Article

Communication Research
2022, Vol. 49(1) 139–166

DOI: 10.1177/0093650219856510
journals.sagepub.com/home/crx
SAGE

Spiral of Silence in the Social Media Era: A Simulation Approach to the Interplay Between Social Networks and Mass Media

Dongyoung Sohn[1]

Abstract

Interpersonal networks and traditional mass media are more intertwined than ever as evidenced by the proliferation of social media. However, it remains unclear how the interplay between the two shapes the way individuals monitor opinion climates, which play a critical role in public opinion dynamics. Using an agent-based modeling (ABM) approach, this study aims to explore the conditions under which social networks and mass media interact to facilitate or hinder the emergence of large-scale spirals of silence. The simulation results show that the spiral of silence in a networked environment may be locally observable, but not likely on a global scale—unless the opinion representation of mass media becomes extremely homogeneous, individuals are hyperconnected, or both, the majority-minority opinion gap found locally seldom escalates to the global silence of the minority.

Keywords

social media, social networks, public opinion formation, mass media

The image of public opinion has long been described in a polarized fashion, as either a manifestation of mass media influence (Lippmann, 1922) or a mere aggregate of "individual, personally derived opinions" (Back, 1988, p. 279). This oscillation between opposites is, however, increasingly inappropriate as the interpersonal realms

[1]Hanyang University, Seoul, South Korea

Corresponding Author:
Dongyoung Sohn, Professor, Department of Media & Communication, Hanyang University, 222 Wangsimni-ro, Seongdong-gu, Seoul 04763, South Korea.
Email: dysohn@hanyang.ac.kr

of individuals and the mass media, such as traditional news media, become more intertwined than ever due to the proliferation of social media. The advent of such a complex, networked communication environment redraws our attention to the very nature and processes of public opinion—how social networks of various types facilitate or impede the influence process of mass media[1] (Chaffee, 1982; Hoffman, Glynn, Huge, Sietman, & Thomson, 2007; Southwell & Yzer, 2007). Of particular relevance to this issue among conventional communication theories is the *Spiral of Silence* (Noelle-Neumann, 1974).

The spiral of silence theory posits that individuals tend to avoid voicing a minority opinion publicly, due primarily to a fear of isolation (Neuwirth, Frederick, & Mayo, 2007), which propels "a self-reinforcing spiral of silence" (Lang & Lang, 2012, p. 370). Although criticized for its undue emphasis on fear of isolation (Lasorsa, 1991) or being an oversimplified account of public opinion processes (Katz & Fialkoff, 2017; Scheufele & Moy, 2000), research efforts have been persistently devoted to testing its major theoretical claims, particularly whether people whose opinions appear in the minority do indeed tend to remain silent (for a review, see Glynn & Huge, 2014; Matthes, Knoll, & Sikorski, 2018; Scheufele, 2008; Shanahan, Glynn, & Hayes, 2007). Confirming the psychological tendency of avoiding social awkwardness or sanctions alone, however, cannot be a sufficient explanation for the spiral of silence, which is essentially a dynamic social process that emerges from the efforts of individuals monitoring *opinion climates* across contexts and times (Matthes, 2015; Sohn & Geidner, 2016).

Scholars have long noted that people acquire information regarding opinion climates not just from the mass media but also from reference groups or *social neighbors* (Glynn & Park, 1997; Hoffman, 2013; Hoffman et al., 2007; Mutz & Martin, 2001; Oshagan, 1997; Southwell & Yzer, 2007). In a social media environment where individuals' interpersonal networks are greatly expanded, the meaning of neighbors is no longer confined to a group of people geographically and socially proximate but includes a much wider range of individuals sharing less in common. This then raises the question of whether such an expansion of the social neighborhood would make the spiral of silence more (or less) likely. It has indeed been found that the larger, on average, the size of an individual's social network, the more likely spiraling might occur on a global scale (Sohn & Geidner, 2016). Some studies report that people are less willing to express their minority opinions in social media than in face-to-face settings (Gearhart & Zhang, 2015; Hampton et al., 2014).

If a large-scale spiral of silence should be more likely in an expanded communication network as found in social media, will it become even more likely if there were "a universally accessible information source or aggregator" (Sohn & Geidner, 2016, p. 39) similar to traditional news media? Perhaps due to this belief, the majority of prior studies have been heavily oriented toward mass media (e.g., McDonald, Glynn, Kim, & Ostman, 2001; Neuwirth et al., 2007; Noelle-Neumann, 1993), even equating the spiral of silence to a theory of media effects (McQuail, 2014; Scheufele, 2008). Slater (2007), however, pointed out that such strong media effects on the spiral of silence should be more observable in a *closed* system characterized by "a uniformly hostile media environment and a lack of competing alternative media" (p. 296). In an *open* system akin to contemporary society, in contrast, the opinions advocated by the mass media (*media opinions* hereafter) might not be *singular*, but *plural*, so that individuals are exposed to multiple sources of media providing inconsistent, often contradictory, viewpoints (Mutz & Martin, 2001). As media consonance is not a dichotomy, but on a continuum, of course, it is an open question how much consonance in media is required for a strong spiral effect to occur.

Furthermore, increased diversity of media opinions alone might not entirely negate the possibility of the spiral of silence. The influence of mass media, whether singular or plural, might sometimes be substituted or offset by an individual's social references. Studies have found that people often rely more on the opinions of their peers than the mass media to gauge the opinion climate (e.g., McDonald et al., 2001; Moy, Domke, & Stamm, 2001; Oshagan, 1997; Scheufele, Shanahan, & Lee, 2001). Interpersonal discussion has also been found to exert a greater influence on voter choice than the mass media (Beck, Dalton, Greene, & Huckfeldt, 2002). If individuals belong to a large social network that enables them to reach and interact with socially distant others, their opinions are more likely to eventually converge to the larger mainstream like downward spirals or opinion polarization despite being exposed to diversity in media opinions (Dvir-Gvirsman, Garrett & Tsfati, 2018; Knobloch-Westerwick & Johnson, 2014; Mutz, 2006; Song & Boomgaarden, 2017).

Such possibilities suggest that the unfolding dynamics of the spiral of silence in social media might be far more complex and unpredictable than previously thought, which requires examining how a number of individuals, locally connected and distributed globally, interact with their immediate social environments as well as diverse media opinions. However, it would be extremely cumbersome to do so within a traditional variable-based approach, as it is hard to track the complex social dynamics of numerous individuals over time (Axelrod, 1997; Macy & Willer, 2002; Miller & Page, 2007). An alternative computational method that provides a way to observe a large number of distributed actors' interactions over time in a simulated environment is agent-based modeling (ABM; Page, 2015; Smith & Conrey, 2007).[2] ABM is particularly suited for experimenting with a variety of statistical and topological distributions of agents and their characteristics from which various macroscopic patterns and regularities, such as public opinion, the spread of fads, or disease, emerge (Epstein, 2007). Using ABM, this study aims to explore various conditions under which social networks and mass media interact to facilitate or hinder the emergence of a large-scale spiral of silence.

Perspectives on the Interplay Between Social Networks and Mass Media

The idea that the influence of mass media might not always be direct but is somehow mitigated by interpersonal communication is not new but foundational to communication research. A classic, influential approach is to portray interpersonal communication as a *mediating* process for information originating from mass media, as exemplified in the *multistep flow of communication* (Katz & Lazarsfeld, 1955) and the *communication mediation model* (Shah et al., 2007). This *mediation* perspective has turned out to be particularly suitable for studying the contagion process as shown in the susceptible-infected-recovered (SIR) model (Kermack & McKendrick, 1927) or the diffusion of innovation (Rogers, 2003; Valente, 1995). From this perspective, extensive research efforts have been concentrated on describing the underlying connection structures (to determine the patterns of communication) as well as identifying influential players, namely, the *opinion leaders*.

