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Cascades Across Networks are Sufficient for the Formation of Echo Chambers: An Agent-Based Model

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Abstract: Investigating how echo chambers emerge in social networks is increasingly crucial, given their role in facilitating the retention of misinformation, inducing intolerance towards opposing views, and misleading public and political discourse (e.g., disbelief in climate change). Previously, the emergence of echo chambers has been attributed to psychological biases and inter-individual differences, requiring repeated interactions among network-users. Using an idealised population of social network users, the present results suggest that two core components of social networks—users self-select their networks, and information is shared laterally (i.e. peer-to-peer)—might be sufficient to produce echo chambers. Crucially, we show that this requires neither special psychological explanation (e.g., bias or individual differences), nor repeated interactions—though these may be exacerbating factors. In fact, this effect is made increasingly worse the more generations of peer-to-peer transmissions it takes for information to permeate a network. This raises important questions for social network architects, if truly opposed to the increasing prevalence of deleterious societal trends that stem from echo chamber formation.

Keywords: Echo Chambers, Source Credibility, Information Cascades, Agent-Based Modeling, Bayesian Modeling

Introduction

1.1 As we navigate social media platforms, we are free to customise our networks according to our individual needs: we choose to connect with users we like while we ignore others, we follow 'Influencers' that inspire us, and we selectively share and repost content. Combined with curated News Feeds, selective attention to and sharing of content has been associated with spreading of digital misinformation (Del Vicario et al. 2016a) and false news stories (Vosoughi et al. 2018). Over the past decade, several researchers investigated the spreading and retention of misinformation and false news on social media platforms (Starbird et al. 2014; Bessi et al. 2015; Bakshy et al. 2015; Del Vicario et al. 2016a) and their implications for e.g., the polarisation of opinions (Bessi et al. 2016; Sikder et al. 2020). However, the scientific community still lacks clear answers to fundamental questions relating to the general prevalence of misinformation and false news and their effects on individuals (Lazer et al. 2018).

1.2 To understand the spreading of misinformation and false news, recent work has investigated the impact of echo chambers on digital misinformation. Echo chambers are enclosed epistemic systems where like-minded individuals reinforce their pre-existing beliefs (Madsen et al. 2018). The enclosing nature of echo chambers has been shown to induce intolerance towards opposing views (Takikawa & Nagayoshi 2017), misleading public and political discourse (Jasny et al. 2015; Jasny & Fisher 2019) and quantitative analyses suggest that echo chambers may contribute to the spread of misinformation (Törnberg 2018; Del Vicario et al. 2016a). Considering these findings, investigating how echo chambers emerge on social media might offer an important opportunity for understanding and potentially counteracting the occurrence of digital misinformation.

1.3 Importantly, although some social media users might 'live' in echo chambers, using social media does not necessarily imply restricted exposure to information. Compared to non-users, the average social media user experiences more diverse content (Newman et al. 2017a) and it has been suggested that the majority of social media users do not necessarily self-select into echo chambers (Haw 2020). Moreover, recent theoretical work shows that echo chambers might improve individual access to information via optimising the allocation of information resources (Jann & Schottmüller 2018). These findings further highlight the importance of clarifying how echo chambers emerge on social media, and raise questions about the value-free nature of echo-chambers.

1.4 In the present work, we formally study echo chamber formation within simulated populations of social media users. We expand the previous literature through two primary contributions, motivated by two important elements of social networks: 1) users are self-selecting in their peer networks (e.g., form connections based on friendship), and 2) users can share information rapidly in a peer-to-peer manner (i.e. lateral transmission). Specifically, we investigate the emergence of echo chambers as a result of a single pass-through of information prior to repeated interaction between users (contribution 1), and how this is impacted by a user's perceived credibility of their peers (contribution 2).

1.5 We test the robustness of these contributions across a wide range of network setups varying in terms of epistemic authority (expertise strength) of users (robustness check 1), percentage of users sharing their beliefs with their peers (robustness check 2), and their connectivity density (robustness check 3). Moreover, we contrast two hypothetical populations of agents. For the first population ('social agents'), we assume that social media users select their network-peers based on whom they like (i.e. positive credibility). Conceptually, social agents are comparable to social media users that customise their networks based on positive perceptions of others (e.g., friendship). The second population ('asocial agents') functions as control check, selecting their network peers at random and independent of their perceived credibility. Given these considerations, we hope to better understand the *sufficient* causes that lead to the formation of echo chamber on social networks.

Background and motivation

Echo chambers

2.1 To investigate when and how echo chambers emerge, it is important to explore their causes. These might be routed in psychological biases: previous analyses of echo chambers and their impact on digital misinformation identified confirmation bias—seeking information confirming one's prior beliefs (Nickerson 1998)—and social influence—peoples' tendency to align their behaviour with the demands of their social environment (Kelman 1958)—as key driving factors of echo chamber formation (Del Vicario et al. 2016a; Starnini et al. 2016; Sikder et al. 2020). For example, a recent quantitative analysis showed that social influence combined with a preference for forming connections with similar peers and abandoning dissimilar social ties results in rapid echo chamber formation after repeated interaction (Sasahara et al. 2019). Additionally, work in statistical physics has shown that confirmation bias induces clustering of like-minded individuals (i.e. echo chambers) and proliferation of opinions (Ngampruetikorn & Stephens 2016).

