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THE EFFECT OF IN-GROUP FAVORITISM ON THE COLLECTIVE BEHAVIOR OF INDIVIDUALS' OPINIONS

MEYSAM ALIZADEH*, CLAUDIO CIOFFI-REVILLA† and ANDREW CROOKS

Department of Computational Social Science,
George Mason University, Fairfax, VA 22030, USA

Center for Social Complexity, Krasnow Institute for Advanced Studies,
George Mason University, Fairfax, VA 22030, USA
*malizad2@gmu.edu
†ccioffi@gmu.edu

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Empirical findings from social psychology show that sometimes people show favoritism toward in-group members in order to reach a global consensus, even against individuals' own preferences (e.g., altruistically or deontically). Here we integrate ideas and findings on in-group favoritism, opinion dynamics, and radicalization using an agent-based model entitled cooperative bounded confidence (CBC). We investigate the interplay of homophily, rejection, and in-group cooperation drivers on the formation of opinion clusters and the emergence of extremist, radical opinions. Our model is the first to explicitly explore the effect of in-group favoritism on the macro-level, collective behavior of opinions. We compare our model against the two-dimentional bounded confidence model with rejection mechanism, proposed by Huet *et al.* [*Adv. Complex Syst.* **13**(3) (2010) 405–423], and find that the number of opinion clusters and extremists is reduced in our model. Moreover, results show that group influence can never dominate homophilous and rejecting encounters in the process of opinion cluster formation. We conclude by discussing implications of our model for research on collective behavior of opinions emerging from individuals' interaction.

Keywords: Opinion dynamics; in-group favoritism; homophily; radicalization; extremism.

1. Introduction

Experimental studies on in-group favoritism support the existence and propagation of cooperative behavior among individuals. It has been shown that, across a variety of situations, individuals are biased in favor of members of their own group, rather than outsiders [19, 21, 59, 71]. From real-world identities, such as religion [7],

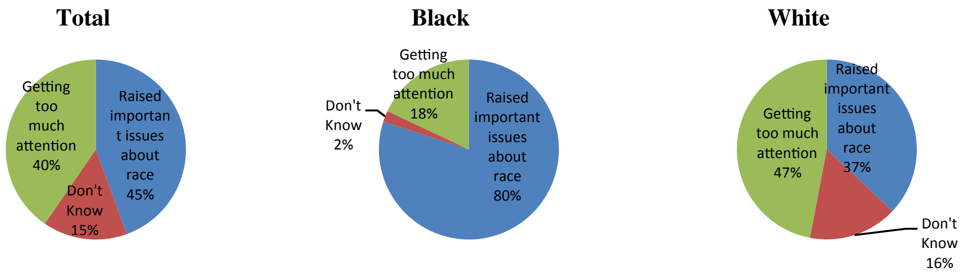
*Corresponding author.

ethnicity [68], political affiliation [52], and sport teams [34], to laboratory-produced groupings [16, 38, 53], research has demonstrated the existence of in-group discriminatory behaviors. Researchers have often studied in-group favoritism along three attributes: (1) emergent underlying cognitive mechanisms [20, 40, 53], (2) the evolution and dynamics of cooperation resulting from individuals' interaction [38, 54, 57], and (3) the emergent high-level behavior of people [31, 34, 43, 55].

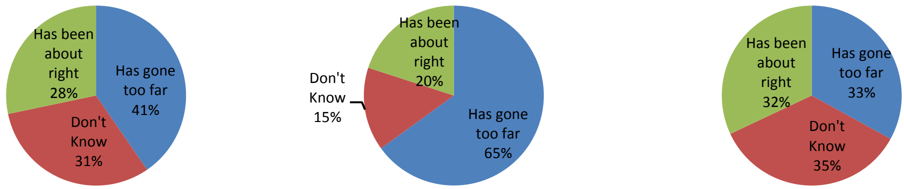
In terms of underlying cognitive mechanisms, empirical evidence from psychology supports the prevalence of a strong individual *predisposition* toward in-group favoritism. Furthermore, behaviors favoring in-groups are also found to be widespread even when they are individually costly; even in the absence of competition, opportunities for reciprocity, or direct self-interested gain [38]. With respect to the evolution of in-group cooperative behavior, experimental findings in the dictator game have shown that Democrat and Republican participants were willing to sacrifice their own well-being and give more to an in-group recipient than to the opposing party [19]. Moreover, it has been shown that the strength of group identification intensifies in-group favoritism. For example, individuals who have strong identification with their political parties tend to give much less to out-groups than do those with weaker affiliations [19].

Given the extensive literature on the emergence and evolution of in-group favoritism, little has been done to explore the extent to which it affects the emergent macro-level collective behavior of opinions. Experimental studies have neglected measuring in-group bias based on changes in opinions. Instead, research has focused on measuring: (1) the evaluative trait rating of group members [7], (2) ratings of group process or product [5], or (3) in-group/out-group resource distribution decisions [51]. Surveys potentially can be an alternative tool to find the effect of in-group favoritism on opinions. For example, a recent survey conducted by the Pew Research Center on the Ferguson Police Shooting in August of 2014 detected significant opinion polarization by race [50]. In Fig. 1, one can see there is major consensus among Blacks that the case has "raised important issues about race" and that the police "have gone too far" in the aftermath of Michael Brown's death. However, Whites were divided on both issues. One can interpret the above racial opinion polarization as a consequence of in-group favoritism. That is, the shooting of Michael Brown magnified the group identification of Blacks, which in turn triggered the in-group favoritism leading to more consensus among Blacks' opinions. Survey results on the shooting of Trayvon Martin also show the same pattern [50]. However, observational studies such as the one presented above fail to provide causal relationships between in-group favoritism and opinion dynamics.

In another survey, the Pew Research Center has recorded a rise in support for same-sex marriage in the United States [49]. While in 2003 only 33% of participants were in favor of legalizing same-sex marriage and 58% opposed to it, in the 2013 survey the percentage of supporters rose to 49% and opponents decreased to 44%. With respect to our study, what is of interest to us is that among those who have changed their opinion, 32% said that it is because they have gotten to know a



(a)



(b)

Fig. 1. Significant opinion polarization by race, in reaction to Ferguson police shooting (9, August 2014). Source: Pew Research Center [50].

family member, friend, or acquaintance who is gay or lesbian, which can be interpreted as an act of in-group cooperation. Thus, *if* opposition to same-sex marriage is considered an extreme opinion, relative to opposition, then in-group favoritism could be seen as having a moderating effect.

While the above examples provide a set of qualitative views on the effect of in-group favoritism on emergent high-level collective behavior in opinion dynamics, there is a need to use computational models to obtain more systematic insights. We turn to formal, computational modeling to move beyond qualitative views, specifically using an agent-based model (ABM) [11]. An ABM is a bottom-up, process-based type of model used successfully in lieu of mathematical models to study collective behavior in groups and societies of many individuals and corresponding macro-level patterns [10, 39, 47]. ABM methodology can integrate computational methods and empirical findings from sociology, psychology, political science, and economics, and results can be used to predict, control, and modify consequent collective patterns of individuals [26].

Although computational models have been previously used to investigate the emergence [27] and evolution [21] of in-group favoritism, no formal ABM has been developed to show how in-group cooperation functions in opinion dynamics. In a previous ABM, Salzarulo [56] modeled in-group/out-group identification through a fuzzy membership function of agents' opinion to predict the formation of groups. In Salzarulo's model, called meta-contrast (MC), agents know the opinion of other agents and try to move closer to the prototypical opinion of their own group while differentiating from out-groups' prototypical opinions. Results show that if the strength of in-group identification is sufficient, agents tend to adopt the prototypical opinion of their own group. However, neither the model nor the goal of the MC study was concerned with the effect of in-group favoritism on the opinions of individuals.