The role of interpersonal communication can, however, go beyond that of an intermediate conduit because sometimes individuals actively engage by filtering information to deal with the cognitive load and/or social tension (Eveland, 2004; Hoffman et al., 2007).[3] Following Chaffee's (1982) seminal discussion, for example, Coleman (1993), using data from New York State residents, found that an individual's health-related risk judgments are influenced by interpersonal communication as well as the mass media, sometimes in a substitutive fashion. Druckman (2004) showed that interpersonal communication can prime alternative criteria for evaluating a focal issue, which might eventually undermine the influence of mass media. Furthermore, it is suggested that the way an individual processes media-based information depends on his or her motivation and prior knowledge structures, which have been developed through interpersonal conversations (Hardy & Scheufele, 2005). In a similar vein, Lee (2009) found that the influence of mass media on health-related behaviors was greater for those engaging less in interpersonal conversations.

Such a filtering or moderation process is not limited to the psychological dimension. In studies of social networks, Granovetter (1973) theorized that the stronger the social ties, the more likely a network becomes closed (i.e., triadic closure) or clustered (i.e., a person's two close friends are likely to be friends themselves). In turn, this implies that individuals in a highly clustered network are likely to be strongly tied to one another, leading to sharing similar information and opinions (Burt, 1995). In the *reinforcing spirals model* (RSM; Slater, 2007), it was also proposed that individuals in a closed community or network are more likely to selectively attend to messages and/or media outlets congruent to their communal identity. Consistent with these theoretical propositions, resistance to persuasion was indeed found to be greater when the members of a network hold congruent rather than incongruent prior attitudes (Neiheisel & Niebler, 2015; Visser & Mirabile, 2004). In a similar vein, local network density or clustering in social media was found to partly determine how far cross-ideological messages could be diffused (Liang, 2018).

Overall, this suggests that the influence of mass media might partly be a function of the extent to which the individuals in a network are internally clustered: People in highly clustered networks are likely to develop mutually congruent attitudes as they are insulated from outside influences like mass media. In contrast, membership in less clustered networks where few closed triads exist means that individuals are likely to be connected with socially distant others, thereby facilitating exposure to novel, media-based information. This might particularly be the case when the sizes of interpersonal networks increase as in social media because larger networks are likely to contain weaker ties (Eveland, Hutchens, & Morey, 2013) and hence more divergent views (Huckfeldt, Mendez, & Osborn, 2004).

Mass Media Influence on Opinion Climate Perceptions

Evidently missing in the discussion thus far is the very component or process to be moderated by social networks—how mass media affect an individual's opinion climate perceptions, namely, *quasi-statistical senses* (Noelle-Neumann, 1974). It has long been acknowledged in psychology that people perceive their social environments through schematic categorization (e.g., good vs. evil, us vs. them) to reduce complexity in reality (Fiske & Taylor, 2013). Quasi-statistical senses of public opinion are largely equivalent to individuals' proportional comparisons of such schematic categories (e.g., majority vs. minority), which are not always reflexive of the actual distribution of opinions in a larger collective (Scheufele & Moy, 2000). The gap between the two (i.e., error in perception), which occurs due primarily to individuals' cognitive biases in probabilistic judgment (Kahneman & Tversky, 1979) as well as bounded scopes of opinion monitoring (Sohn & Geidner, 2016), turns out a crucial determinant of the spiral of silence phenomenon.

With small errors, meaning that individuals' perception of whether they are in the minority is largely accurate, the spiral of silence likely manifests itself; otherwise, different patterns including *dual climates of opinions* (Noelle-Neumann, 1993) might arise. The error-proneness of quasi-statistical senses may be correlated with varying conceptions of *generalized others* (Glynn & Park, 1997), largely formed at the intersection of three classes of factors (Hoffman et al., 2007; Price & Roberts, 1987). These factors are the observer's intrapersonal states, including a prior attitude for an issue of controversy and the fear of isolation (Hayes, Matthes, & Eveland, 2013); reference groups/social networks (Dalisay, Hmielowski, Kushin, & Yamamoto, 2012; Glynn & Park, 1997); and exposure to media outlets (Hoffman, 2013).

Conceivably, individual attitudes and the local opinion climates encountered through social networks might not always coincide with what is represented in mass media (Lang & Lang, 2012; Noelle-Neumann, 1993). If people are exposed to attitudinally congruent media, they may take this mistakenly as an indicator that there are more individuals holding similar opinions outside of a local network. This *false consensus* effect (Ross, Greene, & House, 1977), a phenomenon where people tend to wrongly believe the majority agrees with them when the majority actually disagrees, has been widely documented in the literature. That is, being exposed to attitudinally congruent media might lead to "a false impression of public consensus" (Dvir-Gvirsman et al., 2018, p. 115), making individuals more resistant to social pressure, especially when they are a local minority. As such, overestimating the congruent proportion in generalized others might in turn elevate their likelihood to speak out (Dvir-Gvirsman et al., 2018; Wang, Guo, & Shen, 2011).

If people are exposed to attitudinally incongruent media, in contrast, they might think that there are fewer people with congruent opinions outside of their local network, causing them to underestimate its proportion in the opinion climate. This phenomenon has also been documented as *pluralistic ignorance* (Centola, Willer, & Macy, 2005; Katz & Allport, 1931), meaning that people tend to wrongly believe that the majority disapproves of their private opinions when the majority actually supports them. This is in contravention to the false consensus effect where people incorrectly assume that the majority supports a norm or opinion that they privately disagree with when it is not actually the case. In other words, being exposed to attitudinally incongruent media might cause individuals to underestimate the proportion of congruent people in the general population, lowering their likelihood of speaking out even when they are a local majority (Wojcieszak, 2008; Wojcieszak & Rojas, 2011).

According to the previous findings mentioned above, the effects of attitude-media congruency may, in turn, vary depending on an individual's degree of attachment to or embeddedness into local networks. That is, people surrounded by highly clustered networks (i.e., close-knit networks) may tend to be influenced less by media-based information regardless of its attitude congruency, and instead more by information with local origins with regard to judging the opinion climate (McDonald et al., 2001; Moy et al., 2001). In contrast, those in networks with less clustering (i.e., open-radial networks) may be more relatively attuned to information originating from non-interpersonal sources like mass media. Hence, we may postulate that the degree of network clustering is *inversely* related to the decision weight put on media-based information.

In summary, the congruency between individual attitudes and media opinion may determine the *direction* of media influence—whether the media undermines or reinforces perception of the opinion climate. In turn, the degree of network clustering may affect the *intensity* of media influence, the extent to which the media discounts or augments one's perception of the local opinion climate. Taken together, we may postulate that the unfolding dynamics of the spiral of silence depend on the types of opinion climate that individuals encounter, which is the joint function of how the social networks surrounding individuals and media opinions are distributed in a social system. Given the discussion thus far, the research questions are as follows:

Research question 1 (RQ1): What are the relationships between the structural properties of social networks and the likelihood of a spiral of silence?
Research question 2 (RQ2): How does the distribution of media opinions interact with social networks to differentiate the likelihood of a large-scale spiral of silence?

Model Development and Simulation Settings

A Model of Attitude Change and Opinion Expression

Unlike the *top-down* approach of abstracting attributes or characteristics in common as variables, ABM is characterized by a *bottom-up* approach that starts with setting up the rules individual actors follow to interact with others to examine what macroscopic patterns arise from micro-level interactions (Miller & Page, 2007; Page, 2015). Let us first start with modeling individual attitudes—what it consists of and how it changes. Imagine a society populated by N individuals who hold attitudes, denoted by A, toward a controversial issue, such as the legalization of same-sex marriage. Some may advocate it, whereas others oppose it with varying degrees of intensity. A person i's attitude is conceived as a product of two elements, valence (v_i) and confidence (c_i), where v_i is a dichotomous variable having either $+1$ or -1, and c_i is a continuous vector with real values in the range of [0, 1] (i.e., $A_i = v_i \cdot c_i$). That is, valence indicates the direction of the attitude, whereas confidence is a mathematical weight representing the attitude's intensity.

