Agent-Based Social Systems 17

Muhammad Al Atiqi

Echo Chamber and Polarization in Social Media

An Agent-Based Modeling Approach

Springer

Agent-Based Social Systems

Volume 17

This series is intended to further the creation of the science of agent-based social systems, a field that is establishing itself as a transdisciplinary and cross-cultural science. The series will cover a broad spectrum of sciences, such as social systems theory, sociology, business administration, management information science, organization science, computational mathematical organization theory, economics, evolutionary economics, international political science, jurisprudence, policy science, socioinformation studies, cognitive science, artificial intelligence, complex adaptive systems theory, philosophy of science, and other related disciplines.

The series will provide a systematic study of the various new cross-cultural arenas of the human sciences. Such an approach has been successfully tried several times in the history of the modern science of humanities and systems and has helped to create such important conceptual frameworks and theories as cybernetics, synergetics, general systems theory, cognitive science, and complex adaptive systems.

We want to create a conceptual framework and design theory for socioeconomic systems of the twenty-first century in a cross-cultural and transdisciplinary context. For this purpose we plan to take an agent-based approach. Developed over the last decade, agent-based modeling is a new trend within the social sciences and is a child of the modern sciences of humanities and systems. In this series the term "agent-based" is used across a broad spectrum that includes not only the classical usage of the normative and rational agent but also an interpretive and subjective agent. We seek the antinomy of the macro and micro, subjective and rational, functional and structural, bottom-up and top-down, global and local, and structure and agency within the social sciences. Agent-based model-ing includes both sides of these opposites. "Agent" is our grounding for modeling; simula-tion, theory, and real-worldgrounding are also required.

As an approach, agent-based simulation is an important tool for the new experimental fields of the social sciences; it can be used to provide explanations and decision support for real-world problems, and its theories include both conceptual and mathematical ones. A conceptual approach is vital for creating new frameworks of the worldview, and the mathematical approach is essential to clarify the logical structure of any new framework or model. Exploration of several different ways of real-world grounding is required for this approach. Other issues to be considered in the series include the systems design of this century's global and local socioeconomic systems.

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About the Author

Muhammad Al Atiqi is a computational social scientist who studied at the Tokyo Institute of Technology. His interest lies in the intersection of technology and society, particularly the influence of internet-related phenomena to human behavior. During his graduate study, he researched on the formation of echo chamber and political polarization in social media and identifying important factors to determine policies to minimize their negative influences. Prior to his research career, he taught university-level physics at Nanyang Technological University in Singapore. Aside from his main work, he is also involved in community organizing projects such as various Indonesian communities overseas and an environmental project to provide clean water in rural Bali.

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Chapter 1
Introduction

1.1 The Echo Chamber and Polarization Problem in Social Media

During the US Election in 2016, the term "fake news" got popularized. The term has been associated with other words such as hoax, misinformation, or even disinformation [1]. There are different degrees of mis-/disinformation ranging from relatively harmless satire or parody to completely fabricated contents where it is made with full intention to deceive and do harm. While this is not a new phenomenon, the rise of social media usage has been associated with the increase of misinformation online [2]. Before the Internet, people's exposure to information was only limited to the extent of mass media received by them. Typically the limitation happens within the boundary of a country. Even with this, personalization of media has happened before the Internet [3]. However, the Internet has allowed us to personally pick and access media we like easier. We call this the era of personal media [4]. The option to access more media than what is allowed within our country's limits was thought to make people more exposed to different kinds of opinion. It is true to a certain extent, but another problem was created because people choose the information they want to hear only by creating a form of echo chamber [5–8]. This creates another problem where people sharing the same physical community (neighborhood, town, country, etc.) are not sharing the same facts or extremely different opinions on shared facts, resulting in conflicts from a minor dispute to violent ones [9]. This segregation of opinions in cyberspace has been dubbed as one of the supporting factors contributing to the spread of fake news [5]. Moreover, personal preferences and friends' behavior have been dubbed to be more influential to our posts in social media than the system's algorithmic influence [9, 10]. If our online behaviors could contribute to the spread of fake news via the formation of echo chambers, then it is reasonable to attempt to curb echo chambers in social media. But before attempting to reduce echo chambers, we need to understand better what and how echo chambers are formed in the first place.

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There are different definitions of echo chamber, but essentially they all have "information" aspect and "space" aspect. The first definition is by describing homophily among people [5–8]. When people make clusters among themselves based on similar traits while excluding people with different traits, that can be considered an echo chamber. In this case people group themselves based on their opinions in social media. One example would be Facebook page groups. People who belong to Facebook groups about scientific news tend to be absent from being in a group of conspiracy-related news and vice versa. Therefore, they now surround themselves in a group with people of homogeneous opinion on a particular issue. Other researchers define echo chamber as the lack of information diversity [11]. This could be represented well by the example of Twitter follows and Facebook page likes. The same logic applies, where people who like scientific-themed Facebook pages but not conspiracy-themed pages would only get information based on what the pages provide. Starting from these definitions, here begins our journey in attempting to solve the online misinformation problem throughout this book.

1.2 Contribution Summary

Based on the key issues mentioned previously, the fundamental research question of this book is to understand the factors that influence echo chambers and polarization formation in social media. Considering the problems associated with echo chambers and polarization in social media, our understanding of its formation should also be used to design policy that minimizes echo chamber and polarization. From this generalized research question, the contributions of this book are described as follows:

1. We identify the factors that contribute to the formation of echo chambers and polarization in social media. We use adaptation of classical opinion dynamics modeling, a variant of the bounded confidence model, to simulate information sharing and consumption activity in social media. We highlight the one-to-many information sharing mechanism as the main feature of social media. From the simulation results, we provide policy recommendations that lead to the least echo chamber using multiple parameters we developed. On top of that, we devise a method to study polarization formation at population level based on the SNS users' opinion distribution. We find that within the assumption used in this model, a polarized society could be mediated with some conditions.
2. We develop a model that connects an established research in the field of public opinion, the Zaller Model of Public Opinion, with an agent-based approach. The model extends previous study by adding a mechanism to create a surveying process. We use the model for two cases. The first is to bridge the two studies' observation of echo chambers social media that seemingly contradict with each other. We also find the conditions required to minimize the perceived echo chamber at the bay. The second application is to find out the influence of

vaccination-related Facebook pages to individual users' opinion on vaccination. The simulation results reinforce existing findings that the network has potential to promote anti-vaccine beliefs for individual users. They also support some suggested policies to mitigate this problem through adding caution banners to dubious vaccine information providers as well as censorship of these pages through deplatforming.

1.3 Book Organization

This book is organized in eight chapters. Chapter 1 highlights the motivation and the contribution of this research. Chapter 2 establishes the theoretical background and concepts commonly used in this research. Chapter 3 elaborates the use of agent-based modeling for social science as the main method used in this research. Chapter 4 shows the results simulating the formation of echo chambers and polarization in a network with SNS-styled communication. Chapter 5 provides the fundamental ABM interpretation of the Zaller model followed by its applications in Chaps. 6 and 7. Chapter 6 is the first application that shows the results of implementing the Zaller model of public opinion as the internal model for SNS users to solve the confliction observation of echo chambers in social media. Chapter 7 is another example where we examine the influence of vaccination-related Facebook pages on individual users using the same framework. Finally, the book is concluded in Chap. 8 by summarizing all previous chapters, discussing possible future works and areas of limitations.

Chapter 2
Conceptual Backgrounds

2.1 Echo Chamber and Polarization

As the central topic of this book, it is important to clarify what echo chamber means. One of the definitions is a condition when a person is only surrounded by opinions similar to their own [12]. Consider the case of American politics. If a person comes from an area where the Republican Party constantly wins the local and national election, it is very common for them to have most of their closest people to be Republican Party supporters too. This results in the person to not be exposed with opinions that support Democratic Party. A more general concept defines echo chamber as the lack of information diversity a person is exposed with [11]. The opinion does not necessarily have to be agreed by the person, but the type of opinions surrounding them should be homogeneous. A non-political example as suggested by Pentland is in the case of online trading. In one online trading platform, people can either choose their trading strategy or follow another person's strategy. Suppose there is a trader whose opinion is highly adopted by many users; their trading strategy is thus adopted widely among its users. When the users follow the trading strategy of different people but originated from the opinion leader, the trading strategy used in the platform becomes homogeneous. The lack of opinion diversity in this case is also considered as an echo chamber. We use both interpretations of echo chambers in this research. Some are measured depending on the opinions of the surrounding person. Some others are measured with the kind of information that the person is being exposed with.

Similarly with polarization of public opinion, there are two different concepts [13]. The first is elite polarization. It is defined as polarization that happens between party-in-government and party-in-opposition. This condition is especially visible in countries where there are only two dominant political parties such as the United States. One example in American politics is how both parties have gotten more polarized in recent years [14]. The political stances and statements exhibited by the Republican Party members during the Trump presidency from 2017 to 2021

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follow the political right-wing sentiment more than the previous Republican Party majority government during the Bush Jr era. Similarly for the Democratic Party, the rise of more socialist leaning politicians such as Bernie Sanders or Alexandria Ocasio-Cortez was compared to the politicians during the Obama presidency. This means that the political elites in the United States grow more polarized because the incumbent and the opposition members have less shared ideologies. The other concept of polarization refers to mass polarization. A mass polarization traditionally refers to how the electorate's public opinion is divided along party lines. A recent example would be about the support of abortion in the United States [15]. Strong agreement or disagreement on the issue of legalizing abortion at federal level is associated with whether one is a Democratic Party or Republican Party supporter, respectively. The division does not have to be along political beliefs; it could be along any demographic marker such as ethnicity, religion, etc. The second type of polarization is what we are referring to throughout this research. We use a few metrics determining how polarization works at the individual level as well as societal level based on people's opinion.

2.2 Communication and Public Opinion in Social Media

The second most central theme in this book is social media or social networking system (SNS). Before discussing the significance of social media in shaping public opinion, we shall first discuss how public opinion is shaped in the more traditional media. Pre-SNS media has some distinct characters [16]. Firstly, there is a strong presence of mass media at the national level. A mass media is originally defined as a communication that reaches a large audience. The form could be many things such as newspapers, radio, or television. However, the operations and the contents typically follow strongly with the law and the political climate of the nation in which they operate. For example, in communist countries such as the Soviet Union, most of the news that are publicly available to the masses are more pro-government compared to the news in the United States with more diversity of opinion during the same time. The country limit also exists as a single market for the citizens that everyone more or less consumes the same content. Secondly, the contents are produced top down. Before social media, information was produced and distributed by dedicated professionals. News was written by journalists and checked by editors before they can be published. The same process is also observed for other traditional mass media. Thirdly, personal networks only cover a limited distance. Personal network could mean conveying information through word of mouth. In this setting, the news could not spread widely because of the limited network an individual has.

On the other hand, communication in social media has the opposite of the highlighted characteristics of traditional media. Firstly, the influence of traditional mass media at a national level is weaker. As the Internet gains popularity, TV viewership as well as news subscription decreases in many countries [17]. It is noted that there are social activisms that originated from some particular countries that

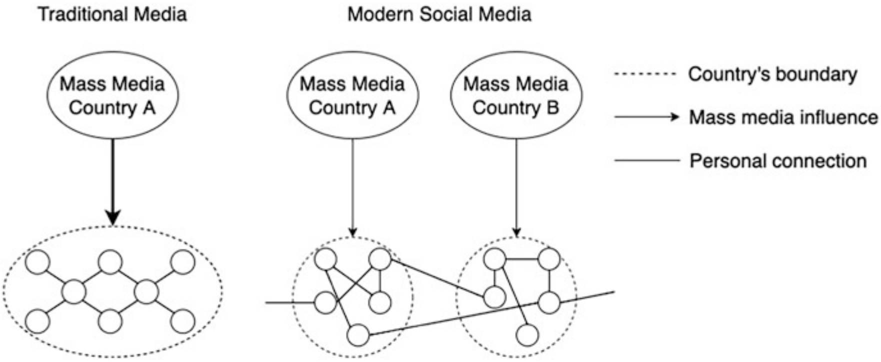

Fig. 2.1 In traditional media, mass media dominates narrative limited by country's boundary. Word of mouth only covers a limited distance. In modern social media, mass media's appeal decreases. Stronger emphasis on global connections of the users. Users can also broadcast information by themselves

are adopted and reached popularity in different countries in which the movement originated due to the use of social media such as the Arab Spring in Tunisia and the #MeToo movement in the United States [18, 19]. Secondly, everyone can broadcast themselves in the new media [20]. People have been making personal blogs since the dawn of the Internet. However, the ability to publish yourself is elevated with the features offered by social media added with the fact that created contents do not have to go through editorial system. This leads to new professions that are only enabled by social media such as influencers and YouTubers. Thirdly, personal network allows news to reach wider audience [21]. Most social media have "share" feature where we can share any content to everyone in our network. Depending on the security feature of the post, the ease of sharing allows contents to spread beyond its original target audience. This is how viral contents and Internet meme culture are produced. Many conflicts found in social media are also caused by this reason. Out of these three characteristics, this research focuses on the third part of modeling. Because echo chamber is often defined by the flow of information, the way information is spread is not just one-to-one, but one-to-many is important in this model (Fig. 2.1).

2.3 Modeling Opinion Formation

Modeling opinion dynamics through social influence is an extensively studied subject. There are multiple models developed, and we are covering some of them in this chapter. There are generally four classes of opinion dynamics models: voter model (peer-to-peer interaction model and majority rule model), Snazjd model, culture dissemination model, and bounded confidence model [22]. Specifically, they are characterized by their opinion representations, their local rules of interaction, and their environmental structures. We shall discuss what each element of opinion formation modeling means and briefly summarize the contributions of each model in this section.

Opinion can be represented in three kinds of values: binary values, discrete values, and continuous values [22]. Opinions in the form of binary values are typically representing two distinct mutually exclusive opinions such as agree or disagree. For computing purposes, they are also often represented in numbers such as -1 and 1 like in the simple application of Ising model for financial markets or 0 and 1. Despite being classified differently, opinions represented as discrete values and continuous values are often applied in a similar manner. There is a range of possible opinion values where the extreme ends represent absolute stance for both of them. For example, support for legalizing abortion in the United States could be represented by a discrete value from $0, 1, \ldots, 5$ or any value in the range of [0,1]. In both cases, if the opinion value is 0, it could represent complete disagreement on the issue. However, complete support for legalizing abortion is represented by 5 in the first case and 1 in the second case even though they mean the same thing. The choice of using which representation depends on what kind of interaction we are trying to model. Additionally, a modeled person could have their opinion represented as a singular value or an array of values describing multiple aspects of their opinion. For example, a model might want to have agents with multiple opinions that are orthogonal representing aspects such as belief in religion, support for the football club Manchester United, and how much they like fried rice (assumed to be independently determined for the sake of example). Instead of having their opinion represented as 0.8, agents in this model would have their opinion to be something like [0.8, 0.1, 0.5].

Unlike the opinion representation with its classification, the local rules of interaction have more subtle differences and shall be discussed as a series of examples [22]. In the peer-to-peer interaction version of the Voter model, agents have binary opinions and are connected in a lattice. An agent might change their opinion depending on a randomly selected neighbor in the lattice with a given probability. Another version of the Voter model employs a majority rule to change one's opinion. The agent's opinion will follow the majority of opinions that are present among their neighbors. The Snazjd model is another popular model that could be considered as the extension of the majority-rule Voter model. In the original model, Sznajd considered a 1D lattice of agents with opinions represented by -1 or 1. The model introduces a social validation mechanism by making the neighbors of two agents with the same opinion to adopt their opinion. Then there is a homophily rule introduced by the Axelrod model of dissemination of culture. Agents' opinions are represented by an array, and agents only interact with other agents with similar opinions. Furthermore, the interaction increases when the similarity between them is increased. In our example, if two agents have similar opinions about their belief in religion, support for the football club Manchester United, and how much they like fried rice, they tend to interact more and influence each other further than with agents who do not share similar opinions on the three aspects. Finally, we have a bounded confidence model. In this class of model, opinions are usually represented in continuous values where real vectors and discrete values are adopted in some research. The main feature of this model is the presence of bounded confidence and convergence. Bounded confidence here means that agents will only adjust their opinions bounded by some kind of "acceptance threshold." If an agent interacts with another agent whose opinion is more different than their acceptance threshold, opinion change will not occur. If opinion changes occur, the extent that the opinion changes will depend on the convergence parameter.

The environmental structures in this topic refer to the space that allows agents to interact with each other [22]. The most simple environment is where there is no structure. In research that utilizes such an environment, agents are typically interacting with each other by random chances. Another common environmental structure is a regular lattice. The most common type of lattice is a 2D lattice where a single agent occupies a single point in the lattice. The agents in this lattice can only interact with their neighbors (Von Neumann style is more common than Moore style). Traditionally, 1D lattice is also used such as in the case of the Sznajd model. Lastly, the most common environmental structures in recent research are networks. The networks can be randomly generated through algorithms or obtained from real data. Randomly generated networks are particularly useful when studying a theoretical model where we are just interested in observing emergent properties in different types of networks such as random networks, scale-free networks, etc. On the other hand, real networks are more common to use for data-driven research.

2.4 Zaller Model of Public Opinion

Public opinion is often measured by collecting individuals' opinions in a particular population. Hence, understanding how opinion formation works for individuals is important to understand the total argument of this book. We shall next discuss the Zaller model of public opinion as the building block of the internal model in individuals we want to simulate [23]. The Zaller model of public opinion can be summarized as a theory on how individuals convert their political information consumption from elites and mass media and convert it into their political preferences [23]. Due to the role of social media platforms as a considerable source of political information in this era, we treat them as having the same role as elites and the mass media in the original work. The model has been applied to explain dynamics of public opinion of multiple subjects in the United States. Some of the study cases include the support of the Vietnam war, school desegregation, and various elections. Among the questions answered by the Zaller model is why do people support policies that are seemingly against the interest of their political identity? Why are the moderately educated more militant about their political preference than the most educated ones? In this subsection, we shall discuss how the Zaller model answers these questions and its relevance to this research.

According to Zaller the process of opinion formation is composed of three actions, receive-accept-sample (RAS), that lend itself to be called the RAS model [23]. The process of opinion formation starts when an individual encounters political information by actions such as reading or watching political news. The political information in this context is information that evokes binary choices like “A or B” or “Yes or No” in the reader’s mind. One example based on the previous paragraph, the information could be “America should send more troops to Vietnam” that is appropriately responded by a yes or no. A more complex example would be a piece of news that says “President Ronald Reagan sold arms to the Islamic Republic of Iran” that meant to shed a negative light for Reagan’s candidacy prompting stronger preference for Carter in the context of choosing Reagan or Carter for the reader’s choice of president.

Consider a person who is reading a newspaper article of arbitrary political information. A reception of information is defined as a person’s encounter with the information and an understanding of the information’s political stance [23]. Reception can be different from the intention of the information producer, especially when the person is not equipped with a high political awareness and the information is more complex. In the example of Reagan’s policy of arms dealing, a person who is not aware of the US-Iran’s hostile relationship would not think that the information should discourage them to vote for Reagan in the upcoming election. Once information is received, the reader will decide whether to put the information to their consideration. A consideration here is defined as any reason to side with one of the options or another [23]. If for example above the reader receives the information as anti-Reagan information, which we shall label as a “Carter” information, they might keep it as one of the considerations in their mind. This process will happen every time the person encounters political information on the presidential candidacy topic and fill their mind with “Reagan” or “Carter” considerations. Of course the decision of accepting a consideration is highly dependent on the reader’s political predisposition. We should expect that an ardent Republican Party supporter will have a more positive impression on Reagan than Carter. Therefore, their list of considerations will be filled with more “Reagan” than “Carter.” Once a political survey is conducted, our hypothetical reader here will have to answer the question along the lines of “Would you vote for Reagan or Carter?” They will then gather some of the more recent considerations they have on top of their mind and make an averaged response. While the final response will just be a simple “Reagan” or “Carter” (or abstain in some cases) for individual respondents, these mechanisms are what allow explanations to questions we set earlier.

More fundamentally, the process above is assumed to fulfill four “axioms” [23]. These axioms are not always true in the mathematical sense. Instead, they are more like a set of rules people use to process information every time they consume political information. The four axioms are presented in Table 2.1: These axioms govern people’s decision during the receive-accept-sample process. In this process, receiving news means that people will first be exposed to the news and comprehending the message carried by the news. The detail on how each axiom is built into an ABM will be detailed later in Chap. 5.

Table 2.1 Axioms of Zaller's receive-accept-sample (RAS) model

No.	Axiom name	Explanations
1	Reception	Greater person's level of cognitive engagement with an issue increases the likelihood of exposure and comprehension (reception) of political messages concerning the issue
2	Resistance	People tend to resist argument that are inconsistent with their political predispositions, but only if that they have the contextual information to perceive a relationship between the message and their predispositions
3	Accessibility	The more recently a consideration has been called to mind, the less time it takes to retrieve that consideration or related considerations from memory and bring them to the top of the head use
4	Response	Individuals answer survey questions by averaging across the considerations that are immediately accessible to them

2.5 Argument Against the Anti-vaccination Movements

One of the applications of the ABM interpretation of the Zaller model is to study the influence of vaccination-related Facebook pages to individual Facebook users. Therefore, it is important for us to provide a brief review on the anti-vaccination movements and our stance with regard to the issue. Anti-vaccination or vaccine hesitancy is defined as a range of attitudes of reluctance or refusal to be vaccinated oneself or one's family against contagious disease [24, 25]. Vaccine hesitancy is motivated by various factors in different regions of the world [26]. Some of the most common influences for not vaccinating include cultural/religious reasons, knowledge awareness, and vaccine's risk/benefit (epidemiological and scientific evidence) [27]. Of all the reasons, vaccine hesitancy is mainly related to the risk/benefit from epidemiological and scientific evidence points of view, especially in countries with higher incomes. Most of these concerns are specifically about the adverse events following immunization (AEFIs) and the safety of the vaccine. Sometimes, the risks of vaccination are blown out of proportion by the proponents of the anti-vaccination movement in the form of dubious misinformation or even completely fabricated news. One of the most popular campaigns against vaccination was the misinformation that links causality between MMR vaccination and autism on children that has been debunked by experts [28, 29]. In addition to the overstated risks of vaccinations, some parents do not vaccinate their children because they are not well-informed of the benefits of vaccination.

Next, we shall present additional arguments against the anti-vaccination movement introduced in the introduction section from its relation with online misinformation. As mentioned earlier, social media are a significant source of vaccination information for many people [30, 31]. However, they also come as a medium of vaccination misinformation commonly found throughout various social media platforms like Facebook and Twitter [32]. These kinds of misinformation are mainly promoted by regular users, but those promoted by public figures are typically more influential [33]. Specifically for Facebook, pages that promote the anti-vaccination point of view are more numerous than pages that promote the pro-vaccination view [34]. An international study of 137 countries revealed that the prevalence of foreign disinformation on vaccination is a good predictor of a drop in vaccination coverage over time [35]. Since social media play a significant role as a media of misinformation on vaccination, a systematic strategy to minimize the negative effect of anti-vaccination information in social media needs to be established. Considering its reach, Facebook will be the social medium of choice in this research.