Flache and Mäs [18], in related work, proposed a computational model to explore the effect of demographic fault lines on the performance of teams. The Flache–Mäs model assumes that the demographic attributes of agents are constant and only opinion attributes change over time. Agents are attracted to or reject others based on distances in demographic and opinion attributes. Their results show that strong demographic fault lines within teams leads to opinion polarization in which opinion subgroups form according to demographic similarity. Grow and Flache [28] extended the Flache–Mäs model by including opinion uncertainty, demonstrating a moderation effect with regards to opinion polarization. Both models include homophily and rejection mechanisms (although agents' interaction and opinion shifting are based on demographic attributes) and neither explicitly includes in-group cooperation. Also, the aim of these models is how a subgroup gets to be a subgroup and why; it is not to investigate the effect of in-group favoritism.

In this paper, we present a model that overcomes the limitations of past modeling efforts to specifically explore the effect of in-group favoritism on the emergent high-level collective behavior of opinion dynamics. By collective behavior we mean, following Turner and Killian [62], "the behavior of aggregates whose interaction is affected by some sense that they constitute a group but do not have procedures for selecting or identifying leaders or members." While the purpose of Salzarulo's MC model [56] is to predict the formation of groups based on agents' opinion, we are interested in the fact that although group membership exists *a priori* in the population, such as in political parties, race, or ethnicity, the opinions of individuals are initially independent of their group membership. Indeed, if group membership and opinions are initially correlated, such as in the MC model, and individuals show favoritism toward the member of their own group, then some group-based polarization of opinions is inevitable [56, 61].

Inspired by studies such as those of Kearns *et al.* [38] and Rand *et al.* [51], our aim is to create and analyze an ABM to examine the effect of in-group favoritism on the qualitative and quantitative collective behaviors of opinion dynamics. A key assumption of our model is that direction and strength of opinion changes do not depend only on individual opinions, but are moderated by group memberships as well. Indeed, we introduce in-group cooperation as a mechanism that affects formation and properties of opinions, along with other mechanisms, such as homophily and rejection.

More specifically, our focus is to investigate the effect of in-group favoritism in two ways: (1) the interplay of opinion formation mechanisms, and (2) the process of radicalization. First, we are interested in comparing the effect of *social influence* of group membership on high-level patterns of opinion dynamics, versus effects of homophily and rejection. Homophily is the tendency of being attracted to similar others. On the other hand, according to *Social Judgment Theory* [58], a persuasive effort can induce behavior or attitude changes in a direction opposite to that intended — a mechanism called "rejection" in the social psychology literature. We investigate whether in-group favoritism can cause group-based polarization in which each opinion clusters has agents from only one group. Results from a better understanding of these mechanisms have potential implications for contagion management policies and intervention strategies for countering or mitigating opinion polarization and radicalization [2–4].

Our second research focus is on the emergent phenomenon of drifting toward opinion extremes, or *radicalization*, a process that has received attention in social psychology, political science, and sociology, among other disciplines. A challenging question in radicalization is *why* and *how* extremists become extremists [4, 33]. Do extremists hold radical opinions because they have interacted with other extremists, or could they become radical just by interacting with moderate people? While many explanations have been proposed [9, 35, 61, 64], it has been theoretically shown that the mere rejection mechanism can explain the process of radicalization [32, 33]. That is, people can become extremists by interacting with those who have less extreme opinions [64]. In this sense, the existence of other extremists is not necessary for the emergence of radicalization [35]. Building on this realm of research, our goal is to investigate whether in-group favoritism fosters or moderates the radicalization process using an ABM. We design a virtual experiment to systematically examine the effect of modeling parameters on the average number of emergent extremists.

The rest of the paper is organized as follows: Sec. 2 introduces and summarizes different ABM that have been proposed for opinion dynamics. Section 3 describes our cooperative bounded confidence (BC) model, an extension of the two-dimensional bounded confidence (BC) model with rejection mechanism (BCR) proposed by Huet *et al.* [33]. In Sec. 4, we compare our results with the BCR model and run sensitivity analysis on our ABM's parameters. Finally, Sec. 5 concludes the paper and suggests further research directions.

2. ABM of Opinion Dynamics

The term "opinion dynamics" refers to a wide range of models in social science, physics, and computer science. Opinion dynamics models differ in terms of their phenomena of interest, underlying assumptions and theories, communication regimes, and opinion updating heuristics. Usually, the objective of opinion dynamics models is to explore collective behaviors, such as reaching consensus [32, 33], emergence of extremists [12], and survival and spreading of minority opinions [70].

Generally, there are two main categories of opinion dynamics models. Some are models from statistical physics [22, 65], based on a transition rate among different states of a social system, with opinion dynamics viewed in terms of order–disorder transitions [42]. Castellano *et al.* [8] provide a review of this large set of models.

Other models are agent-based, assumed to have bounded rationality, and emergent behaviors of the social system are studied through interactions of independent and autonomous agents. That is, no specific goal is set for the agents. Rather, they interact based on some communication regime and set of updating rules. One of the most well-known agent-based opinion dynamics model is the BC model [15, 29, 41].

The BC model considers individual opinion as a continuous variable represented by a real number. In the BC model, each agent has an opinion and an uncertainty associated with it. Uncertainty can be interpreted as the extent to which agents are willing to adjust to others' opinion during encounters. Building on the notion of social influence [69], the BC model assumes that when two agents interact, if they are close enough in their opinions, they will be attracted to each other becoming closer in their opinions (i.e., homophily). However, if the difference is greater than their associated uncertainties, they will ignore each other. It is worth mentioning that there are two different versions of the BC model: the Deffuant–Weisbuch model [15] and the Hegselmann–Krause model [29]. The difference lies in their communication regime. While the former assumes that agents interact in dyadic encounters, the latter allows agents to interact with all others who fall within their uncertainty boundary.

Several other extensions of the BC model have been proposed. Researchers have explored different aspects and applications of the model by changing initial belief distributions [36], considering multi-dimensional beliefs [44, 64, 66, 67], imposing heterogeneity of uncertainties [14, 66], analyzing the effect of convergence [45]; including rejection or differentiation mechanisms [33, 42]; considering different averages [30]; implementing different activation regimes [2, 45]; distinguishing between attitude and opinion [63]; including intergroup conflict [4]; and exploring changes in distributional properties of opinions [3].

Although the literature on continuous opinion dynamics under BC is rich, there is need to better understand how and why individuals show spontaneous in-group cooperation, something which is currently lacking in the existing ABM literature. We argue that opinions have different underlying cognitive characteristics and therefore create a whole spectrum of opinion types. Some opinions are differentiating and cause repulsive (i.e., rejection) behaviors when they are not close enough. For example, in the context of intergroup conflict, religious opinions and sacred values are two examples of the kind of opinions that can induce differentiation between members of opposing groups [23]. By contrast, there are opinions that demand cooperative actions if individuals are to obtain the best global outcome [51]. Voting for a presidential candidate in a given political party is an example.

In this paper, we develop a new extension of the BC continuous opinion dynamics model to capture the in-group cooperative behavior of individuals. We call the new model CBC model, which is an extension of the two-dimensional BCR [33]. Assuming that individuals interact in an environment with sufficient incentives to trigger cooperative behavior, we allow agents to show more openness toward in-group members compared to outsiders. In doing so, we define two levels of uncertainty for each agent: in-group uncertainty and out-group uncertainty, where the former is always greater than the latter.

