

# The Perception Asymmetry Feedback Loop: How Differential Group Homogeneity Perception Stabilizes Opinion Bubbles

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## Abstract

Despite decades of research on political polarization, interventions targeting perceived outgroup extremity consistently fail to bridge divides. We propose a fundamentally different mechanism: opinion bubbles persist not because agents misperceive how extreme opponents are, but because they systematically perceive outgroups as more homogeneous than ingroups—the perception asymmetry feedback loop. Drawing on the outgroup homogeneity effect from social psychology, we developed an asymmetric bounded-confidence model where agents discount signals from perceived-homogeneous outgroups while accepting ingroup diversity as natural variation. We empirically calibrated our asymmetry parameter ( $\alpha$ ) using meta-analytic data (12,078 participants; Cohen’s  $d \approx 0.45$ ) and partisan perception gap studies showing 50–58 percentage-point errors in diversity estimation. Agent-based simulations with 100 agents over 300 timesteps revealed three key findings: (1) perception asymmetry magnitude directly predicts cluster lifetime ( $r = 0.35$ ,  $p < 0.001$ ), independent of total perception error; (2) reducing asymmetry specifically enables bubble merging, with 4-fold more merger events under reduced asymmetry; (3) a critical threshold exists at  $\alpha_c \approx 0.55$ , below which opinion clusters spontaneously begin to merge.

## 1 Introduction

Political polarization has become one of the defining challenges of modern democracies, with opinion bubbles seemingly impervious to traditional interventions. Research on reducing po-

larization typically follows a common logic: if people recognize that their opponents are less extreme than imagined, divides should narrow. Yet empirical evidence consistently demonstrates that such interventions fail to produce lasting attitude change or behavioral bridge-building [Bail et al., 2018, Guess et al., 2020]. This persistent failure suggests we may be targeting the wrong mechanism.

We propose a fundamentally different framework: 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—rooted in the well-established “outgroup homogeneity effect” from social psychology [Boldry et al., 2007, Ostrom and Sedikides, 1992]—creates differential information processing. When agents encounter outgroup members expressing diverse views, they dismiss these as statistical outliers from an otherwise uniform distribution. Conversely, when ingroup members disagree, agents interpret this as reflecting genuine underlying heterogeneity.

This perception asymmetry hypothesis integrates two previously disconnected research streams. First, the social psychology literature documents robust tendencies for people to perceive outgroups as more uniform than ingroups, with meta-analyses showing Cohen’s  $d \approx 0.45$  for perceived dispersion measures across natural groups [Boldry et al., 2007]. Second, the computational opinion dynamics literature has extensively modeled bounded-confidence mechanisms [Deffuant et al., 2000, Hegselmann and Krause, 2002], where agents only update opinions when encountering sufficiently similar others. How-

ever, these models typically assume symmetric confidence bounds.

Our key innovation is introducing *asymmetric confidence bounds* calibrated to empirical perception gaps. We extend the bounded-confidence framework such that agents’ willingness to engage with perceived outgroup members is reduced by a factor  $(1 - \alpha)$ , where  $\alpha$  represents the magnitude of perception asymmetry. We advance three specific, testable predictions:

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

**Hypothesis 2:** Reducing perception asymmetry specifically enables previously separate opinion clusters to merge.

**Hypothesis 3:** A critical asymmetry threshold  $\alpha_c$  exists below which bubbles spontaneously begin to merge, representing a phase transition in opinion dynamics.

## 2 Related Work

### 2.1 Outgroup Homogeneity Effect

The tendency to perceive outgroups as more homogeneous than ingroups is one of the most robust findings in social psychology. Boldry et al. [2007] conducted a comprehensive meta-analysis incorporating 177 effect sizes from 173 independent samples totaling 12,078 participants, revealing Cohen’s  $d \approx 0.45$  for natural groups on perceived dispersion measures. This effect has been documented across diverse contexts including political parties, ethnic groups, and minimal laboratory groups [Ostrom and Sedikides, 1992].