Attitudes are not formed in a social vacuum but subject to social influences including the attitudes of others. It has been widely documented that people observe what others say or do to form their attitudes for either informative or normative reasons or both (for a review, see Cialdini & Goldstein, 2004; Sassenberg & Jonas, 2007). Decades of persuasion research has also revealed that important psychological mechanisms, such as *reinforcement* and/or *dissonance reduction*, underlie attitude change (Visser & Cooper, 2007). Depending on one's prior attitude, the opinions of others may be taken as a reinforcement or cause discomfort, making the attitude confidence change accordingly. This suggests that one's present attitude might be modeled as an *iterated function* of two major components, a prior attitude and external social influences at the moment. Thus, a person i's attitude at time t can be expressed as follows:

$$A_i(t) = f\left\{A_i(t-1), O_i \cdot \Delta I_i(t)\right\} \tag{1}$$

where $A_i(t)$ denotes i's attitude at time t, O_i stands for i's direction of attitude (i.e., $+1$ or -1), such as either agreeing or disagreeing with legalizing abortion, and $\Delta I_i(t)$ denotes the differential impact of the local social environment between t and $t-1$ (i.e., $\Delta I_i(t) = I_i(t) - I_i(t-1)$). Here, it is modeled as an additive process, such that the differential impact of the opinion climate at t (i.e., $\Delta I_i(t)$) is summed to a prior attitude at $t-1$, with the assumption that one's prior attitude is not correlated with the impact of the opinion climates encountered.[4] If the direction of the differential opinion climate impact is consistent with one's opinion (i.e., both are positive or negative), this view will get stronger in an absolute sense; otherwise, it will get weaker.

The opinion climate impact I is modeled as the logistic function of the proportional difference between the attitudinally congruent and incongruent opinions observed in a local social network, denoted by δ (for similar examples, see Ross et al., 2019; Sohn & Geidner, 2016; Song & Boomgaarden, 2017). Logistic function assumes non-monotonic change, in which the initial high rate of change gradually decreases to approach the limit asymptotically, which is in line with prior research findings that it requires more for the opinion climate to further influence those already affected (Matthes, Morrison, & Schemer, 2010; Nowak, Szamrej, & Latane, 1990). To delimit the opinion climate impact I in the range of [0, 1] to contain attitudes within a predetermined range, [−2, 2], throughout the simulation, the original logistic model was rearranged as follows[5]:

$$I_i(t) = l * \left(1 + e^{-\delta_i(t)}\right)^{-1} - \frac{l}{2} \tag{2}$$

If the opinions congruent and incongruent in the local networks have equal proportions (i.e., 50:50), δ becomes 0. Therefore, no further change is made to attitudes; otherwise, it deviates from 0.[6] Note that people respond to incremental changes in social environments as opposed to the environment as a whole. If a local opinion climate remains unchanged over time, there is no further change to attitudes. Once the impact reaches its maximum, no further increase will be made as only the differential impact is added to the running total of a person's attitude. Finally, the propensity to express opinions should differ across individuals—some might readily speak out, whereas others do more self-censoring (Hayes, Glynn, & Shanahan, 2005). Following Sohn and Geidner (2016), each individual is assumed to have a constant threshold for expressing own opinion, uniformly distributed, $\varphi \sim U(0,2)$.[7] Thus, a person expresses his or her own opinion outward if the attitude's absolute value exceeds own expression threshold as follows:

$$Pr(\text{expression})_i = \begin{cases} 1, & \text{if } |A_i(t)| > \varphi_i \\ 0, & \text{if } |A_i(t)| \le \varphi_i \end{cases} \tag{3}$$

Modeling Media Influence on Opinion Climate Perception

Besides the influence of local social networks, we also need to consider how mass media interact with social networks to influence individual attitudes. Here, we limit our discussion to the influence of mass media on an individual's quasi-statistical senses or perceptions of the opinion climates. The proportional difference between the attitudinally congruent and incongruent other neighbors in a person *i*'s local social network at time *t* is expressed as follows:

$$\delta_i(t) = \begin{cases} \dfrac{n_s(t) \cdot \omega - n_o(t)}{n_s(t) \cdot \omega + n_o(t)}, & \text{if } n_s(t) + n_o(t) > 0 \\ 0, & \text{if } n_s(t) + n_o(t) = 0 \end{cases} \tag{4}$$

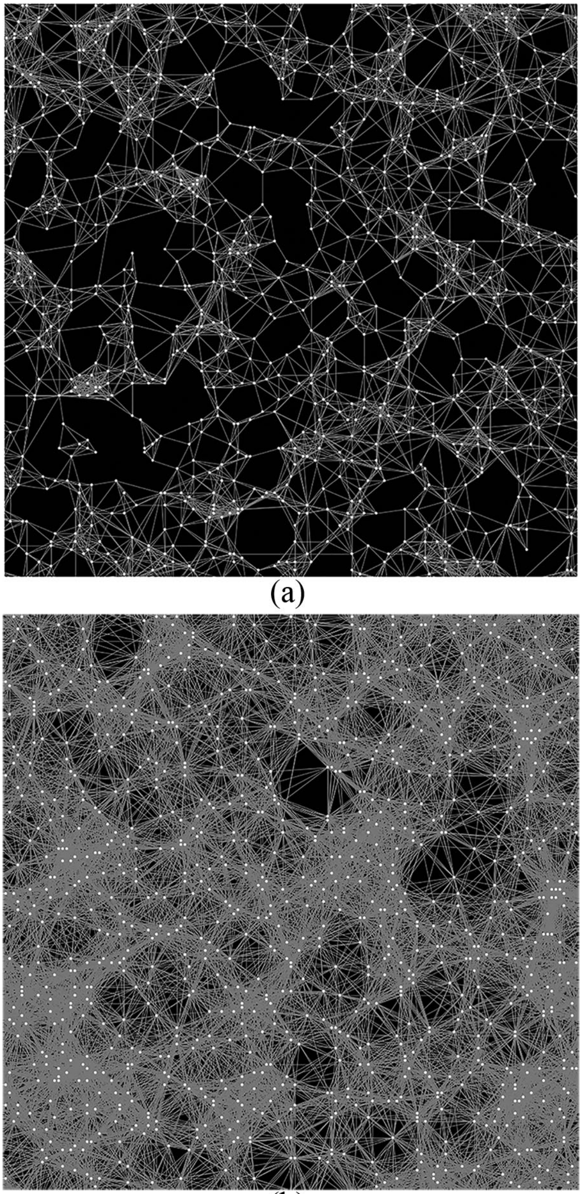
where $n_s(t)$ and $n_o(t)$ denote, respectively, the number of congruent and incongruent opinions observed in a local social network at t, and ω is the weight reflecting media influence. As the susceptibility to media influence may vary across individuals and situations, each person is assumed to have a degree of media dependency, m, in the range of [0, 1]. Therefore, the dependency on a local opinion climate is $1-m$. If a person's m is 0.7 (i.e., 70% dependence on media), for example, his or her local dependency is 0.3. Then, the media influence weight ω is modeled to vary depending on the level of media dependency: For congruent media exposure, the media weight is equal to or greater than 1, inflating the proportion of congruent others up to two times depending on the degree of media dependency (i.e., $\omega = 1 + m$), whereas for incongruent media exposure, the media weight is equal to the local dependency (i.e., $\omega = 1 - m$), depreciating the proportion of congruent others.

As discussed before, the degree of embeddedness into local social networks can affect a person's media dependency. A person belonging to a network in which members are strongly tied to one another might have a greater dependency on the local opinion climate by relying less on media-based information. This possibility suggests that m might change depending on the properties of the social networks that individuals are a part of. Among the many indicators of the structural properties, the local clustering coefficient, $C_L \in [0,1]$, is known to be positively correlated with tie strength (Granovetter, 1973; Watts & Strogatz, 1998) and a tightly knit group, often regarded as "closed" in contrast to "open/radial" networks (Valente, 1995). Thus, individuals in closed networks might be assumed to be relatively less dependent on media, whereas those in open or radial networks are more receptive to media-based information. That is, a person's media dependency is inversely related to the degree to which a network is locally clustered, such that each person's media dependency m can be expressed as $1 - C_L$, meaning that the more locally clustered, the smaller m gets. Therefore, the media influence weight ω comes close to 1.