3. The CBC Model

Our ABM is an extension of the BCR model [33], which we describe first for clarification purposes. The BCR model is based on Festinger's Cognitive Dissonance Theory [17] from social psychology. Cognitive dissonance is a psychological condition that occurs when two or more beliefs are inconsistent, causing "psychological discomfort," which in turn drives an individual to seek a more balanced state. That is, individuals avoid increasing dissonance and alter their beliefs to reduce or, if possible, to eliminate dissonance. We also know from Social Judgment Theory that a persuasion effort can trigger a rejection reaction [58], so a viable way to reduce dissonance is to avoid others with opposing opinions [37, 46, 48].

The BCR model considers a set of N agents, each characterized by opinion variables x_{1i}, $x_{2i} \in [-1, 1]$ and opinion uncertainty variables $u_{1i}, u_{2i} \in [0, 1]$ associated with x_{1i} and x_{2i}, respectively. At each time step in the simulation, a pair of agents is randomly selected to interact and update their opinions, conditioning the update based on values of opinions and uncertainties. Suppose agent i has opinions x_{1i} and x_{2i} with uncertainties u_{1i} and u_{2i}, and agent j has opinions x_{1j} and x_{2j} with uncertainties u_{1j} and u_{2j}. For the sake of simplicity, Huet *et al.* [33] assume that all nodes have similar uncertainties. Then, agent i compares its opinions with those of j and updates them. The general rule is that agents approach each other if they are close enough in both opinions. Otherwise, they ignore each other or differentiate and shift away. More formally, if $|x_{1i}^t - x_{1j}^t| \leq U$ and $|x_{2i}^t - x_{2j}^t| \leq U$, then the two agents' opinions fall within their BC interval. Thus, they get closer to each other based on the following equations:

$$x_{1i}^{t+1} = x_{1i}^t + \mu(x_{1j}^t - x_{1i}^t), \tag{1}$$

$$x_{2i}^{t+1} = x_{2i}^t + \mu(x_{2j}^t - x_{2i}^t), \tag{2}$$

where μ is a constriction factor used to limit the velocity of opinion convergence. The assumption is that μ is constant and equal for all agents throughout the simulation. Another possible state is that two agents are close in one opinion but far in another: $|x_{1i}^t - x_{1j}^t| > U$ and $|x_{2i}^t - x_{2j}^t| \leq U$. In such a situation two cases arise, depending on the difference with respect to an "intolerance threshold" δ, according to Huet *et al.* [33]. If the difference is below the predefined threshold, meaning $|x_{1i}^t - x_{1j}^t| \leq (1 + \delta)U$, the dissonance is not strong enough to trigger a rejection, so the two ignore each other in x_1 and approach each other in x_2 as we show below:

$$x_{1i}^{t+1} = x_{1i}^t, \tag{3}$$

$$x_{2i}^{t+1} = x_{2i}^t + \mu(x_{2j}^t - x_{2i}^t). \tag{4}$$

However, if the difference is significant enough, meaning $|x_{1i}^t - x_{1j}^t| > (1+\delta)U$, then the conflict causes dissonance and triggers repulsive action, causing the two agents to separate from each other in opinion 2. The movement should be large enough to resolve the dissonance as shown below:

$$x_{1i}^{t+1} = x_{1i}^{t}, \tag{5}$$

$$x_{2i}^{t+1} = x_{2i}^{t} - \mu p\,\mathrm{sign}(x_{2j}^{t} - x_{2i}^{t})(U - |x_{2i}^{t} - x_{2j}^{t}|). \tag{6}$$

Here $p\,\mathrm{sign}(\cdot)$ is similar to the sign function, except that it has value $+1$ if the argument is 0. Moreover, the belief values are limited between -1 and $+1$ by incorporating the following rule:

$$\text{if } |x_{1i}^{t+1}| > 1 \text{ then } x_{1i}^{t+1} = \mathrm{sign}(x_{1i}^{t+1}).$$

Since the model is based on Cognitive Dissonance Theory, it assumes that for cases when two agents are far apart in both opinions, there is no dissonance between them and, therefore, there is no influence from one to another; they simply ignore each other on both opinions.

To develop the CBC model, we follow the social identity approach to intergroup relations and group processes as shown in Fig. 2. Social Identity Theory (SIT) is a meta-theory or paradigm that has provided wide-ranging explanations for various phenomena within and among groups [1]. The theory states that group membership creates in-group feelings that can favor in-group traits, values, and characteristics. SIT proposes different levels of identity and differentiates between "social identity" and "personal identity." While social identity involves group and intergroup processes, personal identity concerns individual and interpersonal processes. Here, groups exist as a psychological construct when two or more people share the same identity [1]. Social identification can occur for any type of social categorization (family, work team, political affiliation, gender, religion, race, among others). According

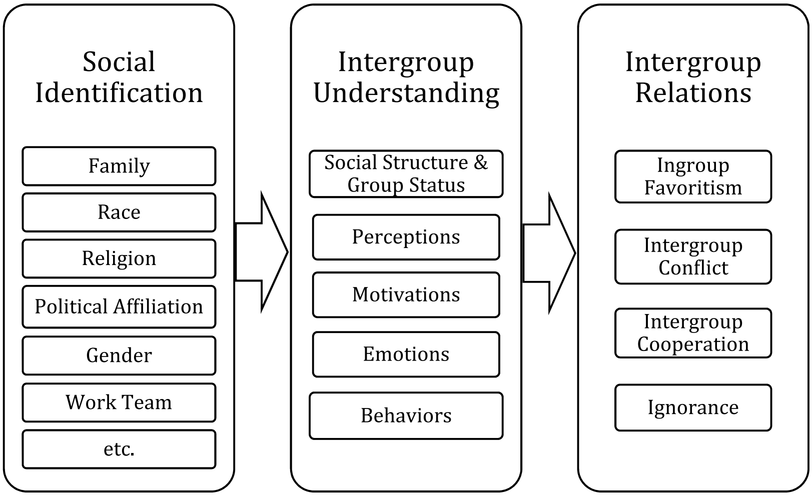


Fig. 2. Social identity approach to intergroup relations and group processes.

to SIT, people's understanding of intergroup relations is psychologically related to their identity, motives, perception, and behaviors [59, 60]. Among intergroup relations options, in-group favoritism and intergroup conflict have greater scientific importance because the other two do not produce any kind of conflict among individuals. This paper focuses on in-group favoritism, while intergroup conflict has been studied by a Bounded Confidence with Intergroup Conflict (BCIC) model reported in [4].

We follow a scenario similar to that by Kearn *et al.* [38], so individual preferences exist and have more flexibility toward their in-groups, ignoring self-preferences to reach a global in-group consensus. Using Rand *et al.*'s [51] empirical finding, we assume that in-group favoritism exists spontaneously within agents and there is no explicit intergroup conflict. To isolate the fundamentals of in-group favoritism, we develop the simplest ABM possible to explore emergent, high-level, collective behavior of opinions, as is common in the ABM research community. For example, Gode and Sunder's [24] model of zero-intelligence traders demonstrated that the demand and supply curve of real-world markets can be replicated with nothing more than a budget constraint and a prohibition against trading at a loss. Such a simple model provides foundations for developing more complex models. For our purposes, we randomly assign each agent to m social groups and let agents show more openness toward their in-group fellows, treating group membership exogenously and assuming that group membership is constant over time. Our model is abstract and is not intended as a realistic portrayal of specific social behaviors.

One can interpret the static nature of group membership based on groupings relatively constant attributes, such as ethnicity, religion, language, and political affiliation, among others. For example, empirical results show that ethnic markers can lead to in-group favoritism even when ethnicity is unrelated to competence in a given domain [6]. Ethnic markers do so even when groups are transient and group boundaries rest on the weakest of distinctions among individuals [57, 59]. Another reason behind the assumption of group membership stability is that, as we have already postulated above, there is no initial correlation between group membership and opinions. That is, group identification is assigned randomly and membership in a particular group is not associated with any particular strategy. Thus, changing group membership because of an opinion change is beyond the scope of this study.