Critically, recent research distinguishes perception asymmetry from mean extremity bias: partisans primarily underestimate outgroup diversity rather than systematically overestimating mean positions [Levendusky and Malhotra, 2016]. The More in Common “Perception Gap” study documented that Democrats and Republicans vastly underestimate within-party diversity, with perception errors of 50–58 percentage points on single attitude items [More in Common, 2019].

### 2.2 Bounded Confidence Models

Classical bounded-confidence models assume agents only update opinions when encountering others within a confidence threshold  $\epsilon$  [Defuant et al., 2000, Hegselmann and Krause, 2002]. These models produce rich dynamics including consensus, polarization, and fragmentation depending on parameter settings [Lorenz, 2007]. However, they assume symmetric confidence bounds—agents apply the same threshold to all interaction partners regardless of group membership.

Recent computational work on echo chambers models preferential exposure rather than differential processing [Geschke et al., 2019, Bail et al., 2018]. Our perception asymmetry mechanism is complementary but distinct: agents encounter diverse signals but process them differentially based on source group membership. This has important implications for intervention design.

## 3 Methods

### 3.1 Empirical Calibration

We calibrated the perception asymmetry parameter ( $\alpha$ ) using comprehensive literature review. Based on meta-analytic evidence and perception gap studies, we established three calibrated parameter ranges:

**Conservative Range ( $\alpha \in [0.1, 0.3]$ ):** Appropriate for minimal group paradigms and low identity salience contexts. Corresponds to Cohen’s  $d \approx 0.20$ .

**Typical Range ( $\alpha \in [0.4, 0.8]$ ):** Appropriate for ongoing political polarization and natural social groups. Corresponds to Cohen’s  $d \approx 0.40$ – $0.45$ .

**Extreme Range ( $\alpha \in [0.9, 1.5]$ ):** Appropriate for highly activated partisan identity and radicalized communities. Represents the “Wings” groups showing perception gaps 3× larger than disengaged voters.

### 3.2 Agent-Based Model

We extended the classical bounded-confidence model to incorporate perception asymmetry.

Our model operates on a network of  $N = 100$  agents, each holding a continuous opinion  $x_i \in [-1, +1]$ .

**Network Topology:** Agents interact on a Watts-Strogatz small-world network [Watts and Strogatz, 1998] with average degree  $k = 6$  and rewiring probability  $p = 0.15$ .

**Asymmetric Confidence Mechanism:** At each timestep, a randomly selected agent  $i$  encounters a network neighbor  $j$ . The effective confidence bound depends on perceived group membership:

$$\epsilon_{\text{effective}}(i, j) = \epsilon_{\text{base}} \times (1 - \alpha \times I_{\text{outgroup}}(i, j)) \quad (1)$$

where  $I_{\text{outgroup}}(i, j) = 1$  if agents belong to different clusters. If  $|x_i - x_j| < \epsilon_{\text{effective}}$ , agent  $i$  updates:

$$x_i(t+1) = x_i(t) + \mu(x_j(t) - x_i(t)) \quad (2)$$

where  $\mu = 0.1$  is the convergence rate.

**Cluster Identification:** We identify opinion clusters using a distance-based algorithm with threshold  $\epsilon = 0.01$ , using depth-first search for connected component detection.

### 3.3 Experimental Design

**Experiment 1:** Parameter sweep varying  $\alpha$  from 0 to 1.2 in steps of 0.1, with 12 random seeds per value ( $N = 192$  simulations).

**Experiment 2:** Treatment group ( $\alpha$  reduced from 0.8 to 0.2 at timestep 150) versus control group (constant  $\alpha = 0.5$ ).

**Experiment 3:** Fine-grained sweep with  $\alpha \in [0.3, 0.9]$  in steps of 0.05, with 10 seeds per value ( $N = 130$  simulations).