Simulation Settings

Studies have found that a variety of networks including the Internet, scholarly collaboration networks, and even metabolic networks follow a particular distribution of connections, often referred to as *long-tail* or *scale-free* distribution (Watts, 2004). A network of people one has known and been in touch with for a long period of time is likely to show a highly skewed, scale-free like distribution (Newman, Strogatz, & Watts, 2001). This, however, might not be the case for the *regular networks* we see around, which normally consist of family members, friends, colleagues, and neighbors who can provide help and support. Even if social media has generally expanded the range of interpersonal reach, studies show that the estimated sizes of regular networks range from 10 to 60, typically around 12 to 20, with people discussing important matters with less than 10 others (Rolfe, 2014). As not all in social networks express opinions all the time, the opinion climates one normally encounters are likely to be much smaller than the networks themselves. The degree of distribution for such regular networks, in general, is found to be well approximated by a slightly right-skewed normal, rather than exponential, distribution (Newman et al., 2001; Rolfe, 2014).[8]

Hamill and Gilbert (2009, 2010) suggested a procedure to create networks that better approximate such regular social environments for ABM. First, a person's range of *social reach* is defined as the circular area with the radius p given, and then individuals are, within their social reach, allowed to tie only with others whose social reach is greater than or equal to their own (Figure 1). That is, only two individuals who can *reciprocate* are connected, the degree of which is well approximated with a Poisson distribution (Hermann, Bathélemy, & Provero, 2003). Then, a portion (e.g., 20%) of the population is assigned a larger social reach than the rest to make the distribution slightly right-skewed as found in prior studies (Newman et al., 2001). Table 1 shows that the networks generated as such have the known properties of regular social networks, including average sizes of around 13 to 60, relatively lower network density,



(a)

(b)

Figure 1. Examples of a simulated network: (a)social reach = 8 (mean network size = 13.38) and (b) social reach = 16 (mean network size = 46.26).

Table 1. Social Reach and the Properties of Networks Generated.

Social reach	Network size (*SD*)	Network density (%)	Global clustering (%)	Average path length
8	13.38 (0.16)	0.67	51.2	10
10	20.02 (0.19)	1.0	53.4	5.13
12	27.41 (0.23)	1.37	54.6	4.5
14	36.36 (0.26)	1.82	55.5	4.04
16	46.26 (0.30)	2.32	56.0	3.66
18	57.34 (0.32)	2.87	56.4	3.35
20	69.91 (0.36)	3.50	56.7	3.1

Note. The numbers reported are the averages from 50 replications of the respective level of social reach.

shorter path length (i.e., a small-world effect), and higher clustering than others (Hamill & Gilbert, 2009; Rolfe, 2014).

Social networks are not static but change in size and composition over time (Hamill & Gilbert, 2010; Lazer, Rubineau, Chetkovich, Katz, & Neblo, 2010). Some drift away, whereas others join in. To incorporate this possibility, namely, *social shifters*, a randomly chosen 5% of the population is allowed to move in space (i.e., choose a random direction of 360° and move a step; Hamill & Gilbert, 2010). Besides social networks, mass media in current simulations are modeled as an environmental variable using *patches*, building blocks of a two-dimensional grid. For each simulation run, a predetermined portion of patches over the grid (i.e., media coverage of the population) is randomly chosen so that the agents in those patches each time are exposed to media opinions. Furthermore, the diversity of media opinions was parameterized as a proportional ratio between two competing viewpoints, ranging from 100:0 (i.e., unanimity or maximal homogeneity) to 50:50 (i.e., equal split or maximal heterogeneity).

The simulation begins with individual agents (N = 1,000) distributed and networked over a 70 × 70, two-dimensional, unbounded grid constructed with a programmable environment for ABM, *NetLogo* version 6.0.4 (Wilensky, 1999).[9]

All agents with randomly assigned initial attitudes and the expression thresholds φ observe the opinion climates within their social networks and media opinions, if any, and decide whether to express own opinions outward at each point in time. This procedure is repeated 200 times for each simulation run. Each simulation run is again replicated 50 times for each combination of parameters (i.e., Social Reach × Media Coverage × Media Opinion Diversity) by assigning different random seeds to account for the stochastic nature of simulations.

Simulation Results

A *global sensitivity analysis* (Thiele, Kurth, & Grimm, 2014) was first conducted to check the sensitivity of simulation outputs to changes not only in the three main input

Table 2. Global Sensitivity Analysis Results.

	Estimate	β	*SE*	*t* value
Social reach (SR)	3.17	0.54	1.15	2.76*
Media coverage (MC)	−0.06	−0.02	0.98	0.06
Media opinion ratio (MR)	0.32	0.00	11.73	0.03
Prop. connectors (PC)	0.44	0.10	0.75	0.59
Social shift (SS)	0.02	0.03	0.06	0.37
SR × MC	0.14	0.02	0.05	2.56*
MC × MR	0.27	0.09	0.55	0.49
SR × MR	0.70	0.00	0.56	1.26
MC × SS	−0.00	−0.00	0.00	0.55
SR × SS	−0.00	−0.00	0.00	0.15
MR × PC	−0.07	−0.01	0.42	0.17
MC × PC	0.02	0.01	0.04	0.58
SR × PC	−0.01	−0.00	0.03	0.22
SR × MC × MR	−0.10	−0.02	0.03	3.59**
SR × MC × SS	0.00	0.00	0.00	1.62
MC × MR × PC	−0.02	−0.00	0.02	1.09
SR × MC × PC	0.00	0.00	0.00	1.39

Note. The global sensitivity analysis shown above was conducted through a linear regression procedure, which tests only how sensitive the focal dependent variable (e.g., averaged majority-minority opinion gap) is to the change (e.g., ±50%) in the values of the independent variables and their interactions.
*$p < .05$. **$p < .01$; Multiple $R^2 = .98$, Adjusted $R^2 = .96$; $F(17, 14) = 50.13$, $p < .000$.

parameters but also two additional parameters: the proportions of *social shifters* (i.e., agents allowed to move on the grid) and *connectors* (i.e., agents with greater ranges of social reach). The values of the parameters were varied ±50% of the criterion values (e.g., 5% social shifters and 20% connectors), yielding 32 conditions (i.e., 2^k conditions for k parameters) for comparison. Table 2 summarizes the results. All the main and interaction effects involving the proportions of social shifters and connectors on the outputs were statistically insignificant, meaning the simulations were robust or relatively insensitive to changes in the parameters. Among the three main inputs, only the range of social reach had significant main effects, $B = 3.17(1.15), p < .05$. Although no main effects of media coverage and media opinion diversity were found, their interactions with social reach were statistically significant for the two-way interaction effects between social reach and media coverage, $B = 0.14(.05), p < .05$, and three-way interactions between all of them, $B = -0.10(.03), p < .01$. In accordance with the initial expectations, the sensitivity analysis results affirm that the simulation outputs varied relatively more by the three main input parameters than the others.

To examine the relationships further, four prototypical conditions were compared as summarized in Table 3. The "baseline" model, in which only the network size was varied with no mass media influence, appears to have largely replicated the previously found patterns in Sohn and Geidner (2016) (see Figure 2).[10] The growth of an opinion

Table 3. Summary of the Simulation Models.

	Baseline	Model I	Model II	Model III
Population	1,000	1,000	1,000	1,000
Simulation length (i.e., time steps)	200	200	200	200
Range of social reach	8-20	8-20	8-20	8-20
Social shift	5%	5%	5%	5%
Mass media influence	None	Present	Present	Present
Media coverage	0%	0%-30%	0%-30%	0%-30%
Media opinion diversity	N/A	Unanimous (100:0)	Uneven (70:30)	Split (50:50)

