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Modeling Confirmation Bias and Peer Pressure in Opinion Dynamics

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Confirmation bias and peer pressure are regarded as the main psychology origins of personal opinion adjustment. Each show substantial impacts on the formation of collective decisions. Nevertheless, few attempts have been made to study how the interplay between these two mechanisms affects public opinion evolution on large-scale social networks. In this paper, we propose an agent-based model of opinion dynamics which incorporates the conjugate effect of confirmation bias (characterized by the population identity scope and initiative adaptation speed) and peer pressure (described by a susceptibility threshold and passive adaptation speed). First, a counterintuitive non-monotonous phenomenon arises in the homogeneous population: the number of opinion clusters first increases and then decreases to one as the population identity scope becomes larger. We then consider heterogeneous populations where "impressionable" individuals with large susceptibility to peer pressure and "confident" individuals with small susceptibility coexist. We find that even a small fraction of impressionable individuals could help eliminate public polarization when population identity scope is relatively large. In particular, the impact of impressionable agents would be greater if these agents are hubs. More intriguingly, while impressionable individuals have randomly distributed initial opinions, most of them would finally evolve to moderates. We highlight the emergence of these "impressionable moderates" who are easily influenced, yet are important in public opinion competition, which may inspire efficient strategies in winning competitive campaigns.

Keywords: agent-based model, confirmation bias, peer pressure, public opinion dynamics, large-scale social networks

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1. INTRODUCTION

People tend to accept claims that adhere to their prior beliefs, i.e., being within their identity scope, and ignore dissenting claims [1–3]. This psychological behavior, known as confirmation bias, could promote more interactions among like-minded people and trigger homophily in public discourse [4]. From this perspective, confirmation bias is considered to be one of the possible factors that may accelerate social polarization and contributes to the emergence of echo chambers [5, 6]. A prominent case for the former effect, social polarization, is the political polarization in the USA, where Republicans are more likely to reject statements supporting Democrats as false and vice versa [7]. Whereas, the latter effect, the echo chamber phenomenon, has been widely discussed and studied in recent years, yet remains controversial [8]. In addition, individuals are likely to reshape their opinions, attitudes, or behaviors according to the position of the majority [9, 10]. Some studies argued that this mechanism, peer pressure, appeared to be a primary driver of opinion evolution [11, 12]. It is sometimes strategically utilized by partisan organizations to obtain more votes in an election, for instance, deploying vast social bots [13] and information gerrymandering [14]. Thus, to comprehensively understand the opinion polarization and to forecast the winner in competing processes requires a model of opinion dynamics to integrate the conjugate effect of confirmation bias and peer pressure.

The development of online networks has radically changed the way people consume information and exchange opinions, which results in substantial impacts on opinion dynamics [15–19]. Individuals can easily seek out content that is coherent with their prior beliefs on a large-scale online discourse, which might amplify confirmation bias [20]. In addition, the wide availability of dissenting content on the web exposes individuals to peer pressure every day [21]. Under such circumstances, opinion dynamics has attracted great attention recently [22]. Classical models including the Friedkin and Johnsen model [23–25], the Sznajd model [26], and the voter model [27] were further explored on large-scale social networks. These models sufficiently considered interpersonal influence including peer pressure between discordant pairs and showed the consensus state where all agents finally share the same opinion.

In addition to group consensus, empirical studies showed the fragmentation and polarization of opinions, which has aroused great concern in diverse fields [28–30]. For instance, political scientists observed markedly increased political polarization in the USA, which threatens democracies [31]. An experimental study unveiling Italian political opinion structures also showed that the peaks emerge at the opposite extreme opinions [32]. Sociologists noted the aggregation of individuals that trust false news and misinformation, which has been recorded as one of main threats to human society by the World Economic Forum [33, 34]. Various classical mathematical models were proposed to explain the ubiquitous phenomena [35–37]. Axelord et al. introduced the homophily mechanism in opinion dynamics, i.e., people are more likely to interact with those who hold similar ideas and illustrated how the homophily mechanism results in global polarization [28]. Centola et al. considered "network homophily" where a network evolves as a function of similarity and found that "network homophily" could lead to stable polarization [38]. Deffuant et al. proposed the bounded confidence model (BCM) where individuals simply accept contents within their identity scope to mimic confirmation bias and found the occurrence of several opinion clusters when identity scope is small [39]. Jager et al. integrated both assimilation and contrast effects in persuasion processes, and qualitatively reproduced the formation of opinion consensus as well as diversity [40]. Vicario et al. incorporated the negative updating rule of opinions among discordant pairs of users into BCM and observed the coexistence of two stable final opinions [41]. Sîrbu et al. proposed a multi-dimensional dynamical model incorporating the possibility of the disagreement among discordant pairs and the effect of mass media, which illustrated the important roles of the initial condition, dimensions, as well as the external information system [42, 43]. Wang et al. introduced an agent-based model integrating external political campaigns and opinion dynamics, which reproduced the 2016 USA presidential election well and yielded intriguing moderate clusters in addition to two polarized clusters [44].

While confirmation bias and peer pressure are not necessarily new phenomena, few attempts have been made to explore how the interplay between the two mechanisms affect opinion evolution [6, 45, 46]. In particular, the moderate clusters, and not the polarized clusters, usually determine the winner in competing processes of opinions. The Presidential election is a typical case where the party who wins the majority of moderates would win. Unveiling the facets of moderates is a meaningful problem which is of vital significance in designing efficient strategies to guide public opinion.

In this paper, we propose an agent-based model with the conjugate effect of confirmation bias and peer pressure, to describe the continuous opinion dynamics on large-scale social networks. First, we consider a population with homogeneous susceptibility to peer pressure. Simulation results show intriguing non-monotonous changes in the number of opinion clusters, which first increases and then decreases to one, with the population identity scope increasing. Moreover, passive adaptation speed shows a similar non-monotonous impact on the number of opinion clusters when population susceptibility to peer pressure exceeds a threshold. Further, we consider a heterogeneous population where impressionable and confident individuals coexist. Results show critical phenomena when considering the critical proportion of impressionable individuals that leads to public consensus: the value is very small when the population identity scope is relatively large, while explosively increases to a large one when the identity scope mitigates less than a threshold. Finally, we highlight that the majority of impressionable individuals would become moderates when the system reaches a steady state. It indicates the emergence of an important but easily influenced group: "impressionable moderates." This result implies the insight that targeting "impressionable moderates" might be an efficient strategy to guide public opinions, even when the system has reached a certain steady state.