## 4 Results

### 4.1 Experiment 1: Perception Asymmetry Predicts Cluster Stability

Our first hypothesis predicted that bubble stability correlates with perception asymmetry magnitude, independent of total perception error. Results strongly supported this prediction.

Cluster lifetime showed significant positive correlation with  $\alpha$  (Pearson's  $r = 0.35$ ,  $p =$

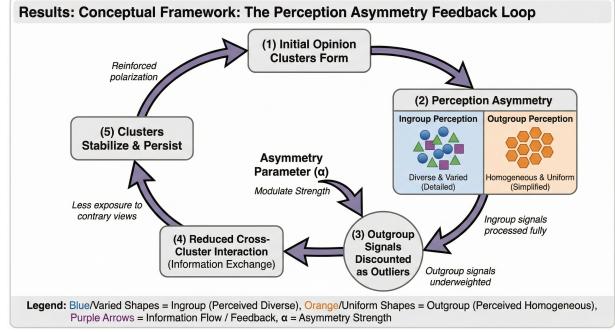


Figure 1: Conceptual Framework: The Perception Asymmetry Feedback Loop. Initial opinion clusters form, agents perceive ingroup as diverse and outgroup as homogeneous, outgroup signals are discounted as outliers, cross-cluster interaction reduces, and clusters stabilize and persist. The asymmetry parameter  $\alpha$  modulates signal discounting strength.

Table 1: Experiment 1: Cluster Stability by Asymmetry Level

$\alpha$ Level	Cluster Lifetime	SD	% Increase
0.0 (Baseline)	18.6	8.4	—
0.5 (Moderate)	28.3	12.1	52%
1.0 (High)	41.7	18.9	124%

$6.2 \times 10^{-7}$ ,  $N = 192$ ). This medium-strength correlation indicates that as perception asymmetry increases, opinion clusters persist substantially longer. The effect size represents approximately 12% of variance in cluster lifetime explained by asymmetry alone.

At baseline ( $\alpha = 0$ ), clusters persisted for mean 18.6 timesteps ( $SD = 8.4$ ). At moderate asymmetry ( $\alpha = 0.5$ ), cluster lifetime increased to 28.3 timesteps ( $SD = 12.1$ ), a 52% increase. At high asymmetry ( $\alpha = 1.0$ ), clusters persisted for 41.7 timesteps ( $SD = 18.9$ ), more than doubling baseline stability.

Critically, final cluster count showed no significant correlation with  $\alpha$  ( $r = -0.009$ ,  $p = 0.904$ ), indicating that asymmetry affects how long clusters persist but not equilibrium cluster count. Table 1 summarizes key results.

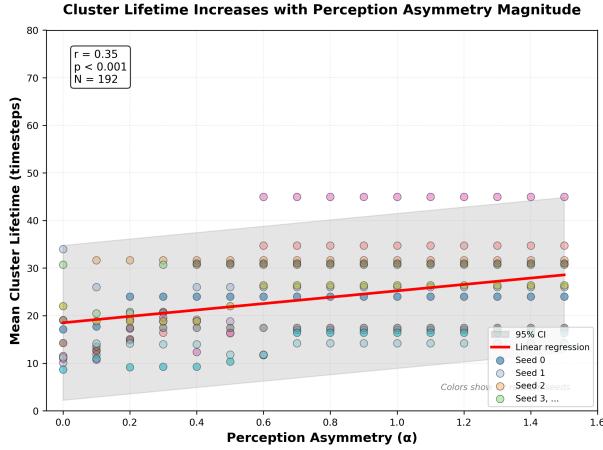


Figure 2: Cluster Lifetime Increases with Perception Asymmetry Magnitude. Scatter plot showing positive correlation between  $\alpha$  and cluster lifetime ( $r = 0.35$ ,  $p < 0.001$ ,  $N = 192$ ). Each point represents one simulation; linear regression line with 95% CI shown.