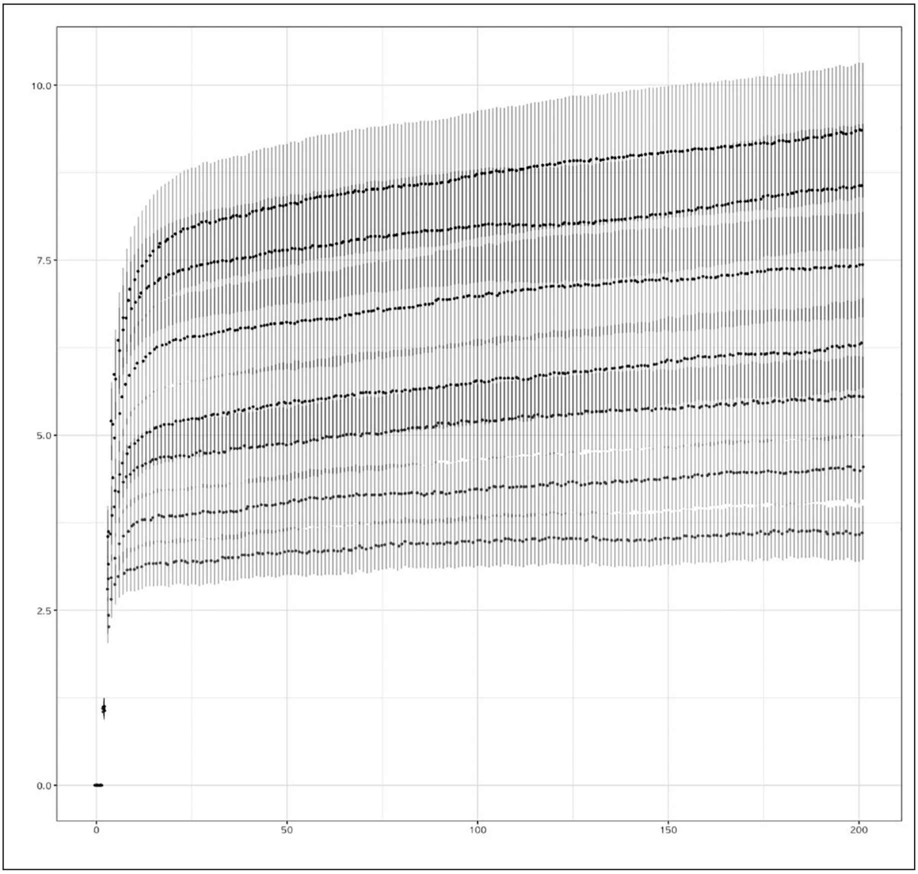


Figure 2. Temporal development of the majority-minority opinion gap (by social reach with no media exposure).

Note. The dark solid dots represent the averaged majority-minority opinion gap across times. The light gray areas are the standard errors. The trend lines show the opinion gap development patterns from social reach = 8 at the bottom through 20 at the top with an increment of 2.

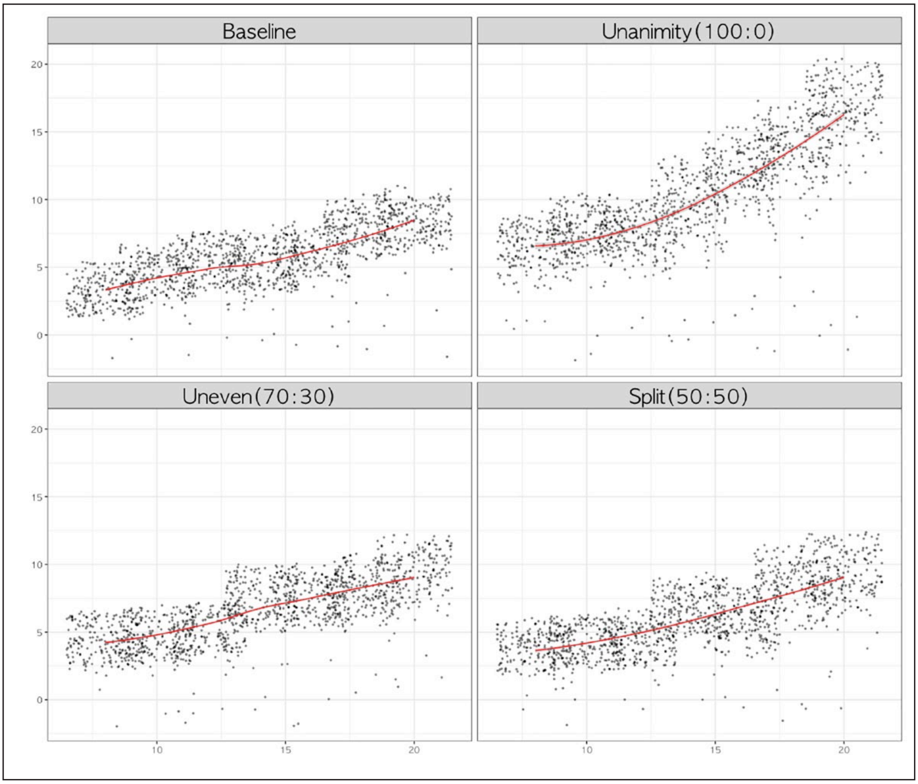


Figure 3. Opinion gap growth patterns: Social Reach × Media Coverage × Media Opinion Diversity.

Note. This graph shows the scatterplots and trend lines between the social reach and majority-minority opinion gap for four conditions in media opinion diversity. From the top left, baseline (i.e., no media influence), Model I (i.e., unanimity in media opinions), Model II (i.e., uneven opinion ratios), and Model III (i.e., equal splits).

gap follows a concave pattern with a decreasing marginal return as if there were upper limits. In Model I, the mass media representing only one side of the competing opinions unanimously were introduced, meaning that everyone whose opinion is different from the opinion advocated by the media would never encounter attitudinally congruent ones. In Model II, there is a clear majority (e.g., 70:30), meaning that individuals are exposed to either side of the media opinion 70% and 30% of the time. In Model III, media opinions were split into equal halves (i.e., 50:50), letting individuals be exposed equally to both attitudinally congruent and incongruent media. Figure 3 illustrates the scatterplots and trend lines for the baseline (with no media) and three models (with 30% media coverage).

The trend line in the baseline model shows a relatively moderate increase in the opinion gap along the horizontal axis (i.e., the range of social reach). When the media advocating one side of the opinions were introduced unilaterally (i.e., Model I), interestingly, the opinion gap became larger even when the social networks were quite small and constrained. The gap also became larger at an accelerating rate when the networks increased in size and were thus more clustered. This implies, as speculated in prior research (Noelle-Neumann, 1993; Scheufele, 2008; Sohn & Geidner, 2016), that the presence of mass media with a unanimous voice might make the spiral of silence relatively more probable, not only when the social networks were smaller/fragmented but also even when they were larger and more clustered.

In modern democratic societies, however, we normally see that multiple media illuminate differently, sometimes in a directly competitive manner, the facets of an identical fact or event of interest depending on the frames or ideologies they embrace. What if the media were split exactly in half for a controversial issue? The fourth graph in Figure 3 (bottom right) illustrates this scenario (Model III). When media were halved equally into two competing sides, the opinion gap turned out not to grow much as individuals' social networks were enlarged, like the baseline model with slightly more variability. This result should not be taken as too surprising, however, because polarization in media opinions might have led to canceling out the changes they caused in public opinion, almost nullifying the media influence.

The third graph of Figure 3 (bottom left), however, reveals an interesting result. What was originally expected from this scenario was the intermediate pattern somewhere between those of Models I and III. However, the outcomes did not seem to be very different from those of the baseline and Model III. Why should this be the case even when a clear majority of the media advocate one side of the opinions? Upon speculation, this might be partly because the gap in the proportion in this scenario (70 to 30 = 40%) was not large enough compared with that of Model I (i.e., a 100% difference). It implies the possibility that the effects of media opinion diversity on the spiral of silence may be *nonlinear*—the incremental effects may remain minimal unless the media were extremely one-sided (e.g., 100:0).

To examine this further, contour plots were drawn, illustrating the relationships among the three variables—social reach, media coverage, and the majority-minority opinion gap—on a two-dimensional plane across 11 different facets of the media opinion ratio (Figure 4). In a contour plot, a surface or region with the same color represents the same level of the dependent variable, here the opinion gap. The top left graph (i.e., the opinion ratio is ~100:0) shows that the colors of the curved regions get darker along both the horizontal and vertical axes, suggesting interactions between the media coverage and the degree of social reach. This illustrates that, like Figure 3, the majority-minority opinion gap may become greater as an individual's social networks are enlarged, which would increase even further as the coverage of media with a unanimous voice increases.