2. MODEL

We introduce an agent-based model of continuous opinion dynamics which integrates the conjugate effect of confirmation bias and peer pressure in this section. Consider a large-scale social network with N agents, whose adjacent matrix is denoted by A. If there is a link between agent i and agent j, $A_{ij} = 1$. Otherwise, $A_{ij} = 0$. Here we denote $\mathcal{N}_i$ the set of all neighbors of agent i, i.e.,

$$\mathcal{N}_i = \{j|A_{ij} = 1\}, \quad i = 1, 2, \ldots\ldots, N. \tag{1}$$

Initially, each agent has an opinion x_i that is uniformly distributed in [0,1]. At each time step, social platforms allow agents to rapidly receive opinions from all their neighbors. According to the well-known confirmation bias, agents just think that opinions that are close enough to their beliefs are reasonable and that corresponding neighbors are supporters of

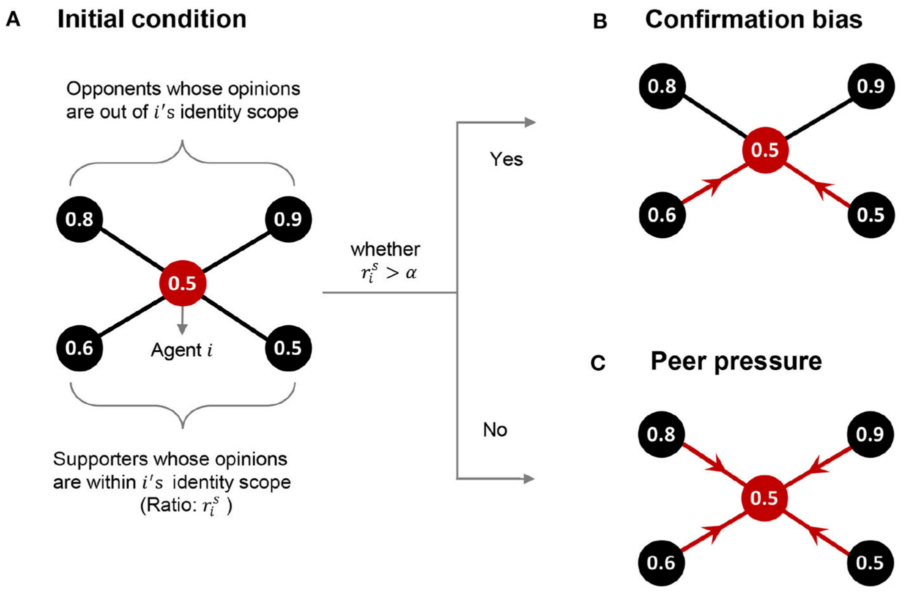

FIGURE 1 | Schematic of dynamical model. **(A)** Initial condition. Agent i passively receives information from neighbors. According to their claims, agent i divides neighbors into two classes: supporters whose opinions are within its identity scope (nodes in the bottom) and opponents whose opinions are out of its identity scope (nodes in the top). If the ratio of supporters is more than a threshold ($r_i^s > \alpha$), agent i would go through **(B)** confirmation bias and tends to update its opinion in its comfortable cognitive region by only interacting with supporters. Otherwise, agent i experiences **(C)** peer pressure and updates its opinion by interacting with all neighbors.

their cognition. Complying with previous studies [44], we define δ as the identity scope to describe the phenomena. Specifically, neighbor j is recognized as a supporter by agent i if $|x_i - x_j| < \delta$. Otherwise, neighbor j is recognized as an opponent. Thus, the set of all neighbor supporters of agent i can be written as

$$\mathcal{S}_i = \{j|A_{ij} = 1\&|x_i - x_j| < \delta\}. \tag{2}$$

In this way, any agent could divide its neighbors into two classes: supporters and opponents (see **Figure 1A**). Confirmation bias means that agents are only willing to receive positive feedback from their supporters.

While confirmation bias describes the initiative change, peer pressure is the main driving force of passive change in opinion dynamics, which means that individuals are likely to reshape their cognition, attitudes, or behaviors when being exposed to vast opponents [47, 48]. Here we adopt the thought of the threshold model to mimic the process. We define threshold α as susceptibility to peer pressure. Thus, we could describe the conjugate effect of confirmation bias and peer pressure as follows. Denote the fraction of supporters in all neighbors of agent i as r_i^s, which satisfies

$$r_i^s = \frac{|\mathcal{S}_i|}{|\mathcal{N}_i|}. \tag{3}$$

If $r_i^s > \alpha$, agent i would strengthen its cognition and only accept the positive feedback from neighbor supporters, which is shown as confirmation bias in **Figure 1B**. Otherwise, agent i would doubt their own cognition due to a lack of support and heavy peer pressure from opponents, which urges them to update their opinions according to all neighbors' position (see **Figure 1C**).

Specifically, our dynamical model goes through the following steps:

(1) At each time step, agent i divides its neighbors into supporters and opponents, according to the following rule: if $|x_i - x_j| < \delta$, neighbor j is recognized as a supporter. Otherwise, j is an opponent.
(2) At each time step, one of the two possible interactions would happen, which depends on the order relationship between r_i^s and α.

   (a) (*Confirmation bias*) If $r_i^s > \alpha$, agent i updates its opinion from x_i to $\tilde{x}_i$ by interacting with supporters:

$$\tilde{x}_i = x_i + \mu_1(\sum_{j\in\mathcal{S}_i} \frac{x_j}{|\mathcal{S}_i|} - x_i) \tag{4}$$

   where μ_1 reflects the initiative adaptation speed in opinion evolution. As this interaction induces homophily, i.e., agents become more similar over time, μ_1 could also be interpreted as the speed of homophily.

