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Dear Professor Dr Zanghellini,

We appreciate the time taken by you and the reviewers in assessing our manuscript and we are grateful for the valuable feedback. In response to these comments, we have made the following changes:

- As suggested by yourself and both reviewers, we made a number of changes to the manuscript in order improve the clarity of our presentation and make our assumptions and reasoning more transparent.
- As requested, we also provide point by point responses and descriptions of our revisions below, interlaced in red among the original review. References to updated passages in the manuscript are emphasised with italics.

This revision has helped us to improve the paper, and we are very grateful for having been given the opportunity to do so. We hope that the revised version of the manuscript is considered fit for publication in Scientific Reports.

Thank you for your time and consideration.

Kind regards,

Jan-Philipp Fränken and Toby Pilditch

Editor's comments:

Editorial Board Member comments: Two key points are apparent in the recommendations of the reviewers: (i) make your assumptions and reasoning and the subsequent consequences more transparent (ii) improve the clarity of your presentation.

Response 1: We first thank the editor and reviewers for their positive evaluation of our work.

We have made a major effort to better bring across the work's assumptions and reasoning and the subsequent consequences. To do this, we have reworked all sections of our manuscript to transparently motivate our formal analysis of echo chambers and the underlying assumptions of our model. We have specifically focused on clarifying technical details of our model, model assumptions, and evaluating the results of our work in context (under consideration of important limitations).

Reviewer 1's comments: The authors proposed an agent-based model of Bayesian learners on a network and simulated temporal changes of agents' beliefs in several different settings. They demonstrated that sequential updates of briefs can form a group of homogeneous beliefs. According to the results, they concluded that self-selection of network peers and peer-to-peer transmissions of information are causally sufficient for the emergence of echo chambers. Although the proposed mechanism is interesting and one way of generating like-minded clusters, the conclusion is overstated and results may depend on the assumptions and settings of the model. I recommend that they tone down the statements. I have the following concerns.

Response 2: We thank the reviewer for their helpful comments. In response we have toned down our statements in the Abstract and Discussion and emphasised our assumptions (e.g., that we are dealing with an idealised social network inhabited by rational (i.e. Bayesian) agents).

Specifically, we have highlighted that our findings are confined to an idealised social network, *:*

- *'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 causally sufficient to produce echo chambers.' (Abstract)*
- *'Our results show that echo chambers emerge in an idealised population of individually rational agents who integrate the beliefs of others with their own prior beliefs in a Bayesian manner.' (p.6)*

Furthermore, although our model illustrates important principles regarding the design of social networks, we have emphasised that additional empirical validation is required to assess the ecological validity our results:,

- *'While these findings suggests that social networks by design can be causally sufficient for echo chamber formation, it is important that further empirical research investigates the ecological validity of our model results in real-world social networks.' (p. 8)*

- 1. I wonder whether the above-mentioned condition is truly sufficient for the emergence of echo chambers. It is highly dependent on the model's design and the definition of echo chambers. For example, Henry et al. (2011) numerically and analytically proved that aversion-based modification of social ties always yields echo chambers, regardless of network structures, if briefs are static. Furthermore, Sasahara et al. (2019) introduced a brief update rule (social influence) into Henry's model (with little extensions for molding the online world), showing that like-minded clusters similarly emerge and the online social network accelerates echo chamber formation. In both cases, if a social tie is selected at random but with aversion-based brief evaluation, then repeated rewiring of social ties eventually yields echo chambers, which is different from the conclusion of the current paper.
    - Henry, A. D., Pralat, P., Zhang, C.-Q. (2011). Emergence of segregation in evolving social networks. Proceedings of the National Academy of Sciences, 108(21), 8605–8610.

– Sasahara, K., Chen, W., Peng, H., Ciampaglia, L. G., Flammini, A., Menczer, F. (2019). On the inevitability of online echo chambers. arXiv:1905.03919, 23.