In the second graph at the top (i.e., the opinion ratio is ~91:9), the pattern still looks like the first one. It dissipates fast as the media opinion ratio deviates from the extreme state. Even in the third one at the top row (i.e., the opinion ratio is ~83:17), the colored

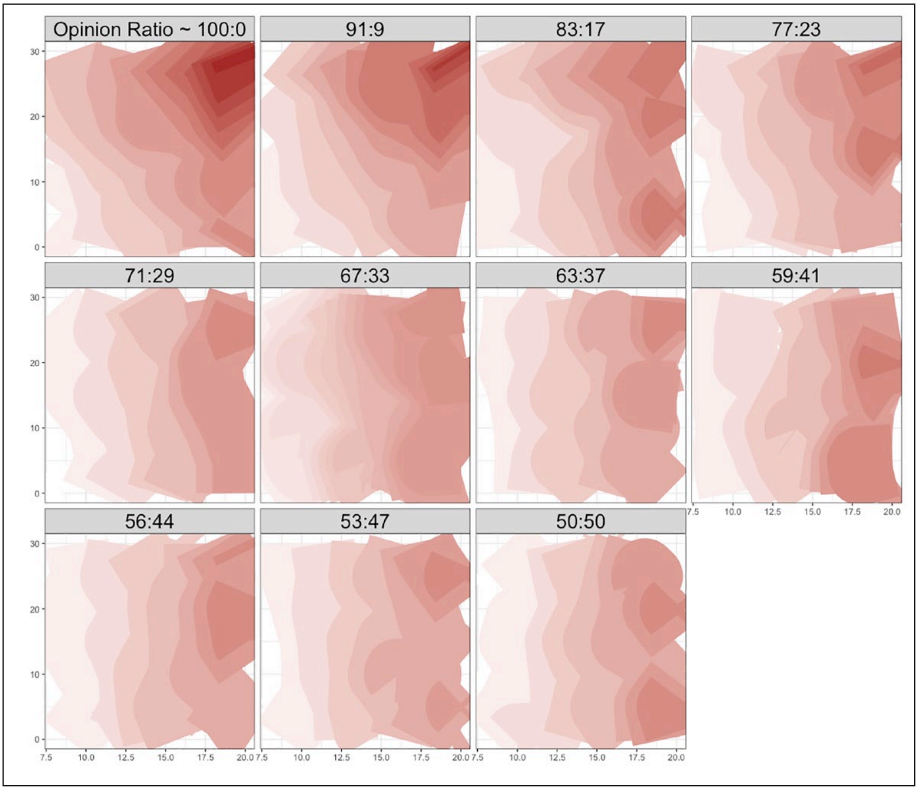


Figure 4. Contour plot (Social Reach × Media Coverage).

Note. This is a contour plot showing the relationships between the three variables (i.e., x = social reach, y = media coverage, z = the average majority-minority opinion gap as a percentage of the population) on a two-dimensional plane. The darker the color gradient, the greater the majority-minority opinion gap. Each facet shows the relationship across the 11 different conditions of media opinion diversity, starting from complete unanimity (upper left) through a complete split (bottom right).

regions start to be aligned vertically, and the darker regions are concentrated to the right, indicating that an opinion gap changes only according to the change in the degree of social reach, not the coverage of media (i.e., the y axis). This pattern becomes clearer and continues as the media opinion ratio moves close to the equal split condition. This nonlinear pattern seems to support previous speculation, which suggests that the effects of media on the spiral of silence may almost disappear unless their extremely one-sided representation of opinions is maintained. Mass media may play a critical role in the unfolding dynamics of the spiral of silence particularly when their voices are unanimous or extremely homogeneous. This might, however, not be the case if there are alternative, competing media voices even if relatively few could hear them. This affirms the view that "spirals of silence do occur but only when the circumstances are conducive" (Lang & Lang, 2012, p. 373).

Discussion and Implications

The current simulation results illuminate the view that mass media and social networks interact in a complementary way: A consonant media environment might propel the process of the spiral of silence when individuals are confined to relatively smaller networks as duly noted in the previous literature (Moy & Hussain, 2014; Slater, 2007), or enlarging interpersonal networks, via social media for example, that may compensate for the nonexistence of such a consonant media influence (Sohn & Geidner, 2016). Interestingly, even when the great majority of media (e.g., ≥80%) supported one side of the competing opinions, the mass media seldom became the driving force of the spiral of silence. This means that whenever there is an alternative voice representing a minority viewpoint, the overall impact of mass media on the spiral of silence process is substantially diminished, almost to none.

This has a striking resemblance to the patterns found in Asch's (1955) classic conformity experiments where the presence of a single dissenter almost nullifies the majority influence. Although Asch's finding is mostly interpreted as resulting from the dissipation of group normative pressure (Noelle-Neumann, 1993), no normative component with respect to mass media was incorporated in the current simulations. Then, why should there be such parallel findings between laboratory experiments and computer simulations? This may appear coincidental but reminds us of an important fact—the opinion distributions, whether in a laboratory or simulated society, are in essence the *aggregate patterns of information*. As Schelling (1978) wrote, "People are responding to an environment . . ., which consists of people responding to an environment of people's responses" (p. 14). In such arrays of distributed interactions, what people encounter is not just normative pressures, but the stochastic distribution of information arising from the choices of others.

With no consideration of a normative component, the rapid, nonlinear change in media influence may be explained using the concept of *information entropy*, which refers to the degree of uncertainty resulting from the stochastic nature of the environment (Shannon, 1948). Information entropy is formally expressed as follows:

$$H = -K\sum_{i=1}^{n} p_i \log_2 p_i \tag{5}$$

where p_i is the probability of an outcome i, and K is the constant reflecting the characteristics of a system of interest. The media exposures were modeled following a *Bernoulli* distribution in our simulations with only two possible outcomes, being exposed to either attitudinally congruent or incongruent media. Hence, the value of information entropy H varies between 0 and 1 (i.e., 0%-100%) depending on the probabilities of the two possible outcomes, p_1 (i.e., congruent media exposure) and p_2 (i.e., incongruent media exposure).

Table 4 shows the values of information entropy along the varying ratios of media opinions. As for the case with the unanimity in media opinions, for example, $H = 0$, meaning no uncertainty in the environment, while $H = 1$ for the case with the complete polarization of media opinions, indicating that the environment is maximally

Table 4. Media Opinion Diversity and Information Entropy.

Media opinion ratio (%)	Information entropy (H)	Difference (Δ)
100:0	0.0	—
91:9	0.44	+.44
83.3:16.7	0.6502	+.2102
77:23	0.7796	+.1294
71.4:28.6	0.8631	+.0835
66.6:33.4	0.9185	+.0554
62.5:37.5	0.9544	+.0359
58.8:41.2	0.9775	+.0231
55.5:44.5	0.9911	+.0136
52.6:47.4	0.998	+.0069
50:50	1.0	+.002

Note. The first column shows 11 conditions with varying ratios of the proportions of two competing opinions represented by the media. For example, the last one, 50:50, means that the media represent two competing stances with equal proportions, that is, a split situation. The second and third column, respectively, contains the entropy values of all conditions and pairwise differences.

uncertain, it is totally random whether to meet attitudinally congruent media or not. Note that information entropy dramatically jumps up from 0% to 44% when the media opinion ratio is 91:9, further to 65% when the ratio becomes 83.4:16.7, and afterward increases at a diminishing rate. This suggests that a slight deviation from the unanimity or extreme bias in the composition of media opinions, the presence of alternative media or voices, may introduce a substantial amount of uncertainty to the environment. This causes the rapid dissipation of media influence in the process of the spiral of silence.

Many prior studies of the spiral of silence have implicitly assumed that if it were empirically confirmed that people in a minority position do indeed remain silent due to a fear of isolation or ridicule, an initially small majority-minority gap would grow larger across times to become a global phenomenon (e.g., Hampton et al., 2014; Neuwirth et al., 2007). Perhaps this implicit conjecture has been why the spiral of silence has attracted so much attention. The simulation results, however, indicate that the silencing process formulated in the theory might be easily disrupted by the existence of some partisan media or whistleblowers. Note that this disruption may result from the probabilistic nature of information with no presumption of an avant-garde or hard-core nonconformist. Given the increasing diversity in the media environment, the spiral of silence might be locally observable, but highly unlikely to occur on a global scale. Unless the opinion representation of mass media becomes extremely homogeneous, individuals are hyperconnected, or both, the majority-minority opinion gap found locally can seldom escalate to the global silence of the minority.