   (b) (*Peer pressure*) Otherwise, agent i updates its opinion from x_i to $\tilde{x}_i$ by interacting with all neighbors:

$$\tilde{x}_i = x_i + \mu_2(\sum_{j\in\mathcal{N}_i} \frac{x_j}{|\mathcal{N}_i|} - x_i) \tag{5}$$

   where μ_2 represents the passive adaptation speed caused by peer pressure.

TABLE 1 | Descriptions of model parameters.

Parameters	Descriptions
Identity scope (δ)	Threshold of opinion distance distinguishing supporters and opponents
Susceptibility to peer pressure (α)	Critical ratio of neighbor supporters that keeps agents from peer pressure
Initiative adaptation speed (μ_1)	Speed of opinion updates when only interacting with supporters
Passive adaptation speed (μ_2)	Speed of opinion updates under peer pressure

For clarity, the descriptions of main parameters in the proposed model are summarized in **Table 1**.

3. RESULTS

3.1. Simulation Results on Erdös-Rényi Networks

3.1.1. Homogeneous Population With Uniform Susceptibility to Peer Pressure

Here we perform simulations of our model on a large-scale Erdös-Rényi (ER) network with $N = 50,000$ nodes, whose average degree is $\langle k \rangle = 40$. In this section, we mainly explore the number of opinion clusters when the system reaches the stable state. Specifically, we divide the opinion interval [0,1] into 100 bins and compute the frequency of opinion values falling into each bin. Complying with previous studies, we utilize the number of peaks in distribution of opinion to represent the number of opinion clusters, where two peaks are regarded as separate if the distance between them is more than 0.1 [41].

In **Figure 2**, we explore how the interplay between confirmation bias and peer pressure affects the evolution of opinion clusters. **Figure 2A** presents phase diagram for the number of opinion clusters under different combinations of identity scope (δ) and susceptibility to peer pressure (α). More specifically, we present the number of opinion clusters with respect to changes in α (**Figure 2B**) and δ (**Figure 2C**), respectively. All simulation results are averaged over five independent runs and we verify the robustness of results (see **Supplementary Figures 1, 2**). In the phase diagram, we find that the number of opinion clusters decreases with susceptibility to peer pressure increasing, which is again confirmed in **Figure 2B**. The result adheres to our intuition that peer pressure promotes the consensus in public discourse. More interestingly, we highlight that the number of opinion clusters first increases and then reduces to one with the identity scope δ growing when $\alpha \neq 0$. The non-monotonous changes are again illustrated in **Figure 2C**, which cannot be observed in the classical Bounded Confidence Model [39]. While the increase of opinion clusters with δ growing is counter-intuitive, it can be explained by the following intuitive reasons. In the same surroundings, individuals with a smaller identity scope think that more opinions deviate from their beliefs, and thus experience more peer pressure, which urges them to make a major change in their opinions to adapt to the public. **Figures 2D–F** show that public opinions would finally converge to several clusters by presenting distribution of final opinions under different situations.

We then explore the effect of initiative adaptation speed (μ_1) and passive adaptation speed (μ_2). It is trivial that the public always reaches consensus when population identity scope is large, no matter what μ_1 or μ_2 is. Thus, we mainly examine the situations where the population identity scope is small ($\delta = 0.05$) in **Figure 3**. We first present the phase diagram for the number of opinion clusters under different values of μ_1 and μ_2 in **Figure 3A**. The number of opinion clusters remains almost the same with μ_1 varying, while it first increases and then decreases with μ_2 growing. It indicates that passive but not initiative adaptation speed plays a significant role in the evolution of opinion clusters; large or small μ_2 could promote clustering of opinions while intermediate μ_2 has the opposite effect. We then examine whether the conclusion above is true under different susceptibilities to peer pressure (α). **Figures 3B,C** present phase diagrams under different values of μ_1 and α as well as μ_2 and α, respectively. These also illustrate the small impact of initiative adaptation speed and the non-monotonous impact of passive adaptation speed under different values of α.

3.1.2. Heterogeneous Population With Different Susceptibilities to Peer Pressure

Note that the susceptibility to peer pressure in the population is heterogeneous. For simplicity, we consider simple heterogeneous scenarios where the population consists of two classes: impressionable individuals who have large susceptibility to peer pressure (α_i) and confident individuals who have small susceptibility to peer pressure (α_c). We denote the fraction of impressionable individuals as ρ.

First, we explore the effect of impressionable individuals on public opinion evolution. To get a comprehensive understanding, we perform simulations under three different combinations of α_c and α_i, where $(\alpha_c, \alpha_i) = (0, 0.5)$, $(0, 0.3)$, and $(0.1, 0.4)$, respectively. For each combination, we present a phase diagram for the number of opinion clusters under different values of identity scope (δ) and the proportion of impressionable individuals (ρ) in **Figures 4A–C**. For the cases $\alpha_c = 0$ (**Figures 4A,B**), an intriguing critical phenomena emerges. To be specific, as δ decreases, the critical value of ρ, leading to public consensus, remains very small (no more than 0.1) when δ is relatively large ($\delta \in [0.16, 0.2]$), while it explosively increases to a large one when δ decreases to a value. It indicates that even when confident individuals are completely immune to peer pressure, a few impressionable individuals could efficiently eliminate public polarization. However, this function only happens when the population identity scope is relatively large. We then consider the situations where confident individuals are also susceptible to peer pressure ($\alpha_c \neq 0$) in **Figure 4C**. Results also show the significant impact of impressionable individuals when δ is large. More interestingly, a small number of impressionable individuals could also lead to public consensus under very small δ but cannot do so under intermediate δ. This phenomena could be explained by the following reason. In this situation, confident individuals