We define two levels of uncertainty for each agent. The first is uncertainty associated with in-group members' opinion (U_{in}), while the second is associated with out-group agents' opinion (U_{out}) where $U_{\text{in}} \geq U_{\text{out}}$. At each interaction encounter, agents follow the same steps as in the BCR model, except that if they are from the same group, they use their in-group uncertainty (U_{in}) to update their opinion (i.e., homophily, rejection, or ignorance). Similarly, if two agents are from different groups, they use their out-group uncertainty (U_{out}) for opinion updating purposes. We consider two cases for in-group encounters: (1) agents do not shift away from in-groups in a dissonance situation (i.e., CBC with No in-group Rejection (CBC-NR)), and (2) agents do differentiate themselves from in-group fellows if the difference in

Table 1. Comparison of the agent-based opinion dynamics models under BC.

Variables	BC	MC	BCR	BCIC	CBC
Supporting theory	Social judgment	Self-categorization	Cognitive dissonance	Intergroup conflict	In-group cooperation
Dimension	1	n	2	2	2
Uncertainty	Constant	NA	Constant	Constant	Constant
Communication regime	Dyadic	Group	Dyadic	Dyadic	Dyadic
Rejection mechanism	×	✓	✓	✓	✓
Intergroup conflict	×	×	×	✓	×
In-group cooperation	×	×	×	×	✓

opinion is sufficiently large (i.e., CBC with in-group Rejection (CBC-R)). We analyze both versions in Sec. 4. Table 1 compares key features of our model with those of others mentioned above.

4. Simulation Results and Analysis

Our CBC model was implemented in Python (see Acknowledgments section). In this section, we first show the general behavior of the two versions of our model (i.e., with and without in-group rejection) and compare it with the BCR model (Sec. 4.1). We distinguish the effect of group influence, versus homophily and differentiation mechanisms, by using appropriate plots. Then we turn to the CBC model and report results from sensitivity analysis by varying the values of specific modeling parameters. These modeling parameters are intolerance threshold, amount of favoritism, and number of initial groupings (Secs. 4.2 to 4.4 respectively). Finally, in Sec. 4.5, we design and conduct a series of virtual experiments to examine the effect of key modeling parameters on the average number of emergent extremists in the population.

4.1. *General behavior and comparison with the BCR model*

We set population size to 1000 agents, each agent having two opinions, to enable comparison of our results with those from the BCR model. Initial opinions are randomly assigned to agents using a uniform distribution between -1 and 1. The uncertainties u_1 and u_2 are assumed to have equal values and are held constant throughout the simulation. Note that uncertainty U in the BCR model is equal to that of out-group uncertainty in the CBC model. The assumption is that there is no initial correlation between group membership and agents' opinions x_1 and x_2.

Figure 3 compares the evolution of opinions in the BCR model and two versions of the CBC model (i.e., CBC-R and CBC-NR). Axes in each plot in Fig. 3 represent agents' opinions, (bound between -1 and 1), so each dot on the 2-opinion space represents an agent's compound opinion position. All other model parameters have the same values. Therefore, we can interpret results as changes in aggregate, *population opinions* when agents interact cooperatively with their in-group fellows.

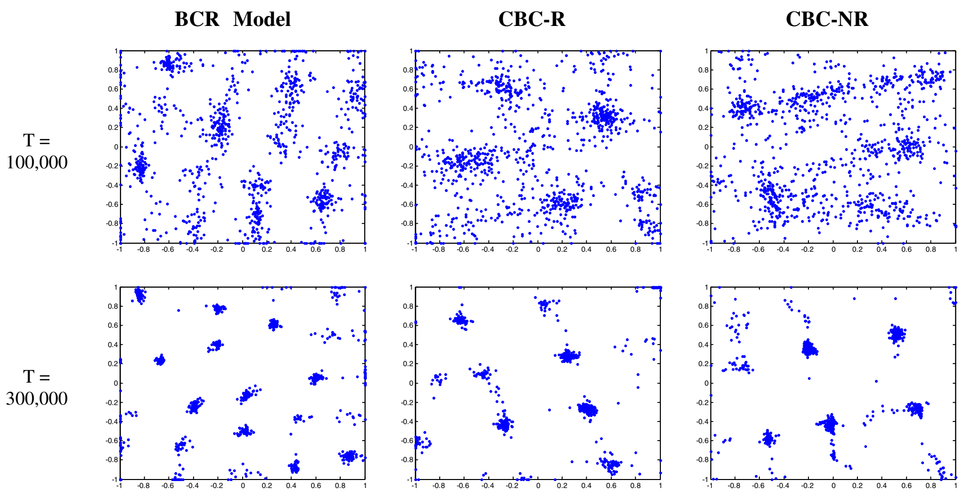


Fig. 3. Comparison of the CBC models and the BCR model ($U = U_{\text{out}} = 0.2, U_{\text{in}} = 0.4, \mu = 0.3, \delta = 1.5, m = 5$). Both axes represent individuals' opinion.

We can see in Fig. 3 that, similar to the BCR model, several stable equilibria emerge after some time as opinion clusters form around such points of nucleation. Clusters represent predominant opinions and over time they attract agents. Two forces cause the formation of these clusters, as discussed earlier (Sec. 3). The first is produced by agents that are close in both opinions, tending to get closer and form groups (i.e., homophily). The second is produced by those with similar opinion in one dimension and dissimilar enough opinion in another, who repel each other and separate (i.e., rejection). As a result, after some steps, some "meta-clusters" emerge in the population [33]. Note that an opinion cluster is an emergent phenomenon, whereas agents' group membership is an attribute initially assigned randomly to agents. As noted in Sec. 1, a goal of our study was to investigate the effect of group membership on the formation of opinion clusters.

The BCR model leads to opinion plurality, whereby several opinion clusters emerge, similar to the original Deffuant–Weisbuch model with low uncertainty thresholds [15]. The number of local equilibria can be used to measure consensus in a population, with the number of opinion clusters inversely related to level of consensus. Visual comparison of simulation results shows that the number of emergent opinion clusters in the CBC models is less than in the BCR model, although computing the number of opinion clusters is beyond the scope of this study. This result was expected, because by including the U_{in} in the CBC model and having $U_{\text{in}} \geq U_{\text{out}}$, the overall uncertainty of the CBC model is higher than that of the BCR model, which in turn (according to the Huet *et al.* [33] findings) reduces the number of emergent opinion clusters. This means that the size of opinion clusters in the CBC model is larger than in the BCR. Therefore, in-group favoritism decreases a population's opinion diversity, enhancing consensus among members of the same group who are under the social influence of in-group favoritism. This is in qualitative agreement with data from Brown's and Martin's shooting cases [50], which showed strong consensus among Blacks but divided opinions among Whites, as discussed in Sec. 1.

Differences between CBC and BCR simulation results arise from the fact that, in a cooperative environment, the rejection mechanism occurs less frequently than in a non-cooperative one. By allowing agents to show more openness to their in-group members, the frequency of encounters that lead to opinion rejection decreases and more individuals are attracted toward each other. In other words, one of the opinion cluster formation forces (rejection) is attenuated and thus the population ends up in fewer but more populated clusters.

Another question is whether all agents in a cluster belong to the same group: does in-group favoritism lead to group-based polarization? If so, this means that emergent polarization can be explained by group influence, dominating both homophily and rejection in opinion formation dynamics. But if clusters include agents from different groups, then the presence of moderate discriminatory behaviors (e.g., $U_{\mathrm{in}} = 0.4$) among self-categorized agents cannot dominate attraction and rejection forces.