2.2 The above findings might be explained by the fact that social influence and confirmation bias lead to selective avoidance of information challenging one's prior beliefs, and consequently, limited access to cross-cutting content on social media such as Facebook (Henry et al. 2011; Bakshy et al. 2015; Ngampruetikorn & Stephens 2016). Along with psychological biases, it has also been argued that cognitive differences between individuals might induce echo chambers (Barkun 2013). Overall, these findings suggest that both psychological variables and cognitive variability among individual agents might be necessary requirements for the formation of echo chambers.

2.3 Aiming to clarify the necessity of psychological variables and heterogeneity, recent simulation-based work has investigated echo chamber formation in an idealised population of homogeneous rational (i.e. Bayesian) agents engaging in repeated interaction and with a preference for similar-minded others (Madsen et al. 2018, 2017). Results provided a formal argument for the inherent susceptibility of social networks towards echo chamber formation despite *absence* of cognitive differences among agents. In other words, the *structure* of social networks, in conjunction with a bias against dissimilar peers, is sufficient for the formation of echo chambers. These findings are in line with earlier work showing that echo chambers inevitably emerge if users engaging in repeated interaction preferentially rewire their social ties to avoid contact with dissimilar peers (Henry et al. 2011).

2.4 Importantly, while previous work on echo chambers (Madsen et al. 2018, 2017) and opinion dynamics (see also Lorenz (2007)) shows that repeated interaction solidifies echo chambers, the present work investigates whether the initial way in which information arrives into the network already 'skews the pitch'. This is motivated by theoretical (Bikhchandani et al. 1992) and simulation-based (Pilditch 2017) work on information cascades, which has shown that single interactions between equally rational agents can result in maladaptive outcomes prior to repeated interaction, and thus in the absence of rewiring of social ties. In other words, the connective density of social networks—including lateral transmission of information and limited access to the knowledge of the entire network—may be sufficient for echo chamber formation, even before repeated interaction, and without recourse to cognitive differences / biases against forming social ties with users entertaining different beliefs.

2.5 To investigate this we employed an agent-based model (in line with prior research on related phenomena (Madsen et al. 2017, 2018)) that allowed us to simulate whether echo chambers emerge among agents as a consequence of network structure (i.e. connective density—what percentage of the network is any given user *directly* connected to?) in the *absence* of repeated interaction (contribution 1). As agents in our simulations were furnished with a homogeneous cognitive architecture, forming beliefs normatively through Bayesian updating, we were able to isolate structural aspects of a network from psychological variables and inter-individual differences among agents. However, unlike this previous work (Madsen et al. 2017, 2018), agents in our simulations do not repeatedly interact. Instead, we focus on a single cascade of information sharing, with beliefs updated sequentially via single interaction. Crucially, this allows us to isolate echo-chamber formations *without repeated interactions and pruning behaviours*.

Source credibility

2.6 The credibility of a source plays an important role when integrating their beliefs with our own observations and prior expectations (Cuddy et al. 2011; Fiske et al. 2007). Moreover, source credibility plays a critical role in persuasion and argumentation theory, especially in the context of politics (Housholder & LaMarre 2014; Robinson et al. 1999; Cialdini & Cialdini 1993), which has become increasingly influenced by online communication systems such as Facebook (Bail 2016). Both heuristic accounts, such as the heuristic-systematic model (HSM) (Chaiken 1999) and dual-process theories, including the elaboration-likelihood model (ELM) (Petty & Cacioppo 1986) have been used to study the influence of credibility on persuasion, showing a positive general impact (Chaiken & Maheswaran 1994).

2.7 Recently, research has investigated the influence of source credibility from a Bayesian perspective, meaning that credibility is modeled as an analytic cue that moderates belief updating (Bovens et al. 2003; Hahn et al. 2009; Harris & Hahn 2009; Oaksford et al. 2007). This Bayesian Source Credibility model (BSCM) moves beyond previous models by providing a quantitative, normative framework for modelling belief updating under consideration of the influence of credibility. Empirical work supports the suitability of Bayesian representations of belief formation and credibility (see e.g., (Harris et al. 2016)). Expanding on previous simulation work (Madsen et al. 2017, 2018), and due to the quantitative nature of our analysis, we deploy a BSCM account (i.e. an agent / social media user) within our model (contribution 2).

2.8 Importantly, by using BSCM, agents in our network form ties irrespective of their beliefs. This distinguishes our model from previous simulation work (Hegselmann & Krause 2002, 2005; Lorenz 2007; Bolletta & Pin 2020) in which ties between agents are interrupted once the difference in their beliefs surpasses a threshold. These "bounded confidence" models have been used to model echo chamber formation. However, such models fail to provide an account of how: 1) interactions between dissimilar agents, and 2) the perceived credibility of a communicating agent, interact with the formation process. We argue, given the demonstrated importance of credibility perceptions to the belief updating process (see e.g., (Harris et al. 2016)), their inclusion in the present model is a novel and important contribution.