We may ask whether the proliferation of social media we see today might have changed the situation. As shown in Figure 3, with the unanimity in the opinions represented by the media, the majority-minority gap can reach up to 15% to 20% of the entire population if the average sizes of an individual's social network are around 6% to 7% of the population (i.e., 60-70 out of 1,000); hence, the global clustering goes beyond 55% (more than 55% of connected triplets were closed triads).[11] Is this condition observable in the real world? Considering South Korea, the most wired nation in the world, the estimated number of Facebook users as of summer 2017 was around 14 million out of a population of 51 million, and individuals have on average approximately 150 to 200 friends, only about 0.001% of total Facebook users in the country, much smaller than those in the current simulations. Furthermore, the degree of global clustering of the Facebook network, though it might vary depending on estimation methods, is likely to range around 35% to 40%, much less than those shown here. This suggests that real-world networks in a social media environment seem far from the hyperconnected networks exemplified here, implying that a spiral of silence on a societal scale should be seen as a very rare phenomenon.

From a Metaphor to Modeling Organized Complexity

For decades, scholars have challenged Noelle-Neumann's thesis in many respects, especially the fear of isolation as the sole motivational mechanism (Lang & Lang, 2012; Lasorsa, 1991) and the oversimplified relations between quasi-statistical senses and opinion expression (Glynn & Park, 1997; Hayes et al., 2013; Scheufele & Moy, 2000). A growing suspicion is that the theory itself is largely untestable or non-falsifiable. Finding statistical evidence for some component propositions comprising the theory as done previously (see Matthes et al., 2018, for a meta-analytic review) is not equivalent to putting the theory itself to test. Checking all the nuts-and-bolts would not tell you if the car runs well—all you need to do is to drive it. In the contemporary media environment, which is increasingly more diverse than the traditional mass media the theory was intended to explain, it seems admittedly more like an amorphous metaphor for an extreme occasion than a scientific apparatus for explaining and predicting universal patterns (Moy & Hussain, 2014). Just as no separate theory is needed for a total solar eclipse, an unusual pattern arising from the orbital movement of the earth, moon, and sun, it may be time to bid farewell to the old theory (Katz & Fialkoff, 2017).

Note here that diversity and fragmentation are not synonyms, however. Increased diversity might not necessarily lead to a fragmented environment with maximal entropy. The rise of social media may, on the contrary, facilitate global assemblages of numerous local interactions from which a far greater range of macrosocial patterns might emerge (DeLanda, 2006). That is, public opinion in a networked environment can be reduced neither to an orderly pattern nor a complete disorder or randomness. In between lies a vast continent of *organized complexity* (Weaver, 1948). As "One molecule of water cannot be wet" (Page, 2015, p. 32), organized complex patterns cannot be inferred directly from the characteristics or states of their constituents. Rather, they grow out of a myriad of interactions among the constituents and their environments, in which final outcomes are contingent on prior outcomes along the way. Due to this *path* *dependency*, small changes in the initial conditions and/or along the process might lead to quite unexpected consequences.

More imperative than abandoning existing theories is, therefore, to find what could inherit their place (Cohen, 2017) by exploring the boundary conditions under which various macrosocial patterns arise. There is no way a single simulation study as exemplified here can achieve this goal, but the expanded application of simulation methods would enable communication scholars to actually run various models under a number of different conditions, allowing for fine-tuning of the parameters for theoretically interesting outcomes. The Nobel laureate Richard Feynman once said, "What I cannot create, I do not understand." Simulation methods will change the way social scientists build, test, and refine theoretical models. In so doing, the spiral of silence will eventually find its place, along many others, as a benchmark showcasing a class of possible consequences.

Limitations and Suggestions for Future Research

The simulations shown here, of course, are mere approximations of otherwise very complex realities. There are important factors that merit careful consideration in future research. In the current simulations, mass media were modeled external to social networks with no consideration of media type (e.g., print vs. broadcast), while in reality, exposure distributions may vary depending on different media types (Leckenby & Rice, 2013). There may also be significant variations in influence across media outlets—some may exert a far greater influence than others, as opinion leaders or central actors in networks have a disproportionate importance in consensus building. Considering this possibility, media outlets may alternatively be modeled as agents in networks (Ross et al., 2019). This approach may be better suited for the purpose of identifying influential players in the process of mediation and diffusion, whereas modeling media as external forces may be more appropriate for examining how an individual is jointly affected by the social neighbors as well as non-interpersonal sources of information.

Besides media exposure, the mechanism of *social selection* or *homophily* may also work in the process of social networking such that individuals selectively form ties with like-minded others, while disconnecting with those with different perspectives (McPherson, Smith-Lovin, & Cook, 2001). As this process goes on, the social networks of individuals may become increasingly homogeneous attitudinally, which would give rise to global network polarization. Although such selective networking was found to be less prevalent than the conformity process, especially in the context of political discussion (Lazer et al., 2010), this possibility certainly merits further systematic investigation, because the response of individuals to opinion climates may differ between true interpersonal and computer-mediated social networks like those in social media.[12] For instance, if individuals are very active with such selective networking online, those in a minority situation might want to change local opinion climates by altering the connections, which would impede the cascades of global silencing.

Furthermore, an individual's degree of media dependency was simplified merely by being inversely related to their local network clustering, which may vary depending on other network properties such as centrality and homophily as well as psychological characteristics (Neiheisel & Niebler, 2015; Visser & Mirabile, 2004). A related issue is that the chance to be exposed to mass media, the frequency of interpersonal discussion, and the likelihood of speaking out may be correlated with the moral or value-laden components of issues (Noelle-Neumann, 1993)[13] and an individual's attitude intensity (Cho, Ahmed, Keum, Choi, & Lee, 2018; Hoffman et al., 2007; Matthes et al., 2010). It is possible that people with strong attitudes on some moral issues may become so loyal to attitude-congruent sources of opinions that they become much less sensitive to alternative voices in media or their local social networks. To construct a more externally valid simulation for future research, more empirical studies would be needed to carefully parse out the factors affecting how people depend on both local and mass-mediated information.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (Ministry of Science and ICT) (No.2018R1A5A7059549).

Notes

1. Note here for clarification that the term "mass media" is used to refer only to a broad class of non-interpersonal channels of information, such as traditional news media, distinguished from the interpersonal networks of individuals. Although social media may often be thought of as mass-mediated channels of communication, here social media is viewed only as the expanded version of interpersonal networks.
2. In agent-based modeling (ABM), *agents* refer to autonomous actors or entities that can represent a variety of things from molecules, organisms, human actors, and organizations to much larger entities like nation states. Distributed in a topological space like geographic regions or networks, agents interact following some given rules with their own local (and possibly global) environments from which various macro-level patterns arise. Local environments individuals face should vary depending on their locations in the topological space given and their ranges/scopes of interaction. In a grid-like space or network, for example, each agent might have its own local environment consisting of neighbors nearby or in adjacent networks.
3. It should be noted here that the mediation and moderation mechanisms are not directly competitive, but rather have a complementary relationship. Thus, attending to the moderation/filtering processes by no means implies that one should abandon the mediation perspective—with no intermediate conduits assumed, no filtering would ever be possible. The difference lies mainly in what to emphasize. The mediation perspective puts emphasis on

how information is diffused and who plays important roles in the processes, whereas with the moderation perspective, one tends to focus on how individuals weigh interpersonal and mass-mediated information sources.