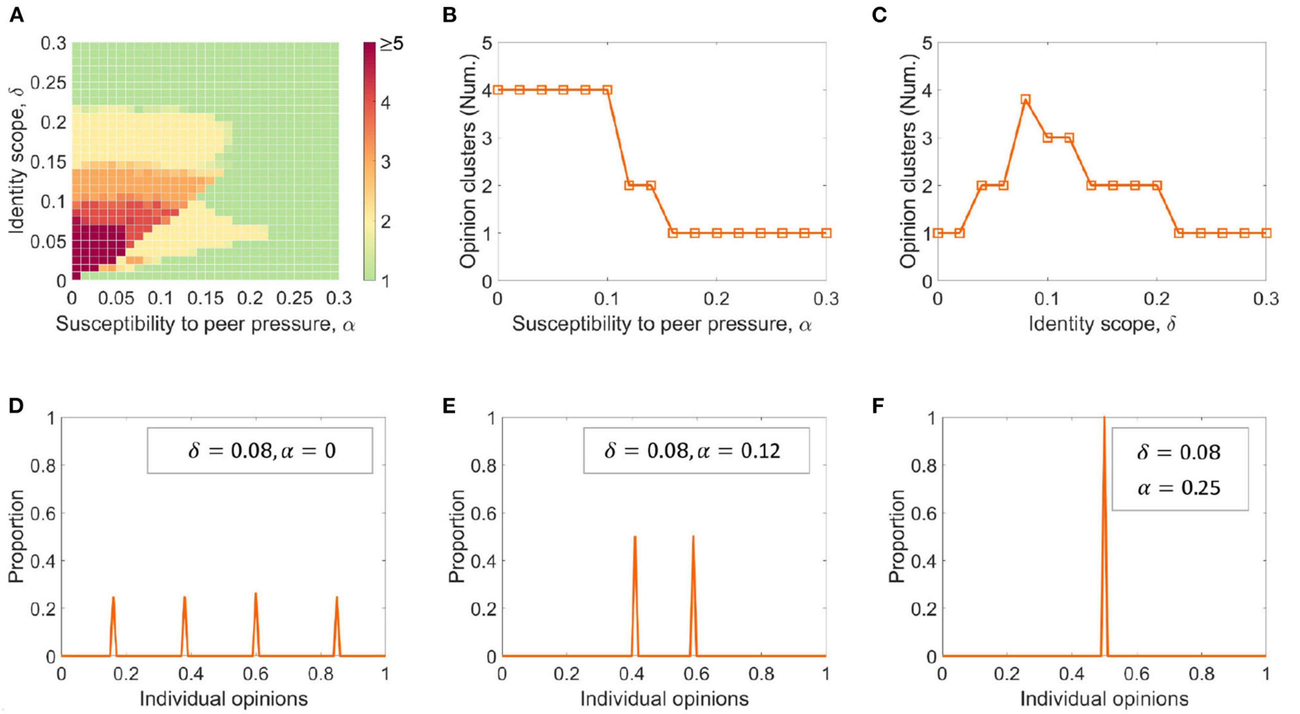

FIGURE 2 | Conjugate effect of confirmation bias and peer pressure. **(A)** Shown is the number of opinion clusters under different combinations of identity scope (δ) and susceptibility to peer pressure (α). **(B,C)** The number of opinion clusters is presented as a function of α and δ, respectively. We highlight the non-monotonous change in the number of opinion clusters with identity scope varying: the number first increases and then reduces to one with δ growing. **(D–F)** We present the distribution of final opinions under some situations. Parameters: $\mu_1 = 0.7$, $\mu_2 = 0.7$. In addition, **(B)** $\delta = 0.08$, **(C)** $\alpha = 0.1$, **(D)** $\delta = 0.08$, $\alpha = 0$, **(E)** $\delta = 0.08$, $\alpha = 0.12$, **(F)** $\delta = 0.08$, $\alpha = 0.25$.

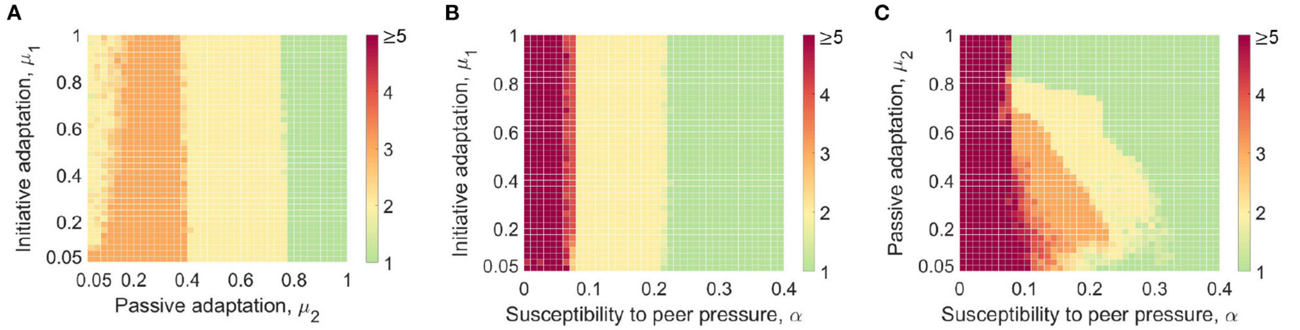

FIGURE 3 | Effect of initiative adaptation speed (μ_1) and passive adaptation speed (μ_2). Phase diagrams for the number of opinion clusters are shown under different combinations of **(A)** μ_1 and μ_2, **(B)** μ_1 and α, as well as **(C)** μ_2 and α, respectively. We find that initiative adaptation speed hardly affects the number of opinion clusters, while passive adaptation speed shows a non-monotonous effect on it. Parameters: **(A)** $\delta = 0.05$, $\alpha = 0.18$, **(B)** $\delta = 0.05$, $\mu_2 = 0.7$, and **(C)** $\delta = 0.05$, $\mu_1 = 0.7$.

possibly experience more peer pressure under a smaller identity scope, which urges them to adapt to the public.