Model design and Simulations

Agent-based models

3.1 Agent-based models (ABMs) are simulated multi-agent systems that provide a formal framework for studying cognitive functions and behaviours in social environments—such as social media—which involve complex

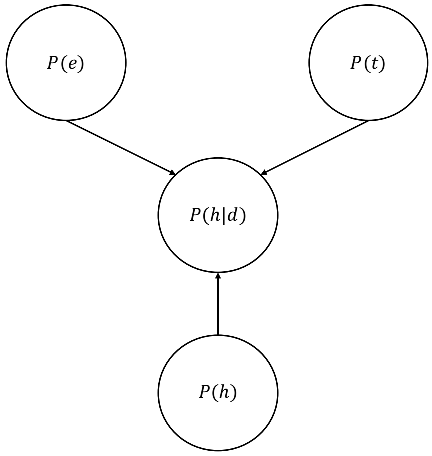

Figure 1: Figure shows how a prior belief $P(h)$ and the perceived credibility of a source (operationalised via expertise $P(e)$ and trustworthiness $P(t)$) interact within the BSCM framework.

and dynamic interactions between users (Wilensky & Rand 2015). Of particular relevance for our work is the advantage that ABMs allow for the capturing of emergent phenomena on a network level which is not possible when studying individual users in isolation from their peers (Madsen et al. 2019). The advantages of ABMs for the study of complex and dynamic systems have been shown in research on belief formation in the context of climate change (Lewandowsky et al. 2019) and micro-targeting (Madsen & Pilditch 2018). In the remainder of this paper, we will refer to aspects of ABMs that are relevant to our model. For further details on how to use ABMs and an elaborate discussion of their general advantages for modelling cognitive phenomena, see (Macal & North 2005; Madsen et al. 2019).

3.2 Here, we reconstructed an idealised social network similar to (Pilditch 2017; Madsen et al. 2018) in which users (i.e. agents) were distributed randomly in a two-dimensional space forming social ties based on proximity, as measured by Euclidean distance (see Methods for details). Agents communicated binary beliefs to their peers and updated them through a single interaction. Binary beliefs in this case means that agents could either believe in a hypothesis—belief h—or not believe in a hypothesis—belief $\neg h$. Conceptually, this can be thought as a group of people that either support a political candidate (h) or not support a political candidate ($\neg h$).

3.3 Our agent-based model (ABM) captured agents' social environment (social ties with peers) and the temporal dynamics of belief change (updating beliefs through interaction), which both form necessary requirements for the observation of echo chambers. Additionally, our ABM accounted for heterogeneity between individual agents (such as different prior beliefs); an advantage of agent-based simulations (Wilensky & Rand 2015). Specifically, though we designed agents such that their cognitive *functions* are the same (homogeneous cognitive architecture), we allowed for the diversity among agents of particular belief *values* (heterogeneous prior beliefs): Each agent was furnished with their own subjective prior beliefs, randomly sampled from a Gaussian distribution. As such, each agent had a unique prior belief about whether they would support a hypothesis or not. Thinking about a group of people again, this means that while they would all share the same mechanism (i.e., process) for updating their beliefs (homogeneous cognitive architecture), each of them would enter a discussion with their own subjective prior opinion (heterogeneous prior beliefs).

Bayesian source credibility model

3.4 Bayesian theories of reasoning and decision making propose that a person's prior belief in a hypothesis can be represented as subjective probability $P(h)$ taking values between 0 and 1 (see e.g., (Hahn & Oaksford 2007; Oaksford et al. 2007)). Upon observing new data, d, the Bayesian framework posits that the posterior probability of a hypothesis, $P(h|d)$, is given by the normalised product of the likelihood $P(d|h)$ and the prior $P(h)$:

3.5

$$P(h|d) = \frac{P(d|h)P(h)}{\sum_{h'} P(d|h')P(h')}. \tag{1}$$

3.6 As in (Madsen et al. 2017, 2018), we wanted to ensure that individual differences and psychological variables would not conflate with the impact of network structure on the formation of echo chambers. Consequently, all agents were idealised reasoners adhering to the principles of Bayesian updating. To include the credibility of a source, we used the Bayesian source credibility model (BSCM) (Bovens et al. 2003; Hahn et al. 2009; Harris & Hahn 2009). In the BSCM framework, credibility has two components, perceived expertise, $P(e)$, and perceived trustworthiness, $P(t)$ (see also (Harris et al. 2016)). Perceived expertise refers to the probability of the source having accurate information, whilst the perceived trustworthiness refers to the communicator's intention to pass on accurate information (to the best of their ability). $P(e)$ and $P(t)$ (which are orthogonal in BSCM) are both incorporated within the belief revision process of the present agent-based model (see Fig. 1).

3.7 The likelihood that a communication target supports a hypothesis $P(h)$ is given by:

3.8

$$P(d|h) = \sum_{e't'} P(h|e',t')P(e')P(t'). \tag{2}$$

3.9 In the same way, the likelihood for an agent that does not support a hypothesis $P(\neg h)$ corresponds to

3.10

$$P(d|\neg h) = \sum_{e't'} P(\neg h|e',t')P(e')P(t') \tag{3}$$

3.11 (see (Hahn et al. 2009; Harris et al. 2016) and Methods, for further details).

3.12 The orthogonal nature of expertise and trust is typically operationalised such that trust being high or low leads to changes in the direction of belief revision (i.e. low trust makes you revise your beliefs in the opposite direction than high trust), whilst expertise moderates the strength (size) of the revision (see (Bovens et al. 2003; Harris et al. 2016)). As a consequence, our manipulation of the perceived expertise strength, ***e***, is a way to control how strongly a communication target is influenced by the credibility of a source (robustness check 1; see Methods). Conceptually, expertise strength can be compared to epistemic authority (see also (Walton 2010)): a source with higher expertise is going to exert stronger influence on a receiver during belief revision. To explore this, we investigated the influence of three expertise strength parameter settings on echo chamber formation (see Table 1).