To answer this question, we plot final opinion values against groupings and plot agents in 3D space, as shown in Fig. 4. In both versions of our proposed model, agents within each opinion cluster belong to different groups. There is no opinion cluster in which members are from only one group. This implies that opinion clustering can mainly be explained by homophily and rejection, not by social influence of group identification. In fact, the effect of in-group favoritism is to reduce the number of minorities and decrease opinion diversity in each group. The second and third columns in Fig. 4, which plot groupings against an opinion, show that as we increase the amount of in-group favoritism (by not allowing agents to shift away from their in-group members in the CBC-NR model), opinion diversity in each group decreases (herd mentality).

As mentioned in Sec. 1, one goal was to examine whether in-group favoritism fosters radicalization. In our model, we define an agent as radical or extremist if the absolute value of at least one of its final opinion values is ≥ 0.9. Figure 5 compares the average number of extremists for different values of intolerance threshold δ across BCR, CBC-R, and CBC-NR models. Clearly, the BCR model produces more extremists than the CBC for all values of δ. In fact, it seems that in-group favoritism mediates the radicalization process in terms of the number of emergent extremists. This is consistent with results from the same-sex marriage survey [49], discussed in Sec. 1. Moreover, the average number of extremists in the CBC-R model is always greater than in the CBC-NR. We will revisit this finding in Sec. 4.5, where we test the effect of key modeling parameters on the average of number of extremists.

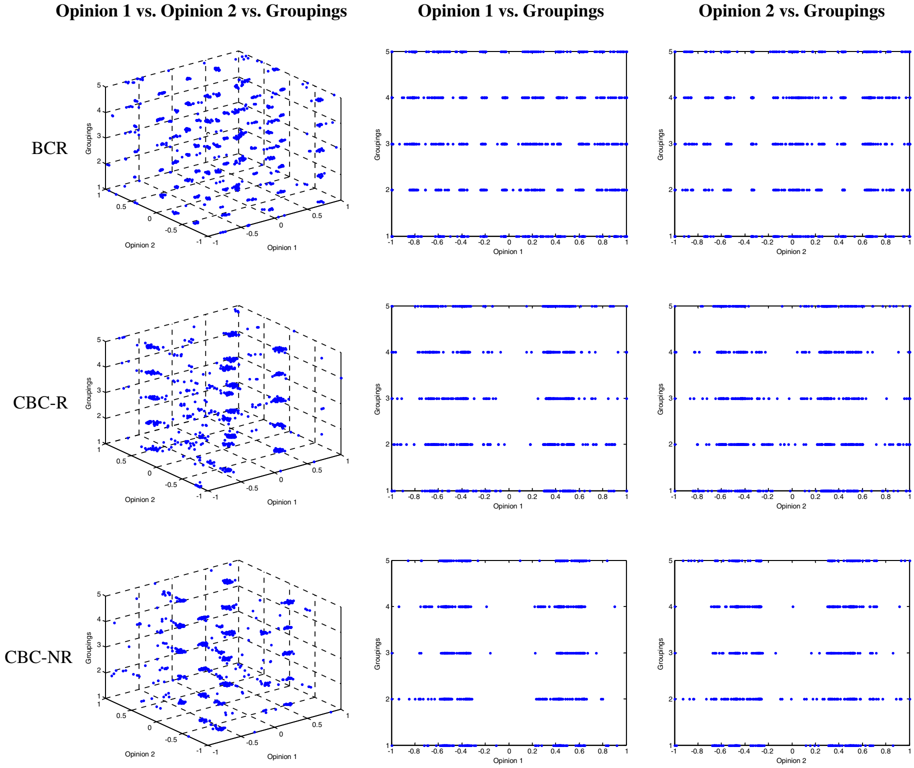


Fig. 4. Analyzing the effect of group influence versus homophily and rejection between models ($U = U_{\text{out}} = 0.2, U_{\text{in}} = 0.4, \delta = 1.5, \mu = 0.3, m = 5$, iteration = 300,000).

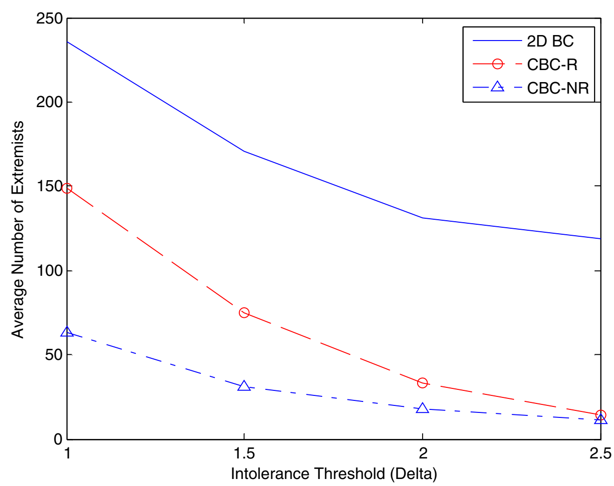


Fig. 5. Comparing the average number of extremists across BCR, CBC-R, and CBC-NR models ($\mu = 0.3, U_{\text{in}} = 0.3, U = U_{\text{out}} = 0.2, m = 5$, iteration = 300,000, runs = 25).

4.2. *The effect of an intolerance threshold*

Opinion clusters in the BCR model form along the same horizontal and vertical lines (separate or quantum-discrete opinion values) when an intolerance threshold increases, as discussed by Huet *et al.* [33]. This is why the number of clusters in the BCR model increases with δ. However, in-group favoritism among agents in the CBC model changes this dynamics. As the intolerance threshold rises, the condition for differentiation is more restricted. This means that neutral encounters in which people neither attract to nor repel each other increase, leaving agents in their same positions at each corresponding time step. This allows for in-group favoritism to play a more effective role in the formation of opinion clusters, by attracting more minorities toward the meta-clusters.

The interaction of the intolerance threshold δ with in-group favoritism, and its effect on opinion dynamics, is shown in Fig. 6, where we plot the final opinion distribution against group memberships in the CBC-NR model. When $\delta = 1$, opinion diversity in each group is high and agents cover a wide variety of opinions within groups. However, as intolerance threshold δ increases, opinion diversity