In summary, when confident individuals are completely immune to peer pressure, a small fraction of impressionable individuals could lead to public consensus at a large population identity scope, while the critical value of ρ explosively increases to a large value at a small population identity scope. The critical phenomena could be explained by the following dynamic perspectives. At each time step, peer pressure might force impressionable individuals to break their identity scope and to update opinions by interacting with all their neighbors. Thus, some impressionable individuals would have opinions falling in between all their neighbors and could act as bridges of communication between others. This could promote public

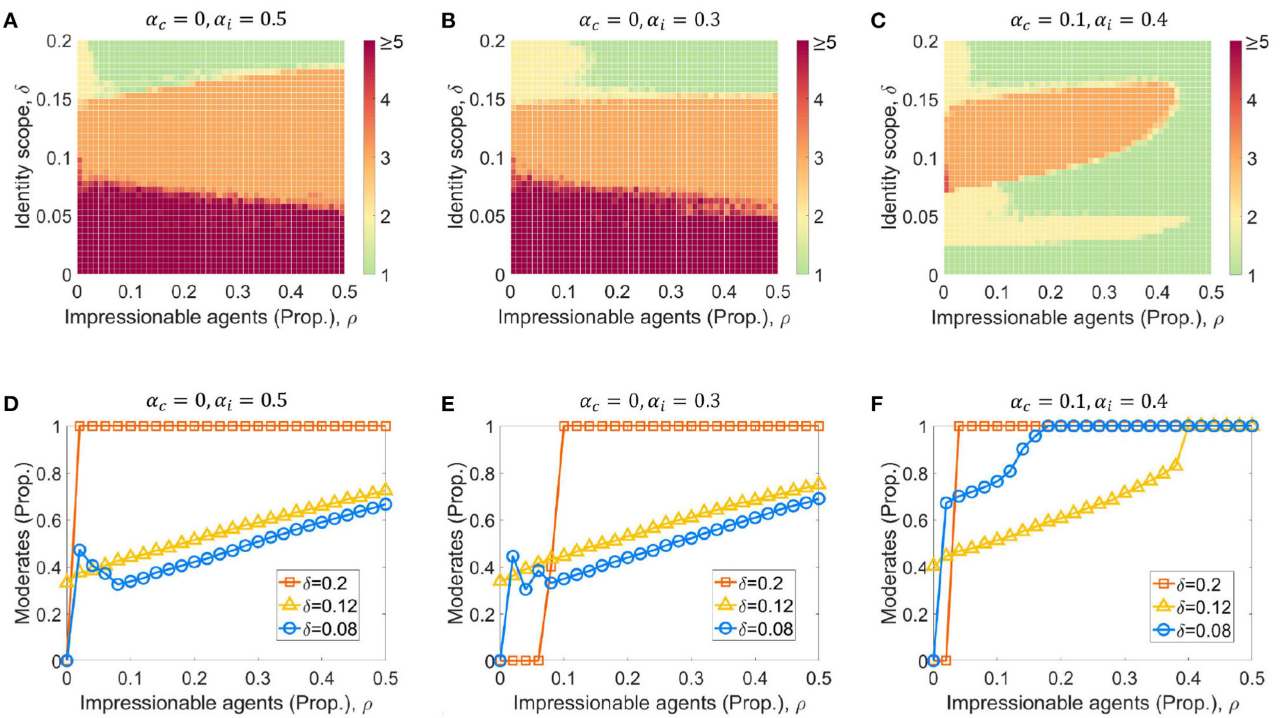

FIGURE 4 | How impressionable individuals affect public opinions. We consider three combinations of α_c and α_i: **(A,D)** $\alpha_c = 0$, $\alpha_i = 0.5$, **(B,E)** $\alpha_c = 0$, $\alpha_i = 0.3$, **(C,F)** $\alpha_c = 0.1$, $\alpha_i = 0.4$. **(A–C)** Shown are phase diagrams for the number of opinion clusters under different combinations of identity scope (δ) and the proportion of impressionable individuals (ρ). **(D–F)** Shown are the proportion of moderates with respect to changes in ρ under different values of δ. For cases $\alpha_c = 0$, small ρ (more than 0.08) could promote public consensus when δ is relatively large, while it could only increase the proportion of moderates slightly when δ is relatively small. For the case $\alpha_c = 0.1$, small ρ could also lead to public consensus when δ is small enough. Parameters: $\mu_1 = 0.7$, $\mu_2 = 0.7$.

consensus. But when population identity scope is very small, even the opinions of these "bridges" would be beyond the identity scope of most confident individuals. Moreover, for the cases where confident individuals are not completely immune to peer pressure, the public could also reach consensus when population identity scope is small. In this situation, peer pressure plays a pivotal role.

In addition, **Figures 4A–C** all include a large region where three opinion clusters coexist. The phenomena are ubiquitous in many real-world scenarios of opinion evolution. A well-known case is The USA Presidential election where people finally form three groups according to their political opinions: Democratic supporter group, Republican supporter group, and the moderate group [44]. In this case, the moderate group plays a very significant role as their choices directly determine the winner in competing processes. This motivates us to explore the main factors influencing the proportion of moderates as well as the characteristics of the moderate group in our dynamical model. Here we define moderates as individuals whose opinions belong to $[0.5 - V, 0.5 + V]$, where V is a boundary parameter. It is proven that the proportion of moderates is almost the same for any $V \in [0.02, 0.1]$ (see **Supplementary Figure 3**). Thus, without loss of generality, we could set V as 0.05.

Figures 4D–F present the proportion of moderates as a function of ρ under different combinations of α_c and α_i, respectively. For all combinations, the case $\delta = 0.2$ shows an explosive increase of moderates at a small value of ρ, which illustrates the pivotal effect of impressionable individuals on public consensus when δ is relatively large. For $\alpha_c = 0$ (**Figures 4D,E**), impressionable individuals could only cause a slight increase of moderates when population identity scope is small. For $\alpha_c \neq 0$, the proportion of moderates rapidly increases with ρ growing even if the population identity scope is small.