Simulations

3.13 Agents were randomly assigned to x-y coordinates in a two-dimensional space, forming links with their nearest neighbours (refer to (Wilensky & Rand 2015), for further details on how to spatially allocate agents in ABMs). Proximity was measured in terms of Euclidean distance, which has been used as a proxy for relational proximity in social networks (Duggins 2017). Prior to the start of a simulation, each agent sampled their own prior belief $P(h)$ and subjective e and t values from univariate Gaussians with μ=0.5 and σ^2=0.20 (for all three estimates, distributions were truncated between [0, 1]). Thus, $P(h)$, e, and t differed heterogeneously within our agent population. Following revision of their prior belief according to BSCM, agents declared for one of the two beliefs based on a deterministic decision rule:

3.14

$$Belief = \begin{cases} h \text{ if } P(h|d) > 0.5 \\ \neg h \text{ if } P(h|d) < 0.5. \end{cases}$$

3.15 If $P(h|d)$ = 0.5, an agent declared either belief with a probability of 50%. The declared belief (i.e. h or $\neg h$) was then made pubic based on the P(Declaration) probability (robustness check 2) which was manipulated between simulations (see Table 1). For example, a declaration of 1 means all agents made their beliefs public, while 0.10 means that there is a 10% probability for each agent making their opinion public. Including different values for P(Declaration) was motivated by recent findings showing *most* social media users do not discuss their political beliefs on social media, but mainly focus on exchanging shared hobbies and passions (Newman et al. 2017b). We wanted to ensure that our simulation results are robust across social networks varying in terms of the percentage of users discussing their beliefs with peers. We thus explored three levels of P(Declaration) as a proxy for manipulating the percentage of people exchanging their beliefs about a particular topic (e.g., politics or news).

3.16 Lastly, we varied the connective density (i.e. what percentage of the overall network is any given user *directly* connected to) from 0.5% to 50.0% (robustness check 3) between simulations. This allowed us to test whether the formation of echo chambers changes as a function of the number of 'generations' it takes for information to fully permeate a network (e.g., 10% connectivity means on average it will take 10 generations of communication

Name	Description	Levels
Connectivity density (%)	(Links per Agent / Total Number of Agents) $\times$ 100	0.5, 1.0, 1.5, ... 50.0
Expertise strength	Manipulating the magnitude of expertise strength (***e***)	0.00, 0.10, 0.20
P(Declaration)	Probability of making a belief public	0.10, 0.50, 1.00

Table 1: Robustness checks.

to permeate the entire network). The more links (connected friends / users) an agent has, the more immediately an agent will see information appearing on the network (and thus the shorter / faster the cascade).

3.17 To measure echo chambers effectively across simulations, we were first interested in measuring global proportions of beliefs across the whole network (i.e. the relative number of agents with belief h compared to agents entertaining belief $\neg h$). Based on previous simulation-based work, we expected that global proportions would consistently approximate 50/50 across both agent populations (Pilditch 2017). This measure was necessary to ensure that echo chambers are not a by-product of a dominant network-wide belief. Following checks for possible network-wide belief confounds, our key dependent measure of echo chamber formation was the average percentage of like-minded neighbours an agent possessed (i.e. the *local* network similarity). Specifically, measuring local network similarity allowed us to assess whether enclosed epistemic systems, which are a key component of echo chambers (Madsen et al. 2018), formed during the simulations.

3.18 Formally, local network similarity corresponded to the average percentage of agents in the target's direct network that shared the same belief as the target. For example, 50% means that, on average, agents had equal proportions for each belief type in their direct network, where direct network refers to the fraction of the whole network that is directly connected to an agent. As such, a higher percentage of agents sharing the same belief as the target is a proxy for a more severe closure of the target's epistemic belief network, which means that it is less likely that the target will be confronted with a rebuttal (e.g., a user entertaining a different belief). In line with previous work (Pilditch 2017), we expected that our population of social agents would show increased percentages of like-minded neighbours (i.e. echo chambers) for low connectivity density values. We did not expect clustering effects in the asocial population in which agents selected network-peers at random (see Methods for details).

Results

4.1 Fig. 2 summarises our central findings. We predicted that for both social and asocial agents, global belief proportions would consistently approximate 50/50. Fig. 2a (social agent population) and Fig. 2b (asocial agent population) confirm these predictions. Specifically, Fig. 2a and 2b show that global proportions of beliefs in both populations consistently approximated 50/50 irrespective of varying P(Declaration), connectivity density, or expertise strength. This finding is important, as it ensures that potential clusters of like-minded others (Fig. 2c-d) do not result from a global bias towards either belief.

4.2 For social agents, the average proportion of like-minded neighbours (Fig. 2c) increased as a function of increasing expertise strength, increasing P(Declaration) and decreasing connectivity density (x-axis). Importantly, to fully reduce the formation of echo chambers, the average network member must be connected to around 15-20% of the network, which is infeasible considering the size of real world social networks which can have several Billion users. The reason for a reduced clustering effect given increased connectivity density is that increasing connectivity density increases agents' access to information across the network (i.e. the beliefs of other agents). Thus, after reaching a connectivity density of around 15-20%, each agents had access to a significant proportion of the beliefs across the entire network, which reduced the formation of epistemic circles isolated from opposing beliefs. Overall, our results showing a negative influence of increased connectivity density on echo chamber formation are comparable to previous simulation-based work exploring echo chambers in a population of stochastic reinforcement learners (Pilditch 2017).

4.3 The finding that an expertise strength of 0 (i.e. neutral) prevented the formation of echo chambers is a natural result of our model (robustness check 1). Specifically, setting expertise strength to 0 reduces the communicative impact of a source to 0, irrespective of their perceived credibility (for details see Methods). Consequently, a receiver won't be influenced by the communicating source, which can conceptually be compared to disregarding the belief of a social media user that has no epistemic authority (e.g., no knowledge about the topic of discussion).