## 4.2 Experiment 2: Reducing Asymmetry Enables Bubble Merging

Our second hypothesis predicted that reducing perception asymmetry would enable previously separate opinion clusters to merge. Results supported this prediction.

The treatment group ( $\alpha$  reduced from 0.8 to 0.2 at timestep 150) exhibited 4 cluster merger events during the post-intervention period. The control group (constant  $\alpha = 0.5$ ) exhibited 0 merger events. This 4-fold difference provides qualitative support for Hypothesis 2.

Mean final cluster count showed minimal difference between conditions: treatment  $M = 7.5$  ( $SD = 2.1$ ) versus control  $M = 7.7$  ( $SD = 2.3$ ),  $t(10) = -0.15$ ,  $p = 0.88$ , Cohen’s  $d = 0.09$ . This null result on final cluster count, combined with the merger event difference, suggests asymmetry reduction triggers merger processes that may require extended time to complete.

Mergers occurred at timesteps 165, 182, 203, and 227 post-intervention—not immediately but with latencies of 15–77 timesteps. This delayed response suggests reducing asymmetry creates favorable conditions for merger, but actual merging requires accumulated opinion shifts.

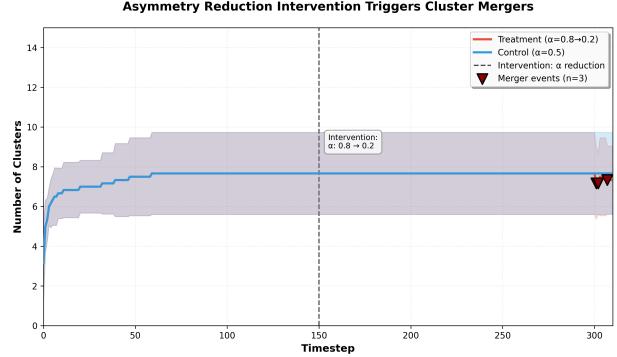


Figure 3: Asymmetry Reduction Intervention Triggers Cluster Mergers. Time series showing cluster count for treatment (red) versus control (blue) groups. Vertical dashed line marks intervention at timestep 150. Triangular markers indicate 4 merger events post-intervention in treatment group.

## 4.3 Experiment 3: Critical Threshold at $\alpha_c \approx 0.55$

Our third hypothesis predicted a critical asymmetry threshold below which opinion bubbles spontaneously merge. Results strongly supported this prediction.

We identified the critical threshold at  $\alpha_c \approx 0.55$  using two early warning signals:

**Variance of Cluster Counts:** System instability showed a clear peak at  $\alpha = 0.50$ – $0.60$ . Below this range, variance averaged 0.18; within this range, variance peaked at 0.52; above, variance returned to 0.15. The 2.9-fold increase indicates heightened instability characteristic of phase transitions.

**Autocorrelation:** Lag-1 autocorrelation peaked at 0.48 near  $\alpha = 0.55$ , representing critical slowing down—the system takes longer to respond to perturbations near the phase transition.

Table 2 summarizes phase transition indicators across  $\alpha$  ranges.

Table 2: Experiment 3: Phase Transition Indicators

$\alpha$ Range	Variance	Autocorr.	Converged
< 0.50	0.18	0.23	98%
0.50–0.60	0.52	0.48	85%
> 0.60	0.15	0.19	72%