After focusing on the platform, we shall discuss the mechanism of vaccination opinion formation for the users. Since there has yet to be a specific study on vaccination opinion formation, we therefore draw parallel from other well-studied topics with similar characteristics. Firstly vaccination is a politically divisive issue with the binary of proponent and opponent [36]. Secondly vaccination sentiment has the property of being backed by scientific evidence, but strongly influenced by other value predispositions like cultural and religious values [24]. We found out that another topic that shares these two properties is the public attitude toward embryonic stem cell research [37]. Aside from the shared properties, this work found that polarization effects along with the increase of scientific knowledge and various value predispositions in attitudes toward embryonic stem cell research are found to follow the mechanism described by the Zaller model [23]. Based on these parallels, we can infer that the Zaller model could be the appropriate basis to model the mechanism users' opinions on vaccination. The detail on how the Zaller model is going to be applied for vaccination opinion in social media is elaborated later in Chap. 7.

Chapter 3
Methodology

3.1 Agent-Based Modeling for Social Simulation

In this book, we focus on applying an agent-based modeling (ABM) approach to study phenomena such as echo chamber and polarization in social media. ABM is one class of computational model to simulate individual agents' actions and their interaction [38]. It is also known as individual-based modeling in some research field because the modeling focus revolves around the behavior of individual agents. Research fields that commonly use ABM include biology, ecology, and social science. The main interest of ABM is to observe the emergent phenomena caused by the collective interactions of the individual agents. The purpose of ABM is to obtain explanatory insights on how interactions governed by the individual rules (microscopic interaction) lead to some complex phenomena (macroscopic phenomena) [39].

One classic example of ABM implementation is for the predator-prey model [40]. The predator-prey model is a model used to predict the dynamic of some animal populations. The original model consists of two differential equations, each describing the rate of change of the prey's and the predator's population, respectively. Instead of using the equations, the ABM interpretation of the same model will have to dedicate three objects: wolf agents (the predator), sheep agents (the prey), and some grassland (environments at which the agents' interactions take place). The sheep agents will then be given rules on how to graze, reproduce, and die under a certain condition. Similarly, the wolf agents are too given rules on how to eat the sheep, reproduce, and die. There are also rules given to the environment such as how long does it take for grass to replenish. After simulating, we can observe how the overall population for each agent evolves over time. Depending on the initial setting and implementation of the interactions, the population of the sheep might go to zero with the wolf completely dominating, or both agents undergo a cycle of population increase and decrease over time. The act of wolf agents eating sheep agents is what is considered as the microscopic interaction, while the total

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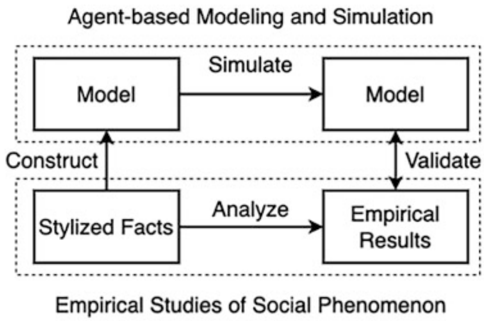

Fig. 3.1 Relationship between ABM and stylized facts obtained for social science research

population of each agent is what is considered as the macroscopic phenomena in this example.

The internal models in this research are built using stylized facts [41]. Stylized fact is defined as a simplified presentation of empirical findings, typically from social science research [42]. Consider the statement "the more knowledgeable (politically) a person is, the less likely they will accept any political information (in general)" as an example of a stylized fact that we use in this book [23]. This statement is based on the findings that Zaller formulated for his own model. Of course, the original work is more nuanced than the quoted statement above. However, since the point of ABM is to get observation of macroscopic phenomena caused by the simple rules, it is necessary to isolate the empirical findings into the factors we want to evaluate for agents to act on. One other problem in modeling is validation. If it is possible to create any model that leads to the outcome we want, how do we make sure that our model is meaningful? This is where the triangulation of the stylized facts is used. Suppose that there is another stylized fact that reads as "the more knowledgeable (politically) a person is, the more consistent their opinion is with their political predisposition" (another stylized fact that we use in our research). From these two facts, we can conclude that if an agent is more politically knowledgeable, we can expect them to a) be less likely in accepting any news and b) produce more consistent opinion that aligns with their political predisposition. In this case, we model only the first fact and see if the second statement is also observed as part of the simulation results. If it is observed, it gives a stronger validity to our model because the second stylized fact can be observed independently just by simulating the first stylized fact deliberately [43]. We also call that the real-life fact is within the landscape that could be produced by our model. A diagram showing this validation process can be seen in the Fig. 3.1.

3.2 Policy Design Using Landscape Search

One application of using ABM is to create an in silico modeling for policy design [44]. Consider devising a set of effective policies to curb the number of casualties of the COVID-19 pandemic based on the example of smallpox simulation. There were many policies that the government could take to achieve this goal. Some of the policies considered include closing borders for non-residents, promoting remote work for office workers, stopping in-person school activities for a few months, delivering vaccines, etc. [45]. Due to the complexity of the situation, it is difficult to determine which policies should be prioritized considering the limited time and resources a government has. Since experimentation on the population is not ethical and difficult to do, ABM could be one alternative to determine which set of policies could be considered when implementing government policies. We can create a virtual city given sufficient demographic data and simulate different policies. A set of policies here is also called scenario. So a single scenario could be when the government does not close its border, stop in-person school activities for 3 months, and administer a million doses of vaccines in the first 6 months in this example. Practically, a scenario is simply a set of variable parameters with an explanation of real-world context. In this book we will see more scenarios in each simulation section in the main bodies.

Once we decide the scenarios we want to simulate, we should determine how to choose the best scenario for a policy recommendation. Firstly, we should define a performance metric. In the example of modeling effective policy to mitigate COVID-19, the number of people infected with the coronavirus would be a reasonable choice of a performance metric. The performance metrics could have multiple variables, where the success of the scenario also depends on the number of people who died because of the virus on top of the number of infected people. Next, we create the landscape of what every possible outcome is within the limitations of the model by simulating all possible scenarios. We map the entire landscape by plotting the performance axis against the parameter axis. The landscape contains at least two points of interest: the closest point resulting from the scenario that resembles our observed reality (as is) and the optimal scenarios we want to achieve (to be). From the two points, we compare the differences between the two scenarios and analyze to get possible explanations on how to reach the optimal scenario from our current society [46, 47]. Another possible point of interest but not limited to is the worst performing axis where we could find explanations on how to not reach that point. Note that the purpose of this method is not to get a robust forecast on what the current society is heading to. Instead, it is most useful in exploring what possible states of the world could be reached and the conditions that lead to it.

Chapter 4
Simulating Echo Chamber and Polarization Problems in Social Media

4.1 Background

One way to understand such formation is by using opinion dynamics model [48–53]. Most opinion dynamics models are based in the interaction between two individuals as the means to spread information. This is no exception for opinion dynamics models in the context of social media [5–8]. The interaction is essential for opinion and group formation as the main interest of many researches. However, most social media are not used for personal one-to-one interaction but instead one-to-many such as for news sharing or status updates in Twitter and Facebook. A new issue of interest concerns the use of one-to-one interaction as the underlying assumption: if people do not form opinion from personal interaction on social media, what if they learn from the news itself instead?

The main purpose of this research is to study how different information consumption could lead to the formation of echo chamber in SNS. But based on the literature review above, the systems that have been developed do not serve our purpose very well. Therefore, we developed a model that can be used to study the phenomenon by having SNS users that interact and learn from the information and can be modified to represent communication style in SNS better. The study is conducted by simulating information spread on SNS with different scenario for news provider. News provider becomes an important stakeholder because many of SNS external contents are obtained from such media outlet. From the results of the simulation, we expect to come to a conclusion for how the news provider should publish news in order to reduce echo chamber in the system as little as possible. Our hypothesis is that users who are exposed to mostly moderately opinionated news will lead to an SNS with least echo chamber.

M. Al Atiqi, *Echo Chamber and Polarization in Social Media*, Agent-Based Social Systems 17, https://doi.org/10.1007/978-981-99-1770-9_4

4.2 Model Summary

Define a set of M agents representing SNS users $User = \{u_1, u_2, \cdots, u_i, \cdots, u_M\}$. These agents are connected with each other via an undirected graph G representing their connection throughout the SNS. Undirected graph is chosen to represent user's connection like friends in Facebook instead Twitter/Instagram followers concept. The graph is a randomized Barabási-Albert graph, chosen for its scale-free property observed in SNS connection [54, 55]. We also have a news provider agent that publish a set of M news $News = \{n_1, n_2, \cdots, n_j, \cdots, n_N\}$ over time t. All news in this model are assumed to only cover a single topic with two extremities, e.g., "government policy to increase sales tax" where sentiments can vary from complete agreement to complete disagreement with everything in between or "Trump's presidential candidacy" where generally there are only the Democratic Party and Republican Party to support.

For any user $u_i \in User$, we define opinion $o_i \in [-1, 1]$ that describes their position on the issue where 1 represents full agreement toward the issue and -1 for full disagreement. Similarly, every news $n_j \in News$ carries a sentiment $s_j \in [-1, 1]$. We use the terms sentiment and opinion to refer to the same concept, to differentiate that one is a quantity of user agents and the other is of news. The choice of value range for opinion and sentiment is based on two concepts, Ising model and Deffuant-Weisbuch model of mixing belief [48, 56]. The formation of echo chamber could be described by the critical system model; hence Ising model application where opinions are represented in binary value in $+1$ and -1 is suitable. However, using binary numbers alone does not allow diversity of opinions in the population. Hence, continuous opinion system from Deffuant-Weisbuch model is used with $+1$ and -1 as the extremes of opinions allowing continuous values of opinion in between the extremes. The news are published by news provider agent throughout the model. If a user u_i sees a news n_j, they will share the news to the SNS given that the difference between the opinion and the sentiment is within some acceptance threshold d such that $abs(o_i - s_j) < d$. Users also have exposure $\varepsilon_i \in \mathbb{R}^+$ that represents the sum of difference between user's opinion and news sentiments they have encountered.

Every user i would have its $State$ representing its relation with respect to every possible news j on the SNS symbolized by

$$S_i^j \in [Uninformed, Exposed, Accepted, Shared]. \tag{4.1}$$

For example, $S_3^4 = Accepted$ means that user u_3 has accepted the news n_4. These states are modified from Zaller-Deffuant model that describes how user interacts with news [57–59]. Their dynamics are simply described intuitively below:

1. All users start with state $Uninformed$ initially.
2. When a user u_i is exposed by news n_j, their state becomes $S_i^j = Uninformed$, and they update their exposure by

$$\varepsilon_i' = \varepsilon_i + abs(o_i - s_j). \tag{4.2}$$

3. If the news has close sentiment with the user's opinion such that $abs(o_i - s_j) < d$ where d is the acceptance threshold, u_i now accepts n_j and $S_i^j = Accepted$ and updates their opinion by

$$o_i' = o_i + \mu(s_j - o_i) \tag{4.3}$$

based on the mechanism in Deffuant model.
4. If u_i's neighbors' u_k opinion's averages have the same sign (positive or negative) with o_i such that $o_i \sum_k o_k > 0$, then user i would share the news due to social validation such that $S_i^j = Shared$ and all neighbors u_k who are still uninformed would change its state to $S_k^j = Exposed$ like u_i in process 1 [60].

Model description via formal mathematical set theory definition is provided in the Appendix A.

4.3 Measuring Echo Chamber and Polarization in SNS

There are different definitions of echo chambers and polarization. We use four criteria to measure the strength of echo chambers and polarization in this chapter. The four criteria are defined as follows:

1. Individual Echo Chamber Coefficient
We define the individual echo chamber coefficient $ECC \in \mathbb{R}^+$ by the following equation:

$$ECC[u] = stdev(f_{Opinion}[v]), \forall v \in Neighbors(u). \tag{4.4}$$

This computes the similarity the opinions of a user's neighbors' opinions. The closer its value to 0, the more user u is in echo chamber due to their neighboring users having opinions of similar value. The higher the value, the lower its echo chamber due to having more diverse opinions in the surrounding.
2. Global Echo Chamber Coefficient
The global echo chamber coefficient is measured by summing the product of neighboring user's opinion's sign for the whole network. This quantity is based on Ising model's energy concept H for a configuration σ where for two adjacent sites i, j of a lattice $\wedge$ with interaction between them $J_{i,j}$ without external field is described by

$$H(\sigma) = -\sum_{\langle i,j \rangle} \sigma_i \sigma_j. \tag{4.5}$$

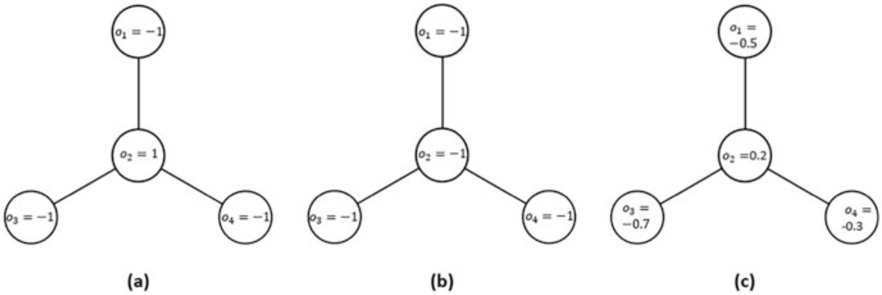

Fig. 4.1 Three examples of global echo chamber parameter calculation

We modify this understanding of Hamiltonian into global echo chamber parameter GEC defined as

$$f_{GEC}[User] = \sum_{E} sign(f_{Opinion}[u])sign(f_{Opinion}[v]), \forall(u, v) \in E. \tag{4.6}$$

This measures whether clusters of opinion polarization present across the network. Consider the example shown in Fig. 4.1.

Based on Eq. (4.6), the values of GEC for configuration (a) and (b) are $f_{GEC}[User_a] = -3$ and $f_{GEC}[User_b] = -3$. In this model, configuration (a) is more desirable than configuration (b) because users are connected to other users with different general alignment of the opinion denoted by its sign. However, this parameter only takes into account whether the users are "generally" supportive or against the issue based on its opinion sign. Hence, configurations (a) and (c) return the same value for this evaluation. This could detect whether the alignments are spread out throughout the network or whether clusters of alignment are present in the network. The value will be maximal when all users have the same alignment. Therefore, the scenario with the lowest GEC will be the better scenario in this parameter.

3. Average Opinion
The average opinion is obtained by averaging the opinions of all agents in the network $f_{Average\ Opinion}[User] \in \mathbb{R}$ by

$$f_{Average\ Opinion}[User] = \frac{\sum_{User} f_{Opinion}[u]}{N}, u \in User. \tag{4.7}$$

This parameter only indicates whether there is overall dominant inclination of opinion in the entirety of the network. The further its value from zero, the more the overall system has inclination to either extreme opinion, i.e., more polarized. The weakness of this measurement is that it will return the same value for any distribution of opinions where it is symmetrical around the neutral opinion zero.

4. Average Exposure
   Another parameter of echo chamber is the lack of diversity of information flow. In this model, the users store exposure internally based on the sum of the differences between user's opinion and exposed news' sentiment. The system's average exposure is defined as

$$f_{Average\ Exposure}[User] = \frac{\sum_{User} f_{Exposure}[u]}{N}, u \in User. \tag{4.8}$$

   The higher the value, the more diversity of sentiments of information that reaches users in the system and vice versa. So a user can have a high exposure through encountering many and/or different news just like how a person would increase their knowledge in real life.

4.4 Simulation Scenario and Parameters

All simulation is done in Python 3.7.0. We use Barabási-Albert graph structure generated by barabasi_albert_graph function from NetworkX library to represent the SNS, where the nodes are the users and the edges are their friendship connection. The value of N and m is chosen so that the graph exhibits small-world and scale-free characteristic of SNS (Table 4.1). Total time T is chosen slightly larger than number of news to ensure that all possible actions by users would have been done. The value of d_1 is varied to describe different level of society's acceptance toward news in SNS. We fix the value of d_2 to be constantly low throughout the simulation as it represents user's sharing news they encounter right away. We choose small value of convergence parameter μ because in reality user's opinion will not change very much after internalizing an information. It also determines how quickly the steady-state formation is reached, but not the distribution of opinion. The function of news generation is dependent on the scenario chosen that will be explained later in this section.

Table 4.1 Table description of parameters used in simulation

No.	Parameter	Description	Value
1	T	Total time of the simulation	30
2	N	Total number of user agents	128
3	m	Edges of the network generated for each node created by the program function	8
4	$\|n\|$	Total number of published news	25
5	d_1	News acceptance threshold parameter shared by one other user	[0,2]
6	d_2	News acceptance threshold parameter shared by news provider	0.1
7	μ	Convergence parameter	0.1
8	F_S	Function of news generator, dependent on the scenario	F_n

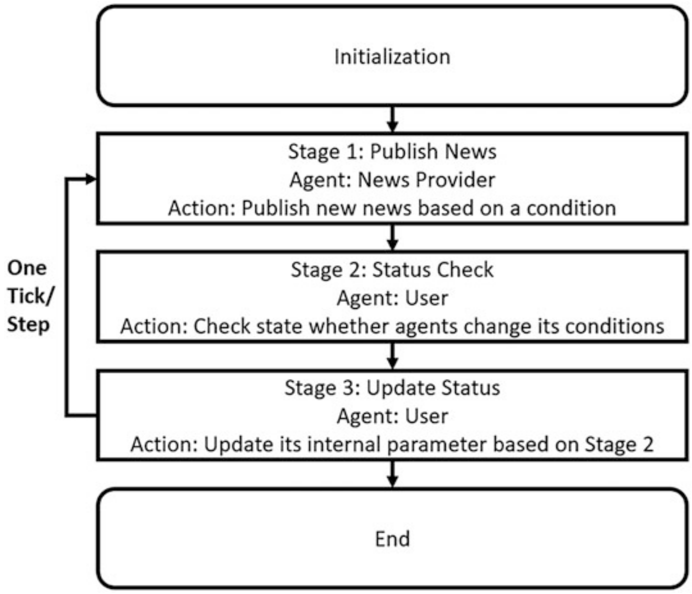

Fig. 4.2 The simulation includes five stages, with three in the main stage. For each time step, there are (1) publish news stage, (2) status check stage, and (3) update status stage to be executed

4.4.1 Simulation Stages

The simulation is described using stage definition. It includes initialization stage, main stage, and end stage. The main stage comprises of all stages done every time step/tick. The detailed description is presented below (Fig. 4.2).

The stages are as follows:

1. Initialization stage
   Action: Creates N user agents, one news provider agent, and one network G to represent the SNS. Each user u_i has time-dependent variables such as opinion, state, and exposure o_i, S_i^j, and ε_i. They also have static parameters such as the threshold (acceptance and external shared) d_1 and d_2 as well as the convergence parameter μ is pre-assigned uniformly for all user agents.
2. Publish news stage
   Agent: News provider
   Action: At each time step t, publish new news n_j with sentiment s_j based on the function F_n dependent on the chosen scenario. All user $u \in User$, if $|u_i - s_j| < d_2$, u_i will share n and updates its state and exposure to $S_i^j = Shared$ and updates its exposure by Eq. (4.2).

3. Status check stage
   Agent: All users
   Action: All users u_i check its state S_i^j for each news n_j and indicates whether it is going to change its status in the next stage based on the conditions mentioned in the Model Summary section.
4. Update status stage
   Agent: All users
   Action: If u_i decides to change its status based on the results of previous stage, then it changes its status according to the state transition described in the Model Summary section.
5. End stage
   Condition: The end stage is met when $t = T$.
   Action: Data collection of users' final statuses are collected based on the need. Data includes their final opinions and final exposures that will be further processed to observe the different echo chamber parameter we will describe in the Echo Chamber Analysis subsection.

4.4.2 Scenario Description

In this simulation, we focus on how different kinds of news would affect the overall opinion formation of SNS users. We introduce five kinds of scenarios based on the news sentiment shared by media provider to the SNS. The five scenarios are as follows:

1. Random news
   In this scenario, the generated news has completely random sentiments where for arbitrary $s_j, s_j \in [-1, 1]$.
2. Extreme news (positive)
   In this scenario, the generated news has completely random sentiments from possible values of positive extreme sentiments where for arbitrary $s_j, s_j \in [0.9, 1]$.
3. Extreme news (negative)
   In this scenario, the news are generated randomly with sentiments around the negative extreme side where for arbitrary $s_j, s_j \in [-1, -0.9]$.
4. Extreme news (both-sided)
   In this scenario, each news' sentiment could be in either side of the extreme opinion where for arbitrary $s_j, s_j \in [-1, -0.9]$ or $s_j \in [0.9, 1]$.
5. Moderate news
   In this scenario, news are randomly generated around the neutral sentiment of $s_j \approx 0$. In this case, $s_j \in [-0.1, 0.1]$.

Note that all randomizations are based on uniform distribution function.

4.5 Results and Discussion

4.5.1 *Role of News in Echo Chamber and Polarization Formation*

Before we attempt to measure the echo chamber, we first need to understand what kind of opinions is formed based on each scenario. We collected final opinions of all users for ten repeated simulations based on the same network structure and initial opinion. The final results are compared in Figs. 4.3, 4.4, and 4.5.

These figures give us how different value of d_1 affects the opinions in general. The three figures are results of three simulations under the same input parameters but d_1 but have different randomized graph and initial opinion among the users. The main point of these figures is to illustrate how the final opinions' distributions change after the simulation is done. This evaluation is done by comparing the distribution visually. If there is no opinion changes among the users, subfigure labeled (b)–(f) will have the exact same look with subfigure (a) with the frequency multiplied by 10. The more different the shape from (b)–(f) looks like compared to the shape of (a), the more changes of opinions happen in the simulations.

Originally, d_1 only serves as acceptance threshold where lower value means that users are less likely to accept an information and updating its opinion subsequently. But from these figures, we also observe that d_1 determines whether information can flow and updates the opinion of other users significantly. From here we will denote low d_1 as low information diffusion system and high d_1 as high information diffusion system. Based on Fig. 4.3, the shape of the histogram does not change much from before the simulation is done and final simulation results from different scenarios compared to the other figures. From Fig. 4.4 and even more obviously Fig. 4.5, we can see that higher value of d_1 leads to more different shape of opinion and distribution. This is especially apparent in one-sided extreme news and two-sided extreme news. In the case of one-sided extreme news, most users are polarized into one extreme for high value of d_1 as opposed to the presence of few users at the opposite side of the spectrum in medium value of d_1. Interestingly in the case of two-sided extreme news, medium value of d_1 leads to more extremists (user with extreme opinion) as compared to when d_1 is high. When d_1 is high in the two-sided extreme news scenario, we have more evenly distributed opinions across the network. Based on figures above, random news scenario provides histogram that resembles normal distribution the best that might describe real-world users where most users belong in the moderate opinion and fewer users at the extremes.