Furthermore, we explore the relationship between impressionable/confident individuals and moderates from evolutionary perspectives. Clearly, all individuals would finally hold moderate opinions if population identity scope were large. Thus, we mainly analyze the case where δ is small. **Figures 5A–C** shows how many impressionable/confident individuals would finally become moderates when the systems reach a steady state under different combinations of α_c and α_i. We highlight that while initial opinions of impressionable individuals are randomly distributed, more than 80% of them finally hold moderate opinions. The proportion is much larger than that of confident individuals becoming moderates. We then perform simulations under more different situations, which also show the above evolutionary relationship (see **Supplementary Figure 4**). These imply the existence of vast "impressionable moderates" when a system with impressionable agents reaches a steady state. This group is easily influenced but important; impressionable

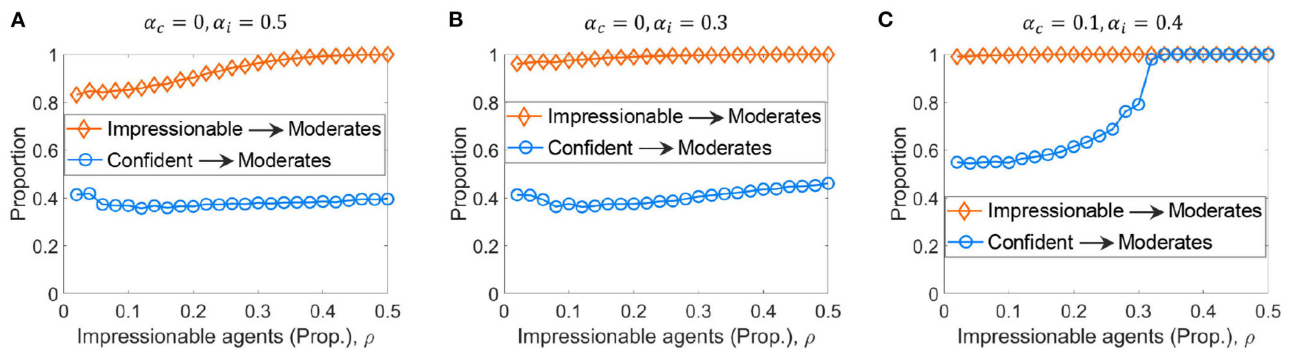

FIGURE 5 | Evolutionary relationship between impressionable/confident individuals and moderates. Three situations are considered: **(A)** $\alpha_c = 0$, $\alpha_i = 0.5$, **(B)** $\alpha_c = 0$, $\alpha_i = 0.3$, **(C)** $\alpha_c = 0.1$, $\alpha_i = 0.4$. In each situation, we present the proportion of impressionable individuals evolving to moderates (red diamond) and the proportion of confident individuals evolving to moderates (blue circle) with respect to changes in ρ. More than 80% of impressionable individuals finally hold moderate opinions in all situations. The proportion is much larger than that of confident individuals evolving to moderates. Parameters: $\mu_1 = 0.7$, $\mu_2 = 0.7$, $\delta = 0.1$.

characteristics make them more likely to be affected by external peer pressure, but their choices directly determine the winner in competing processes. It naturally provides us with an insight on how to persuade individuals with moderate opinions when the system has reached a steady state. To guide "confident moderates," it is required to continually inform them on opinions close to their beliefs because confident individuals only value opinions within their identity scope, which is consistent with previous studies [44]. On the contrary, to guide "impressionable moderates," deploying zealots with extreme views might be an efficient strategy because impressionable individuals are more likely to be forced to readjust their opinions according to the surroundings. In this situation, extreme views could maximumly influence their opinions.

3.2. Simulation Results on Scale-Free Networks

In the real world, social networks often have power-law degree distribution, i.e., $p_k \sim k^{-\gamma}, (2 < \gamma < 3)$. To mimic this situation, we further examine how the proposed model behaves on scale-free networks. Here we consider a scale-free network with $N = 50,000$ and power-law exponent $\gamma = 2.2$.

Figure 6 presents simulation results on homogeneous populations with uniform susceptibility to peer pressure. In **Figure 6A**, we explore how the interplay between identity scope (δ) and susceptibility to peer pressure (α) affects the evolution of opinion clusters. Results show that the number of opinion clusters first increases and then decreases to one with identity scope growing when $\alpha \neq 0$, which is similar to results on Erdös-Rényi (ER) networks. Quantitatively, the critical values of α, leading to consensus, are slightly larger on scale-free networks (comparing **Figures 2A**, **6A**). We then discuss the impact of initiative adaptation speed (μ_1) and passive adaptation speed (μ_2) in **Figures 6B–D**. The number of opinion clusters is almost unchanged as μ_1 varies, while it displays non-monotonous changes as μ_2 grows (**Figure 6B**). These conclusions, including the small impact of initiative adaptation speed and the non-monotonous impact of passive adaptation speed, are also true under different values of α (**Figures 6C,D**). In summary, when all individuals have uniform susceptibility to peer pressure, simulation results on scale-free networks are qualitatively similar to those on ER networks.

Figure 7 presents simulation results on heterogeneous populations, where impressionable agents with large susceptibility to peer pressure (α) and confident agents with small α coexist. To comprehensively understand the impact of impressionable agents, we discuss two strategies of selecting impressionable agents: random selection (randomly select impressionable agents) and target selection (prefer to select those with large degree). First, we explore the situations where confident agents are completely immune to peer pressure ($\alpha_c = 0$). **Figures 7A,B** present the number of opinion clusters under different values of δ and ρ when random selection strategy and target selection strategy are adopted, respectively. Similarly, we find that a small proportion of impressionable agents could help eliminate polarization when δ is relatively large. The qualitative conclusions are similar to the results on Erdös-Rényi networks, while the critical proportion of impressionable agents, leading to consensus, is slightly larger on scale-free networks when a random selection strategy is adopted (comparing **Figures 4B**, **7A**). It is worth noting that the critical proportion under the target selection strategy is much smaller than that under the random selection strategy when δ is relatively large. This indicates that selecting hubs as impressionable agents could effectively facilitate the depolarization process compared to the random selection strategy. Moreover, **Figure 7C** shows that there is no significant difference in the proportion of moderates under intermediate δ when comparing the two selection strategies. The phenomena might be explained by the following reasons: confident individuals are immune to peer pressure from external sources including hubs ($\alpha_c = 0$), which implies that impressionable hubs only have limited ability of persuading confident agents. We then consider the cases where confident agents have positive susceptibility to peer pressure ($\alpha_c \neq 0$). **Figures 7D,E** present a phase diagram for the number of opinion clusters under the random selection strategy and