Response 3: We are grateful for the provision of additional references, and we have included their findings in the present manuscript to better evaluate our work in the broader context. Specifically, we have made the following changes to the section Echo chambers:

– First, we cited (Sasahara et al., 2019) to illustrate the relevance of social influence and preferential wiring with similar others for the formation of echo chambers: , *'[...] 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 (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). (p.2)*

– Second, we referred to (Henry, Prałat, & Zhang, 2011) as another relevant study showing how a bias against dissimilar others can induce proliferation of opinions and echo chamber formation: , *'[...] 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, Bailey, & Pilditch, 2017, 2018) [...]. In other words, the findings by (Madsen et al., 2018) suggest that 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). ' (p. 2)*

While we agree with Reviewer 1 in the inclusion of additional references to better evaluate our work in context, we do not necessarily agree that the findings of Henry et al. (2011) and Sasahara et al. (2019) point to a different conclusion. Rather, their work incorporated different psychological variables (i.e. social influence and a bias against dissimilar others which influenced rewiring of network connections), which have not been examined in the present model. We thus believe that the present results offer a novel contribution that is different from previously cited work (Bakshy, Messing, & Adamic, 2015; Henry et al., 2011; Madsen et al., 2018; Ngampruetikorn & Stephens, 2016) focusing on psychological variables and repeated interaction between users. Specifically, our goal was to investigate sufficient conditions of echo chamber formation in the absence of psychological variables and repeated interaction. Again, we would like to thank Reviewer 1 for pointing out that our results depend on the specific model design, which purposefully omitted repeated interaction and psychological variables. To make this intent more clear in our manuscript, we made additional changes to motivate our design focusing on a single interaction in the absence of cognitive differences / bias against forming ties with dissimilar others:

– , *' [...] This is motivated by theoretical (Bikhchandani, Hirshleifer, & Welch, 1992) and simulation-based (Pilditch, 2017) work on information cascades, which showed that single interactions between individually rational agents can result in maladaptive collective outcomes prior to repeated interaction, and in the absence of rewiring of social ties. Consequently, a single pass-through of information between generations of agents with fixed social ties that update their beliefs sequentially might suffice for the emergence of echo chambers.*

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.' (p.2)

- 2. Can the simulation results in Fig. 2(A and C) and Fig. 3 be deemed as "echo chambers"? It is dependent on the definition of echo chambers.

  Response 4: In the present manuscript, we followed (Madsen et al., 2018) and defined echo chambers as 'enclosed epistemic systems where like-minded individuals reinforce their pre-existing beliefs' (p. 1). We thus believe that the simulation results in Figs. 2 and 3, which show that social agents tend to bundle in closed epistemic groups (i.e. those believing h are grouped together, engaging in limited interaction with those believing $\neg h$, who form their own distinct groups). However, we agree with Reviewer 1 that we might not have been clear in pointing out how the definition of echo chambers is connected to our simulation results shown in Figs. 2-3. To make this connection more transparent, we have made the following changes:

  – , *'[...] 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 as a result model simulations.' (p. 5)*

  – *'[...] 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).' (p. 5)*

- 3. What kind of network structures were used for simulations? Random graphs?

  Response 5: Thank you for pointing this out. We added additional details to our Agent-based model section to address this concern:

  – , *'Here, we reconstructed an idealised social network similar to (Madsen et al., 2018; Pilditch, 2017) 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. Our agent-based model (ABM) captured agents' social environment (social ties with peers) and temporal dynamics of belief change (updating beliefs through interaction), which both form necessary requirements for the observation of echo chambers.' (p. 3)*

  Additionally, we have added details to our Methods section to further clarify what kind of network structures were used:

  – , *'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.' (p. 9)

- 4. I have no idea why a larger network density prevented the formation of echo chambers. What is the implication of this result?

