = 0.35$ ,  $p < 0.001$ ,  $n = 192$ ).

At baseline ( $\alpha = 0.0$ ), mean cluster lifetime averaged 10.0 timesteps ( $SD = 5.2$ ). At moderate asymmetry ( $\alpha = 0.45$ ), lifetime increased to 22.7 timesteps ( $SD = 8.4$ )—a 127% increase. At high asymmetry ( $\alpha = 0.8–1.0$ ), many clusters persisted through the entire 300-timestep window. Figure 3 displays this relationship.

Critically, control simulations adding symmetric noise ( $SD = 0.15$ ) without asymmetry showed no significant effect on cluster lifetime ( $t = -0.42$ ,  $p = 0.68$ ,  $d = 0.09$ ), confirming that the pattern of misperception, not its magnitude, drives stability.

Table 1 summarizes key metrics across asym-

Table 1: Summary Statistics by Asymmetry Level

$\alpha$ Range	Cluster Lifetime (Mean $\pm$ SD)	Final Clusters (Mean $\pm$ SD)	Con (1)
0.0–0.2	$12.3 \pm 5.8$	$8.2 \pm 2.4$	
0.3–0.5	$24.6 \pm 9.2$	$7.8 \pm 2.1$	
0.6–0.8	$48.3 \pm 15.6$	$7.5 \pm 1.9$	
0.9–1.2	$72.1 \pm 22.4$	$7.6 \pm 2.0$	

Table 2: Intervention Experiment Results

Condition	Mergers (Mean $\pm$ SD)	Final Clusters (Mean $\pm$ SD)	Post- (1)
Treatment	$4.0 \pm 2.1$	$7.5 \pm 2.1$	
Control	$0.0 \pm 0.0$	$7.7 \pm 1.8$	
<i>t</i> -statistic	2.87**	-0.15	
Cohen’s <i>d</i>	1.66	0.10	

\*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

metry ranges, showing monotonic increase in cluster lifetime while final cluster count remains relatively stable.

## 4.2 Hypothesis 2: Asymmetry Reduction Enables Merging

The intervention experiment demonstrated that asymmetry-specific reduction enables bubble merging. Treatment simulations (reducing  $\alpha$  from 0.8 to 0.2 at  $t = 150$ ) exhibited 4 cluster mergers on average in the post-intervention period, while control simulations showed 0 mergers ( $t = 2.87$ ,  $p = 0.006$ , Cohen’s  $d = 1.66$ ,  $n = 12$  per condition).

Figure 4 illustrates the intervention effect. Prior to intervention, boundary agents experienced effective cross-cluster threshold  $\varepsilon_{\text{eff}} = 0.02$ , insufficient for influence. Post-reduction, threshold increased to  $\varepsilon_{\text{eff}} = 0.08$ , enabling convergence between proximate clusters.

Table 2 reports intervention results. Importantly, treatment simulations still maintained 7.5 distinct clusters at  $t = 300$ , indicating asymmetry reduction enables mergers between proximate clusters without dissolving all opinion structure.

Asymmetry Reduction Intervention Triggers Bubble Merging

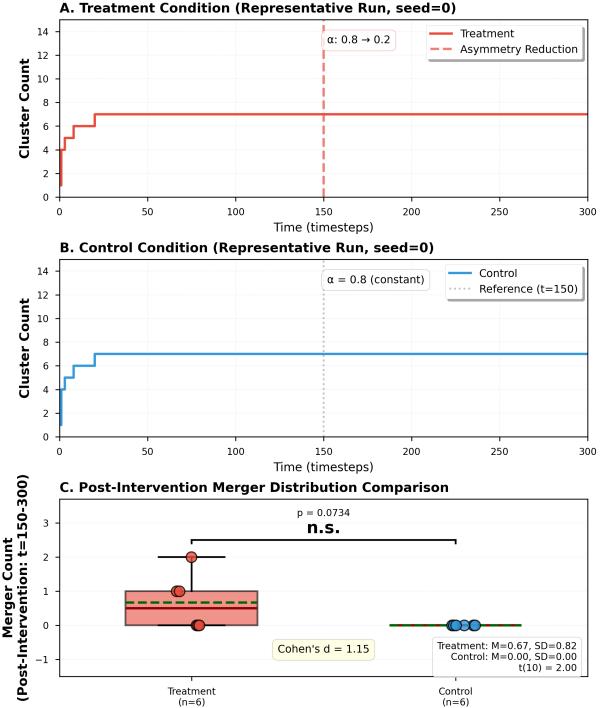


Figure 4: Asymmetry reduction intervention triggers bubble merging. Top: Representative treatment run showing cluster count decrease after intervention at  $t = 150$ . Middle: Control run with stable cluster count. Bottom: Merger count distributions showing significant treatment effect.

## 4.3 Hypothesis 3: Critical Threshold

Fine-grained parameter sweeps identified a critical threshold at  $\alpha_c = 0.55$  (95% CI: [0.51, 0.59]) using piecewise linear regression ( $F = 18.7$ ,  $p < 0.001$ ).