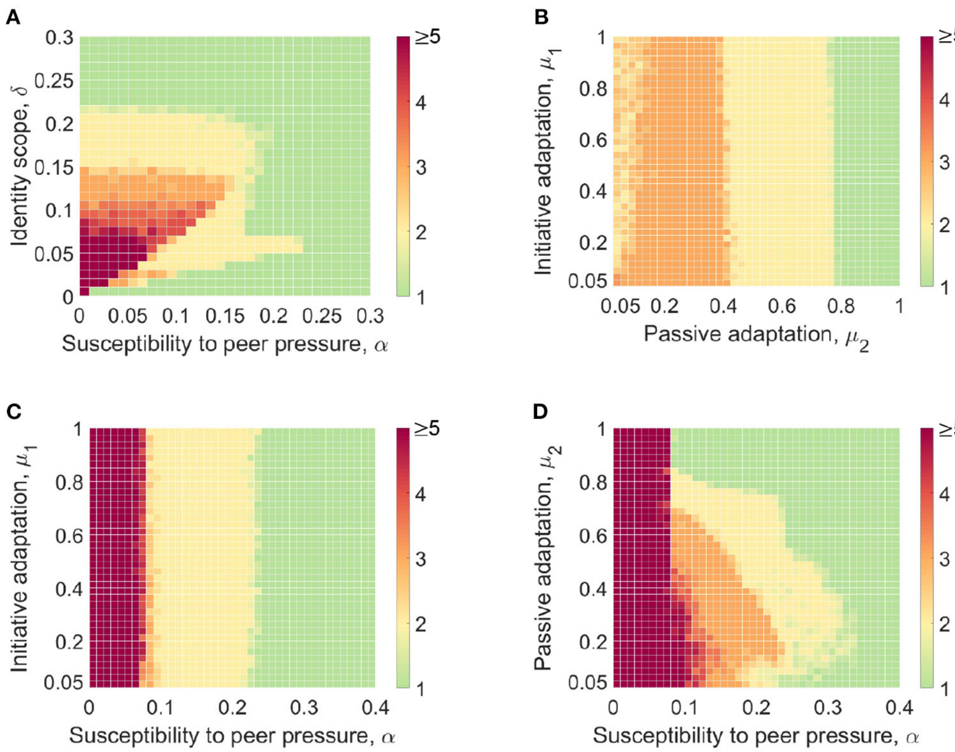

FIGURE 6 | Simulation results on homogeneous populations. The number of opinion clusters is shown under different combinations of **(A)** identity scope (δ) and susceptibility to peer pressure (α), **(B)** initiative adaptation speed (μ_1) and passive adaptation speed (μ_2), **(C)** μ_1 and α, as well as **(D)** μ_2 and α, respectively. Results highlight that the number of opinion clusters first increases and then decreases as identity scope or passive adaptation speed grows. All simulation results are averaged over five times. Parameters: **(A)** $\mu_1 = 0.7$, $\mu_2 = 0.7$, **(B)** $\delta = 0.05$, $\alpha = 0.18$, **(C)** $\mu_2 = 0.7$, $\delta = 0.05$, **(D)** $\mu_1 = 0.7$, $\delta = 0.05$.

target selection strategy, respectively. Both figures illustrate the giant impact of impressionable agents under large or small δ. Interestingly, target selection strategy significantly improves the efficiency of depolarization compared to the random selection strategy. In addition, selecting hubs as impressionable agents results in a larger proportion of moderates (**Figure 7F**).

To conclude, the giant impact of impressionable individuals on promoting public consensus is also observed on scale-free networks when δ is relatively large. More importantly, selecting hubs as impressionable agents could improve the efficiency of depolarization compared to randomly selecting impressionable agents. This is intuitive as hubs have many connections in networks, which means that hubs have the potential to affect more individuals. However, when δ is relatively small, the difference between the impact of the two strategies is small when confident individuals are completely immune to peer pressure ($\alpha_c = 0$), while the difference is huge when $\alpha_c \neq 0$.

4. CONCLUSIONS AND DISCUSSIONS

Opinion evolution on large-scale social networks has been widely discussed [49–51]. People are more likely to accept claims within their identity scope and ignore the dissenting claims [52, 53]. On the contrary, people might alter their decisions if they are receiving vast opposing views [54]. Both confirmation bias and peer pressure were proven to be core factors in opinion dynamics, separately [55, 56]. However, it remains unclear how the interplay between these two mechanisms affects opinion evolution.

In this work, we propose an agent-based model of opinion evolution which considers both confirmation bias (characterized by population identity scope and initiative adaptation speed) and peer pressure (described by a susceptibility threshold and passive adaptation speed). By performing simulations in a homogeneous population, we find the non-monotonous conjugate effect of these two mechanisms. To be specific, the number of opinion clusters first increases and then decreases to one with population identity scope growing when individuals are susceptible to peer pressure. The non-monotonous change is completely different from insights of the classical bounded confidence model [39]. The counter-intuitive phenomena can be explained by the following microscopic reason: agents with a smaller identity scope consider that more opinions deviate from their beliefs and thus they receive more peer pressure which urges them to adapt to the public. Moreover, we find that initiative adaptation speed has very little impact on the evolution of opinion clusters, while passive adaptation speed could play a pivotal role.