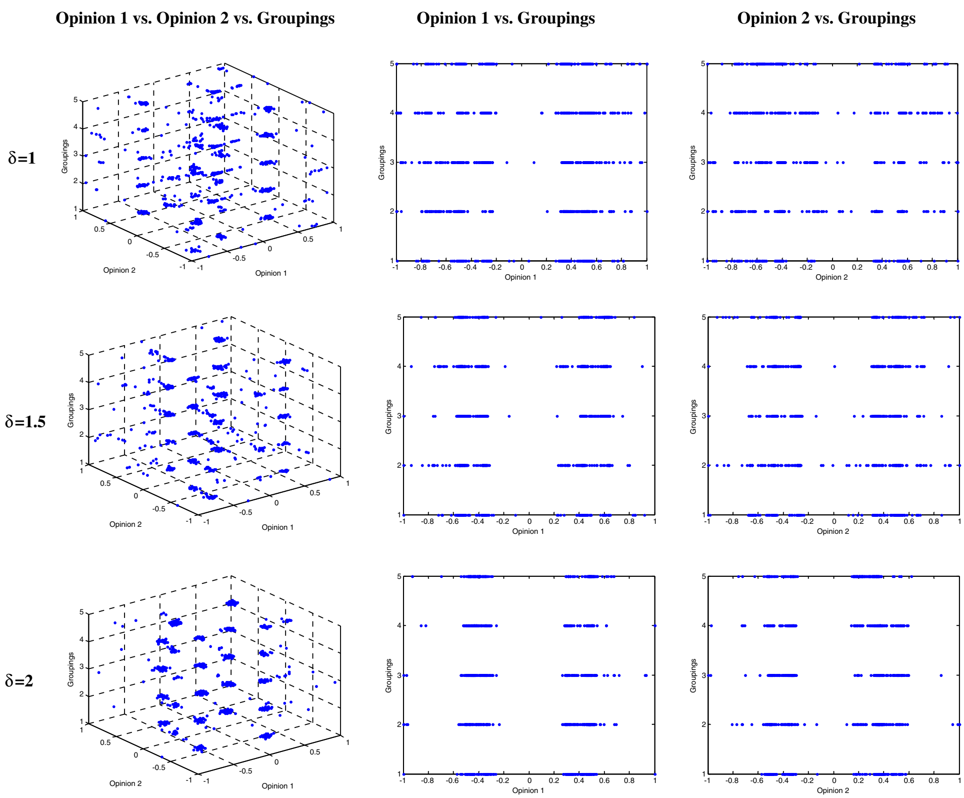


Fig. 6. Analyzing the interaction of intolerance threshold δ and group influence in CBC-NR model ($U = U_{\text{out}} = 0.2, U_{\text{in}} = 0.4, \mu = 0.3, m = 5$, iteration $= 300{,}000$).

within groups decreases. We call this phenomenon *in-group polarization* — i.e., agents' opinions within a group divide into a small number of factions with high internal consensus and sharp disagreement among them. For example, for $\delta = 2$, we see in-group opinion polarization around points -0.4 and 0.4. Although the 3D plot shows that all opinion clusters have agents from all groups, comparison of second and third column plots between various levels of δ shows a partial surge of group influence on opinion formation. Simulation results for the CBC-R model show the same pattern.

4.3. *The effect of the amount of in-group favoritism*

We measure the amount of favoritism Δ by subtracting in-group uncertainty U_{in} from out-group uncertainty U_{out}. Figure 7 shows the interaction between the amount of favoritism toward in-group members and group influence by plotting final opinion values against initial groupings. We hold out-group uncertainty constant at $U_{\text{out}} = 0.2$ and incrementally increase in-group uncertainty. Results demonstrate that increasing favoritism toward in-group members enhances group influence on

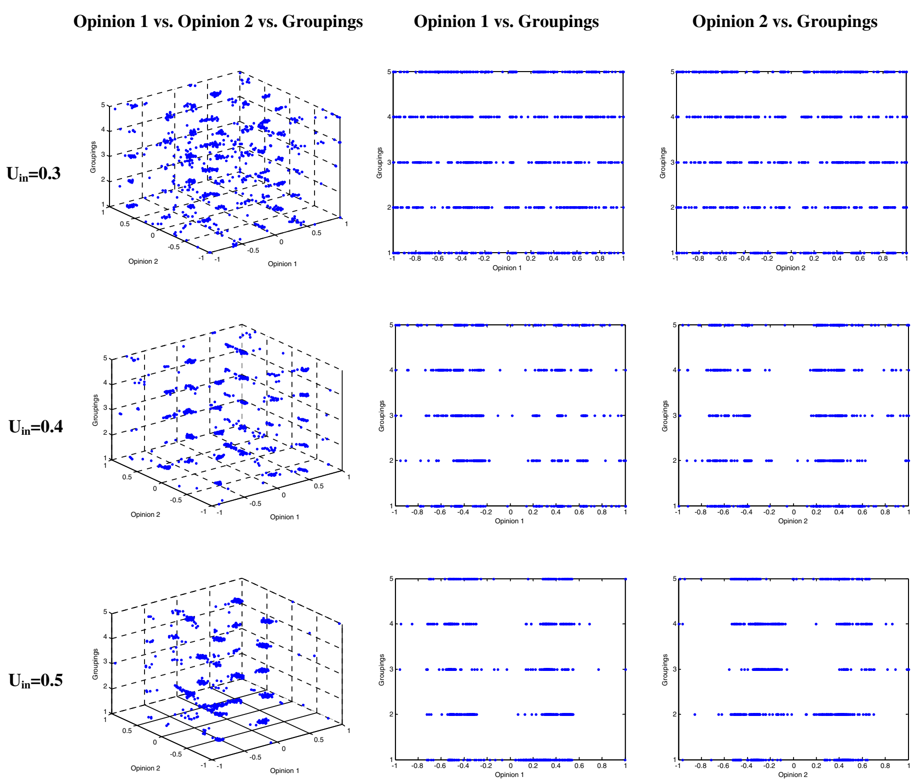


Fig. 7. Analyzing the interaction of uncertainty and group influence in CBC-NR model ($U = U_{\text{out}} = 0.2, \delta = 1, \mu = 0.3, m = 5$, iteration$\,=\,$300,000).

agents' opinion. Increasing from $U_{\text{in}} = 0.3$ to $U_{\text{in}} = 0.5$, decreases opinion diversity in each group, in contrast to results obtained from $U_{\text{in}} = 0.4$ to $U_{\text{in}} = 0.5$. When all other parameters are constant, increasing favoritism increases in-group polarization and decreases opinion diversity within each group of agents. The CBC-R model shows a similar pattern.

4.4. *The effect of the number of exogenous groups*

We next examined the effect of the number of initial membership groups m on the dynamics of the CBC model with and without in-group rejection. Keeping all other parameters constant and increasing m, we observe the same pattern evolved in both cases, as shown in Fig. 8. The number of emerging opinion clusters increases as m

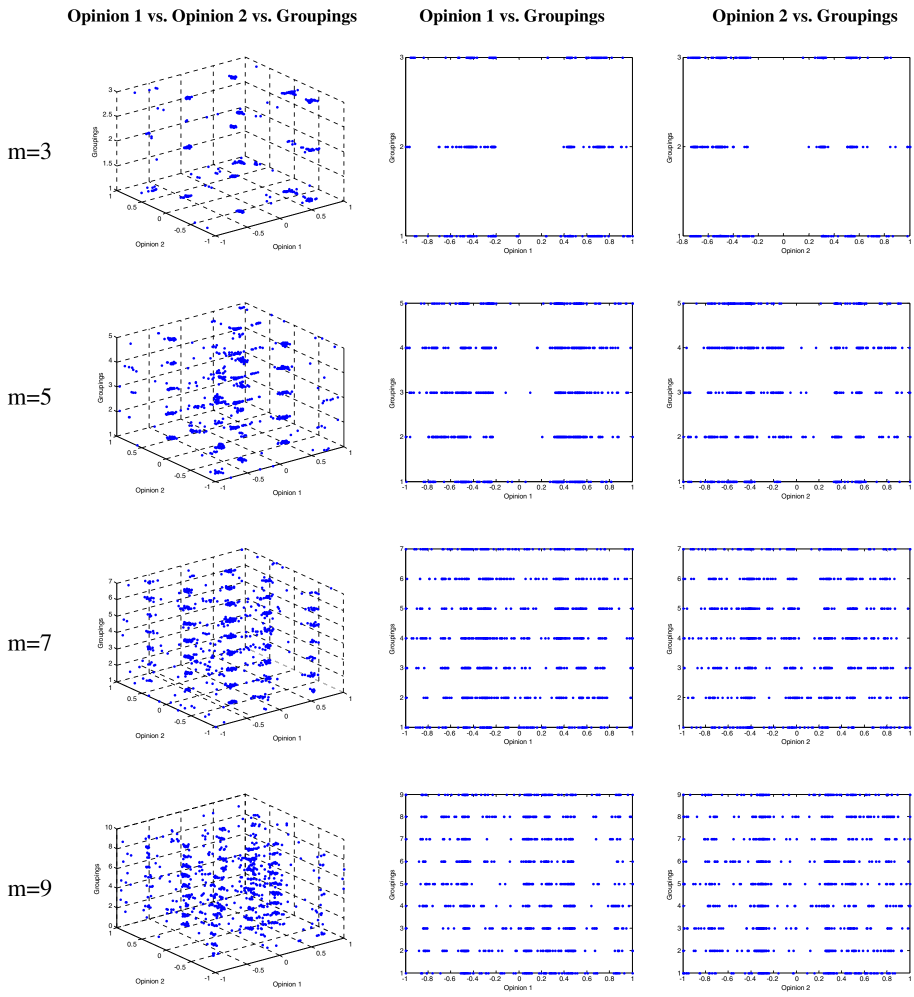


Fig. 8. Analyzing the interaction of initial groupings and group influence in CBC-NR model ($U = U_{\text{out}} = 0.2, U_{\text{in}} = 0.4, \mu = 0.3, \delta = 1$, iteration = 300,000).

increases, highlighting the critical role of initial conditions for emergent macro-level patterns in population dynamics. Increasing the initial number of groups increases local consensus and decreases consensus in the population.