  Response 6: Larger network density prevented formation of echo chambers as each agent is connected to a higher percentage of the total agents. This means that cascades contain fewer "generations" (from 0 to saturation), which limits the capacity for localised (small) echo-chambers to form. After reaching a density of around 15-20% of the entire network, each agent's individual network then included a large number of other agents (proportional to the size of the network), which is why it was impossible to form enclosed clusters of agents with a single opinion. In other words, if agents were exposed to a very large number of other agents, this increased the diversity of the beliefs of those they were connected to, and an implication is that real-world social network users that are connected to a very large percentage of the entire social network (e.g., Facebook) would almost certainly be exposed to a range of opinions which are different from their own opinions. Notably, this number is so much larger, that it is almost impossible to achieve such high levels of connectivity density (e.g., 15% from 2.45 Billion Facebook users would mean that people have several hundred million friends on Facebook).

  To clarify the implication of this result and further emphasise why increased network density prevented echo chambers, we have made the following adjustments to the Results section:

  - , *'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 increased 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 closed 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).' (p. 5)*

- 5. The descriptions of the results are too concise and difficult to follow. Especially in Fig. 3, it would be important to provide more details about how these are related to echo chambers.
  Response 7: To make the descriptions of our results more transparent and accessible, we made additional changes:

  - , *'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 others in which most agents were connected to agents entertaining the same belief and only 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 were connected to an equal proportion of similar and dissimilar beliefs, which is illustrated by the absence of distinct colour patterns.' (p. 6)*

- 6. There are many computational models relevant to echo chambers, social segregation, and opinion polarizations. The current manuscript does not cite or refer to relevant papers in addition to the above-mentioned ones. It is important to put this work in context and to contrast it with other studies.

  Response 8: We thank Reviewer 1 for pointing us to important references, and as shown in Response 3 above, we have included the suggested sources to better place our work in context. We are aware that our paper currently has 50-60 references, which is at the upper range of the suggested 30-50 references for a scientific reports paper. There are certainly other relevant models that could not be discussed in the present work, but we hope that after carefully considering the additional suggestions by Reviewer 1, our manuscript covers an important range of related work. We also included two additional references which might be relevant to better evaluate the formation of echo chambers and opinion polarisation in context:

  - *, Haw (2020)*
    - *'Compared to non-users, the average social media user experiences more diverse content (Newman, Fletcher, Kalogeropoulos, Levy, & Kleis Nielsen, 2017) and it has been suggested that the majority of social media users not necessarily self-select into echo chambers (Haw, 2020)' (p. 1)*
  - *Williams, McMurray, Kurz, and Lambert (2015)*
    - *' 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, Dodds, & Newman, 2002), (dis)belief in climate change (Lewandowsky, Pilditch, Madsen, Oreskes, & Risbey, 2019; Williams et al., 2015) and micro-targeting (Madsen & Pilditch, 2018).' (p. 8)*

- Minor comments:
  - In Fig. 2, please add x-labels and y-labels.
  - In Fig. 2, it is difficult to distinguish between two kinds of dashed lines. Please use other marker types (e.g., with colors).
  - P6 L5: "in a a population" "a" is duplicated.
  - P6 Para 4: There is a description saying, "A and C correspond to our asocial agent population." Here, "asocial" must be "social".

  Response 9: We thank Reviewer 1 for spotting these issues and have addressed all of them.

Reviewer 2's comments: The paper is a study of the emergence of echo chambers in social media and the reason behind this phenomenon. The authors' intuitions about the nature of the interaction between users (self-selecting of their peer, and lateral transmission of content) are potential explanations of the emergence of echo chambers. However, a simulated experiment is sufficient for arriving at their conclusions. The controlled nature of simulated studies of social media users is limited in terms of the insights from real-world data.

I do believe that the models (Agent-based model and Bayesian source credibility model) that the authors choose to use in this study are a promising way to capture the relationship between users. However, the simulated study's results can serve as a starting point to embark on further study of the emergence of echo chambers in the real world. It would be a significant project to use real-world data to valid your hypothesis.

Response 10: We thank Reviewer 2 for their feedback. We have sought to provide a formal analysis of a simulated social network, allowing us to disentangle network properties as a sufficient cause for echo-chamber formation from previously conflated causes such as biases in human cognition. Although empirical work is out of scope for the present work, the approach and findings discussed in our paper might serve as a starting point for new lines of research, including empirical validation.