4.4 Fig. 2d shows the clustering results from our asocial agent population. If agents randomly connect with their network-peers, no echo chambers emerge. This finding highlights the implications of selecting network-peers

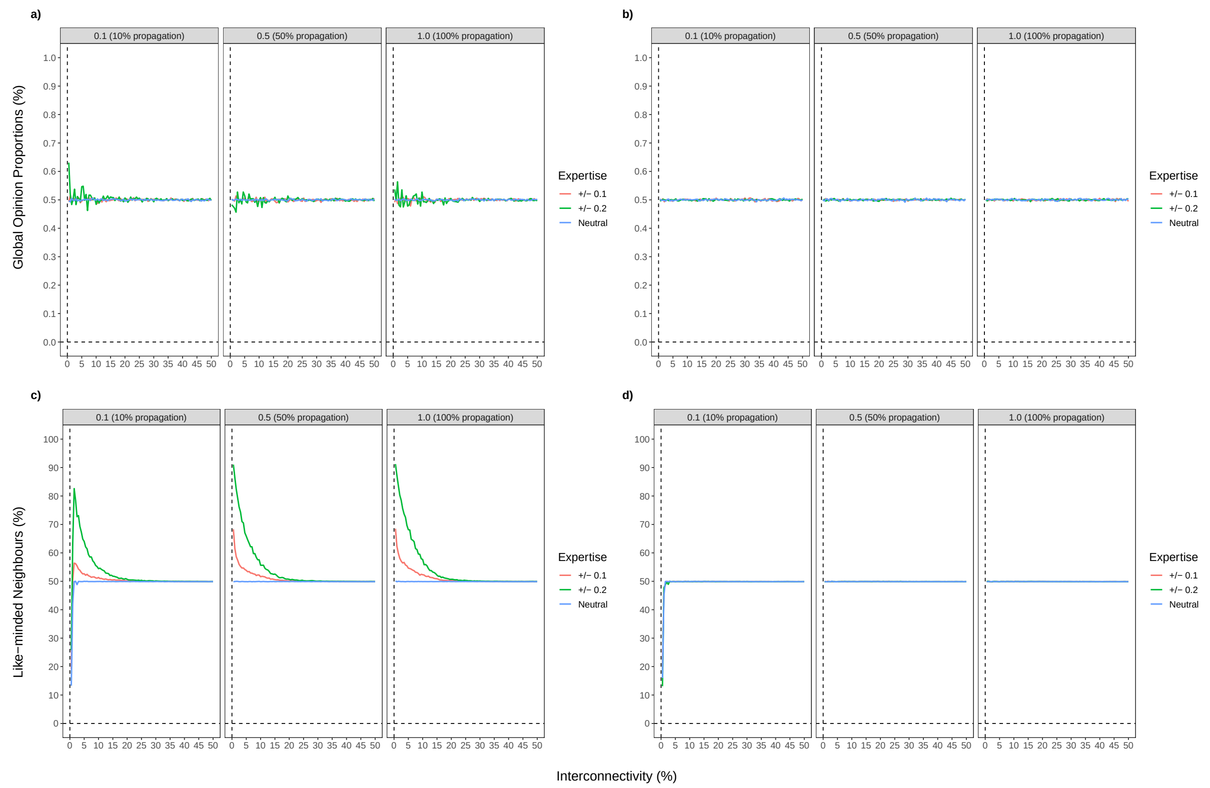

Figure 2: Main results. a) global belief proportions, social agents. b) global belief proportions, asocial agents. c) average percentage of like-minded neighbours (i.e. echo chambers), social agents. d) average percentage of like-minded neighbours (i.e. echo chambers), asocial agents.

based on positive credibility perceptions (e.g., friendship): while stochastic selection prevents echo chambers, selecting network peers based on whom one likes is a key requirement for echo chamber formation. The results in the left panels of Figs. 2c-d (P(Declaration) = 10%) showing a reduced clustering effect for connectivity density values of 0.5% can be fully attributed to the effective fracturing of the network (i.e. no information cascade occurred; robustness check 2). This demonstrates that lateral exchange of information is a *necessary* requirement for the occurrence of information cascades.

4.5 To visualise the above findings, Fig. 3 includes example outcomes of post-cascade belief proportions with 1% and 5% connectivity density. a) and c) correspond to our social agent population and b) and d) pertain to the asocial population. Red and blue colours illustrate clusters of similar-minded agents holding different beliefs. Specifically, as seen in Fig. 3a and Fig. 3c, social agents formed two polarised clusters of similar-minded agents, with limited communication between clusters. Fig. 3b and Fig. 3d show the results from the asocial agent population, which did not show any signs of echo chambers. Here, most agents connected to an equal proportion of similar and dissimilar beliefs, which is illustrated by the absence of distinct colour patterns.

Discussion

5.1 The aim of this work was to disentangle previously conflated causes of echo chambers on social media. Specifically, we examined whether echo chambers emerge in a population of homogeneous, equally rational users that engage in a single interaction. Our results show that echo chambers emerge in an idealised population of equally rational agents who integrate the beliefs of others with their own prior beliefs in a Bayesian manner, taking into account perceptions of credibility regarding fellow network users.