With the display above, we classify societies into some different types based on the presence of opinions in the system. We classify societies based on their opinion distribution as follows (Fig. 4.6):

1. Normal society
   This is when the distribution of opinions follows roughly normal distribution with most users having moderate opinion and getting fewer toward the end of both sides.

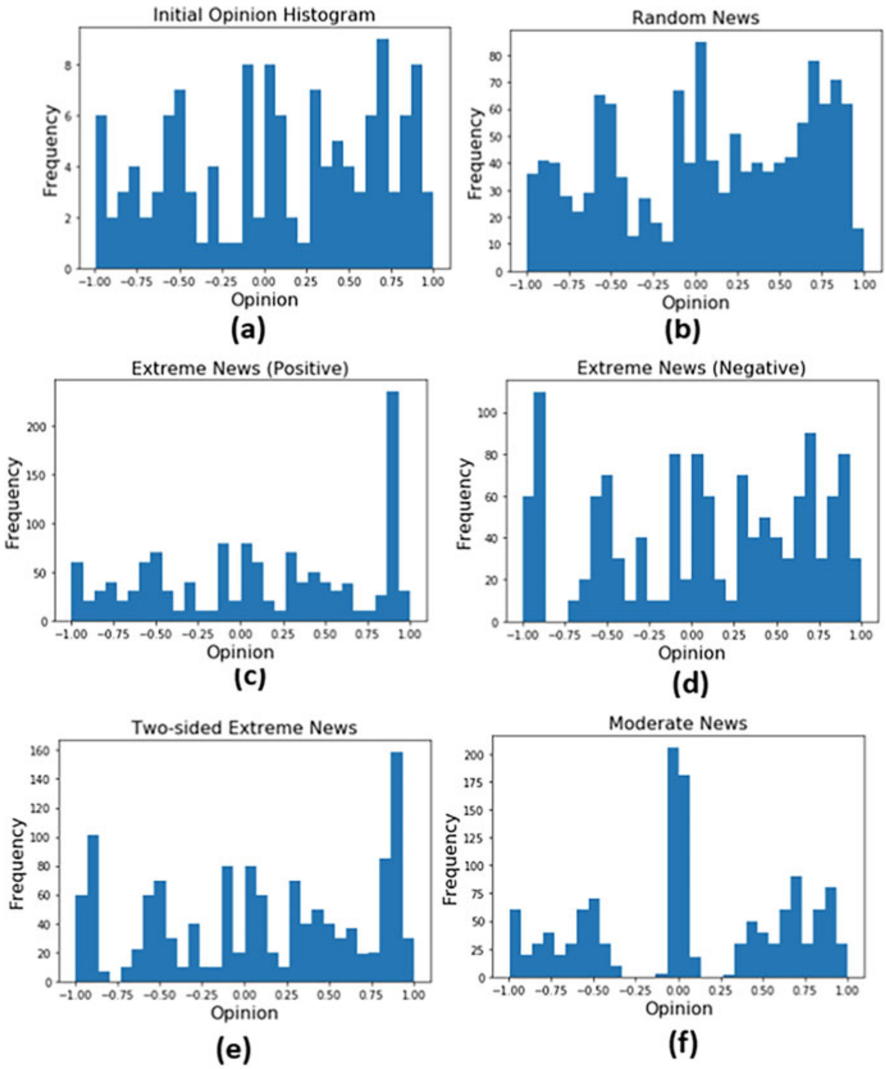

Fig. 4.3 Histogram of opinions from original system before news are spread indicated by (**a**) compared to the final opinions after exposed by news from different opinions distributions (**b**)–(**f**) for *ten* repetitions with low acceptance threshold of $d_1 = 0.25$

2. Extreme society
   Society where there are many users with extreme opinions distributed in a small range in either end of the spectrum
3. Separated society
   When there are more users with strong opinion in both sides but few having moderate opinion on the middle

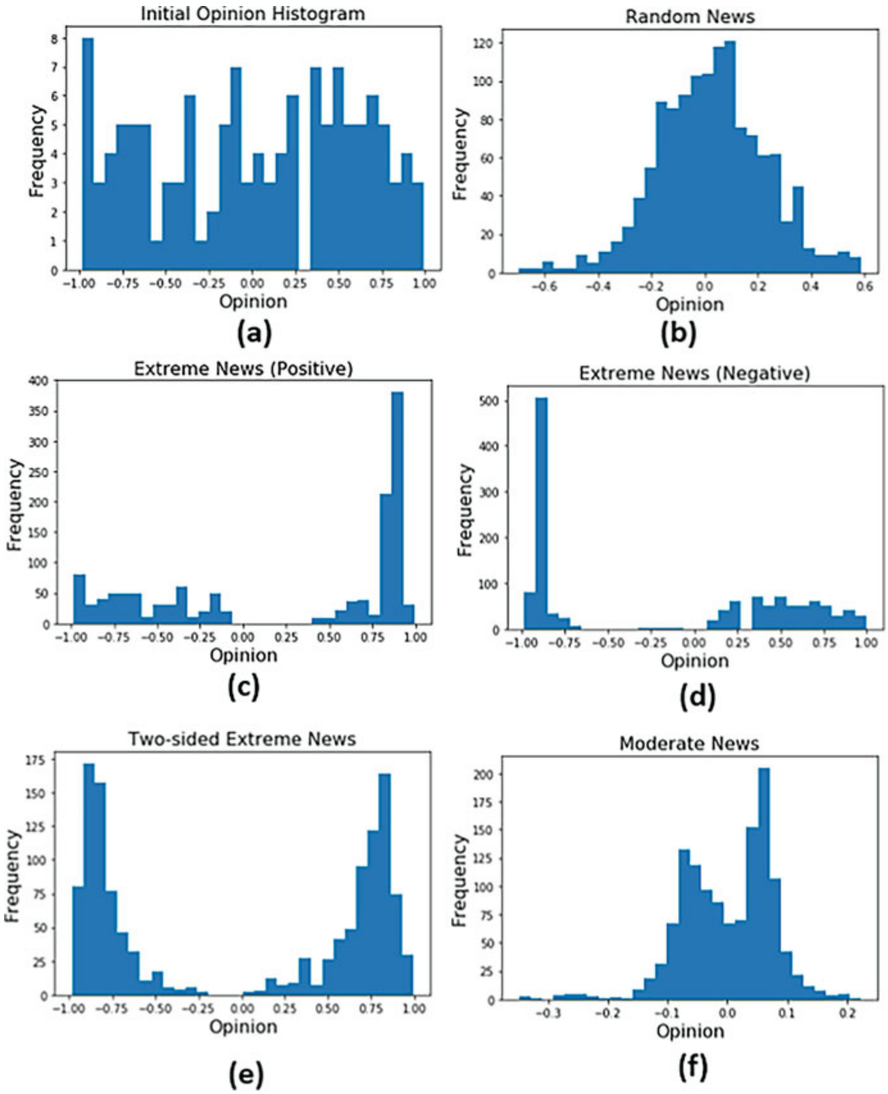

Fig. 4.4 Histogram of opinions from original system before news are spread indicated by (**a**) compared to the final opinions after exposed by news from different opinions distributions (**b**)–(**f**) for ten repetitions with medium acceptance threshold of $d_1 = 1$

4. Diverse society
   If there is no noticeable peak, we classify this type of society as diverse society. There is no significant polarization of opinion among users. Opinions of all kinds are found in this type of society.

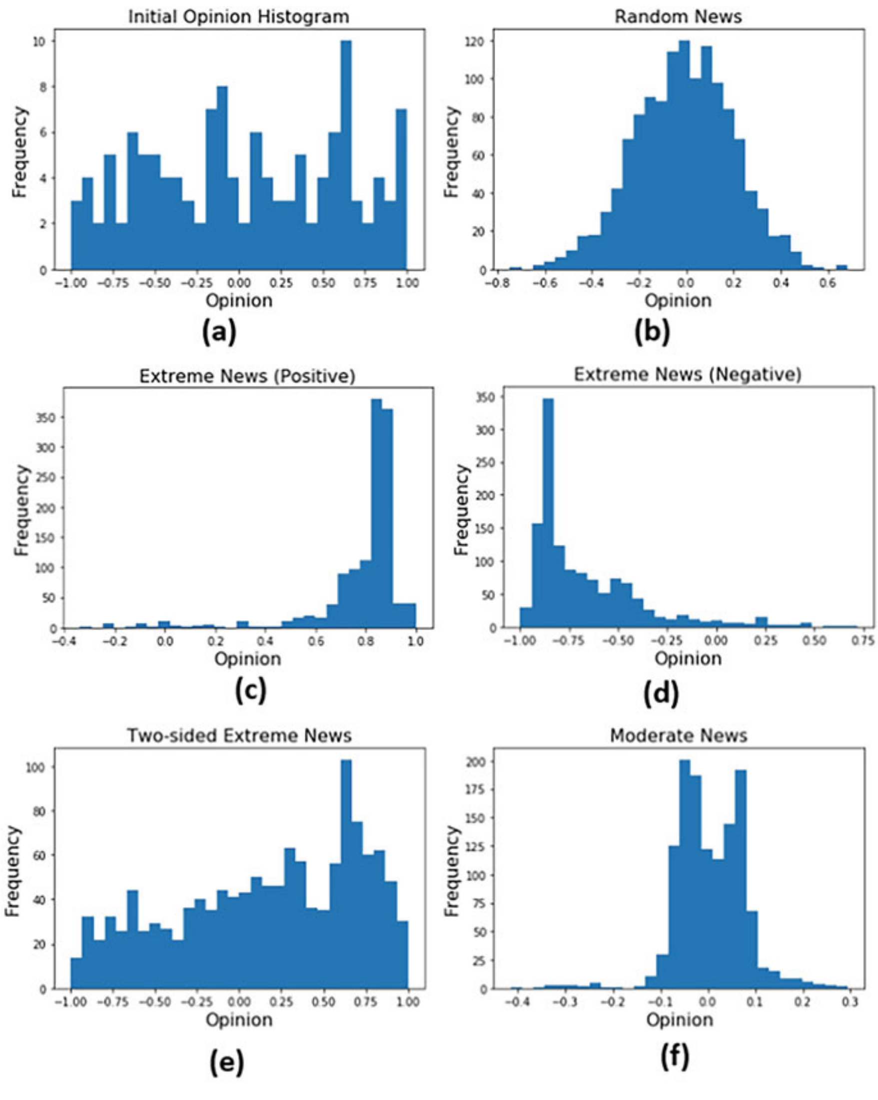

Fig. 4.5 Histogram of opinions from original system before news are spread indicated by (**a**) compared to the final opinions after exposed by news from different opinions distributions (**b**)–(**f**) for ten repetitions with high acceptance threshold of $d_1 = 2$

At a glimpse, extreme society which is caused by extreme news scenario seems to fit our intuitive understanding of echo chamber where many users are having similar opinions without alternatives. On the other hand, two-sided news scenario on high information diffusion fits the random society form with less dominant peak compared to the other scenario of different value of d_1. Another interesting finding is that the range of final opinions in the case of moderate news scenario with medium-

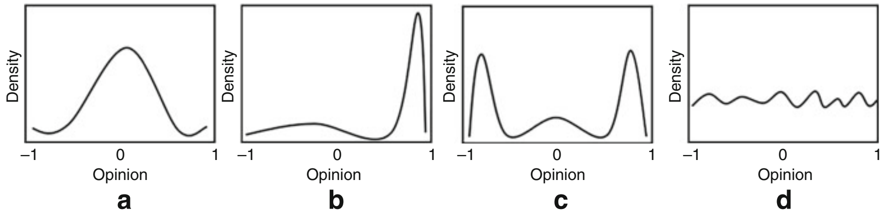

Fig. 4.6 Example of four different types of society based on its opinion density distribution. The subfigure each represents (**a**) normal society, (**b**) extreme society, (**c**) divided society, (**d**) random society

high information diffusion is smaller than the full range of possible opinions $[-1, 1]$. The final range of opinions ends up being narrower than $[-0.5, 0.5]$ in both cases, without any users having extreme opinion. From these observations, we might want to conclude that two-sided news scenario is the best at maintaining diversity of opinions. However, we only know that there exist SNS users with these values of opinion without knowing whether they are forming echo chamber structure in relation to its position in the network. At the same time, limitation of news in the moderate news scenario is also appealing because of the absence from extreme opinions that might correspond to potential conflict which is useful. In order to complement the above analysis, we shall look at the various parameters of echo chambers to determine which scenario is best in keeping the least echo chamber in the system in the next section.

4.5.2 Echo Chamber Analysis

For each echo chamber parameter, we compare the results for all possible scenarios. Because different societies have different personal threshold in accepting information and rate of information diffusion, we compare parameters indicating certain aspect of echo chamber for different value of threshold d_1. The results presented below are average from ten runs based on one single randomly generated network with randomly initialized opinions to take into account the randomness of sentiments in news generation process. We present results from only one initial condition of graph and users because the same parameters could result in different initial conditions. One example of how such randomization could affect the result would be the initial opinion of the user. Since the assignment of initial opinion is randomized, we can have $f_{Opinion}[u] = -1$ or $f_{Opinion}[u] = 1$ for user with the most neighbors. Other case that is affected by the randomization would be the exact network structures where we only fix the number of nodes and edges but not the connection between them. Hence, we decided that it is more meaningful to present results from one single initial graph structure and initial opinions. The

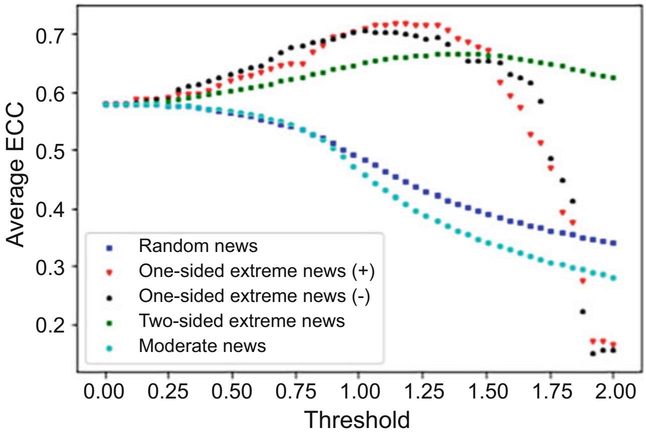

Fig. 4.7 Average echo chamber coefficient for all users in the SNS for various values of threshold d_1

following are the results for different parameters that measure echo chamber for different scenarios.

Individual Echo Chamber Coefficient Evaluation

From Fig. 4.7 we can observe that the average ECC for larger d_1 typically falls off in larger threshold except for two-sided news scenario. If we consider that at $d_1 = 0$ where there is no news diffusion yet as the starting point, random news and moderate news constantly decrease the average ECC subsequently. Conversely, the other three scenarios increase the average ECC as d_1 increases before it falls off after a certain value of d_1 around 1.2 for both cases of one-sided extreme news and 1.5 for two-sided extreme news. The drop is significantly steeper for one-sided extreme news scenarios with even lower average ECC at very high value of d_1 nearing 2. Although dependent on the society's level of acceptance threshold, two-sided extreme news provides more diversity of opinions among neighbors of every agent in average for other cases comparatively. However, in medium value of d_1, it leads to separated society as shown in Fig. 4.4 part (e) where most users have opinion on the extremes. This situation could be interpreted as society where individuals who have strong opposing opinions such as in bipartisan politics but are still connected to each other even though there may not be information exchange between dissenting users.

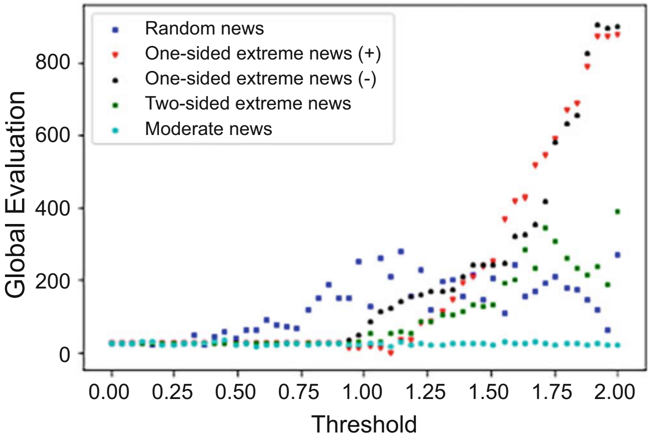

Fig. 4.8 The global echo chamber coefficient evaluation for the entire system of the SNS for various values of threshold d_1

Global Echo Chamber Evaluation

This evaluation indicates whether there is cluster of users in the network that has similar inclination on the opinion, i.e., group of users who either support or are against the topic only connected to each other with little to no connection with the user having the opposite sign of opinion. Based on the results, moderate news keep the GEC lowest in all scenario. This could be caused by neutral news having better reach closer reach to user with any opinions as compared to news with stronger sentiments. In this parameter, random news and two-sided extreme news scenario also keep their GEC in moderate level unlike one-sided extreme news that shoots out starting around $d_1 \approx 1.00$ (Fig. 4.8).

Average Opinion Evaluation

This parameter is useful to see whether there is overall tendency for the system to go in either direction of opinion. From the result, we can see that there is no significant shift of users' opinions unless in the cases of one-sided extreme news scenarios from both sides. This parameter also shows us that extreme news from either side change the society in a similar fashion and there is no bias that favors positive or negative sentiments news in particular. Based on this parameter, any scenario aside from one-sided extreme news scenario is equally favorable for the SNS's echo chamber (Fig. 4.9).

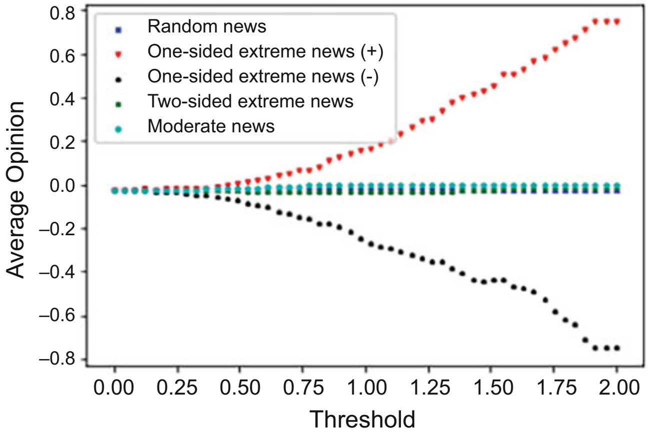

Fig. 4.9 Average opinion for all users in the SNS for various values of threshold d_1

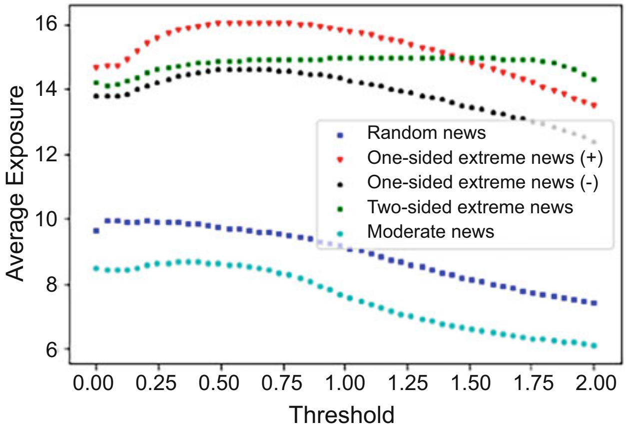

Fig. 4.10 Average exposure for all users in the SNS for various values of threshold d_1

Average Exposure Evaluation

Based on the concept of echo chamber as the lack of information flow diversity, we use average of user's exposure of news' sentiment to measure the echo chamber. Since by definition more extreme news lead to higher exposure, it is expected that the three cases of extreme news scenarios would lead to higher exposure of users. This figure also shows the similarity of plot behavior for both one-sided extreme news scenarios as it should be. A noticeable observation would be how the average exposure for two-sided news scenario does not drop significantly even for larger d_1. Since our goal is to maximize user's exposure, two-sided extreme news is our choice for this parameter (Fig. 4.10).

Overall Discussion

From the simulation results, we decided that two-sided extreme news scenario leads to SNS with the least echo chamber presence for most type of society with different acceptance level of news. It is only superseded by moderate news scenario in the GEC evaluation. This might be caused by our model that presents moderate news scenario as weakly opinionated news instead of news that offer balanced perspective on the topic. Therefore, users can only get balanced perspective on the topic if there is provider for such news which is only realized in two-sided extreme news. This could also be applied as a strategy for campaigning in any issue. In the case of one party decided to publish strongly opinionated news from one point of view, the opposing party could publish series of news with strong opinions from the other direction. It keeps the society well informed with what sentiments are there toward the topic. On the other hand, we also suggest one particular use of moderate news scenario for a specific purpose. It can be used for news provider to keep SNS users from having extreme opinions since the final opinion distributions do not present any users with strong opinions. However, this scenario is difficult to implement in real life unless there is strong authority that regulate news publishing similar to government-controlled media prior to Internet era.

4.5.3 Model Validation

The validation of this model is done through triangulation of the stylized fact we model and qualitative analysis of the simulation results. Firstly, the main stylized fact we use to model the interaction is that people who are more similar tend to influence each other [61]. This behavior is expected to lead to either consensus or fragmentation of opinion [51, 62]. This is the second stylized fact as a modeling target. Through simulations, we have obtained different distributions of opinion indicating consensus, polarization, as well as fragmentation as in real world shown by Figs. 4.3, 4.4 and 4.5. Thus, we have included the empirical finding within the possibility of our model.

4.6 Reversing Polarization

4.6.1 Model, Measurements, and Simulation

This model has two main entities, the social network comprised of individual user agents and the news from external sources. Let there be SNS users $Users = \{u_1, u_2, \cdots, u_N\}$. Every user $u \in Users$ is defined by three characteristics, its opinion, acceptance, and convergence. The detail of the characteristics is given in the following list:

1. Opinion
   The opinion of a user $opinion(u) \in [-1, 1]$ represents the user's opinion on an arbitrary issue. However, the issue is assumed to be only polarized into two extremes where $opinion(u) = 1$ means the user u fully supports the issue and $opinion(u) = -1$ means the user fully disagrees with the issue. Generally, any value in between can exist where a positive opinion means a support on one the issue vice versa with negative opinion. Some example issues are support on a particular government policy such as mandatory COVID-19 vaccination for government workers. Another example could be options that lie such as the support for the Republican Party vs the Democratic Party in the United States.
2. Acceptance
   The acceptance parameter of a user $accept(u) \in [0, 2]$ represents the user's threshold on accepting opinion from other sources. The higher the value, the more likely a user accepts other's opinion.
3. Convergence
   The convergence parameter of a user $converge(u) \in [0, 1]$ represents how much the user changes its opinion upon acceptance. The higher the value, the more the user adjusts to an accepted opinion.