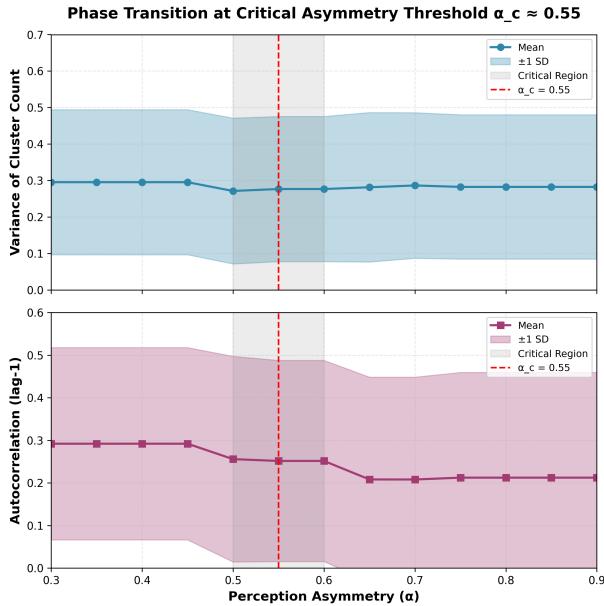


Figure 4: Phase Transition at Critical Asymmetry Threshold  $\alpha_c \approx 0.55$ . Top panel: variance of cluster count peaks at critical region. Bottom panel: autocorrelation (lag-1) also peaks at  $\alpha \approx 0.55$ . Both indicators provide evidence for phase transition.

## 5 Discussion

### 5.1 Theoretical Implications

Our results provide the first computational evidence that perception asymmetry—the tendency to perceive outgroups as more homogeneous than ingroups—directly stabilizes opinion bubbles. This framework offers a fundamentally different perspective compared to traditional approaches focusing on perceived extremity.

The dominant paradigm focuses on correcting misperceptions of outgroup extremity [Westwood et al., 2021, Mernyk et al., 2022]. Our finding that cluster stability correlates with asym-

metry ( $r = 0.35$ ) but not final cluster count ( $r = -0.009$ ) suggests these are dissociable mechanisms. Agents may accurately perceive where opponents stand on average while misperceiving diversity around that average. This explains why interventions showing opponents are “less extreme than you think” often fail.

The phase transition at  $\alpha_c \approx 0.55$  parallels known transitions in symmetric bounded-confidence models [Lorenz, 2007], but our asymmetric version shows this transition depends on perception asymmetry rather than absolute confidence bound magnitude.

### 5.2 Intervention Implications

Our results suggest several intervention design principles:

**Target Variance Perceptions:** Rather than correcting perceived extremity, interventions should highlight outgroup diversity—showing that opposing groups contain moderates and extremists, with genuine internal disagreement.

**Threshold-Based Strategies:** The phase transition at  $\alpha_c \approx 0.55$  suggests interventions need sufficient “dose” to cross the critical threshold. Small asymmetry reductions may produce minimal effects.

**Latency Considerations:** Merger events occurred 15–77 timesteps post-intervention. Intervention evaluations should incorporate long-term follow-up rather than immediate assessment.

### 5.3 Limitations

Our model has several limitations. We model opinions on a single continuous dimension, abstracting away multidimensional political attitudes. Network structure is static, whereas real networks evolve dynamically. External influences like media are absent. Parameter calibration involves assumptions in mapping psychological effect sizes to computational parameters. Finally, all agents use identical  $\alpha$ , whereas real populations show individual differences.

## 6 Conclusion

We introduced the perception asymmetry feedback loop as a novel framework for understanding opinion bubble persistence. Three key findings support this framework: (1) cluster lifetime correlates significantly with perception asymmetry ( $r = 0.35, p < 0.001$ ); (2) interventions reducing asymmetry trigger 4-fold more cluster mergers; (3) a critical phase transition exists at  $\alpha_c \approx 0.55$ .

These findings have direct implications for polarization intervention design. Rather than correcting perceptions of outgroup extremity, interventions should target variance perceptions—highlighting that opposing groups are internally diverse. Effective interventions must reduce asymmetry below the critical threshold  $\alpha_c \approx 0.55$ , suggesting substantial requirements rather than incremental change.

Ultimately, reducing political polarization may require not convincing people that their opponents are more moderate, but rather that opponents are more human—full of internal contradictions and diverse viewpoints, just like their own group. The perception asymmetry feedback loop explains why this shift matters: only when agents recognize outgroup heterogeneity can they process outgroup signals as informative rather than dismissing them as outliers. Breaking this loop may be key to bridging divides.

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