Further, we consider the heterogeneity of susceptibility to peer pressure. In particular, the heterogeneous population is divided into "impressionable" individuals with large susceptibility and "confident" individuals with small susceptibility. We explore

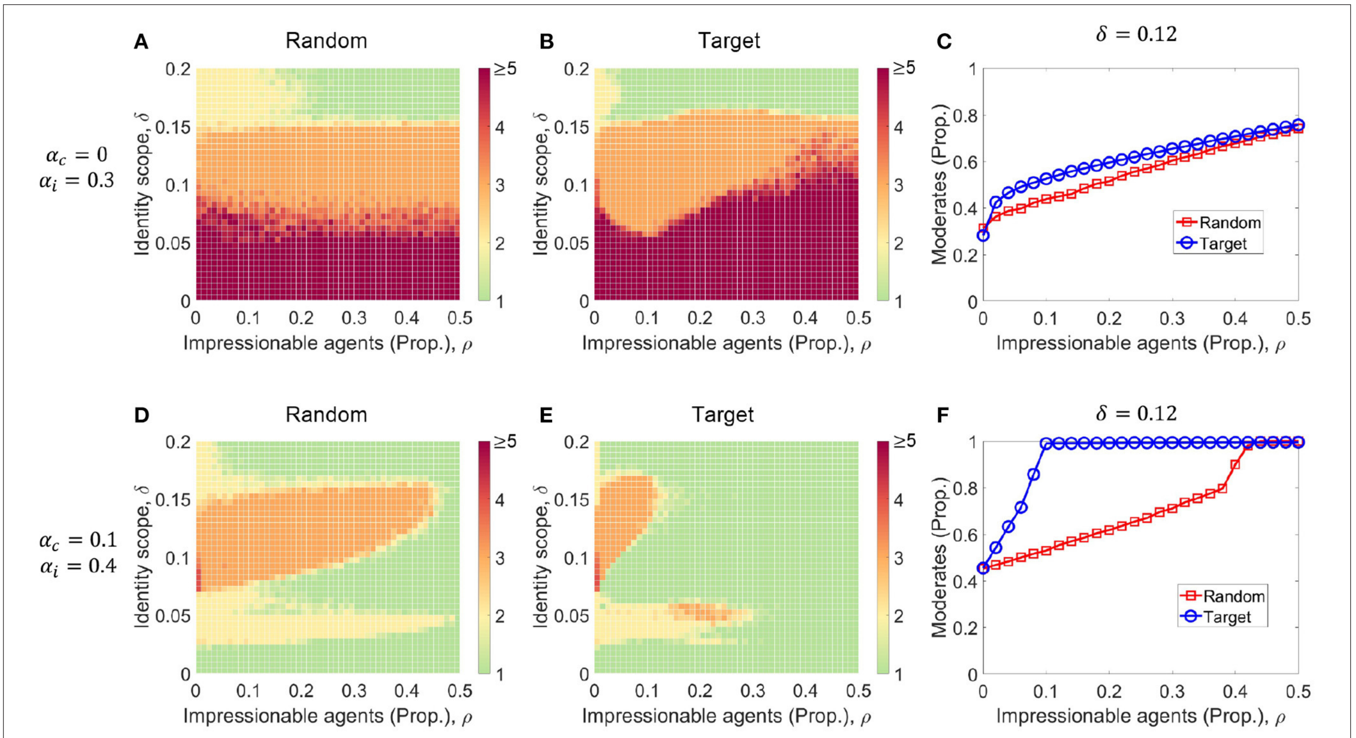

FIGURE 7 | Simulation results on heterogeneous populations. We consider the impact of impressionable individuals under two different situations: **(A–C)** $\alpha_c = 0$, $\alpha_i = 0.3$ and **(D–F)** $\alpha_c = 0.1$, $\alpha_i = 0.4$. **(A,D)** Shown is the number of opinion clusters under different combinations of identity scope (δ) and the proportion of impressionable agents (ρ), when impressionable agents are randomly selected (Random selection). **(B,E)** Shown is the phase diagram when agents with a large degree are preferentially selected as impressionable ones (Target selection). **(C,F)** The proportion of moderates is presented as a function of ρ under the two selection strategies. Compared to random selection, target selection could promote the efficiency of depolarization. However, the difference between the two strategies is limited when $\alpha_c = 0$, while it is large when $\alpha_c \neq 0$. Parameters: $\mu_1 = 0.7$, $\mu_2 = 0.7$. In addition, **(C,F)** $\delta = 0.12$.

the detailed effect of impressionable individuals. First, we find intriguing critical phenomena: a few impressionable individuals could efficiently eliminate public polarization when population identity scope is relatively large, while the critical proportion resulting in public consensus explosively increases to a large one when population identity scope mitigates less than a threshold. In particular, when confident individuals are not completely immune to peer pressure, a small proportion of impressionable individuals could also lead to public consensus at a small population identity scope. Moreover, the critical proportion would become smaller if hubs are preferentially selected as impressionable agents. Finally, we highlight that while impressionable individuals' initial opinions are randomly distributed, more than 80% of them finally become moderates when the system reaches the steady state. It implies the existence of an important but easily influenced group: "impressionable moderates."

Our work utilizes simple dynamical mechanisms to integrate the conjugate effect of confirmation bias and peer pressure, reveals the non-monotonous effect of population identity scope, and explains the counter-intuitive phenomena from a microscopic level. Furthermore, the study on the effect of impressionable individuals shows us that deploying a few impressionable individuals would be a powerful method of eliminating the public polarization when population identity scope is relatively large. More interestingly, our model shows that "impressionable moderates" might be an important part of the whole population when the system with impressionable agents reaches steady states. The group is important but easily influenced, which shows us that persuading "impressionable moderates" might be a new insight for guiding public opinions. Since our results are currently limited to the theoretical stage, future research may incorporate model-data comparisons to obtain more realistic understandings. In addition, the method of persuading "impressionable moderates" could be completely different from that of persuading "confident moderates." Mixed strategies of persuading both types of individuals with moderate opinions should also be studies further.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

LL and XW conceived the study model and wrote the paper. LL and XC conducted the simulations. ST and

ZZ provided the funding and supervised the research. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fphy.2021.649852/full#supplementary-material

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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