These parameters are not new and adapted from the classic work on opinion formation. Users are also connected in an undirected network G representing a social media. Each edge represents the connections between two users similar to Facebook's connection. For a user u, her neighbors are all other agents that are connected through the edges of G such that $neighbors(u) \subset Users$.

The other entity is a news. Assume that there is a set of news $News = \{n_1, n_2, \cdots, n_M\}$. A news is only characterized by the following:

1. Opinion
   A news carries an opinion just like a user. For any news $n \in News$, the opinion is given by $opinion(n) \in [-1, 1]$. The opinions of the news and the users are assumed to be about the same topic. The value interpretation is also the same as the opinion of the users. The news' opinion is static and does not change via any means.

The news is assumed to come from external sources outside the SNS. This could be analogous to the fact that SNS does not produce their own news but relies to externally sourced news to be shared to their platform.

The opinion formation we use here is similar to many other works in this topic. However, users update their opinion from information instead from other users in this paper. If a user encounters a news either from direct source or shared by another user, the user will consider to update her opinion if it is within her accepted threshold or $|opinion(u) - opinion(n)| \leq accept(u)$. Once acceptance happens, the user's opinion will be updated such that

$$opinion(u)[t+1] = opinion(u)[t] + converge(u)(opinion(n) - opinion(u)[t]) \tag{4.9}$$

where the time indicator $[t + 1]$ and $[t]$ indicate the describe the state after and before acceptance, respectively. For clarity we will omit the time indication in the rest of the paper. If a user u accepts a news from direct source, she will then share it to all agents v belonging to her neighbors such that $v \in neighbors(u)$. All agents in $neighbors(u)$ will update their opinion with news n given acceptance following the above rules. In contrary to accepting a news from direct source, news shared by another user agent will not make in this model.

Public Opinion and Polarization Measurement

In this paper, we measure a society's polarization by the visual representation of its opinion distribution. One common method to visualize opinion distribution is by using a histogram. In the context of our data, the bins of a histogram represent the range of opinion values, and the frequency represents the number of agent with opinion that falls in the bin's range. Here we can classify the polarization of a society based on the modality of the histogram. We shall describe a society represented by a histogram with a unimodal distribution as a normal society. Although many observed opinions in social media follow a unimodal distribution, the naming choice refers to how the default unimodal distribution is associated with the normal distribution. More examples on what we define as a normal society will be discussed in this subsection later. Next, a polarized society is when the opinion distribution has a bimodal distribution. Since the opinions in this research are modeling real-life opinions where there could be only two options to support, the presence of two modes indicates that the society is polarized. Lastly, we call a society with more than two modes to be a diverse society because the presence of groups with opinions that are not existing in the extremities of opinions could exist.

Measuring modalities can be done easily by visual investigation. However, this method poses two problems. First, visual investigation is not rigorous and standardized. There are no exact criteria on what makes a single mode in histogram. Secondly, it takes too much human effort to do this manually for thousands of histograms produced by our simulations. Therefore, we use the parameter mvalue to measure the modality of a histogram. Consider a histogram H with n bins. We denote x_i, $1 \leq i \leq n$ as the frequency of data belonging to the i-th bin. The $mvalue$ is given by the formula

$$m(x) = \frac{1}{M} \sum_{i=2}^{n} |x_i - x_{i-1}| \tag{4.10}$$

where M is the maximum bin value. The mvalue of a histogram sums the absolute value of elevation difference followed by normalization for the height of the plot. Single continuous ascent and descent of the histogram from left to right will correspond to an approximate mvalue of 1 separately. Therefore, a histogram x with a unimodal distribution will have an mvalue $m(x) = 2$. Additional mode in the distribution will add the mvalue by about 2 such that a bimodal distribution mvalue will revolve around $m(x) = 4$, a trimodal distribution will revolve around $m(x) = 6$, and so on. When multiple modalities exist and they differ in sizes, the mvalue contribution from the minor mode will be less than the major mode with mvalue of less than 2 due to being divided by the larger mode. Note that mvalue is also highly dependent on the choice of bins. There are other methods of finding modes of a distribution; one of the more established one is by calculating from the kernel density estimates. The merit of using mvalue is that it is simple to calculate and suitable with our purpose to evaluate if a society has more diverse opinion distribution. The concept of mvalue is also related to the concept of total variation for a real continuous function.

Next we will present some examples of histograms and the corresponding mvalues. In Fig. 4.11, we present four cases on the commonly observed figures relevant to our discussion. The four cases are artificially generated data representing

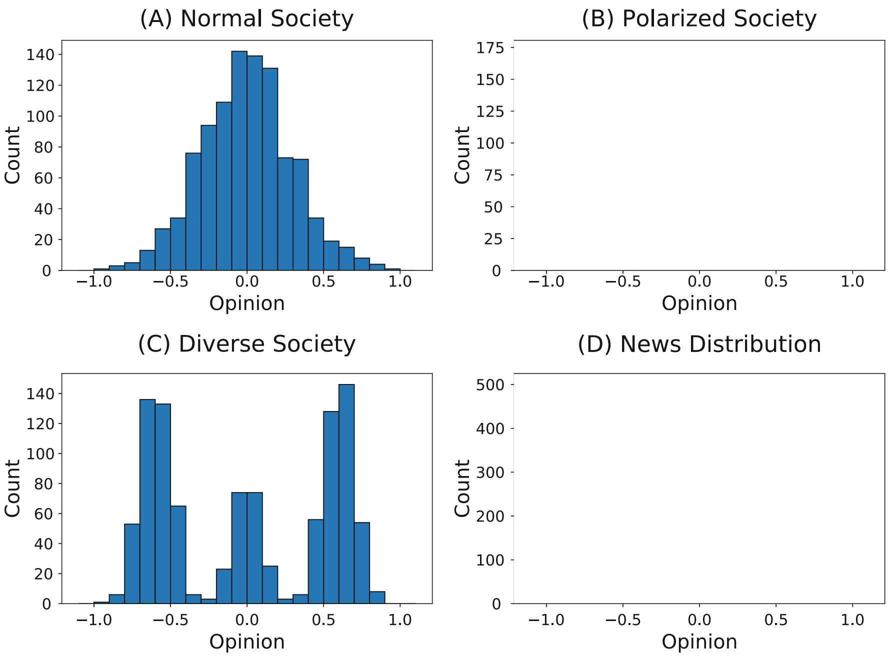

Fig. 4.11 Three different kinds of society's opinion distribution shown by the example (**a**), (**b**), and (**c**). In example (**d**), we show the news' opinion distribution following the two-sided extreme news scenario in Sect. 4.4

the three types of society plus the news sentiment simulated in this research. The mvalue for cases (a), (b), and (c) is given by 2.0, 3.9, and 4.8, respectively. For both examples (a) and (b), the value for each peak is counted to be close to 2.0. However, when the middle peak in case (c) is significantly smaller than the other peaks, its contribution to mvalue is less than 2. Although the mvalue does not correspond directly to the number of modes, higher mvalue is associated with more distinct modes observed. For the last example in case (d), we get the mvalue to be exactly 4.0. This is treated as a perfect bimodal distribution because there are two sets of incline-decline pattern in the histogram. This opinion distribution might be expected because the news' sentiment has this distribution.

4.6.2 Simulation

We use stages to describe the simulation process as the diagram in Fig. 4.12. The stages are an initialization stage, a main stage, and an end stage. We first generate the users and the graph that connects them. The users are then assigned with their opinion that are randomly generated from a normal distribution that is truncated along -1 to 1. Next, we generate the news for the entire simulation. Since the

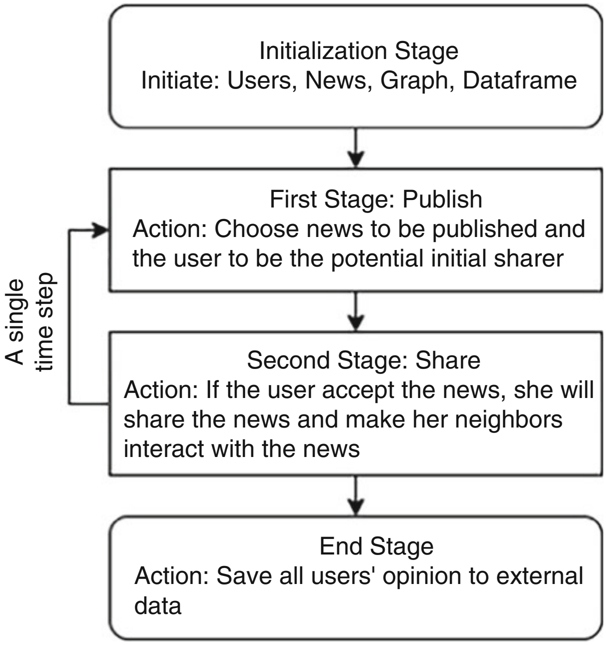

Fig. 4.12 Simulation stages of this model. At every time step, there will be a published news followed by a user who will reshare the news given acceptance

news are meant to induce polarization, we make any news $n \in News$ to carry opinion value of $opinion(n) \in [-1, -0.9]$ or $opinion(n) \in [0.9, 1]$ with random probability. The number of news generated is equal to the number of simulation time T because we only simulate to publish a single news in a single time step. At every time step, we have two stages. The first stage is the publish stage. During this stage, a news n is chosen from the news list $News$. The news is then accessed by a randomly chosen user u. If the difference between the agent's opinion and the news' opinion is less than the agent's acceptance threshold, the user will update her opinion following Eq. (4.9). If acceptance happens, the user becomes a sharer of news n. The next stage is sharing stage. In this stage, user u shares the news n to all of her neighbors $v \in neighbors(u)$. Each user v will then undergo the same interaction with news n that also follows 4.9. After the simulation and data collection, we use the data to calculate the mvalue. First, the opinions of all users are gathered to make a histogram. We use Python's Matplotlib library to create the histogram. In this implementation, the histogram's range is set to the range of -1.2 to 1.2 with 24 number of bins. The range value and bin number are chosen so that we can make sure that the leftmost and rightmost bin in the histogram is empty to ensure that the mvalue calculation always starts with a rise and ends with a drop. Once the histogram is created, we obtain the mvalue for a particular set of parameters using the formula in Eq. (4.10).

The parameter that we use in this simulation is specified in Table 4.2, and the reasoning of the number is explained as follows. The simulation time was chosen as long as possible to allow more time for the expected reversibility of the public opinion to happen. Following the time, the number of news is chosen to be the same as the total simulation time due to the assumption of only a single news published at every single time step. The number of user is chosen to be as minimum as possible but in the order that the characteristic of a particular graph appears. In this simulation, we assume the SNS follows the random graph pattern. The graph is created using the function fast_gnp_random_graph from the Python library NetworkX version 2.8. The number of nodes is the number of user and the number of edge. We use the same graph with a particular seed throughout the simulation to minimize the randomness caused by graph structure. On the other hand, the

Table 4.2 List of fixed and variable parameters used in this simulation

Parameter	Notation	Value	Type
Time	T	10,000	Fixed
No. agents	N	1000	Fixed
No. news	M	10,000	Fixed
Edge creation probability	$G_{edgeprob}$	0.1	Fixed
Initial opinion mean	μ	0	Fixed
Initial opinion spread	σ	0.25	Fixed
Convergence	$converge(u)$	$0.1, 0.2, \cdots, 1.0$	Variable
Tolerance	$tolerance(u)$	$0.2, 0.4, \cdots, 2.0$	Variable

initial user opinions are distributed randomly according to a normal distribution. The opinion distribution is assumed to be centered in "neutral opinion," i.e., $opinion(u) = 0$, and the spread is chosen arbitrarily so that the value of the opinion falls within the range of $opinion(u) \in [-1, 1]$ up to 6σ spread from the center. To further limit the spread, we make sure to use the truncated normal distribution function truncnorm from the Python library SciPy version 1.8.0. Other than the above fixed parameters, we have two variable parameters that are $converge(u)$ and $tolerance(u)$. Each of the variable parameters is varied for 10 possible values, starting from the 0.1 and 0.2 with the same amount of increment for $converge(u)$ and $tolerance(u)$, respectively. We call the combination of the variable parameters as scenario, and hence we have 100 scenarios. For each scenario, we repeat the simulation for 10 times to take into account the randomness created by the initial distribution, news generation, as well the choices of user who distributes the news.

4.6.3 Results and Discussion

Before discussing the results, we first explain how to interpret the figures presented in this section. The main simulation results of this paper, Figs. 4.13 and 4.14, are presented in two heat maps. Each heat map is comprised of 10×10 cells where each cell represents the average of simulation result for a particular scenario as described in the previous section. The x-axis and y-axis refer to the $tolerance(u)$ and

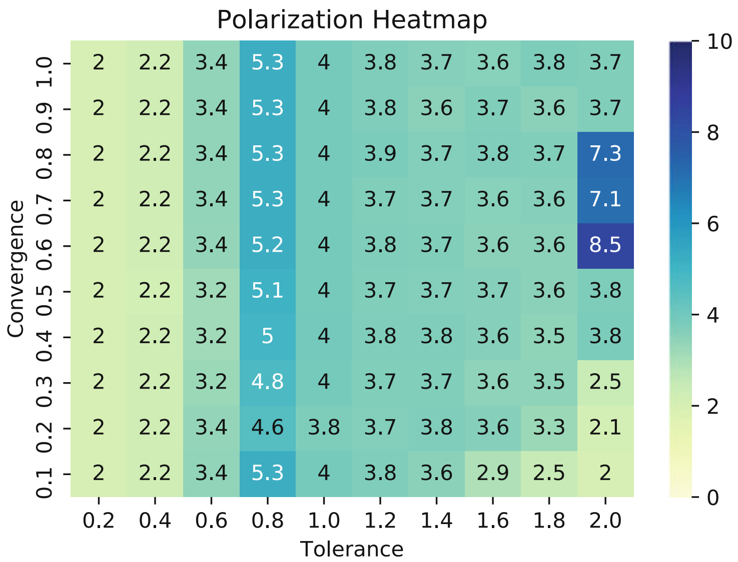

Fig. 4.13 Polarization heat map for all convergence and tolerance parameter combinations. The different values of cells show that not every society in this model is polarized

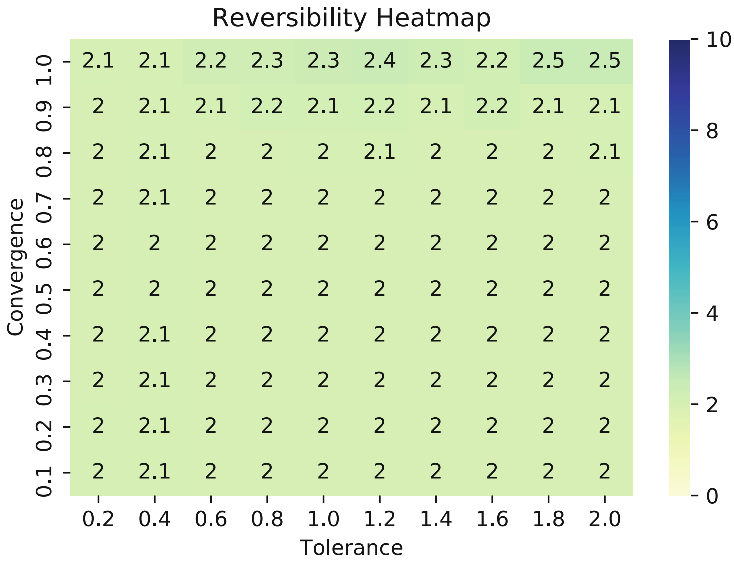

Fig. 4.14 Reversibility heat map for all convergence and tolerance parameter combinations. All cells show that a society with each combination of parameters is reversible after being polarized

$converge(u)$ shared by every user agent $u \in Agents$ in the particular scenario. The value of the averaged mvalue over repeated simulations of a scenario is presented by the number in the cells as well as the color of the cell. Darker color indicates a higher mvalue that means there are more modalities in the histogram opinion. There is no theoretical limit of the maximum value of mvalue to our current understanding, but the color is limited indicating $mvalue(x) = 10$ as the smallest multiple of two that is higher than our obtained maximum simulation result of $mvalue(x) = 8.5$. Note that while the mvalue is not a hard measurement of modality, every addition of approximately 2 indicates a modality.

First, we will observe the polarization results. At the beginning of the simulation, the opinion distribution is assumed to be following the normal distribution. Since a normal distribution corresponds to a single ascent followed by a single descent in the $mvalue(x)[t = 0] = 2$ for every scenario. The heat map shown in Fig. 4.13 shows the mvalue of the opinion distribution of the user after the simulation is stopped at $t = 10000$. The final mvalue ranges from 2 to 8.5. Following the change of both variable parameters vertically and horizontally, we can conclude that both convergence and tolerance influence the polarization. However, the relationship between the parameters is not so clear-cut with the changes not following commonly observed patterns. When the tolerance is low, ranging from 0.2 to 0.4 in our simulation, any increase of convergence does not increase the polarization. We can conclude that polarization happens in every situation given that the tolerance reaches a certain threshold. This condition applies at any value of tolerance larger than 0.4 in our simulation except when the tolerance is 2.0 that is reserved for later discussion. On the contrary, the mvalue varies along the change of tolerance at any value of convergence. The mvalue peaks at around $tolerance(u) = 0.8$ for most of the scenario landscape except for some specific value of convergence when the tolerance is maximized.

Next, we shall discuss the results for our attempt of reversing polarization. Referring to Fig. 4.14, we observe that the value is relatively uniform for every possible value of convergence and tolerance. The final mvalue ranges from 2 to 2.5. This range of mvalue corresponds to opinion distribution with a single mode. It means that for every combination of convergence and tolerance parameters, an already polarized society can be reversed. We notice that the mvalue increases a little bit along with the increase of tolerance for very high convergence value. This indicates that when users are changing their opinion very similarly to every kind of news, the opinion distribution is less stable and creating uneven modality. Assuming that people's opinion formation process can be reduced simply to be influenced by their tolerance (likelihood of accepting another opinion) and the convergence (how much one adapts their opinion in the light of accepting another opinion), an already polarized society can always be moderated. The condition for moderation is to that the circulating news should follow the moderate news scenario as shown in Sect. 4.4.

Chapter 5
Agent-Based Interpretation of the Zaller Model

5.1 Background

Despite the success of applying ABM in this field, there are some significant problems in trying to model opinion dynamics in the context of SNS. One problem is that the way opinion is assessed in many opinion studies in SNS differs from the traditional public opinion studies. For many studies about opinion in SNS, opinion is often measured implicitly. Text data such as tweets on a particular topic are first collected. Then, sentiment analysis is performed using a computer algorithm to determine the tweet's opinion [63]. On the other hand, research on public opinion was not traditionally done using computer algorithms. Instead, opinion dynamics was originally studied by conducting a survey containing a set of questions on a set of population [23]. A survey repository like the World Value Survey or European Value Survey would ask explicitly the opinion of the citizens of the target countries with questions about values such as "When jobs are scarce, men should have more right to a job than women." The responses could have different formats. Oftentimes they are choices of a relatively fine-grained "quasi-continuous" scale from 1 to 10 where they are interpreted as an agreement level from strongly disagree to strongly agree. Considering how established the traditional public opinion research is, incorporating some aspects from there could strengthen some theoretical assumptions in ABM of opinion dynamics in the SNS.

We use the Zaller model of public opinion as a baseline from the traditional public opinion studies to build the rules for our research [23]. As elaborated in the literature review chapter, the Zaller model can be summarized as a model that describes how an individual person's political information consumption can be converted to public opinion. This concept fits the two important criteria in ABM for social science really well. The process of information consumption and individual person's opinion formation is analogous to the microscopic action. On the other hand, the overall public opinion of the society is analogous to the macroscopic phenomena. Because opinions in SNS are often measured from the user's online

M. Al Atiqi, *Echo Chamber and Polarization in Social Media*, Agent-Based Social Systems 17, https://doi.org/10.1007/978-981-99-1770-9_5

activity, it is also highly related with the information consumption process in the Zaller model. More importantly, there have been previous attempts of modeling the Zaller model as an ABM. Even if they are interpreted very differently, it gives a guideline to implement important features of the Zaller model as an ABM.

In this book, the implementation of the Zaller model in ABM framework is applied for two cases. The first case is to resolve the conflicting observation of online echo chamber in SNS. One study based on information consumption pattern in SNS claims that there exists strong echo chamber behavior [5, 64]. On the other hand, another study based on traditional survey claims that people see enough political information they do not agree with in SNS frequently [65]. To bridge the two methods, we use the Zaller model to relate the two processes and confirm if the two observations could indeed coexist. Additionally, we can also explore what kind of policy that minimizes echo chambers observed by the users by simulating different scenarios. The second case is to understand how the current network of Facebook pages related to vaccination information influences individual user's vaccination sentiment. We let individual user agent to subscribe to these pages based on the pages' recommendation network and a Zaller model-inspired decision-making process. The network influences are then calculated based on the user's subscription. The model is also used to evaluate the influence policies to reduce the influence of anti-vaccination information online by adding caution banners from healthcare authority to dubious pages and deplatforming pages that promote anti-vaccine believes.

5.2 Agent-Based Interpretation of the Zaller Model

Here we shall discuss essential components of the ABM interpretation of the Zaller model. To stay true to the original model, the ABM interpretation should implement the four axioms and the three stages of interaction elaborated in the literature review section. Each stage includes at least an axiom with the following pairings (Fig. 5.1):

1. Receive stage: Reception axiom
2. Accept stage: Resistance axiom
3. Sample stage: Accessibility axiom and response axiom

This extends the previous work of the Zaller-Deffuant model developed by Malarz [58]. In that study, only the reception axiom and the resistance axiom were implemented. We therefore propose to model the opinion formation using the accessibility axiom and response axiom too. Instead of having the SNS user's opinion to be represented by some internal value inherent to the agent, the opinion/sentiment should be formed based on the concept of "consideration." In the original work, a consideration means any reason to choose on a side or another. SNS users should also have a mechanism to collect this consideration using the first two stages implemented with the reception axiom and the resistance axiom. The detail on the

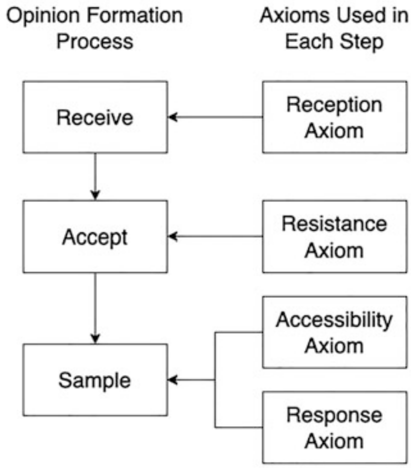

Fig. 5.1 Mapping of the four axioms in Zaller model to the receive-accept-sample process in creating opinion

consideration collection and opinion formation will be elaborated further in each case of the study.