Pros: The intuitions behind the study are insightful. And the analysis of the problem is excellent.

Using the Agent-based model and Bayesian source credibility model are very promising for these types of problems.

Response 11: We feel similarly.

Cons: Not using real-world data to further conduct the experiments. Both the Agent-based model and Bayesian source credibility model need to be explained better. Especially, how did you use them? And What are the alternatives?

Response 12: Re: not using real-world data: The aim of the present project was to provide a formal analysis of an idealised social network which could then be contrasted with previous simulation-based work such as (Del Vicario, Bessi, et al., 2016; Del Vicario, Vivaldo, et al., 2016; Lewandowsky et al., 2019; Lorenz, 2007; Madsen et al., 2018; Pilditch, 2017; Sikder, Smith, Vivo, & Livan, 2020).

We hope that the results of our formal analysis, which suggest that the structure of social networks might be causally sufficient for the formation of echo chambers, offer important methodological insights for social network architects. Furthermore, we hope that the formal environment of the present model provides a framework for further lines of research in which specific cognitive processes can be investigated in more detail. For example, we have recently started to investigate whether people down-weigh the evidential value of sequentially updated beliefs (Fränken, Theodoropoulos, Moore, & Bramley, 2020). This and further related work such as (Whalen, Griffiths, & Buchsbaum, 2018) might serve as (empirical) input validation for such further lines of research. Before reaching this point, it is however important to provide a proof-of-concept version under idealised conditions and without recourse to individual difference explanations or heterogeneous cognitive architectures (to disentangle system-level and agent-level contributions to echo chambers). In the present, we investigated the system-level contributions, and we thus believe that the results or our work have their own value prior to further analyses including empirical work and comparison of different cognitive functions.

Notes:

In Agent-based model:
The explanation for patches is not clear.
What are binary beliefs, and how are they related to ABMs?
How does the ABMs capture the heterogeneity? This point is important for your work, yet it's not explained well.

Response 13: To make the agent-based model and Bayesian source credibility model more accessible and transparent, we have made additional changes:

- We emphasised relevant references for more details on how to use ABMs, since a full discussion of ABMs and their use is out of scope: , *'Further details on how to use ABMs and an elaborate discussion of their general advantages for modelling cognitive phenomena can be found elsewhere (Macal & North, 2005; Madsen, Bailey, Carrella, & Koralus, 2019).' (p. 3)*
- We made the definition of patches more transparent and clarified why they are not relevant for the present model: , *'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-level.' (p. 9)*
- We explained binary beliefs in more detail: , *'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 ($\neg h$).' (p. 3)*
  Additionally, we would like to clarify that binary beliefs are not necessarily related to ABMs. ABMs can capture a wide range of belief representations, including binary beliefs, continuous beliefs (e.g., numbers between 1 and 100), or probabilistic beliefs (e.g., full probability distributions such as Gaussians). The choice of letting agents communicate binary beliefs was due to parsimony and potential real-world parallels (e.g., when we vote to show or support for a political candidate, we usually do so through a binary vote—support or not support—and not through a continuous assessment of our support or a probability density).
- To address the issue of heterogeneity, we made the following changes: , *'Additionally, our ABM accounted for heterogeneity between individual agents (such as different prior beliefs), which is an important general 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 support a hypothesis. Thinking about a group of people again, this means that while they would all share the same mechanism for*

updating their prior beliefs (homogeneous cognitive architecture), each of them would enter a discussion with their subjective prior opinion (heterogeneous prior beliefs).' (p. 3)

In the simulation section:
Why did you use those parameters ($\mu = 0.5$, $\sigma^2 = 0.2$) for the Gaussians distribution? Did you try other configurations?