5.2 These results suggest that previously identified causes of echo chambers, including psychological biases and inter-individual differences in cognition, are not strictly necessary for the observation of echo chambers. Additionally, extending previous work (Hegselmann & Krause 2002; Lorenz 2007; Madsen et al. 2018; Sasahara et al. 2019), agents interacted irrespective of differences in their prior beliefs. As such, we showed that limiting interactions based on a bounded confidence threshold (Hegselmann & Krause 2002) was not necessary for

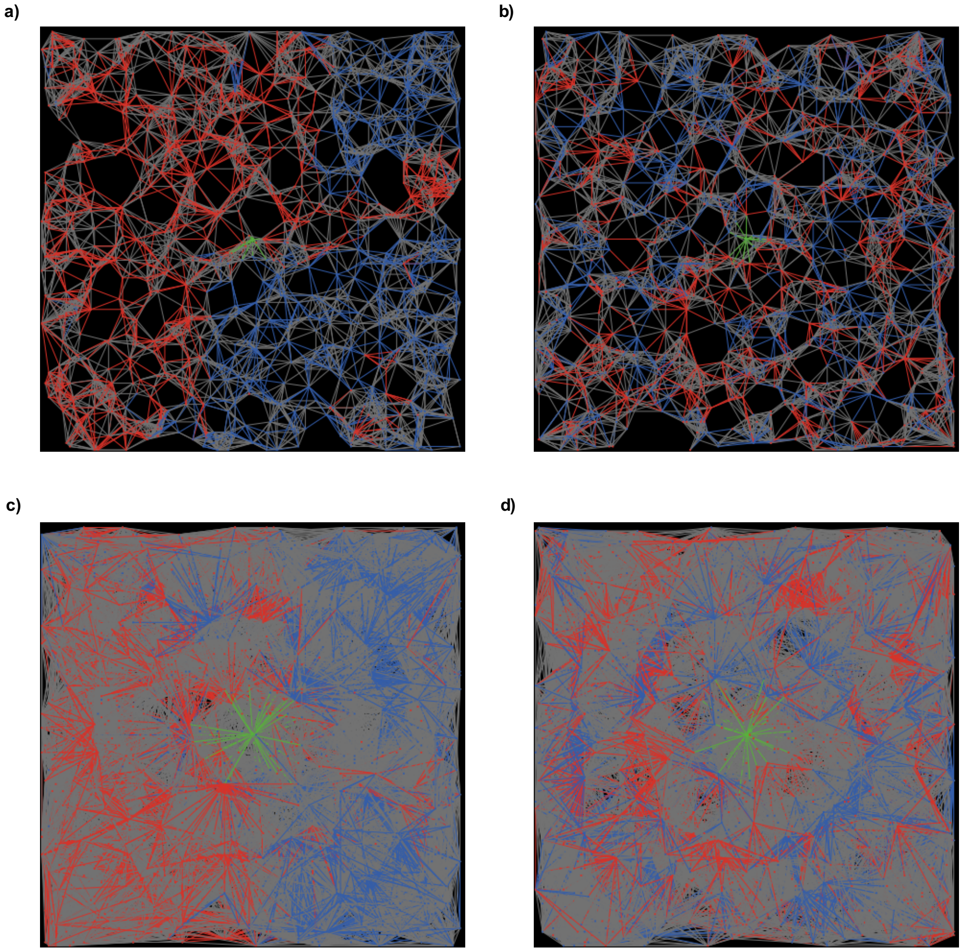

Figure 3: Example post-cascade networks. Grey = agents that did not declare a belief; blue = agents believing $\neg h$; red = agents believing h. Connectivity density values of upper networks: a) social agents: 1%; b) asocial agents: 1%. Connectivity density values of lower networks: c) social agents: 5%; d) asocial agents: 5%.

the formation of echo chambers. Moreover, our findings suggest that repeated interaction between agents may not be required to form echo-chambers. More precisely, while results of previous models (Hegselmann & Krause 2002; Lorenz 2007; Madsen et al. 2017, 2018) revealed that echo chambers emerge and strengthen as a consequence of repeated interaction between similar-minded agents, we have shown here that a single interaction between generations of agents is sufficient to produce local echo chambers. Importantly, on average, each belief was equally represented in our simulations. Thus, our results further show that segregated groups were not a consequence of global dominance of one belief (see Figs. 2-3). We do however note that repeated interactions, as well as threshold adoptions, are likely to then further exacerbate echo-chamber effects found here after single cascades. This raises concerning implications for the prospects of echo-chamber amelioration attempts, as we show a single cascade already lays a flawed foundation for any subsequent interaction thereafter.

5.3 Furthermore, and central to the present paper, we find that the emergence of echo chambers was confined to populations in which network-peers were selected on the basis of positive credibility estimates. Specifically, we showed that self-selecting peers based on whom one likes carries a potentially deleterious consequence for the formation of echo chambers. If network-peers were selected at random, and thus independent of whom one likes or perceives positively (asocial agents), no echo chambers emerged. Importantly, self-selection based on positive credibility estimates differed from previously studied rewiring mechanisms (Lorenz 2007; Henry et al. 2011; Madsen et al. 2018) which prevented interactions between dissimilar peers. In the present social agent population, agents interacted with each other irrespective of their beliefs, evaluating the credibility of a communicating agent based on the beliefs of all peers in their network (see Methods, for details).

5.4 Overall, our findings illustrate that echo chambers, which might induce spreading and retention of misinformation(Vosoughi et al. 2018), conspiratorial thinking(Del Vicario et al. 2016a), and political polarisation(Bessi et al. 2016; Del Vicario et al. 2016b), are not necessarily caused by the inhabitants of social networks directly.