Aside from this, there are some universal assumptions needed to construct the ABM interpretation of the Zaller model for the study of echo chamber and polarization. Firstly, all news or information are deemed to be political or at least politically related as to how the original work was validated with. Secondly, we assume that the political environment represented by the news or information has two polarities similar to the Republican Party and the Democratic Party in the United States or Labour Party and Conservative Party in the United Kingdom as the general available affiliations. Similar to the previous modeling, the opinion or sentiment in our ABM implementation of the Zaller model should have two polarities. However, instead of having opinion with continuous values like the bounded confidence model, information should carry consideration with which value is either 1 or -1 to represent the two polarities, i.e., every news about US presidential election can always be mapped to either support for the Democratic Party or the Republican Party in the case of US politics. As for the user agents, we can have either a singular or multiple users or information providers depending on the cases as long as the opinion formation process takes place. Any other assumption will be specified for each study case separately.

Chapter 6
Application 1: Resolving the Conflicting Observation of Online Echo Chambers

6.1 Motivation

There are many interpretations of what constitutes an online echo chamber. One of them is selective information sharing among SNS users. Del Vicario showed that there exist selective information sharing patterns on Facebook[1] based on the online behavior of conspiracy-related and science-related Facebook page followers [5]. Despite consuming information from contrasting types of sources, the conspiracy-related groups and science-related group have a tendency to propagate information only among themselves which indicates the presence of echo chambers. In Twitter,[2] network clusters within the Republican Party and the Democratic Party supporters are also observed to share information among themselves [64]. These observations suggest that echo chambers are prevalent on the Internet across different platforms.

However, not all researchers share the same view that online echo chambers are influential and ubiquitous. Tanaka found that there is no correlation between the increase of Facebook usage and the increase of polarization among its users [66]. This counters the observations that the increase of online echo chambers leads to stronger polarization in the SNS. In addition, Dubois and Blank argued that the concern about online echo chambers is overstated [65]. They analyzed a nationwide survey based in the United Kingdom on how people perceive SNS echo chambers. Among the question is "How often do you disagree with political content friends post on social media?" They found out that most of the population regularly encounters information shared by their friends they disagree with. These findings argue that the problem of echo chambers may not be as serious as previously thought. Even more fundamentally, they may not even be as prevalent as what is claimed by other researches.

[1] https://www.facebook.com/.

[2] https://twitter.com/.

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The two arguments above raise a question: how can there be arguments claiming that echo chambers are prevalent and overstated at the same time? On one hand, we have evidence that echo chambers characterized by selective information sharing are prevalent on social media. On the other hand, we have evidence that people regularly encounter information with different views implying that most of them are not in an echo chamber. We noticed that the two conflicting arguments were obtained using different methods. The first argument is based on direct observations of information cascade on SNS platforms [5]. Conversely, the second argument is based on self-reported survey results from individuals [65]. Since these are two different phenomena, the use of a single term "echo chamber" may lead to the conflicting account of the state of online echo chamber. In addition, Zaller postulated that people's survey responses are shaped by the information that they consume in his model [23]. From this idea, we want to confirm whether it is possible for an SNS with strong selective information sharing behavior leading to its users perceiving that they are exposed to significant amount of political information they disagree with.

To answer that question, we develop an agent-based model (ABM) of selective information sharing in SNS based on Zaller model of mass opinion. We adopt the Zaller model of public opinion as the internal model of the agents to take into account how people convert political information into survey results [23]. The model is implemented using ABM framework because it is suitable to explore how microscopic interaction of agents (information sharing by SNS users) can influence macroscopic phenomena (overall survey result) [43]. It is also beneficial because we can model different real-life scenarios and policy interventions as opposed to the traditional statistical models in social science [43]. There has been formulation of ABM Zaller model, but the model only deals with information sharing among agents and not to the extent of converting it into public opinion survey [58]. We expect the results from some of the scenarios we simulate could explain how selective information sharing in SNS would lead to minimal echo chambers perceived by its users. The simulation results will also be analyzed to explore what policies we can suggest that minimizes echo chambers on the Internet.

6.2 Model Overview

To study the conflicting observations of echo chambers, the model should incorporate three features. Firstly, the users should have a selective information sharing mechanism as the base of the echo chamber as presented by Del Vicario. Secondly, the users should be able to "answer" survey questions like the self-perceived echo chamber on SNS done by Dubois and Blank. Thirdly, there should be a feature to connect the two considerations above. The focus of this model is constructing the third feature by reinterpretating the Zaller model of public opinion as the internal model of our agents.

Table 6.1 Axioms of Zaller's receive-accept-sample (RAS) model

No.	Axiom name	Explanations
1	Reception	Greater person's level of cognitive engagement with an issue increases the likelihood of exposure and comprehension (reception) of political messages concerning the issue
2	Resistance	People tend to resist argument that is inconsistent with their political predispositions, but only if that they have the contextual information to perceive a relationship between the message and their predispositions
3	Accessibility	The more recently a consideration has been called to mind, the less time it takes to retrieve that consideration or related considerations from memory and bring them to the top of the head use
4	Response	Individuals answer survey questions by averaging across the considerations that are immediately accessible to them

To construct this model, we require some assumptions (Table 6.1). Firstly, we assume that the political environment is bipolar similar to the American political landscape with the Republican Party and the Democratic Party or Labour Party and Conservative Party in the United Kingdom as general affiliations. Secondly, we do not specify which social media to model, but the feature is more similar to Facebook where every connection between users is symmetrical rather than Twitter where connections are based on the directed network. Thirdly, the SNS does not produce its own news, i.e., all news came from external sources created by online media such as news outlets like CNN, BBC, or Fox News in real life. Fourthly, the network is static, and there is no preferential connection where users tend to connect with other users of similar political support. One example would be a typical SNS user who would connect with their school friends/colleagues due to personal connection regardless of the friends' political preferences. Lastly, all the works on selective information sharing, the survey on perceived echo chamber, and Zaller model referred here are assumed to be observable in a single demographic of society modeled in this research.

6.2.1 News and Media

We define a set of unique finite politically related news represented by its id $News = \{1, 2 \cdots, N\}$. We assume that the political environment is bipolar such that for each $n_j \in News$, it has political predisposition $p_j \in \{-1, 1\}$. The political predisposition represents political affiliation in the political environment, e.g., -1 for support for the Republican Party and 1 for support for the Democratic Party in the United States. At any given time $t \in Time = \{1, 2, \cdots, T\}$ of the simulation, we have news space variable $NewsSpace(t) \subset News$. News space contains all news that are available to users of online media at any given time t. We assume once a news is published online, the exact same news is not going to be republished. This implies every news space is unique such that any two points of time $t_1 \neq$

t_2, $NewsSpace(t_1) \cap NewsSpace(t_2) = \emptyset$. Note that it means, for simplicity, each news space has the same number of news. For example, for $News = \{1, 2, 3, 4\}$, we have $NewsSpace(1) = \{1, 2\}$ and $NewsSpace(2) = \{3, 4\}$.

6.2.2 User Agents and SNS

We define a set of unique agents $Agents$ representing M number of SNS users. We will also use the term users/agents to refer to SNS users interchangeably. For an arbitrary agent $u \in Agents$, they have immutable parameters:

- Political predisposition $p_u \in \{-1, 1\}$
- Polarization $l_u \in [0.5, 1]$
- Political awareness $a_u \in [0, 1]$

The political predisposition p represents agents' political leaning similar to the news. Political polarization l represents individual polarization of the agent, manifested in probability of sharing the news with other political predisposition $P(Share)_u$ which will be explained further in the next section. Political awareness a represents how knowledgeable and engaged the agents in politics in general, manifested in the probability of agent to understand its cognitive-based action correctly $P(Cogn)_u$ such that:

$$P(Cogn)_u = \frac{1}{1 + \exp(-k(a_u - 0.5))}, \tag{6.1}$$

where $k \in \mathbf{R}^+$ is the coefficient of comprehension universal for every user agent. The higher the political awareness be, the more likely the agent to possess necessary political information needed to comprehend the political information correctly with probability following the logistic function [23]. The SNS is represented by an undirected simple graph $G = (V, E)$ with vertices $V = Agents$ and edges $E \subset V \times V$. We define feed/newsfeed of agent u as the set of its neighboring agents $\phi_u = \{v | v \in Agents, (u, v) \in E\}$.

Next we define set of considerations representing the perceived political predisposition of news n_j by agent u as $c(u, n_j) \in \{-1, 1\}$. If agent u perceives news n_j to have political predisposition $p_j = 1$, then $c(u, n_j) = 1$ regardless of the actual value of p_j. Conversely, $c(u, n_j) = -1$ if u perceives n_j to have political predisposition of $p_j = -1$. Initially, every agent is not exposed to any news such that its exposure is just an empty tuple $X_u(t = 0) = ()$. Everytime agent u is exposed to a news n_j, it will update its exposure by concatenating the consideration $c(u, n_j)$ to itself such that

$$X_u(t) \leftarrow X_u(t)^\frown c(u, n_j) \tag{6.2}$$

where $\frown$ is the concatenation operator. The mechanism on how the news is perceived by the agents and how the exposure is updated will be explained in the next section.

6.2.3 Agents' Dynamics

We use stage-based description for the simulation (Fig. 6.1). We describe every event happening in a single time step $t \in Time$ to be the main stage. The main stage comprises of two stages with its respective actor and action. The following actions are explained chronologically for an arbitrary agent u at time t:

1. **Initialization**
   Create M number of agents connected with a graph G with their respective p, l, and a as well as N number of news with their respective $NewsSpace$ and p according to the scenario. The detail of available scenarios is going to be explained in the next section.
2. **Stage 1: Access**
   Some agents $Agents_{Access} \subset Agents$ are chosen to be able to access one news available in $NewsSpace(t)$. Agent u can successfully access randomly chosen news $n_j \in NewsSpace(t)$ with probability $P(Cogn)_u$. If u successfully accessed n_j, it will update its exposure with $c(u, n_j) = p_j$ according to Eq. (6.2). If $p_j = p_u$, u is now a sharer for n_j.
3. **Stage 2: Share**
   If u shares n_j, all of its neighboring users $v \in \phi_u$ who have not been exposed to n_j will be exposed to the news. Before updating its exposure, agent v must successfully comprehend news n_j with probability of $P(Cogn)_v$. If the

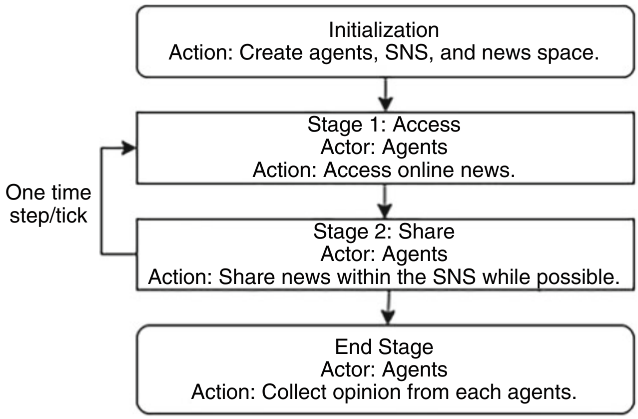

Fig. 6.1 Simulation stages that are comprised of initialization stage, two main stages where agents' activities happen, and end stage

comprehension is successful, then $c(v, n_j) = p_j$; otherwise the agent will perceive the political predisposition of the news randomly such that $c(u, n_j) = p_j$ or $c(u, n_j) = -p_j$ with 50% chance for each possibility. User v will then update its exposure with $c(v, n_j)$ according to Eq. (6.2).
If the comprehension is successful, v can be a sharer of news n_j if either

- n_j was shared along homogeneous edge where $p_u = p_v$
- Otherwise share n_j with probability $P(Share)_v = 1 - l_v$

If the comprehension failed, the agent u only updates its exposure without the possibility of sharing the news n_j. This process is different from the original model where information can only be passed along homogeneous edges, motivated by the concept of polarization intensity not captured in the original model and observations of people's inconsistence on political issue as mentioned in the second axiom [23]. Agents can only share the same news once and be exposed once. This process is repeated over and over until no news can be shared anymore.

4. **End Stage**
At some designated simulated time $T_{survey} \subset Time$, we simulate the process of surveying agents on the question *"How often do you disagree with political content friend post on social media?"* and collect their responses. Every agent $u \in Agents$ will make a multiset of recalled considerations $R_u = \{(c, m_u(c)) : c \in \{-1, 1\}\}$ where $m_u(c) \in \mathbf{Z}^+$ is the number of recalled considerations for each possible consideration. The recalled considerations are constructed by recalling each consideration from the latest one added with probability $P(Cogn)_u$. The latest consideration added in the sequence will be recalled first based on the third axiom. Agents will keep recalling consideration until either all considerations $c \in X_u(T)$ are recalled or R_u reach its maximum length that is limited by the maximum recalled considerations $L \in \mathbf{Z}^+$ such that $|R_u|_{max} = \lceil a_u \times L \rceil$. We assume agents with higher political awareness are more capable in taking into account more considerations into their opinion; hence agents with higher political awareness can recall more considerations.
Applying the fourth axiom, agents will average the recalled consideration to form opinions represented by survey results. If agent is unable to recall any considerations such that $R_u = \emptyset$, agent will answer with opinion $o_u(t) = NoAnswer$. Otherwise, opinions are formed by first calculating the averaged answer ans_u defined as fraction of the number of all recalled considerations with the same political predisposition to the agent's total number of consideration recalled such that

$$ans_u = 5 \times \frac{m_u(c)}{m_u(1) + m_u(-1)}, \text{ for } c = p_u. \tag{6.3}$$

Table 6.2 Opinion mapping table

ans_u	$o_u(t)$	Interpretation
[0, 1)	0	$Nearlyalways$
[1, 2)	1	$Mostly$
[2, 3)	2	$Sometimes$
[3, 4)	3	$Rarely$
[4, 5]	4	$Almostnever$

The answers $ans_u \in [0, 5]$ are then mapped to the set of opinions described in Table 6.2 where the possible values of $o_u(t) \in \{0, 1, 2, 3, 4\}$ with interpretation following the survey results [23]. The higher the opinion, the more the agent to perceive itself in an echo chamber.

6.3 Simulation

All the simulation was done in the MacOS Catalina version 10.15[3] using Python 3.7[4] with ABM framework chosen to be MESA version 0.8.6.[5] We have some fixed parameters and variational parameters for the simulation. The number of agents is chosen to be in the order of the original model by Del Vicario and within the limitation of memory and simulation timing. The simulation time and survey time are chosen under the assumption that we will reach steady-state condition of agents' opinion. We set the number of news available at any time t to be $|NewsSpace(t)| = 10$ because the variational parameter associated with the news' political predisposition is in the multiplication of 10% as the minimum number to show reasonable representation of the distribution. Initial access ratio is the ratio of agents that are given access to the $NewsSpace(t)$. Since we want to focus on the influence of news shared within the network, we limit the ratio to be small. The coefficient of comprehension $k = 8$ is chosen arbitrarily to represent our explanation within the value range of a_u. Note that the value of k does not have to be unique as long as it still represents the logistic function qualitatively as intentioned in the explanation done by Zaller [23], i.e., not too close to 0 that it becomes a uniform line or not high that it becomes a step function. The graph chosen for this simulation

[3] https://www.apple.com/macos/catalina/.

[4] https://www.python.org/downloads/release/python-370/.

[5] https://mesa.readthedocs.io/en/master/.

is a Watts-Strogatz graph, constructed using Python's NetworkX 2.4[6] package's $connected\_watts\_strogatz\_graph$ function. Any parameter with subscript $graph$ is the parameter used to build the graph. We use the same structure of graph for every simulation because we are only interested in replicating similar structure used by Del Vicario and not the influence of various networks. Each set of parameters is used to simulate ten times repeatedly to take into account the randomness.

Each simulation is run under a particular scenario. Scenario in this case is defined as a set of chosen variational parameters that describe the state of the society. The variations that make the scenario are as follows:

1. **News' political predisposition distribution**
   The p_j is assigned randomly for every news at every time step with probability of $p_j = -1$ is given by P_{Media}. The possible values are $P_{Media} \in \{0.5, 0.7, 0.9\}$, which we refer as $balanced$, $biased$, and $extreme$ media, respectively. Since the probability of $p_j = 1$ depends only on P_{Media}, it is not necessary to be specified individually.
2. **Agents' political predisposition distribution**
   The p_u is assigned randomly at the beginning with probability of $p_j = -1$ which is given by P_{Agents}. The possible values are $P_{Agents} \in \{0.5, 0.7, 0.9\}$. Similar to the previous parameter, we call the value associated as $balanced$, $biased$, and $extreme$ society, respectively, and not specify the parameter for $p_u = 1$.
3. **Polarization Distribution**
   The polarization l_u for u is drawn from a truncated normal distribution such that $l_u \in [0.5, 1]$ with mean $\mu_l \in \{0.5, 0.7, 0.9\}$ and constant variance $\sigma_l = 0.2$. We call the value associated with the mean as low, med, and $high$ polarization, respectively.
4. **Political Awareness Distribution**
   The political awareness a_u for u is drawn from a truncated normal distribution such that $a_u \in [0, 1]$ with mean $\mu_a \in \{0.25, 0.5, 0.75\}$ and constant variance $\sigma_a = 0.2$. We call the value associated with the mean as low, med, and $high$ political awareness, respectively.

In total, we have four variable parameters with each having three possible values that make 81 scenarios describing the state of the society. All parameters are given by Table 6.3.

[6] https://networkx.github.io/documentation/networkx-2.4/.

Table 6.3 Parameter list

Parameter name	Symbol	Value
Number of agents	M	1000
Total time	$Time$	$\{1, 2, \cdots, 50\}$
Survey time	T_{survey}	$\{5, 10, \cdots, 50\}$
No. of news	$\lvert NewsSpace(t)\rvert$	10
Initial access ratio	r_a	0.1
Coefficient of comprehension	k	8
Maximum recalled considerations	L	50
No. of nodes	M_{graph}	1000
No. of nearest neighbors	K_{graph}	8
Probability of rewiring	P_{graph}	0.1
News' political predisposition distribution	P_{Media}	$\{0.5, 0.7, 0.9\}$
Agents' political predisposition distribution	P_{Agent}	$\{0.5, 0.7, 0.9\}$
Polarization mean	μ_l	$\{0.5, 0.7, 0.9\}$
Political awareness mean	μ_a	$\{0.25, 0.5, 0.75\}$

6.4 Results and Discussion

6.4.1 Landscape Analysis

Next, we are interested in the average opinion of the agents given by the expression

$$\overline{o} = \frac{1}{M} \sum_{u \in Agents} o_u(t = 50), \tag{6.4}$$

where M is the number of agents. Only the opinions at the end of the simulation are used because the number of considerations is maximized at $t = 50$ hence more representative for agents' opinions. We use scenario-based landscape analysis to analyze how different parameters can influence the average opinion [47]. The results are presented using a color map where each cell represents the $\overline{o}$ from one of the 81 scenarios averaged for 10 times repetition as shown in Fig. 6.2. The figure comprises of 3×3 matrix where the rows and columns represent variations in the user's political predisposition and news' political predisposition, respectively. Each element of the submatrix comprised of another 3×3 matrix where the rows and columns represent the variations in the mean of the polarization and the mean of the political awareness.

First, let us revisit the main question of this example: can echo chambers defined as selective information sharing among SNS users as presented by Del Vicario lead to relatively low echo chamber perceived by individuals as shown by Dubois and Blank? Note that instead of having news to be shared exclusively along homogeneous edges [5], we allow news to be shared along the non-homogeneous edges depending on the polarization of the agents. However, the results from set of

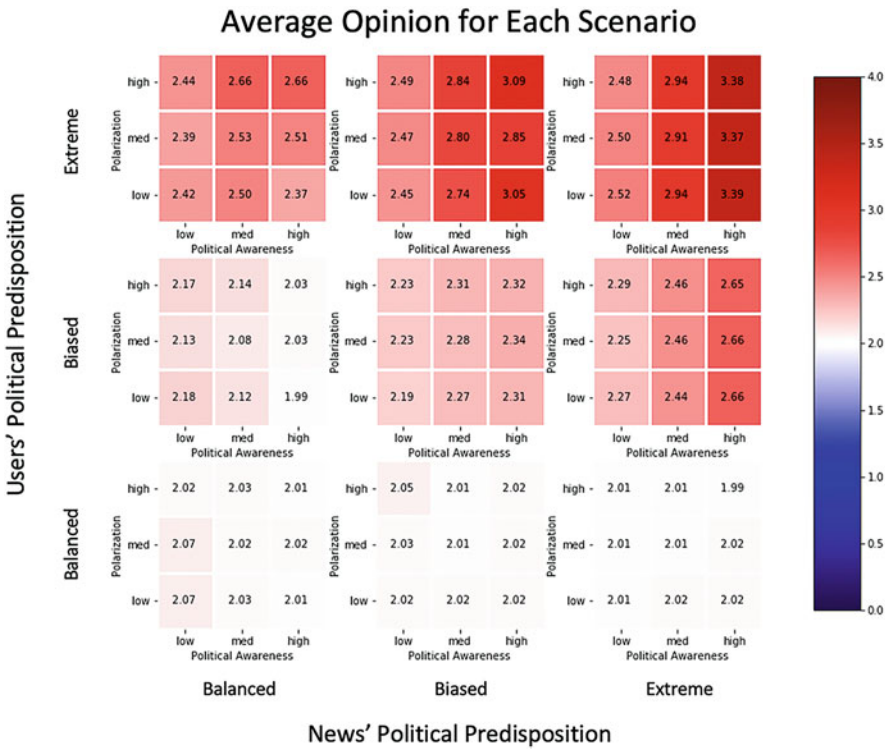

Fig. 6.2 Average opinion for each scenario $\overline{o}$ is represented by individual cells of this color map. Stronger red color indicates stronger perceived echo chamber among SNS users

scenarios where the polarization mean is $high$ is shown on the top row of each submatrix as the closest condition. Under this assumption, we can confirm that it is possible to observe the perceived moderate amount of echo chamber even when most people share news exclusively among agents with the same political predisposition. The value of the average opinion is $\overline{o} \approx 2$ in all submatrices with $Balanced$ users' political predisposition's top rows. The two observations coexist as long as the distribution of the political predisposition of users is $balanced$. However, we also found out that the increase of average individual polarization in society does not appear to influence the average perceived echo chamber as shown in the change of $\overline{o}$ vertically in any submatrix.

Next, we can observe that the value of $\overline{o}$ increases as the value of P_{Agent} increases from bottom to top for each submatrix indicated by the shift to stronger red color. Similarly, with P_{Media}, we can observe a stronger echo chamber for submatrix from the left to the right but only when the society is classified as $biased$ and even more when it is $extreme$. The changes are not observed when the users' distribution of political predisposition is $balanced$. From here we can infer that a more polarized media can contribute to a stronger perceived echo chamber but only if the society is already polarized. Conversely, it shows that media that presents balanced news will lead to less perception of the echo chamber even when the society is polarized.