To understand the social influence of in-group identification, we looked inside opinion clusters to see whether agents in each cluster belong to the same or different groups. Figure 8 shows the distribution of final opinions for groups in the CBC-NR model. Increasing the number of initial groupings increases opinion diversity in the population and increases local consensus. But if we look at the second and third columns of Fig. 8, we can see that for all values of m, there is a wide range of opinion diversity in each group. In other words, there is no opinion homogeneity within groups and agents in clusters belong to different groups, consistent with results in Sec. 4.3. However, we can see that opinion diversity within groups decreases as the number of initial groupings decreases, implying that increasing m enhances opinion diversity in the population as well as within groups. The same experiment using the CBC-R model produced similar results.

4.5. *Virtual experiment on the number of emerging extremists*

To understand the effect of in-group cooperation on the average number of emergent extremists in a population, we designed a virtual experiment to systematically test the effect of three new parameters introduced by the CBC model: (1) in-group uncertainty, (2) number of initial groupings m, and (3) absence or presence of in-group rejection. Prior research has investigated the effect of an intolerance threshold [33], convergence [30], number of agents [30], and level of uncertainty [33]. We controlled for these parameters and varied the three new parameters to understand their effects, as summarized in Table 2. Each parameter combination ran 25 times to calculate the average number of extremists. As before, an agent is extremist if the absolute value of at least one of its final opinions is equal to or greater than 0.9.

Table 2. Virtual experiment configuration.

Independent variables	No. of test cases	Values used
In-group uncertainty	4	0.3, 0.4, 0.5, 0.6
Number of groups	4	3, 5, 7, 9
In-group rejection	2	Yes, No
Control variables	**No. of test cases**	**Values used**
Number of agents	1	1000
Intolerance coefficient (δ)	1	1.5
Out-group uncertainty (U_{out})	1	0.2
Convergence parameter (μ)	1	0.3
Initial belief distribution	1	Random
Maximum iteration	1	300,000
Number of runs	1	25
Dependent variables	**No. of test cases**	**Values**
Average number of extremists	—	—

Table 3. Summary of inter-correlations between variables.

Variables	1	2	3
1. Number of initial groupings	1	0.000	0.080*
2. In-group uncertainty	0.000	1	−0.808**
3. Average number of extremists	0.080*	−0.808**	1

Note: *Correlation is significant at 0.05 level (2-tailed). **Correlation is significant at 0.01 level (2-tailed).

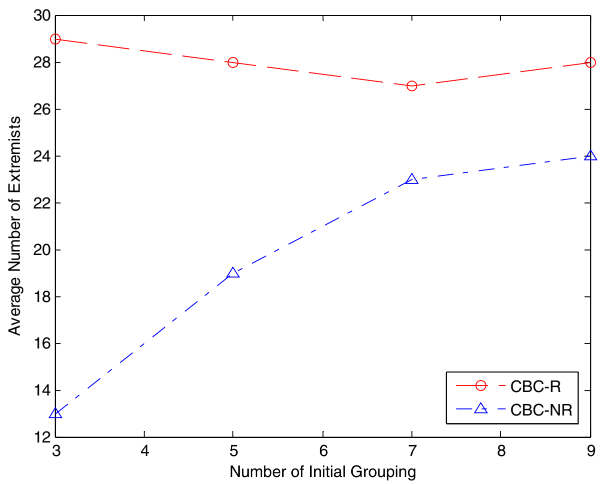


Fig. 9. Effect of number of initial grouping on the average number of extremists ($U\_\text{out} = 0.2, U_{\text{in}} = 0.4, \mu = 0.3, \delta = 1.5$, run = 25, iteration = 300,000).

Before conducting the ANOVA to examine overall variation in the number of extremists under various scenarios, we examined the matrix of Pearson correlation coefficients, including dependent (average number of extremists) and independent variables, shown in Table 3. Since the "in-group rejection" is a categorical variable, it was excluded from the correlation analysis. The correlation between number of initial groupings and average number of extremists is positive and statistically significant at the 5% confidence level. However, as can be seen in Fig. 9, that correlation holds only without rejection among in-group members (the CBC-NR model). When agents show rejection behavior toward their in-group fellows, the initial groupings have no significant effect on the number of emergent extremists. By contrast, in-group uncertainty is negatively correlated with the average number of extremists and significant at 1% level. Figure 10 shows that the average number of extremists decreases as agents exhibit more openness toward their in-group members.

Now we turn to ANOVA results in Table 4 to examine the effect of our three independent variables (in Table 2) and their interactions with the average number of extremist. Table 4 contains the sources of variation, including degrees of freedom (DF), sum of squares (SS), mean square (MS), F-ratio (F), and corresponding significance levels (p-values). In general, the higher the F-ratio or the smaller

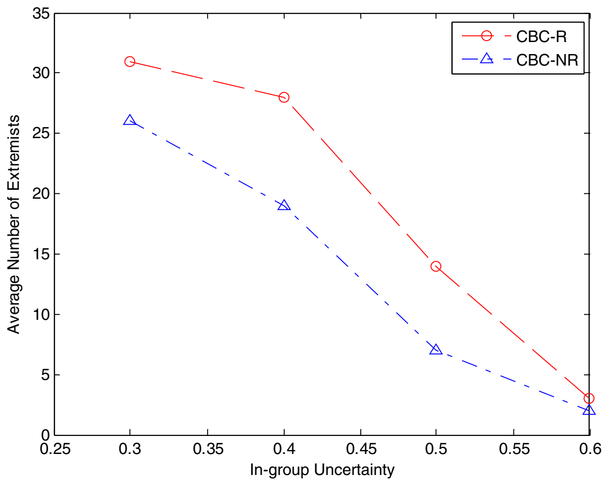


Fig. 10. Effect of in-group uncertainty on the average number of extremists ($U_{\text{out}} = 0.2, \mu = 0.3, \delta = 1.5, m = 5$, run $= 25$, iteration $= 300{,}000$).

Table 4. ANOVA results for the effect of key parameters on the average number of extremists.