Rather, the *structure* of social networks, and notably the lateral (i.e. peer-to-peer) transmission of information, can be sufficient for echo chamber formation, when a network is built on self-selecting peers. The degree of making opinions public (P(Declaration)) did affect echo chamber formation only if it was so low that it effectively fractured the functional message passing around the network. Additionally, the magnitude of expertise strength modulated the influence of credibility, resulting in increased echo chamber effects for higher levels of expertise. This suggests that being friends with expert users might exacerbate the formation of echo chambers. Given that the present simulations included rational Bayesian agents, it is further expected that incorporation of additional psychological variables, such as the confirmation bias (Del Vicario et al. 2016a; Ngampruetikorn & Stephens 2016; Starnini et al. 2016), might intensify the strength and persistence of echo chambers (see also (Pilditch 2017)).

5.5 More generally, our results show that agent-based models, which enable capturing of dynamic interactions between individuals, provide a valuable opportunity for studying the formation of emergent phenomena such as echo chambers. This is in line with a growing body of literature employing agent-based models to investigate several related phenomena, including opinion polarisation (Duggins 2017), identity search (Watts et al. 2002), (dis)belief in climate change (Williams et al. 2015; Lewandowsky et al. 2019) and micro-targeting (Madsen & Pilditch 2018). Given the potential of agent-based models for the study of emergent behaviours, further work could focus on developing interventions aiming to reduce the occurrence of opinion segregation. Such interventions might extend previous work using 'educational broadcasts' (Madsen et al. 2018) or behavioural changes allowing for the interaction between dissimilar peers (van der Maas et al. 2020).

Appendix A: BSCM Details

6.1 Table 2 shows the conditional probability table which specified how the different components of the likelihood were computed. To ensure that the direction of the influence of expertise strength (***e***) matched an agent's prior belief (i.e. towards 1 if $P(h)$ > 0.5 and towards 0 if $P(h)$ < 0.5), we flipped the impact of expertise strength based on the prior. Similar to an indicator function, ***I*** thus returned 1 for agents having a prior belief $P(h)$ > 0.5 and -1 for agents having a prior belief $P(h)$ < 0.5. τ is an additional constant that quantifies the presence vs. absence of expertise. Manipulating values of τ results in stronger differences between varying levels of expertise strength. For all simulations, τ = 2, meaning that the magnitude of belief change for a medium expert (i.e. (***e***) = 0.1) ranged from -0.2 to 0.2 while the magnitude for a high expert (i.e. (***e***) = 0.2) ranged from -0.4 to 0.4. For ***e*** = 0, there was no effect on belief change.

	e, t	¬e, t	e, ¬t	¬e,¬t
h	0.5 + e$\mathbf{I}_{P(h)>0.5} \times \tau$	0.5 + e$\mathbf{I}_{P(h)>0.5}$	0.5 - e$\mathbf{I}_{(P(h)>0.5} \times \tau$	0.5 - e$\mathbf{I}_{(P(h)>0.5}$
¬h	1 - (0.5 + e$\mathbf{I}_{P(h)>0.5} \times \tau$)	1 - (0.5 + e$\mathbf{I}_{P(h)>0.5}$)	1 - (0.5 - e$\mathbf{I}_{P(h)>0.5} \times \tau$)	1 - (0.5 - e$\mathbf{I}_{P(h)>0.5}$)

Table 2: Conditional Probability Table.

6.2 The BSCM architecture provides a general framework for updating one's belief under consideration of a source's credibility. It does not specify how individual agents estimate the perceived expertise and perceived trustworthiness values of a source during interaction. Here, we refer to an important element of social networks: selecting network-peers on the basis of whom one likes (i.e. positive credibility estimates). We operationalised this self-selection property in a hypothetical population of 'social agents' who weigh the perceived credibility of a communicating source based on the beliefs of their peers. Specifically, following observation of a source's belief in a hypothesis, a target agent (receiver) weighs the expertise and trustworthiness of a communicating source based on the proportion of agents in the receiver's direct network entertaining the same belief as the source and the number of agents in the network entertaining the opposite belief of the source. More formally, this can be written as

6.3

$$e_{com} = \frac{\sum_{i=1}^{N_h} e_i}{\sum_{i=1}^{N_h} e_i + \sum_{i=1}^{N_{\neg h}} e_i} \tag{4}$$

6.4

$$t_{com} = \frac{\sum_{i=1}^{N_h} t_i}{\sum_{i=1}^{N_h} t_i + \sum_{i=1}^{N_{\neg h}} t_i} \tag{5}$$

where e_{com} and t_{com} correspond to the specific (weighted) credibility estimates that a communication target assigns to a communicating source.

6.5 We contrasted the above population of social agents with a second population of asocial agents in which connections with peers were established at random. Random selection of peers was operationalised by sampling perceived expertise and perceived trustworthiness estimates randomly from a uniform distribution [0,1]. This means that asocial agents computed stochastic credibility estimates for a source irrespective of the beliefs of their network peers. For simulations across both hypothetical populations (social and asocial), the weighted expertise e_{com} and trustworthiness t_{com} estimates were plugged into Equations 2-3 to replace $P(e)$ and $P(t)$, respectively.