Political awareness also influences the echo chamber. However, its influence is less obvious than the other three variable parameters. We can see the color shifts to a darker shade of red from left to right, but only when there is a combination of $biased$ and $extreme$ user's political predisposition alongside with $biased$ and $extreme$ news. What we know from the Zaller model is that higher political awareness makes people more consistent in their political opinion [23]. In our case, it is confirmed that an already polarized environment will be perceived to be polarized by people given that people are aware of the political information they consume. One interesting case is that for $biased$ users and $balanced$ news, higher political awareness reduces the perceived echo chamber slightly. More investigation on this specific case in real life can be explored for future research.

We also want to highlight a problem commonly encountered when doing social simulation that is commensurability of a social phenomenon. Here we infer that within the definition used in this chapter, high polarization does not seem to influence the echo chamber significantly. However, when the term of increased polarization is used, it could mean different things. Some researchers say "increasing polarization" to describe the increasingly widespread of polarization, while others use the same term to mean increasing intensity of polarization. There are also limitations associated with how we quantify the verbal responses of the respondents into our agents' opinions. While the original work assigned the survey answers into numerical values using the Likert scale for analysis, it is difficult to estimate what the actual fraction of exposed news the respondent disagrees on that corresponds to which answer. However, since the focus of this work is to explore what possible states could exist and what are the conditions that minimize the echo chamber, the current configuration is sufficient to achieve that purpose.

6.4.2 Model Validation

Since we are applying Zaller model within ABM context, we use stylized fact from the original model itself to validate our model. The first stylized fact is people who are more politically aware tend to be more selective with what information to accept. This is part of the fact that we model. The other stylized fact that we are trying to prove is one of the finding confirmed by Zaller model. People who are more engaged politically, i.e., higher political awareness, have more consistent opinion in general [23]. We measure the consistency of an agent's opinion over time as the standard deviation of its opinions over time σ_o from $t \in T_{survey}$. Because the statement was suggested to be applicable generally, we plot σ_o with a_u for all runs of the scenario as shown in Fig. 6.3. Due to the large number of the data, we use only 5000 data points drawn randomly with uniform distribution. Based on this graph, we could observe that an agent with higher political awareness has tendency to have lower standard deviation of opinion. Using linear regression of $y = mx + b$, we obtain the

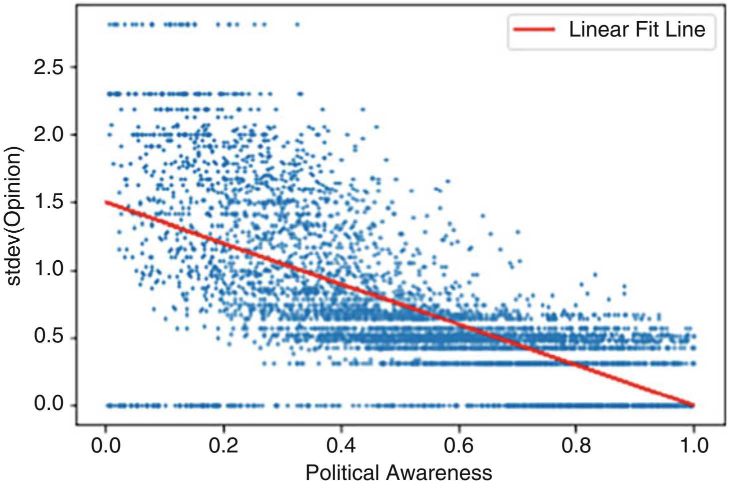

Fig. 6.3 Negative relationship between agent's opinion consistency σ_o and its political awareness a_u to confirm Zaller's finding

values of $m = -1.50$, $b = 1.50$, and $r^2 = 0.43$. The negative slope indicates that we could expect the overall trend of higher consistency of opinion, or lower σ_o, with the increase of political awareness a_u. Hence, our model's microscopic interaction built based on Zaller model managed to reproduce the same macroscopic result of the original model.

Chapter 7
Application 2: Simulating the Influence of Facebook Pages on Individual Attitudes Toward Vaccination

7.1 Motivation

Vaccination is considered by some as one of the biggest accomplishments in public health. Since its dawn, vaccination has contributed to the extinction of some diseases such as the smallpox [67]. The World Health Organization (WHO) also estimated that vaccination has prevented two million child deaths in 2003 alone [68]. One reason why vaccination is very effective is because of its mass adoption resulting in herd immunity [69]. In most of the Organisation for Economic Co-operation and Development (OECD) member countries, common vaccines such as the DPT and MMR vaccine have more than 90% uptakes among their residents leading to fewer than 20 cases per 100,000 residents in average [70]. The achievement is not limited to developed countries alone. From the first implementation of the Expanded Program on Immunization, developing countries such as Bangladesh have managed to increase their DPT vaccination rate from 16% in 1988 to 92% in 2013 [71].

Unfortunately, vaccination campaigns also experience setbacks. One of the main obstacle is the anti-vaccination attitudes among people which is also associated with some negative consequences [72]. For example, the drop of vaccination uptakes caused by vaccine hesitancy leads to the incidence rate of the corresponding disease as exhibited by the HPV vaccine hesitancy case in Japan [73]. Additionally, anti-vaccination attitude is also associated with distrust of government and anti-scientific attitude culture [74, 75]. The negative effect of vaccine hesitancy might be amplified further following the trend of decreasing confidence of vaccination observed in many countries globally such as Indonesia, South Korea, and Poland [76]. For the above reasons, addressing the vaccine hesitancy problem from a policymaker's point of view is a worthwhile public health effort.

Media consumption plays a role in forming people's opinions on vaccination [77]. Being the largest social media by userbase, Facebook is one of the most significant sources of vaccination-related information on the Internet through their various pages and community-led groups [30, 31]. Unfortunately, the ease of getting

M. Al Atiqi, *Echo Chamber and Polarization in Social Media*, Agent-Based Social Systems 17, https://doi.org/10.1007/978-981-99-1770-9_7

information on Facebook also comes with the cost of getting misinformation easily. Once spread, misinformation, especially that which is related to political issues, is generally found to be persistent and difficult to correct [78]. A possible reason for this persistence is that people consume vaccination-related information on Facebook following the echo chamber pattern [79]. The echo chamber effect here refers to the phenomenon where Facebook users who support the anti-vaccination movement will only read, interact, and share the content of similar sentiment with very little exposure of pro-vaccination content and vice versa for the pro-vaccine users. Once a user consumes information from a particular side of sources, it will be difficult for them to get a counterargument to correct their opinion. Therefore stakeholders such as platform owners and governments should ensure that social media users can acquire the right information about vaccination and minimize the influence of anti-vaccination points of view in social media. To build the appropriate policy suggestions for these stakeholders, we shall next investigate further how anti-vaccination information is spread on Facebook as our platform of focus.

Another recent work agreed that the influence of anti-vaccination pages among the vaccination-related pages network on Facebook is pervasive [34]. However, the revealed presence of vaccine-neutral pages, which was not considered in the previous study, is the most dominant element in the network and also contributes indirectly to the proliferation of anti-vaccination information [79]. Additionally, these findings were done by analyzing the observed information consumption pattern without considering how individual Facebook users' decision-making reaches the current state. To our best understanding, there has yet to be a specific study describing the mechanism of how people convert information consumption into vaccination opinions. Therefore we want to know how the current vaccination-related pages network on Facebook influences vaccination sentiment from the individual Facebook user's perspective. More importantly, this understanding should help us to determine possible solutions to limit the negative influence of anti-vaccine information on Facebook.

To answer these questions, we construct a model of the individual user who forms part of their opinion on vaccination from Facebook pages. The user in this simulation consumes vaccination information through subscribing vaccination-related Facebook pages found in the previous study [34]. The user's subscription decision-making and opinion formation are based on our interpretation of the Zaller model of public opinion, a model that is used to explain how people form opinions on polarized issues similar to vaccination [23]. On top of that, we have included neutral pages to have a more realistic feature that is not included in the previous works. The model is implemented using the agent-based modeling (ABM) framework for the ease of simulating interpretable scenarios and custom policies that can be applied to the users, as well as implementing interactions with a Facebook user with heterogeneous Facebook pages. Once the influence of the network to individual users can be estimated, we shall investigate which policies can be implemented to reduce the negative influence of anti-vaccination point of view. There are two policies suggested for this purpose that has worked other social media. The two policies are adding caution banners from health authorities and engaging in censorship [80, 81]. We use this model to simulate scenarios with the two policies above and evaluate if the results support the evidence for existing policy suggestions.

7.2 Model Overview

We develop a model that simulates how an individual Facebook user forms their vaccination-related information consumption behavior through Facebook page subscription. The model is built using an agent-based modeling (ABM) framework based on the Zaller model of public opinion [23]. The Zaller model is chosen as the internal model of the agent because the vaccination issue is parallel to the issue of embryonic cells in that inherent value predisposition plays a role in determining one's opinion [37]. The model is implemented using the ABM framework primarily to model the heterogeneous interaction between the user and Facebook pages with different attitudes to vaccination [38]. Further, the ABM framework makes modeling different real-life scenarios and policy interventions easier, unlike the traditional statistical models in social science [46]. As system-driven research, we use stylized facts as our primary data. We gather various items of information from previous scientific works and interpret them as mathematical expressions for our model. The validity of the model is examined by the triangulation of the stylized facts. We observe how well the simulated results correspond to the consequences of the stylized facts we use to build our model found in the studies to which we refer. Other than stylized facts, we also use real graph data in constructing our model to give a more accurate representation of the state of the world. To compare the effects of different scenarios to simulate, we use a simplified landscape search to choose the best policy of all possible outcomes [39]. A landscape search is performed by drawing the simulation results of various policy interventions on a landscape of a vertical performance axis with a horizontal axis and other graphing indicators representing policies. Policy interventions are simulated using different scenarios in the form of modification of the baseline model that would be the state of the simulated world. The best scenario is that which scores best on the performance axis, in our case, a scenario where the sentiment on vaccination is the most positive. We shall then perform path analysis to unveil the mechanism necessary to reaching the best "to be" outcome from the "as is" state. The mechanism of the model will be discussed further as a parallel of the real-life intervention policy prescription we are trying to model in this research.

The model can be roughly summarized as an individual Facebook user subscribing to vaccination-related Facebook pages. We have two entities in this model, a single Facebook user agent and a network of 1326 vaccination-related Facebook pages based on a real data set [34]. Other ABM implementations might consider objects like our individual Facebook page to be an agent, but in this research we only use "agent" to refer to the single Facebook user agent [82]. These pages are identified by their polarity on the vaccination-related issues and their position in the network. The user starts by subscribing to one page. The user then browses and subscribes to pages according to simple rules representing their internal model. There are assumptions we make in making this model. Firstly we limit the scope of this research to that of vaccination-related information consumption on Facebook and not other media. Secondly we do not consider external influences such as interaction with other users, news from mass media, nor other possible factors to form the user's consumption behavior on vaccination. Thirdly we assume that there is no change to the network of pages, i.e., the network pages connection remains static. These assumptions are chosen because we want to focus our work on the possible influence of the current network on individual user's information consumption behavior based on the latest available data.

7.2.1 Basic Percolation Model

Before modeling the specific interactions between a Facebook user and vaccination-related pages, we first need to know if the network has a tendency to polarize the individual user to either side of the sentiment. This model is constructed using a simple network analysis, that is, to find the maximum size of subgraph comprised of all nodes that can be reached for each individual nodes' starting point. Consider a set of Facebook pages $Pages = \{\phi_1, \phi_2, \cdots, \phi_N\}$. For any page $\phi \in Pages$, its polarity and pages recommendation are given by $polarity(\phi) \in \{a, p, n\}$ and $reccomendation(\phi) \subset Pages$, respectively. The polarity is the page's stance on vaccination where a represents support for anti-vaccination view and p is for pro-vaccination view. The pages are connected in a directed graph $G = (V, E)$ where $V = Pages$ and every page ϕ_R recommended by ϕ is defined as $(\phi, \phi_R) \in E$ for all page $\phi_R \in recommendation(\phi)$. The graph is static and the recommendation does not change over time. When a Facebook user u starts subscribing a page $v \in Pages$, we define the initial subscription of the user to be $subscription_0(u, v) = \{v\}$. If there is a path from page v and w where $v, w \in Pages$ through the recommendation edges E, we define that there is a path between $(v, w) \in Path \subseteq V \times V$. The maximum subscription of user u starting from a page v is defined as

$$subscription_{max}(u, v) = \{w | (v, w) \in Path\}. \tag{7.1}$$

From the maximum subscription, we can analyze how much of the network can be reached by the user. Furthermore, we can get the distribution of opinion the user can have for all possible starting subscription. The formula for the opinion will be explained by the end of baseline model section.

7.2.2 Baseline Model

The baseline model follows a modification of agent-based model interpretation of the Zaller receive-accept-sample (RAS) model [83]. We have a set of Facebook pages $Pages$ that are connected through a graph G defined in the same way as the previous section. In addition to the Facebook pages, we define a user agent u representing a Facebook user who browses and subscribes to vaccination-related Facebook pages on Facebook. A user is defined by its polarity $polarity(u) \in \{a, p, n\}$ and a set of subscribed page $subscription(u) \subset Pages$. In addition, a user is also defined by their cognitive capability $cognitive(u) \in [0, 1]$ and default page subscribing probability $default(u) \in [0.5, 1]$. The cognitive capability refers to the capability of the user to recognize whether a page has an anti-/pro-vaccine supporting view upon encounter [23]. The default page subscribing probability is the probability of a user subscribing to the page if a user manages to understand that the page that it encounters has the same polarity as the user's own polarity. The value is chosen so that when in the maximum value possible, the user will subscribe to the page encountered. We shall next describe the dynamics of this model to explain further how these parameters influence the user's behavior.

Following the RAS model [23], we divided the dynamics of the agent into three stages that are receive-accept-sample as shown in Fig. 7.1. We employ two steps of reasoning, where the first is a logical test to determine whether the user understands the value that the pages promote. The second reasoning is akin to emotional reasoning, where the acceptance of the idea represented as page subscription is

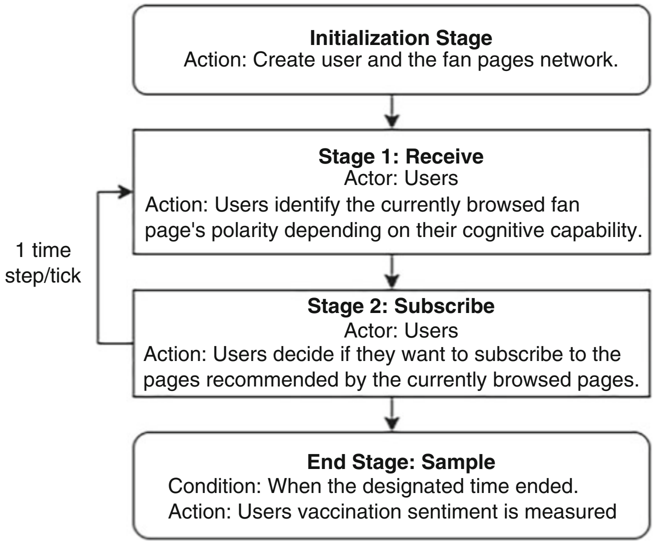

Fig. 7.1 Simulation stages of the simulation. Other than the initialization stage and the end stage, stages 1 and 2 are performed every single time step

eventually influenced by whether the perceived polarity of the pages matches the user's polarity as observed in the case of support on embryonic research [37]. The sampling stage is adapted directly from the original Zaller model similar to a previous work [83]. In this model, we also assume that a neutral page does not influence the user's sentiment on vaccination. Neutral pages only act to bridge one page to another. The stages are elaborated below:

1. Receive: When a user encounters a new Facebook page, the user will use their cognitive ability to identify the page's polarity. The probability of receiving the page's polarity correctly is given by the equation

$$P_{Identify}(u) = \frac{1}{1 + \exp(-k_R(cognitive(u) - 0.5))}, \tag{7.2}$$

   where $k_R \in \mathbf{R}^+$ is the receiving coefficient. This is part of the behavior that is inspired by the user's logical reasoning and not related to any value predisposition that the user has.
2. Accept: We reinterpret Zaller model's accept as a user subscribing to a page in this model. User subscribes to a page probabilistically according to the value predispositions, the polarity. Aside from the value predisposition, the user also subscribes depending on whether they successfully identify the polarity of the pages they encounter in the previous receive phase. In the case of successful page's polarity and the $polarity(u) \neq n$,

$$P_{Subscribe}(u, \phi) = \begin{cases} default(u), & \text{if } polarity(u) = polarity(\phi) \\ 1 - default(u), & \text{if } polarity(u) \neq polarity(\phi) \\ 0.5, & \text{if } polarity(\phi) = n, \end{cases} \tag{7.3}$$

   where $default(u) \in [0.5, 1]$ is the range of the default accepting probability. The default value $default(u = 1)$ means otherwise; the probability $P_{Subscribe}(u, \phi) = 0.5$ for other cases.
3. Sample: Because of the difficulty of measuring the influence of Facebook pages on one's opinion regarding vaccination, we only assume that the influence is proportional to the number of subscribed pages with positive polarity with respect to the entire subscription. Therefore we use $sentiment(u)$ that is calculated by

$$sentiment(u) = \frac{|subpro(u)|}{|subpro(u) + subanti(u)|} \tag{7.4}$$

   where $subpro(u)$ and $subanti(u)$ are the number of subscribed pages with pro-vaccine polarity and anti-vaccine polarity of a user u. However, the user will only subscribe to neutral pages in some cases. In these cases, we decide that the influence of Facebook pages on user's sentiment on vaccination cannot be determined and will not be analyzed further. We also use the terms "sentiment" and "opinion" interchangeably in this chapter to refer to the sentiment concept introduced here.

7.3 Simulation

7.3.1 Simulation Overview and Settings

In every simulation, we have one user agent representing a Facebook user and one graph where each node represents one single page of the vaccination-related pages network on Facebook. Other than the simulation of basic percolation model, every other simulation is conducted with some fixed parameters and variable parameters implemented in the model. The fixed and the variable parameters are given as shown in Table 7.1:

We refer to each set of parameter configurations as a scenario S. A scenario is defined as a combination of parameters to be simulated that describe the real world. In this example, we have three variable parameters to be varied that make basic scenarios. The three variable parameters are the user's polarity $polarity(u)$, cognitive capability $cognitive(u)$, and the default accepting probability $default(u)$. These three parameters make a characteristic of the user agent we want to simulate. The three possible values of the default accepting probability are also referred to as low, medium, and high values for the possible values 0.6, 0.75, and 0.9, respectively, for discussion purposes.

We assume that a user agent always starts by subscribing to one page first. Since we want to know how a user agent with a given characteristic could be influenced by the currently existing vaccination-related Facebook pages, we shall simulate the user to start subscribing to every page in the network. While, in reality, it is unlikely for a pro-vaccine user's first exposure to the vaccination-related Facebook pages to be an anti-vaccine page, we assume that every page has an equal chance to be user's first subscription since we want to know the influence of the network in general and we do not have the data to determine the user's prior sentiment in their first subscription. This assumption is applied to the user in every scenario. The result of the simulation starting from different nodes will then be averaged uniformly.

Table 7.1 Simulation parameters

No.	Variable name	Possible values
1	Polarity	$\{a, n, p\}$
2	Cognitive capability	$\{0.05, 0.1, \cdots, 0.1\}$
3	Default accepting probability	$\{0.6, 0.75, 0.9\}$
4	Starting node	$\{0, 1, \cdots, 1325\}$
5	Receiving coefficient	10
6	Simulation time	50

The same scenario will be repeated for $r = 20$ times to take into account the randomness of the subscribing process. Other than the basic scenarios, we shall also explain scenarios that include policy intervention and the measured parameters in the following subsections. The simulation is conducted using Python programming language version 3.8. The pseudocode required to simulate this model is elaborated further in the appendices. The code required to run this simulation is also provided in a public repository.

7.3.2 Simulating Policies

One of the purposes of conducting agent-based modeling is the ease of modeling different policies using scenario-based modeling [46]. This chapter explores two scenarios to minimize the influence of anti-vaccination pages on Facebook. The first is to simulate how the user's adherence to health authority affects the vaccination sentiments. This simulation is performed by flagging pages that contain dubious information about vaccination with a banner. The other scenario is to simulate censorship on anti-vaccination pages conducted by the platform. The overall dynamics of this model are still the same as the baseline model as described in the previous section with minor modifications. The scenario modifications are explained in more detail as follows:

1. Scientific authority adherence: Some pages are marked with a banner that directs users with information from established health information providers such as the CDC or WHO website. In this scenario, all pages $\phi \in Pages$ have an additional property that is $banner(\phi) \in \{0, 1\}$ where $banner(\phi) = 1$ indicates that the page is flagged with this information. This banner is used to model the influence of flagging policy given the user's adherence to scientific authority. Assuming users have scientific authority, they should be more critical in subscribing to pages that are flagged by Facebook. This criticism is captured in the acceptance stage by halving the subscription probability such that

$$P_{Subscribe}(u, \phi | banner(\phi) = 1) = 0 \tag{7.5}$$

   We choose 0 to observe the maximum influence of scientific authority adherence on users. Everything else is modeled in the same way as the model with neutral pages.
2. Platform censorship: We simulate platform censorship by gradually removing pages with anti-vaccine polarity. We first sort the pages according to their eigencentrality as a node in the overall graph. We then remove some of the anti-vaccine pages starting from pages with the highest centrality. The proportion of the removed pages is elaborated in the simulation section. In short, this model has the same component and dynamic as the baseline model except for the reduced number of anti-vaccine pages.

7.3.3 Parameter Measurement

Our main interest is to know which scenario leads to the minimum influence of negative views of vaccination on an individual user from the baseline scenario. We therefore first have to calculate the average sentiment for a single scenario S by averaging the final sentiment of an individual user from all starting nodes and repetition by the equation

$$avg(sentiment_S(u)) = \frac{1}{r}\frac{1}{|Pages|}\sum_{i}^{r}\sum_{\phi}^{Pages} sentiment(u|\phi, i)_S, \tag{7.6}$$

where u, ϕ, and i are the user, starting node, and simulation repetition index, respectively. Only simulation results with a defined sentiment as elaborated in Eq. 7.6 are included in the calculation. We compare the average sentiment with respect to the user's cognitive capability $cognitive(u)$ as the x-axis. The graph will present six plots of average sentiment, each representing a single combination of user's polarity $polarity(u)$ and default subscribing probability $default(u)$. The same kind of plot is used for the scenario with policy implementation on a separate graph.