Source	SS	DF	MS	F	p-value
Number of initial groupings	851.114	3	283.705	6.990	0.000
In-group uncertainty (U_{in})	84,905.934	3	28,301.978	697.347	0.000
In-group rejection	4507.751	1	4507.751	111.069	0.000
Groups * U_{in}	1367.901	9	151.989	3.745	0.000
Groups * In-group rejection	1061.854	3	353.951	8.721	0.000
U_{in} * In-group rejection	1377.794	3	459.265	11.316	0.000
Groups * U_{in} * In-group rejection	882.181	9	98.020	2.415	0.010
Error	31,169.440	768	40.585		
Total	343,759.00	800			

Dependent variable: Average number of extremists
R-squared $= 0.753$ (adjusted R-squared $= 0.743$)

the p-value, the more important the corresponding factor. Results show significant differences between levels of in-group uncertainty ($F(3, 768) = 697.347, p = 0.000$) when more extremism emerges $U_{\text{in}} = 0.3$ ($M = 28.6$, SE $= 0.45$), compared to, for example, when $U_{\text{in}} = 0.6$ ($M = 2.86$, SE $= 0.45$). When examining the initial number of groupings m, we observe a significant difference ($F(3, 768) = 6.99$, P-value ≤ 0.01), resulting in more extremists when $m = 9$ ($M = 17.5$, SE $= 0.45$) than for a smaller number of groups, such as $m = 3$ ($M = 14.09$, SE $= 0.45$). Finally, the absence or presence of in-group rejection is significant ($F(1, 768) = 111.069$, P-value $= 0.000$). In fact, more extremists emerge when individuals are allowed to shift away from their in-group fellows ($M = 18.86$, SE $= 0.319$) compared to when they do not show in-group rejection behavior. The R-square value indicates that 75.3% of the variance in number of extremists can be explained by the tested factors.

ANOVA results also show that there are significant interactions among the number of initial groupings × in-group uncertainty ($F(9, 768) = 3.745$, p-value = 0.000), number of initial groupings × in-group rejection ($F(3, 768) = 8.721$, p-value = 0.000), in-group uncertainty × in-group rejection ($F(3, 768) = 11.316$, p-value = 0.000), and in-group uncertainty × in-group rejection × number of initial groupings ($F(9, 768) = 2.415$, p-value = 0.000). This means that the simultaneous influence of independent variables on the average number of emergent extremists is not additive. Rather, the relationship between each of the independent variables and the dependent variable depends on the value of other interacting variables.

5. Discussion and Conclusions

One of the reasons behind the current trend toward the use of computational models in social science is to be able to explore, predict, and potentially influence undesirable collective behaviors. While traditional methods tend to use rules and orders to dictate an intended outcome [25], this new promising approach attempts to study the final outcome of a crowd through self-organizational methods. That is, the desired collective outcome can be facilitated by leveraging social influence of groups on individuals. For example, instead of directly asking people to buy a certain product, the same outcome can be achieved by telling them that many people have already bought it [55].

Studying in-group favoritism is of critical importance. Elements of in-group cooperation are ubiquitous, such as in election campaigns for candidates [52], diffusion of extremism in a given society [13], and the evolution of fairness [53], among others. Thus, there is a need for more informed policies based on a deeper understanding of different conditions under which people act cooperatively with their in-group fellows and the consequent collective behavior that emerges. Our results provide a link between the literature on intergroup relations and emergent macro-level opinion constructs such as social polarization, segregation, network topology, and information diffusion.

Researchers have explored the cognitive basis of in-group favoritism. While some have concluded that human beings are "conditional cooperators" [20], recent findings show that people develop "cooperative heuristics" in their everyday life because they typically benefit from cooperation [51]. In other words, cooperation can become "intuitive." Regardless of the primordial origin of cooperation, it is valuable to understand if cooperation evolves through social networks (groups of individuals); and, if so, what would be the micro-level opinion dynamics of emergent, group-level collective behavior.

Empirical findings from the group decision-making literature show that in some cases, even contrary to individuals' preferences, individuals can coordinate behavior to reach global in-group consensus. Building on this, the aim of our study has been to examine the collective behavior of in-group favoritism in terms of opinion dynamics. Collective behaviors are those that are not included in the model *a priori*, but emerge out of simple interactions among a large number of individuals. More specifically, we focused on the effect of in-group favoritism on the number of extremists that emerge, and the extent to which homophily, rejection, and group influence affect pluralism and polarization in a population (society).

We used the agent-based modeling approach and developed a new extension of the BC opinion dynamics model (entitled CBC in Sec. 3), which was developed to capture individual's in-group cooperation behavior. Our model is an extension of the two-dimensional BCR [33]. Assuming individuals interact in an environment that provides sufficient incentives to trigger cooperation, we randomly assigned agents to m groups and allowed them to show more openness to their in-group fellows rather than out-group (alien) members. Simulation results demonstrated some findings that suggest possible applications for intervention policies:

(1) **In-group favoritism influences the radicalization process by affecting the number of emergent extremists. However, when present, in-group favoritism decreases opinion diversity in a population.** Comparing simulation results from the BCR model to those from the CBC models (in Sec. 4.1) demonstrates the effect of in-group favoritism on emergent group-level opinion characteristics. Similar to the BCR model, eventually some point-equilibria nucleated and opinion clusters emerged. However, the number (set cardinality) of emergent opinion clusters is very different between the CBC models and the BCR model. In fact, we observe a lesser number of clusters in the CBC simulation results. The reason for this phenomenon lies in the formation mechanism of opinion clusters. Two forces bring about the emergence of equilibrium points: homophily and rejection. In a cooperative environment, people exhibit more openness to their in-group fellows and therefore attraction occurs more frequently, which in turn leads to fewer clusters. This implies that, *if we define extremism as the number of people who hold radical beliefs*, *in-group favoritism significantly mitigates the radicalization process*. However, *if we define extremism as the state of low opinion diversity in the population* (i.e., polarization), *in-group favoritism amplifies the radicalization process*.

(2) **Group influence can never preclude homophily and rejection in opinion cluster formation.** If agents are only allowed to attract like-minded agents, shifting away from negatively evaluated others, and exhibiting more openness only to in-group members, under no circumstances will in-group favoritism dominate the other two social interaction forces in such a way that at least one opinion cluster forms with agents from only one group — i.e., in-group favoritism would not lead to opinion homogeneity within groups.

(3) **The average number of emergent extremists is positively and negatively related to initial number of groupings and in-group uncertainty, respectively.** Counter-radicalization policies should aim at influencing in-group uncertainty, since the number of groupings seems less amenable to

change. The existence of in-group rejection also increases the number of extremists. ANOVA test results (Sec. 4.5) also showed that the average number of emergent extremists is a function of in-group favoritism conditions. This explains why a society can become suspicious of extremism, even when this susceptibility is not pre-determined by populating opinion extremes with highly closed-minded agents.

In this paper, we have shown that opinion-cluster formation, degree of consensus in society, and emergent extremists can be modeled as a function of in-group favoritism, and that small changes in micro-level individual interactions lead to different macro-level patterns. We used the term "opinion dynamics" in our model and in our results for consistency with the literature on social influence models. However, we would argue that our results can be generalized to behaviors, beliefs, attitudes, norms, customs, or other cultural traits that individuals consider relevant and that are susceptible to change by social influence.

Future research should test the effect of unexamined control variables and promising extensions, such as:

(1) Analyzing the effect of different network topologies — e.g., random, small worlds, or scale-free, among other social structures — to test for invariance and universality [10].
(2) We assumed that agents' initial opinions are uniformly assigned. Other distributions — e.g., normal, power law, or other non-equilibrium distributions — should be used to measure resulting effects on emergent group-level patterns.
(3) We also assumed that group membership is relatively static. Another research thrust would be to investigate emergent opinion patterns when agents are affiliated with more than one group, or when they change membership dynamically.
(4) Another productive extension of this study would be to assign the agents' initial social network structure based directly on the homophily effect. That is, people who are connected to each other in a network tend to have more similar characteristics and opinions, compared to others disconnected from them (aliens).
(5) Finally, exploring the effect of in-group favoritism on the co-evolution of (i) opinion dynamics and (ii) the structure of the social network at the group level would shed new light on group membership dynamics and the emergence of radical individuals in society.

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