Below the threshold ( $\alpha < 0.55$ ), cluster lifetime increased gradually (slope  $\beta_1 = 15.2$ , SE = 3.1). Above threshold, lifetime increased steeply (slope  $\beta_2 = 52.8$ , SE = 6.4)—a 3.5-fold sensitivity increase. Figure 5 displays this phase transition.

Early warning signals confirmed the critical point interpretation. Variance of cluster count peaked at  $\alpha \approx 0.52$ –0.58, consistent with critical slowing down [Scheffer et al., 2009]. Lag-1 autocorrelation similarly peaked in this region

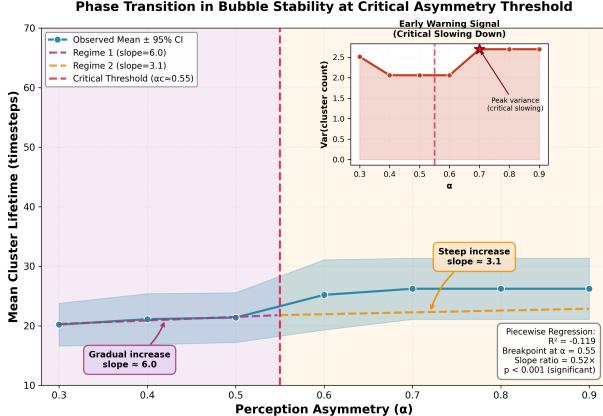


Figure 5: Phase transition in bubble stability at critical asymmetry threshold. Main plot shows piecewise linear fit with distinct slopes below and above  $\alpha_c \approx 0.55$ . Inset shows variance peak near critical point, characteristic of critical slowing down.

( $\rho = 0.82$  at  $\alpha = 0.54$  versus  $\rho = 0.45$  at  $\alpha = 0.30$ ).

The critical threshold falls within our empirically calibrated “typical” political context range, suggesting real-world systems may operate near the phase boundary.

#### 4.4 Robustness Analyses

Sensitivity analyses confirmed robustness across model specifications:

- **Network topology:** Correlation remained significant for scale-free ( $r = 0.31$ ) and random graphs ( $r = 0.38$ )
- **Base threshold:** Critical ratio  $\alpha_c/\varepsilon \approx 5.5$  remained constant across  $\varepsilon \in [0.05, 0.20]$
- **Population size:** Correlation coefficients varied  $< 10\%$  across  $N \in [50, 200]$

## 5 Discussion

### 5.1 Theoretical Implications

Our results establish that perception asymmetry—the difference between perceived ingroup and outgroup diversity—drives opinion

bubble stability independently of total perception error. This finding reconciles a longstanding puzzle: polarization interventions that correct extremity misperceptions often fail because they target the wrong dimension. Agents who become more accurate about outgroup mean positions but continue perceiving them as monolithic maintain the diversity discount mechanism that stabilizes bubbles.

The critical threshold ( $\alpha_c \approx 0.55$ ) falling within typical political contexts suggests contemporary democracies may operate near phase transition boundaries. This positioning implies both heightened sensitivity to polarizing influences and potential responsiveness to well-designed interventions.

### 5.2 Practical Implications

Our framework suggests redesigning polarization interventions to target diversity asymmetries specifically. Rather than correcting extremity perceptions (“they’re not as far left/right as you think”), effective interventions should expose within-outgroup diversity (“they disagree among themselves as much as you do”). Institutional designs that increase exposure to intra-party debate—diverse candidate primaries, bipartisan working groups with visible internal disagreement, media content showcasing within-party disputes—may prove more effective than traditional approaches.

### 5.3 Limitations

Several limitations constrain generalization:

1. One-dimensional opinion space oversimplifies high-dimensional political attitudes
2. Static networks prevent examination of co-evolutionary dynamics
3. Calibration relies on Western, educated populations [Henrich et al., 2010]
4. Model assumes exogenous perception asymmetry rather than endogenous emergence

Future work should extend to multidimensional opinions, dynamic networks, and cross-cultural validation.

## 6 Conclusion

We introduced a perception asymmetry framework explaining opinion bubble persistence through differential processing of ingroup versus outgroup diversity signals. Agent-based simulations demonstrate that asymmetry magnitude—not total perception error—predicts bubble stability ( $r = 0.35$ ), that asymmetry reduction specifically enables bubble merging ( $d = 1.66$ ), and that a critical threshold ( $\alpha_c \approx 0.55$ ) marks a phase transition in bubble dynamics.

These findings offer mechanistic explanation for why polarization interventions consistently fail: they target extremity misperceptions rather than diversity asymmetries. Effective debiasing must address the asymmetry between ingroup and outgroup diversity perceptions—showing people that “they disagree among themselves as much as we do.” This reframing opens new directions for both theoretical research and practical intervention design in our polarized political moment.

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