7.4 Results and Discussion

7.4.1 Basic Percolation Results

Before presenting the main simulation results, we first present the results of basic percolation simulation. As elaborated in the model and simulation section, the results below represent the situation where the decision of subscription is purely through recommendation of pages alone, without considering the internal model of the user agent. We obtain the distribution of maximum nodes reached through percolation from all 1326 starting nodes (Fig. 7.2). From this figure, we observe that there are only 21 unique maximum node values, with a significant majority of maximum nodes having the value of either 1 or 1094. About 40% of the nodes that belong in the network are actually not connected with other nodes. If users subscribe from one of these pages, the page will be the extent of their exposure on vaccination-related Facebook pages that influence their vaccination opinion. This corresponds to the opinion values of 1.0 or 0 as indicated in Fig. 7.3 if they are first subscribed to pro-vaccine and anti-vaccine pages, respectively. If users are subscribed to a neutral fan page first, their opinion will not be measurable and not included in Fig. 7.3 following the definition in the model section. Interestingly, most fan pages are closely connected with each other, and most of them will end up subscribing to 1094 pages which corresponds to the value of opinion 0.26. From

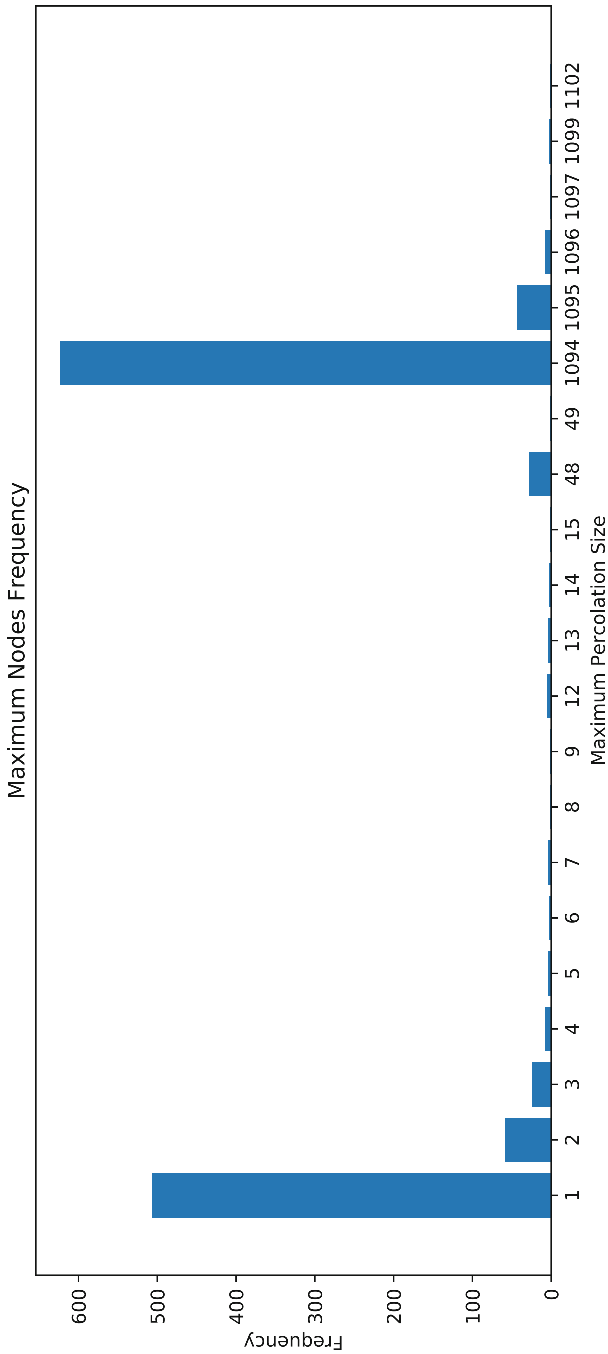

Fig. 7.2 This figure shows the histogram of maximum nodes reached by percolation from every node without internal model

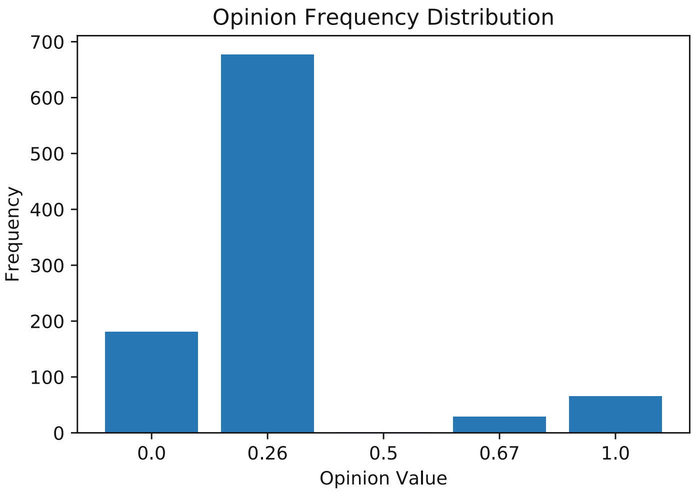

Fig. 7.3 This figure shows the histogram of all valid opinions from every maximum percolation

these opinion distributions, we can conclude that the network as it is has a tendency to lead users toward anti-vaccine opinion. This can be inferred from the significantly higher frequency of users with lower valid opinion value from all possible starting points. In the rest of the discussion section, every data point presented in each vaccination sentiment versus cognitive capability graph will be the average value of valid sentiment as shown in Fig. 7.3 for the repeated 20 simulations. For this plain percolation simulation, the average sentiment value is $avg(sentiment(u)) = 0.27$. This suggests that the network alone has a tendency to make an individual user subscribe to more anti-vaccine pages, similar to what was suggested in a previous research [34]. In the next section, we shall present how implementing users' internal decision-making process using the adaptation of the Zaller model changes the users' final opinion.

7.4.2 Baseline Model Results

Firstly we present the results of the basic simulation. In Fig. 7.4, we show how the sentiment of one user agent in a scenario where the $polarity(u) = a$ and $default(u) = 0.9$ evolves over time repeated 20 times starting from a chosen page with $polarity(\phi) = a$. Every data point in each graph below would be the averaged value of the user's sentiment at $t = 50$ for the 20 repetition of a single scenario. Figure 7.5's y-axis presents how a user u's vaccination sentiment $sentiment(u)$ at the end of simulation varies along the increase of cognitive capability $cognitive(u)$ in the x-axis. This figure contains 9 line plots in which the colors red, green, and blue represent the averaged simulation results for user agent with anti-vaccine, neutral,

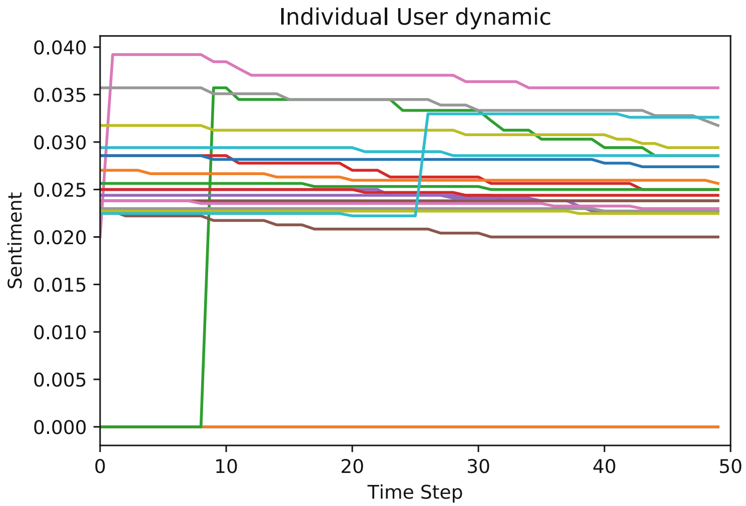

Fig. 7.4 The simulation results for the baseline model of a single scenario. Each line in this figure represents the result for a repeated simulation of a single scenario

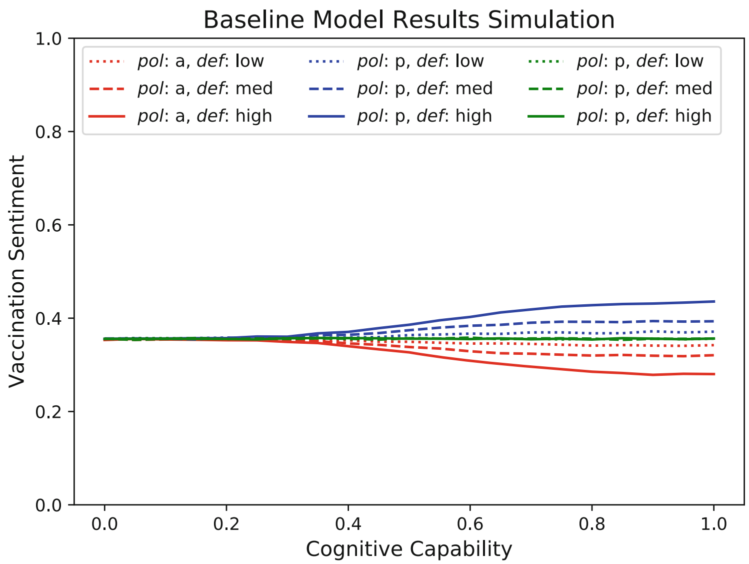

Fig. 7.5 The simulation results for the baseline model. The variables *pol* and *def* in the legend represent the scenario's $polarity(u)$ and $default(u)$ with value low, med, and $high$ for each variable set according to the explanation in the simulation section

and pro-vaccine $polarity(u)$, respectively. Each color has three line plots where the dotted lines, dashed lines, and solid lines represent the results for low, medium, and high users' default subscribing probability $default(u)$. We can observe that, at lower cognitive capability, users of both polarity and all default subscribing probability values have similar values with averaged sentiments. As the cognitive capability increases, the vaccination sentiments diverge for pro-vaccine users and anti-vaccine users. However, this divergence is more apparent when the default subscribing probability is increased. This leads to the biggest difference between pro-vaccine users and anti-vaccine users which occurs when both have high value of default subscription probability and high cognitive capability in either case.

One takeaway point from this result is that the user in our model behaves similarly to the subject in the RAS model. The finding in the RAS model can be summarized as the idea that people with stronger cognitive capability are more consistent with their value predisposition [23]. From our results, we also observe that along with the increase of a user's cognitive capability, the value of sentiments tends to go up for a pro-vaccine user and lower for an anti-vaccine user. The consistency serves as one validation of our model, in that the interaction between the user and Facebook pages leads to a similar behavior observed in a real public opinion survey [37]. Even though vaccination and embryonic stem cell research are two distinct issues, opinions on both of them are highly determined by one's internal value predisposition as well as other reasons as we have presented in the literature review section. Additionally, the subscribing probability plays a role in that it amplifies the difference of sentiment between pro-vaccine users and anti-vaccine users when both have a high cognitive capability. This is a logical consequence of increasing high subscribing probability because it also means that the particular user is more easily influenced by external factors in general.

From this result, we can also infer the influence of having an internal model of information consumption. The average value of sentiments is $avg(sentiment(u)) = 0.36$. This value indicates that the network still has a tendency to make a user more supportive toward the anti-vaccine point of view. Out of 1326 Facebook pages in the data set, there are 317, 124, and 885 anti-vaccination, pro-vaccination, and undecided (neutral) pages, respectively. Since the number of anti-vaccine pages is more than that of pro-vaccine pages, this result is also expected. However, the value is still higher than that of the basic percolation simulation with $avg(sentiment(u)) = 0.27$. This implies that using an internal model with a preferential information consumption behavior, i.e., a user with anti-vaccine polarity tends to subscribe to anti-vaccine pages and vice versa, a user will end up with a more positive sentiment in general. This value will also be used as our baseline in the scenario analysis presented next.

7.4.3 Scenario Analysis

The first policy we shall discuss is the addition of banners from scientific authorities in influencing individual users' sentiment on vaccination [84]. In this scenario we assume that users have a strong adherence to scientific authority such that a user will not subscribe to Facebook pages that are marked with a banner. Since most of the pages with banner are anti-vaccine pages followed by neutral pages, we expected that subscription to anti-vaccine pages and neutral pages is decreasing. This should lead to a higher average value of vaccination sentiment due to lower contributions from anti-vaccine pages. The result presented in Fig. 7.6 supports our hypothesis of the influence of banners from health authority on a science authority-adhering user. Within the limitation of our model, we found out that adding cautionary banners indeed increase the sentiment on vaccination. This also aligns with a previous observation on Twitter where such flagging increases vaccination sentiment [80]. Note that we assume that a user has to have respect for scientific authority in the first place and this cannot be expected of every single social media user. One solution to this is to improve trust in scientific authorities with education in how education in vaccination administered to parents is associated with higher rates of vaccination [85, 86].

Other than the implementation of banners, we also simulate a scenario of platform censorship using this model. We interpret platform censorship as page removal performed by Facebook as the platform owner [87]. The result is presented in four graphs as shown in Fig. 7.7 below. With every increase of censorship number,

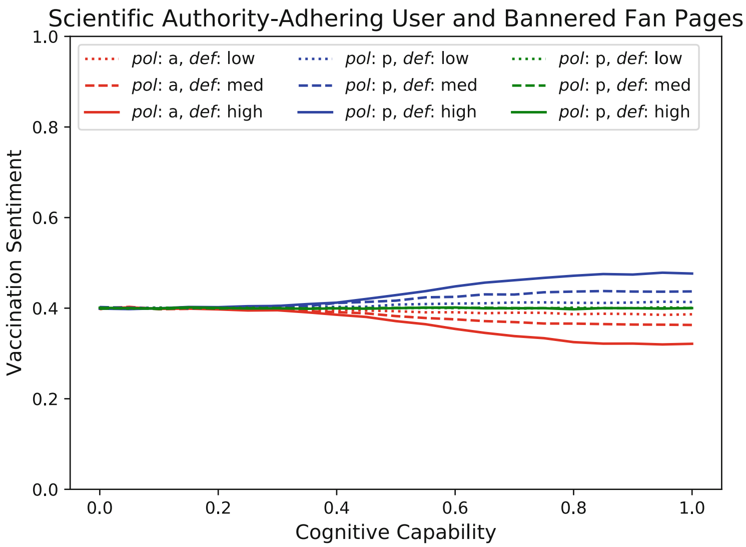

Fig. 7.6 The simulation results for health authority-adhering users with a banner from CDC/WHO

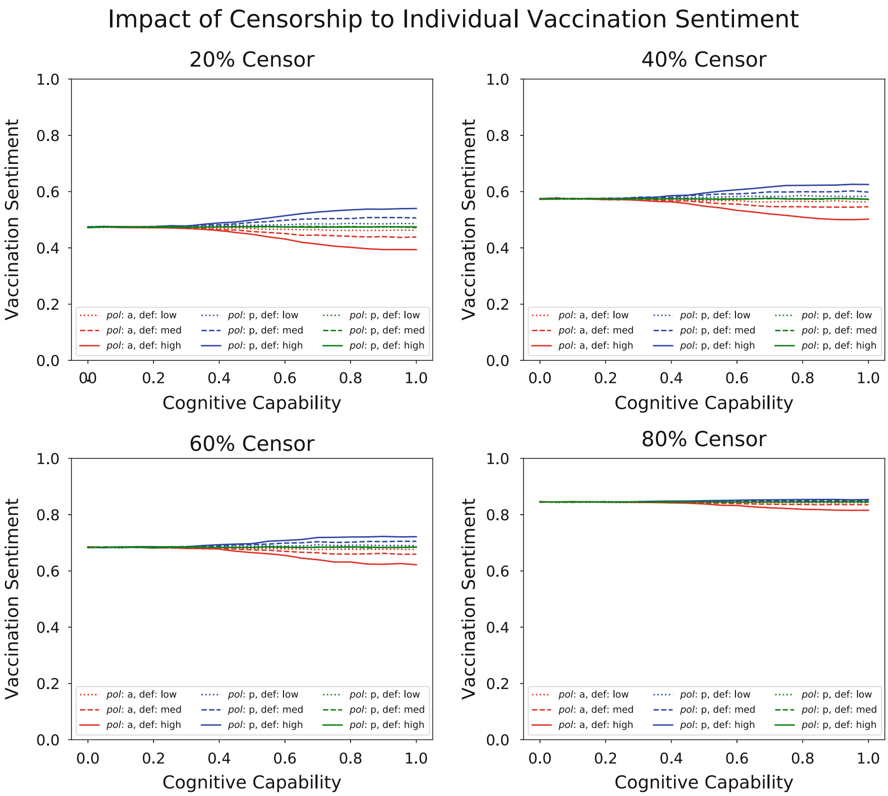

Fig. 7.7 The results for censored pages. Starting from 20% censorship at the top left, 40% censorship at the top right, 60% censorship at the bottom left, and 80% censorship at the bottom left

the average vaccination sentiment increases. This result is expected because the only source that reduces vaccination sentiment is decreased; but if we observe carefully, the censorship does not increase the sentiment linearly. The censorship value from 60% to 80% gives the highest increase of average sentiment by about 0.16 point compared with averaged 0.11 points in all the previous increments of censorship. To examine the nonlinear increase of sentiment, we also plot the graph of the average sentiment versus percentage of censorship in Fig. 7.8. We plot one scenario where a user has high cognitive capability and default subscription probability to maximize the number of subscriptions leading to more visible difference between the pro-vaccine and anti-vaccine user. The sentiment is expected to converge to 1, i.e., complete support of pro-vaccine sentiment, as there are no more anti-vaccine pages to contribute to user's sentiment. Consistent with Fig. 7.7, the sentiment shows sharper increase when the censorship is increased from 70% to 80% especially for an anti-vaccine user especially for the anti-vaccine agent. While the increase of sentiment for any kind of user is expected from the censorship, we can conclude

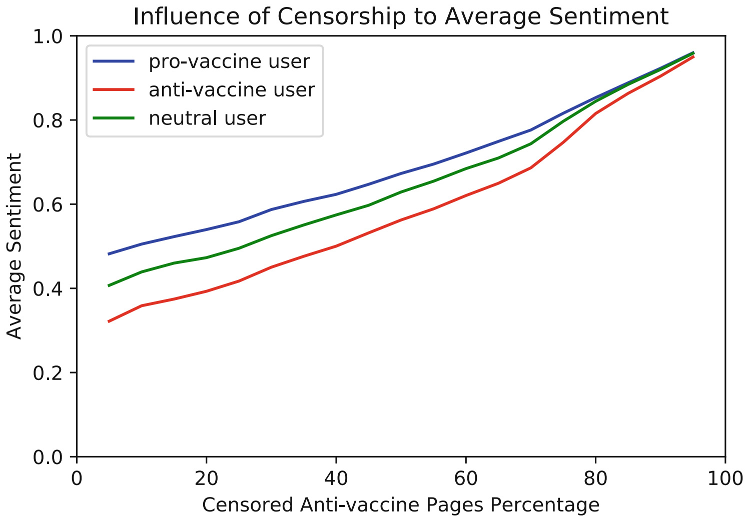

Fig. 7.8 Plot of the average sentiment versus various levels of censorship

that even a user who has a stronger tendency to be an anti-vaccine supporter would benefit the most from the reduction of anti-vaccination supporting information sources. This result agrees with the finding that censorship through deplatforming has been shown to limit the transmission of vaccination misinformation, but it does not eradicate the problem [81]. However, censorship in social media is also a controversial subject because it often acts as a precedent to a more controlling approach taken by social media as well as a more radicalized activism from anti-vaccine activists [88]. Whether to implement censorship goes to the ethical discussion that has to be decided among the relevant stakeholders and is beyond the scope of this research [89].

Finally, we want to discuss the overall results for all scenarios and the choice of scenarios. For three types of agent's polarity, three possible values of default subscription probability, and six distinct interventions (baseline, banner, and four different censorship), we simulated 54 scenarios in total. Figure 7.9 shows the box plot of the average of 20 repetitions for each scenario. The average standard deviation of the 20 values for all scenarios is approximately 1% of its mean with the highest standard deviation's being only 2%. From this we can justify that the 20 repetition is sufficient to reach a stable value of simulations. The lowest sentiment observed occurs when an agent with anti-vaccination propensity has high default subscription probability and cognitive capability. We can also see that for all parameters considered, the first 9 scenarios that include banner and scientific-adhering users lead to higher sentiment than the following 9 where we do not include banners. We acknowledge that some of the scenarios do not represent common understanding of what a typical profile of an "anti-vaxxer" or the "pro-vaxxer" are. For example, we simulate a user with a strong scientific adherence while

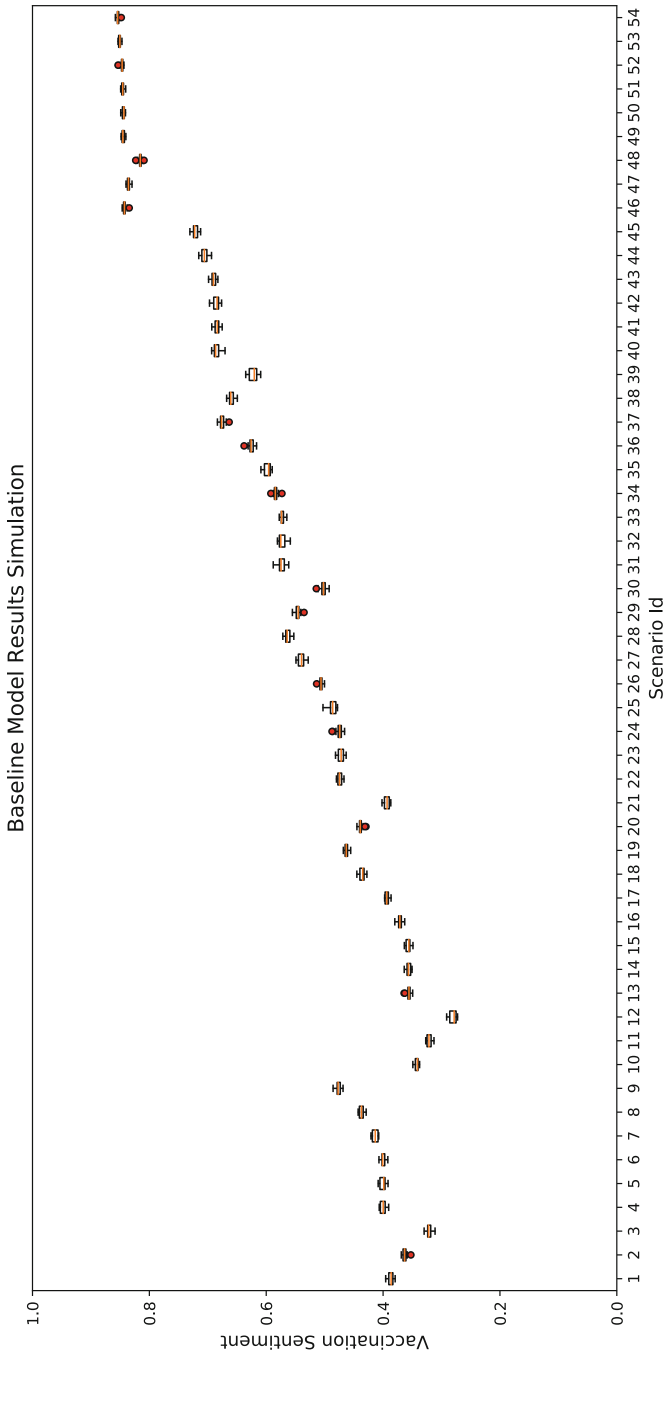

Fig. 7.9 Plot of the total landscape of the simulation

having anti-vaccine polarity. While this kind of combination of cultural traits sounds implausible, existing literature shows examples of these non-intuitive combinations such as people who have stronger belief in science and pseudoscientific information at the same time [90]. We therefore decided to keep simulating all the possible combinations.