Response 14: Yes, we tried other configurations, and as long as the mean is .5, results are comparable. If the mean deviates from .5, this means that there will be a prior bias for a specific belief, since the decision threshold for declaring / communicating belief $\neg h$ is $<$ .5 and $>$ .5 for belief h. The variance determines the degree of heterogeneity of beliefs across the population. If it is very small, and the mean deviates from .5, this would mean that the agent population is more homogeneous and initially more inclined to hold one of the two beliefs. Since we truncated the distributions of prior beliefs (and trustworthiness and expertise), increasing the variance significantly would not have resulted in relevant changes to the prior distributions, since both sides would have roughly equally thick tails (if the mean was .5). We went with this specific configuration for all Gaussians since we 1) wanted to ensure that there is no prior bias towards either belief that could have induced echo chambers as a result of a system wide dominance and 2) we wanted to keep the mean and variance of expertise and trustworthiness of agents at roughly the same levels as their prior beliefs.

Why did you use a deterministic decision rule for declaring beliefs?
How does it affect the simulations? Did you investigate other alternatives?

Response 15: We used a deterministic decision rule for communicating beliefs because it is parsimonious and potentially bears some empirical relevance (see response 13). A potential alternative might have been probability matching (Shanks, Tunney, & McCarthy, 2002), meaning that agents communicate their beliefs proportional to the posterior (e.g., if the posterior is euqal to .8, they would communicate h with a probability of 80 % and $\neg h$ with a probability of 20 %. For the present work, however, this was of no further relevance since we were simply interested in the impact of the self-selection of peers and lateral transmission, and not in the specific communication functions of agents. We are grateful that Reviewer 2 pointed this out, and a potential step for a future project might include a comparison of various communication functions that could be extracted from empirical analyses.

In the discussion section:
More explanation is needed on how you get from your results to your conclusions.

Response 16: We adapted the following sections to better explain how we arrived at our conclusions / tone down conclusions / propose alternatives for future work:

- , *'These results suggest that previously identified causes of echo chambers, including psychological biases and inter-individual differences in terms of the cognitive architecture of agents, might not be necessary for the observation of echo chambers. Specifically, agents in the present model were furnished with a homogeneous cognitive architecture, meaning that they shared the same belief updating mechanisms irrespective of their subjective prior beliefs. They also did not rewire their social ties based on a bias against agents holding different beliefs, which has been addressed* *in previous models of echo chambers (Henry et al., 2011; Madsen et al., 2018; Sasahara et al., 2019). Moreover, our findings suggest that repeated interaction, a key component of previous related work Madsen et al. (2017, 2018), might not be required for the observation of echo chambers. More precisely, while the results of such previous models revealed that echo chambers emerged and amplified as a consequence of repeated interaction between similar-minded agents, we showed that a single cascade involving only one interaction between generations of agents resulted in the formation of echo chambers.' (p. 6)* ,

- *'Importantly, self-selection based on positive credibility estimates is different from rewiring social ties based on a preference for beliefs. While agents in previous work (Henry et al., 2011; Madsen et al., 2018) were* unwilling *to exchange their beliefs with dissimilar peers, the present social agent populations did not exclude peers with different beliefs from their network. Instead, they evaluated the credibility of a communicating agent (operationalised via trustworthiness and expertise) based on the beliefs of all peers in their network (see Methods, for details).' (p. 7)*

- , *'An important avenue for further work might be a closer examination of the belief updating process of the present agent populations. Specifically, agents in the present populations updated beliefs sequentially based on the declarations of previous generations. Recent empirical studies demonstrated that people are sensitive to such statistical dependencies in social learning. For example, (Whalen et al., 2018) showed that when beliefs of others were formed sequentially, people updated their prior beliefs less. Considering such findings, an important step for follow-up simulations involves testing the robustness of echo chambers between varying levels of belief dependencies in a network. An additional extension might focus on the declaration functions used prior to communicating beliefs. In the present work, agents used a deterministic decision rule. Potential alternatives that might be contrasted in future work include probability matching (Shanks et al., 2002) or the communication of full probability densities.' (p. 8)*

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