Appendix B: Simulation Details

7.1 The three central components of ABMs are agents, patches, and links. Agents are the actors, and in our social network they correspond to individual users. Agents were furnished with cognitive functions and possible behaviours, including attention (detecting public declarations of others), belief revision (updating a prior belief-state based on observing another agentâĂŹs belief), and declaration (commit to a belief using a decision rule). All agents were furnished with the same cognitive functions and possible behaviours. Links represent edges between agents. In the present model, bidirectional links were employed to enable signaling of public belief declarations between agents. Links thus represent the (social) network connections between users. Patches are the building blocks of the environment in which agents act. For example, patches can represent trees in a forest or the number of fish in a specific location of a lake. Agents can interact with patches—if agents were fishermen, they could move around and fish from specific locations (Bailey et al. 2018). For the present model, patches have no further relevance as there is no interaction between agents and patches. Specifically, our simulations are confined to the cognitive architecture and belief states of agents, and all relevant interactions occur on an agent-to-agent-level. The model was implemented in NetLogo version 6.0.4 (Wilensky et al. 1999). All simulations were performed in R version 3.6.3 (R Core Team) using the package `RNetLogo()` (Thiele 2014). Each system specification (connectivity density (100) x expertise strength (3) x P(Declaration) (3)) was ran independently 50 times, taking an average set of values for each specification. The total number of agents (n = 1000) was consistent across simulations. Simulations were conducted independently for each of the two agent populations.

7.2 In the following, we outline the basic technical details of our model. Algorithm 1 shows the setup procedure of the network, including placing agents in space, sampling prior $P(h)$, e, and t values, and forming connections with peers based on proximity as measured by Euclidean distance (a proxy for relational proximity in social networks; see (Duggins 2017)). Specifically, each agent was randomly assigned to a x-y coordinate in a two-dimensional environment. After all agents were allocated to a position in space, each agent formed n bidirectional ties with other agents that were closest as measured by Euclidean distance. This means that ties between agents were formed at random and irrespective of subsequent beliefs of agents. Additionally, ties were static, meaning that after having established all connections between agents, the network structure did not change during subsequent simulations.

7.3 Simulations were initiated through a neutral event node. Neutral in this case means that the first agent sampled randomly from the set of beliefs $\{h, \neg h\}$ each time it communicated to a target. Due to this stochastic process, on average, half of the 1^{st} generation agents receiving input from the neutral event node should arrive at belief h while the other half will arrive at belief $\neg h$ after BSCM integration. Specifically, this included attending to the declared beliefs of the neutral event node, revising initial beliefs based on the perceived credibility of the neutral event node, and deciding whether to declare an opinion public according to P(Declaration).

Algorithm 1 Setup network

```
procedure PLACE AGENTS
    Create N agents
    for i = 1 to N do
        set i position random x-y coordinate
    end for
end procedure
procedure SETUP PRIORS AND LINKS
    for i = 1 to N do
        P(h)[i]←X∼N(μ, σ^2)
        e[i]←X∼N(μ, σ^2)
        t[i]←X∼N(μ, σ^2)
        create links with n nearest neighbours        ▷ based on Euclidean distance
    end for
end procedure
```

7.4 The number of agents the neutral event node communicated to was determined by the connectivity density. Connectivity values above 50% were omitted as this would have enabled every other agent to be connected to the neutral event node in the 1st generation, precluding the occurrence of a cascade. To improve the readability of plotted example networks (Fig. 3), the initial neutral event node was placed in the center of each simulation (i.e. central x-y-coordinate).

7.5 After revising their prior beliefs, the first-generation agents (those that received input from the neutral event node) made their beliefs public based on the manipulated P(Declaration) value. Their communication targets (i.e. second-generation) then used the communicated opinion of the first-generation agents as input for their own belief revision following the same procedure. Algorithm 2 shows the basic steps involved in a single instance of belief revision (i.e. from one generation to the the next). Here, source refers to an agent from the previous generation that already publicly declared a belief (i.e. h or $\neg h$) and the connections of the source refer to the potential communication targets of the next generation. As we investigated whether a single pass-through of information (i.e. single interaction) was sufficient for the formation of echo chambers, we did not allow for repeated interaction, meaning that agents could not qualify as communication targets after declaring for a belief.

Algorithm 2 Updating beliefs

```
procedure SOURCE SELECTS COMMUNICATION TARGET
    if matchCounter ≤ 1 then
        for i = 1 to n_source do                    ▷ n = source's connections
            if i = neutral then      ▷ check if target did not already declare a belief
                belief[i] = BSCM(source, n[i])      ▷ n = target's connections
                if random(0.01,1.00) > P(Declaration) then
                    propagate belief to next generation
                end if
            end if
        end for
    end if
end procedure
```

7.6 The process of transmitting beliefs continued down successive generations until the network was either completely saturated (i.e. all agents committed to a belief) or the number of believers (i.e. h or $\neg h$) did not change for two consecutive time periods. Algorithm 3 illustrates how this procedure was implemented in our model.

Algorithm 3 Stop simulation

```
procedure CHECK IF NETWORK IS SATURATED OR FRACTURED
    matchCounter = 0                ▷ counts how often no change occurred between generations
    Count_h = 0
    Count_¬h = 0
    for i = 1 to N do                                              ▷ N = all agents
        if belief[i] = h then
            Count_h = Count_h + 1
        end if
        if belief[i] = ¬h then
            Count_¬h = Count_¬h + 1
        end if
    end for
    if Count_h = Count_¬h then
        matchCounter = matchCounter + 1
    end if
end procedure
```

Model Documentation

The code of the multi-agent model and simulation configurations are available on CoMSES Network—Computational Model Library as: Cascades across networks are sufficient for the formation of echo chambers: An agent-based model (version 1.0.0), https://www.comses.net/codebases/0654205c-5645-4da7-888f-4aecca8fafd5/releases/1.0.0/. Model code and simulation results can also be accessed via *GitHub*.

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