7.4.4 Model Validation

Since both models are based on the Zaller model, the validation process is very similar. The difference is that we first need to gather reasonable evidence through various stylized facts to justify that the vaccination opinion problem is something we can study using Zaller model. As mentioned in the model overview, we make analogy of vaccination issue with embryonic cell issue because of the importance of value predisposition in determining one's opinion on both issues [37]. Next, we use the same two stylized facts as the previous case: (1) people who are more politically aware tend to be more selective with what information to accept, and (2) people who are more engaged politically have more consistent opinion in general [23]. The first fact we deliberately model resulting in the second fact that can be seen in every plot of vaccination sentiment against cognitive capability as shown by Figs. 7.5, 7.6, and 7.7. In these figures the pro-vaccine user (indicated by blue line) has generally higher vaccination opinion and conversely for the anti-vaccine user (indicated by red line) to have lower opinion with increasing cognitive capability.

Chapter 8
Conclusions and Future Works

8.1 Conclusions

The contribution of this book is as follows:

1. Firstly, we have established an ABM for echo chamber and polarization formation through information sharing in the context of SNS style communication. Based on the simulation, we find out that the convergence parameter is not the only factor determining the shape of opinion distribution. Contrary to most of the bounded-confidence model variations, the convergence parameter also influences the final distribution of the opinion [91].
2. Secondly, based on the four parameters of echo chamber and polarization measurements, we come up with the scenarios that minimize them as elaborated in the table below: The two-sided extreme news scenario leads to the least echo chamber and polarization for most types of society in every acceptance level of news based on Table 8.1; only the moderate news scenario wins in a single parameter that is the GEC evaluation. This falls along with the idea that keeping information diversity is necessary in minimizing echo chambers as only the two-sided extreme news scenario provides news with distinctly different opinions.
3. As discussed in Sect. 4.6, we have established a model and simulation framework to study the mitigation of opinion polarization in society. Within the limitation of this model, we discover that generally a sufficiently high tolerance or acceptance threshold is necessary for polarization in terms of opinion distribution in the network to occur. However, this process of polarization can be reversed provided the circulating news follows the normal distribution.
4. We developed an ABM implementation of the Zaller model of public opinion specifically to connect existing studies about online echo chambers. The ABM version of the model manages to exhibit macroscopic phenomena observed in the original model where a more politically aware agent has more consistent opinion with their own political predisposition [23]. With this model, we can

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Table 8.1 Table of comparison on which scenario leads to the most favorable overall value of parameters indicating echo chamber

No.	Parameter	Scenario
1	Average ECC	Two-sided extreme news
2	GEC	Moderate news
3	Average opinion	Two-sided extreme news
4	Average exposure	Two-sided extreme news

confirm that selective sharing behavior in social media could still lead most SNS users to observe moderate amounts of news that they disagree with. The model also shows that the distribution of the user's political predisposition matters the most in influencing the perceived echo chamber. It is more significant than the news political predisposition distribution, the user's political awareness, as well as the user's polarization (selective sharing behavior). The model also extends the existing ABM version of the Zaller model by modeling the public opinion survey process [58].

5. Using another interpretation of the Zaller model, we explored how the network of vaccination-related Facebook pages influences individual users. Our findings reinforced existing studies that the network has tendency to lean to the anti-vaccine sentiment stronger [34]. We are also able to model the possible influence of the two policies we simulate, that is, the promotion of health authority adherence and platform censorship. We found out that increasing adherence to health authority only slightly increases the overall sentiment on vaccination for the average user. On the contrary, platform censorship works in reducing the negative influence of anti-vaccination fan pages. Both of these policies do not exist in a vacuum, and much ethical consideration should be taken into account beyond whether the policy is effective or not.

8.2 Future Works

We would like to extend this work in a few directions. Referring to a review on models of social influence, the works could be extended in two directions, theoretical and empirical approach [91]. The possible future works using theoretical approach are as follows:

1. To compare models with different theoretical approaches. One example would be considering more focus on the mechanism of social media. The model of SNS in this book so far only provides a very simplistic aspect of news sharing in SNS. It does not incorporate important features of SNS such as making/cutting connections between users or a more holistic decision-making process for agents that affect opinion formation in the SNS. Another possibility would be using a completely different internal model assuming a different case. If a study on echo

chamber and polarization were to be applied for non-political topics, there could be a more suitable assumption rather than the Zaller model.
2. To develop different aspects of the model from the same fundamental assumptions. For example, the echo chamber parameters we provided here were based on simple definitions of the lack of information diversity or high homophily of opinion/person. Even in this book, we managed to create multiple measurements based on these two statements alone. Similarly, the Zaller-Deffuant model developed by Malarz also uses the same assumption with the Zaller ABM model in this book but ends up having a completely different format [58].

Similarly, the possible future works using empirical research are as follows:

1. Validation and calibration of micro assumptions with experiments. Many of micro assumptions used in opinion dynamics modeling, most notably the assimilation of opinion in this research, were obtained from social influence experiments. One critical component of this model is the confidence threshold in which more difference leads to the social influence to not happen. However, the quantification of the threshold and its distribution in a population have yet to be studied. Having data from empirical research like this allows simulation of meaningful heterogeneous agents as a further step in making a more realistic research of opinion dynamics modeling. Therefore, more experimental research is necessary to test social influence mechanisms in the way that we are quantifying components in social influence dynamic.
2. Testing macro-prediction for overall trends. Opinions at macroscopic levels are commonly recorded as done by different large-scale social surveys such as the World or European Value Survey [92]. These kinds of surveys ask the same questions periodically in the same countries, showing the trends for the value surveyed. Questions are often answered in discrete scales from 0 to 10 just like how opinions are modeled in some research. The opinion distributions from these surveys might exhibit some stylized behavior analogous to some of the opinion distributions we have in Chap. 4, i.e., very significant peaks in the middle of the opinion, one of the extreme peaks being larger than the other, etc. Landscape analysis on these opinions could be the start of more data-driven research in this field.

8.3 Afterword

In the very last section of this book, there are general discussion topics we want to bring that require the context of this entire research. Firstly, what do other scientists think about the conclusions that we have here? In short, it is complicated. In part of this book, we suggested providing two-sided extreme news to the population positively because it is beneficial for reducing echo chambers. Another study found that exposing people with news from the side that they do not believe in apparently increases polarization, especially for respondents who are affiliated as Republican

Party supporters [93]. This result is not contradictory to our findings, as we use the scenario to create a polarized society to study polarization reversibility. The question is how can the exact same thing be considered positively in our research and negatively in their research? The results presented in this book are consistent with the definition of polarization and echo chamber we proposed here. However, the discrepancy is resulted from the fuzzy definitions of echo chamber and its relation with polarization. For example, would a society with stronger state-controlled news leading to a more homogeneous political opinion among the citizens such as China be in a stronger echo chamber compared to Democratic Party supporters in the United States where they see conflicting ideas from their Republican counterparts on a daily basis? We can point out that the latter demographic lives in a more polarized society, but from a system design perspective, it is not easy to point out which one is the "goal." Therefore, until there is further study specifying the relationship between echo chamber and polarization problems, we stand with our position.

Finally, we want to reestablish what this research is about and what it is not about. While the purpose of this kind of research (ABM) has been well elaborated in the methodology chapter, this research belongs to a kind of qualitative computational social science research. What it does is to give explanatory explanation about what the society could be given the various boundary conditions included in the model [39]. For example, we can now tell what are the conditions that lead to a polarization in a society given a society with a randomly distributed opinion initially. However, this research is not about numerically predicting what would happen in the future, i.e., winning chance of a particular party during election. Other social scientists also have a tendency to make research for observational purpose as indicated by some models we refer here [48, 51]. This is not that kind of research. This is applied research where we believe the outcome should be directly applicable for societal needs. In particular, this research was originally motivated as a possible solution to the problem of fake news on the Internet. We also request for any reader to not use the knowledge from this research for malicious purpose such as to manipulate opinion for the gain of a particular party while potentially harming society at large.

Appendix A
Additional Information

A.1 Formal Definition of Modeling Echo Chamber and Polarization in Social Media

Def. 1 (Time)
This model runs through discrete time set $Time$ defined by Eq. (A.1),

$$Time = \{0, 1, 2, \cdots, T\}, T \in \mathbb{N}. \tag{A.1}$$

Def. 2 (Topic)
Define a set of finite independent political news topic $Topic$,

$$Topic = \{\alpha, \beta, \gamma, \cdots\}. \tag{A.2}$$

Assume that each topic is distinct and has no direct relation with each other. Example of topics could include and not limited to $\alpha =$ Trump's Presidency, $\beta =$ China's One Belt One Road policy, etc.

A.1.1 News

Def. 3 (News Set)
Define set of sentiment carrying object $News$ that is mapped from $Topic$ by a function F^{-1} such that for a chosen topic $\alpha \in Topic$,

$$F : News \rightarrow Topic, \tag{A.3}$$

$$News[\alpha] = \{n | n \in News, F(n) = \alpha\}. \tag{A.4}$$

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Every $n \in News$ only represents one topic such that for all $\alpha, \beta \in Topic$, $News[\alpha] \cap News[\beta] = \emptyset$. For this model, we are only focused on a single topic $\alpha \in Topic$, therefore any mention on news will only refer to the particular topic chosen.

For example: For $\alpha =$ Trump's Presidency, $News[\alpha] = \{n_1, n_2, \cdots, n_N\}$, $N \in \mathbb{N}$ where $n_1 =$"Trump's bankruptcy record," $n_2 =$"White House policy leads to strongest economy in decades," etc.

Def. 4 (Sentiment)
Sentiment defined as the extent of agreement/disagreement carried by the news towards the issue it represents such that for any news $n \in News$,

$$f_{Sentiment}[\alpha](n) : News \to [-1, 1]. \tag{A.5}$$

This sentiment represents agreement towards the topic α, where -1 means complete disagreement towards α and 1 means complete agreement. Every value in between represents partial agreement/disagreement towards the topic.

For example: For $n_1 \in News$ where $n_1 =$"Trump's bankruptcy record" is represented by $f_{Sentiment}[\alpha](n_1) = -1$.

A.1.2 User Agent

Def. 5 (User Agent Set)
Define a set of user agents representing social network system (SNS) users,

$$User = \{u_1, u_2, \cdots, u_M\}, M \in \mathbb{N}. \tag{A.6}$$

For example: $User = \{Alice, Bob, Carol, Dave, Eve\}$

Def. 6 (Social Network System (SNS))
Define SNS that is used by the users as an undirected graph $G = (V, E)$ with:

- Nodes

$$V = User. \tag{A.7}$$

- Edges

$$E \subset V \times V, \forall (u, v) \in E, (u, v) \to (v, u). \tag{A.8}$$

Def. 7 (Neighbors)
Define $Neighbors$ as power set of $User$ where for each $u \in User$ there exists set of users $Neighbors(u)$ connected with u via SNS G who receive every news shared by u as

$$f_{Neighbors}[u] : User \rightarrow \mathcal{P}(User), \tag{A.9}$$

$$Neighbors(u) = \{v | v \in User, (u, v) \in E\}. \tag{A.10}$$

For example: $f_{Neighbors}[Alice] = \{Bob, Carol, Dave\}$

Def. 8 (Opinion)
Opinion is defined as user's extent of agreement/disagreement towards the chosen topic. We use the term $Opinion$ to indicate that it belongs to users instead of $Sentiment$ that belongs to news. For $u \in User, n \in News, t \in Time$,

$$f_{Opinion}[u, \alpha](t) : Time \times User \times Topic \rightarrow [-1, 1]. \tag{A.11}$$

Opinion of the user towards topic α, where 1 represents full agreement towards the topic and -1 is full disagreement on the topic. Every value in between represents partial agreement/disagreement on the topic.

For example: If $f_{Opinion}[Alice, \alpha](t) = -1$, it means that $Alice$ completely disagrees with $\alpha =$"Trump's Presidency" at time t.

Def. 9 (State)
State represents the status of interaction between all user $u \in User$ and news $n \in News$, we have state defined as:

$$State = \{Uninformed, Exposed, Accepted, Shared\}, \tag{A.12}$$

$$f_{State}[u, n](t) : User \times News \times State \times Time \rightarrow State, \tag{A.13}$$

$$f_{State}[u, n](t + 1) = H[f[u_1, n](t), f[u_2, n](t), \cdots , f[u_M, n](t)], \tag{A.14}$$

where H is the state transition function. The state represents user u's interaction status with news n. The detail of the state transition function H is detailed in the "User's State Transition Model" subsection.

Def. 10 (Distance)
Distance is defined as the difference between user's opinion and the news' sentiment such that for $u \in User$ and $n \in News[\alpha]$ at time $t \in Time$,

$$f_{Distance}[u, n](t) \rightarrow User \times News \times Time, \tag{A.15}$$

$$f_{Distance}[u, n](t) = abs(f_{Opinion}[u, \alpha](t) - f_{Sentiment}[\alpha](n)). \tag{A.16}$$

Def. 11 (Exposure)
Exposure is defined as sum of distances over time

$$f_{Exposure} : Time \times User \times State \times News \to \mathbb{R}^{+}. \quad (A.17)$$

For all user $u \in User$ at time $t \in Time$ and $n \in News$ where $f_{State}[u, n](t) = Exposed$ and $f_{State}[u, n](t-1) = Uninformed$, the exposure function dynamics is

$$f_{Exposure}[u](t = 0) = 0, \quad (A.18)$$

$$f_{Exposure}[u](t + 1) = f_{Exposure}[u](t) + f_{Distance}[u, n](t). \quad (A.19)$$

The detail of the function is described later in the "User's State Transition Model."

Def. 12 (Hostility) For user $u \in User$ and $v \in Neighbor(u)$ at time $t \in Time$, hostility is defined as the neighbor $v \in f_{Neighbor}(u)$'s perception of u's opinion

$$f_{Hostility} : Time \times User \times Opinion \to \mathbb{R}, \quad (A.20)$$

$$Hostility[u](t) = f_{Opinion}[u](t) \sum_{v} f_{Opinion}[v](t), \quad (A.21)$$

where $f_{Hostility}(u) > 0$ is associated with positive perception of u's opinion and $f_{Hostility}(u) < 0$ as negative perception of u's opinion.

A.1.3 User's State Transition Model

For each user $u \in User$ and $n \in News$ has different action associated with its current state. User u's state transition is formally defined as a state by state dynamic transition function H that depends on other's state as written in Eq. (A.14). The state transition is governed by series of condition is defined by the function

$$H : State \times Condition \to State \quad (A.22)$$

where

$$Condition = \{a_0, a_1, a_2, a_3\} \quad (A.23)$$

described by Fig. A.1, Table A.1, and detailed function below:

- When $f_{State}[u,n](t) = Uninformed$,

$$f_{State}[u,n](t+1) = \begin{cases} Exposed, & \text{if } a_1. \\ f_{State}[u,n](t), & \text{otherwise.} \end{cases} \tag{A.24}$$

a_1 : If there exist $v \in Neighbors[u]$ s.t. $f_{State}(v,n) = Shared$.
User u also updates its exposure by:

$$f_{Exposure}[u](t+1) = f_{Exposure}[u](t) + f_{Distance}[u,n](t). \tag{A.25}$$

- When $f_{State}[u,n](t) = Exposed$,

$$f_{State}[u,n](t+1) = \begin{cases} Accepted, & \text{if } a_2. \\ f_{State}[u,n](t), & \text{otherwise.} \end{cases} \tag{A.26}$$

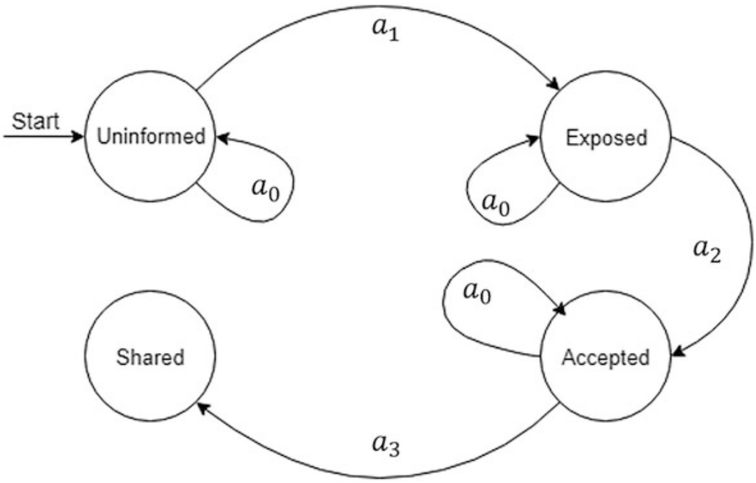

Fig. A.1 State transition diagram for each user agent $u \in User$ with respect to each news $n \in News$

Table A.1 Table description of state transition function H

	a_0	a_1	a_2	a_3
$Uninformed$	$Uninformed$	$Exposed$	–	–
$Exposed$	$Exposed$	–	$Accepted$	–
$Accepted$	$Accepted$	–	–	$Shared$
$Shared$	–	–	–	–

a_2 : If $f_{Distance}[u, n](t) < d$, where d is constant parameter defined as acceptance threshold $d \in [0, 2]$.

User u also updates its opinion by:

$$f_{Opinion}[u](t+1) = f_{Opinion}[u](t) + \mu(f_{Sentiment}(n) - f_{Opinion}[u](t)), \tag{A.27}$$

where μ is the convergence parameter $\mu \in [0, 1]$.

- When $f_{State}[u, n](t) = Accepted$,

$$f_{State}[u, n](t+1) = \begin{cases} Shared, & \text{if } a_3. \\ f_{State}[u, n](t), & \text{otherwise.} \end{cases} \tag{A.28}$$

a_3 : If $f_{Hostility}[u](t) > 0$.

- When $f_{State}[u, n](t) = Shared$,

$$f_{State}[u, n](t+1) = f_{State}[u, n](t). \tag{A.29}$$

A.2 Formal Definition of Agent-Based Interpretation of the Zaller Model

A.2.1 Model Entities and Assumptions

Consider a discrete time tick $t \in T = \{1, 2, \cdots, t_{max}\}$, $t_{max} \in \mathbb{Z}^+$. Let there be a set of people agent $Agents$ with $m \in \mathbb{Z}^+$ number of people representing real-life people who consumes news and a subject of public opinion survey. Let there be one media agent $Media$, representing combinations of various media such as online news company, newspapers, TV news, etc. At every time step $t \in \mathbb{Z}^+$, $Media$ publishes n number of news that are accessible to the people agents.

A.2.2 Media Agent

Every news $N_j = (j, C_j) \in News$ is defined by its:

1. News unique id j attached to each news distinctively where

$$j \in \mathbb{Z}^+. \tag{A.30}$$

2. Consideration C_j any reason that might invoke someone to choose side on an issue in one way or another. Consideration is formally defined as

$$C_j \in C = \{-1, 1\}. \tag{A.31}$$

Each value of C_j represents level of agreement-disagreement that it invokes on the issue where a value of $C_j = -1$ means general disagreement on the issue and $C_j = 1$ means general agreement on the issue.

A.2.3 User Agents

Each people agent represents individual people who consumes media. Every agent is defined by its:

1. People unique id i attached to each agent distinctively where

$$i \in \mathbb{Z}^+. \tag{A.32}$$

2. Value predisposition V_i represents internal tendency of the agent's favorability on the issue, where

$$V_i \in V = \{-1, 1\}. \tag{A.33}$$

   This value is assumed to be immutable as agent's fundamental characteristic in this model.
3. Political awareness A_i describes the level of understanding of an agent in understanding political-related news and information.

$$A_i \in A = \mathbb{R}^+. \tag{A.34}$$

   Higher value of political awareness of agent is also associated with general cognitive capability and the level of education the agent has.
4. Internalized consideration I_i represents all news that have been accepted by agent i defined as

$$I_i \in \mathcal{P}(News). \tag{A.35}$$

A.2.4 Process of News Consumption

1. Exposure is defined as the encounter of an agent i with news j at time t that is governed by probability function $P(E)$ described as

$$f_{Exposure} : (V_i, A_i, C_j, t) \mapsto P(E) \in [0, 1], \tag{A.36}$$

$$P(E) = \frac{1}{1 + \mathbf{exp}(-a_0 - a_1 D_{ij} + a_2 A_i)}. \tag{A.37}$$

The higher agent's awareness A_i, the more likely agent's exposure to the news. Also the more difference $D_i j$ the agent's value predisposition and the news' consideration defined as

$$D_{ij} = \mathbf{abs}(V_i - C_j), \tag{A.38}$$

the less probability of the agent from getting that news' exposure.

2. Reception is defined as agent i's complete comprehension in reading/watching the news j with probability defined as

$$f_{Reception} : (A_i, P(E)) \mapsto P(R|E) \in [0, 1], \tag{A.39}$$

$$P(R|E) = 1 - \frac{1}{1 + f + \mathbf{exp}(b_0 + b_1 A_i)}. \tag{A.40}$$

The higher agent's awareness A_i, the more likely agent to receive the news.

3. Acceptance is defined as internalization of the news that agent previously received. The probability of acceptance is defined as

$$f_{Accept} : (V_i, V_i, C_j) \mapsto P(A|R) \in [0, 1], \tag{A.41}$$

$$P(A|R) = \frac{1}{1 + \mathbf{exp}(-c_0 - c_1 D_{ij} - c_2 A_i)}. \tag{A.42}$$

The higher agent's awareness A_i and difference $D_{i,j}$, the lower the probability of agent to accept the news j.

A.2.5 Survey Process

At some designated time t, agents will be surveyed by asking their individual opinion o_i defined as

$$f_{Survey} : (I_i, A_i, t) \mapsto o_i \in \{\{\}, -1, 1\}. \tag{A.43}$$

Before agents reach to conclusion, they will try to recall as many internalized consideration that the agent can. The internalized consideration that agents can recall is defined as

$$O_i \subset I_i. \tag{A.44}$$

For each $N_j \in O_i$, they are recalled by the probability

$$f_{Recall} : (I_i, A_i, t) \mapsto P(Re) \in [0, 1], \tag{A.45}$$

$$P(Re) = 1 - \frac{1}{1 + \mathbf{exp}(d_0 + d_1 A_i)}. \tag{A.46}$$

The final opinion of the agent during survey process is defined as the closest integer to the average of the considerations that the agent manage to recall, formally written as

$$o_i = \mathbf{int}\left(\frac{1}{|O_i|}\sum_{N_j \in O_i} N_j\right). \tag{A.47}$$

In the case of agent not being able to recall any consideration due to the lack of internalized consideration or other reason, the agent will respond with $o_i =$ which correspond to abstaining from answering.

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