4. In a multiplicative model in which the opinion impact is multiplied to the prior attitude, the differential impact on a person whose prior attitude score is close to 0 would be much smaller than one with a higher prior attitude with an absolute value.
5. For the current study, the normalizing constant l is set to 2 so that the maximum impact would lead attitudes close to ± 2.
6. Here the range of δ, originally between −1 and 1, was adjusted to be $-5 \le \delta \le 5$ so that it could approximately be within the predetermined range. If $\delta > 0$, the impact of the opinion climate increases the absolute value of the attitude (i.e., $|A_i|$), whereas it decreases the attitude if $\delta < 0$. If $\delta = 0$, the impact becomes 0.
7. The expression threshold (ϕ) refers to a person's minimum degree of attitude intensity or confidence, necessary to express his or her opinion outward (Sohn & Geidner, 2016). With the same degree of confidence, some with lower expression thresholds would readily speak out, whereas those with higher ones would not. In reality, expression thresholds may follow a normal rather than uniform distribution that tends to inflate the portions of those with extreme values. Due to the paucity of relevant empirical evidence, here, a uniform distribution was assumed to serve as the baseline condition for further research.
8. The degree distribution of networks has been found to be better represented by an exponential function, especially when the costs associated with maintaining the relations are low (Newman et al., 2001).
9. Thus, 1,000 agents are distributed over 19,881 patches, making the population density around 2%.
10. The gap was widened up to around 10% of the population, meaning the majority-minority difference among the opinions expressed was as large as one tenth of the population when the mean network size or average degree reached around 60.
11. The global clustering coefficient (C_G) is the proportion of closed triads or triplets among all the connected triplets existing in a network (Newmann, 2010). The degree of local clustering tends to vary greatly when an individual's social reach is small, while its variance gets smaller as social reach increases (Hamill & Gilbert, 2009). This means that, as interpersonal networks become larger, the social networks of individuals are more likely to overlap with one another, increasing the degree of global clustering.
12. Although the silencing effects online were found not to be significantly different from those in the offline environment (Matthes et al., 2018), interpersonal networks can be qualitatively different in many respects from computer-mediated social networks like those in social media—in an offline environment, the relationships could be multiplex (e.g., friends and business partners, simultaneously), which might make the silencing effects stronger than with uniplex relationships (Gearhart & Zhang, 2015). In future research, more careful considerations of the online-offline differences would be in need.
13. Most prior empirical studies were done with respect to such controversial issues as affirmative action (Moy et al., 2001), abortion (Salmon & Neuwirth, 1990), or genetically modified food (GMO) foods (Scheufele et al., 2001), among many others. Due to the paucity of studies using uncontroversial issues, unfortunately, there are little empirical evidences regarding the effects of issue controversiality on the spiral of silence (Matthes et al., 2018). Although such an issue characteristic might be modeled in simulations as part of individuals' sensitivity/susceptibility to the opinion climate impact, more reliable empirical evidences would be needed to do so.

ORCID iD

Dongyoung Sohn https://orcid.org/0000-0001-5599-0054

References

Asch, S. E. (1955). Opinions and social pressure. *Scientific American*, *193*(5), 31-5.

Axelrod, R. (1997). *The complexity of cooperation*. Princeton, NJ: Princeton University Press.

Back, K. W. (1988). Metaphors for public opinion in literature. *Public Opinion Quarterly*, *52*, 278-288. doi:10.1207/s15327965pli0104_5

Beck, P. A., Dalton, R. J., Greene, S., & Huckfeldt, R. (2002). The social calculus of voting: Interpersonal, media, and organizational influences on presidential choices. *American Political Science Review*, *96*(1), 57-73. doi:10.1017/S000305540200423

Burt, R. S. (1995). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Centola, D., Willer, R., & Macy, M. (2005). The emperor's dilemma: A computational model of self-enforcing norms. *American Journal of Sociology*, *110*, 1009-1040. doi:10.1.1.399.6386

Chaffee, S. H. (1982). Mass media and interpersonal channels: Competitive, convergent, or complimentary? In G. Gumpert & R. Cathart (Eds.), *Inter/media: Interpersonal communication in a media world* (pp. 57-77). New York, NY: Oxford University Press.

Cho, J., Ahmed, S., Keum, H., Choi, Y. J., & Lee, J. H. (2018). Influencing myself: Self-reinforcement through online political expression. *Communication Research*, *45*, 83-111. doi:10.1177/0093650216644020

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*, 591-621. doi:10.1146/annurev.psych.55.090902.142015

Cohen, J. (2017). Is public opinion still a thing: A response to Katz's six concepts in search of retirement. *Annals of the International Communication Association*, *41*, 100-104. doi:10.1080/23808985.2017.1288552

Coleman, C. (1993). The influence of mass media and interpersonal communication on societal and personal risk judgments. *Communication Research*, *20*, 611-628. doi:10.1177/009365093020004006

Dalisay, F., Hmielowski, J. D., Kushin, M. J., & Yamamoto, M. (2012). Social capital and the spiral of silence. *International Journal of Public Opinion Research*, *24*, 325-345. doi:10.1177/009365093020004006

DeLanda, M. (2006). *A new philosophy of society: Assemblage theory and social complexity*. London, England: Bloomsbury.

Druckman, J. N. (2004). Priming the vote: Campaign effects in a U.S. Senate election. *Political Psychology*, *25*, 577-594. doi:10.1111/j.1467-9221.2004.00388.x

Dvir-Gvirsman, S., Garrett, R. K., & Tsfati, Y. (2018). Why do partisan audiences participate? Perceived public opinion as the mediating mechanism. *Communication Research*, *45*, 112-136. doi:10.1177/0093650215593145

Epstein, J. M. (2007). *Generative social science: Studies in agent-based computational modeling*. Princeton, NJ: Princeton University Press.

Eveland, W. P. (2004). The effect of political discussion in producing informed citizens: E roles of information, motivation, and elaboration. *Political Communication*, *21*, 177-193. doi:10.1080/10584600490443877

Eveland, W. P., Hutchens, M. J., & Morey, A. C. (2013). Political network size and its antecedents and consequences. *Political Communication*, *30*, 371-394. doi:10.1080/10584609.2012.737433

Fiske, S. T., & Taylor, S. E. (2013). *Social cognition: From brains to cultures*. New York, NY: SAGE.

Gearhart, S., & Zhang, W. (2015). "Was it something I said?" "No, it was something you posted!": A study of the spiral of silence theory in social media contexts. *Cyberpsychology, Behavior, and Social Networking*, *18*, 208-213. doi:10.1089/cyber.2014.0443

Glynn, C., & Huge, M. E. (2014). Speaking in spirals: An updated meta-analysis of the spiral of silence. In W. Donsbach, C. Salmon & Y. Tsfati (Eds.), *The spiral of silence: New perspectives on communication and public opinion* (pp. 65-72). New York, NY: Routledge.

Glynn, C., & Park, E. (1997). Reference groups, opinion intensity, and public opinion expression. *International Journal of Public Opinion Research*, *9*, 213-232. doi:10.1093/ijpor/9.3.213

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360-1380. doi:10.1086/22546

Hamill, L., & Gilbert, N. (2009). Social circles: A simple structure for agent-based social network models. *Journal of Artificial Societies and Social Simulation*, *12*(2). Retrieved from http://jasss.soc.surrey.ac.uk/12/2/3.html

Hamill, L., & Gilbert, N. (2010). Simulating large social networks in agent-based models: A social circle model. *Emergence: Complexity and Organization*, *12*, 78-94. doi:10.1002/9781118974414

Hampton, K. N., Rainie, L., Lu, W., Dwyer, M., Shin, I., & Purcell, K. (2014). *Social media and the spiral of silence*. Washington, DC: Pew Research Center.. Retrieved from http://www.pewinternet.org////social-media-and-the-spiral-of-silence/20140826

Hardy, B. W., & Scheufele, D. A. (2005). Examining differential gains from Internet use: Comparing the moderating role of talk and online interactions. *Journal of Communication*, *55*, 71-84. doi:10.1111/j.1460-2466.2005.tb02659.x

Hayes, A. F., Glynn, C. J., & Shanahan, J. (2005). Willingness to self-censor: A construct and measurement tool for public opinion research. *International Journal of Public Opinion Research*, *17*, 298-323. doi:10.1093/ijpor/edh073

Hayes, A. F., Matthes, J., & Eveland, W. P. (2013). Stimulating the quasi-statistical organ: Fear of social isolation motivates the quest for knowledge of the opinion climate. *Communication Research*, *40*, 439-462. doi:10.1177/0093650211428608

Hermann, C., Bathélemy, M., & Provero, P. (2003). Connectivity distribution of spatial networks. *Physical Review E*, *68*, 026128. doi:10.1103/PhysRevE.68.026128

Hoffman, L. H. (2013). When the world outside gets inside your head: The effects of media context on perceptions of public opinion. *Communication Research*, *40*, 463-485. doi:10.1177/0093650211435938

Hoffman, L. H., Glynn, C. J., Huge, M. E., Sietman, R. B., & Thomson, T. (2007). The role of communication in public opinion processes: Understanding the impacts of intrapersonal, media, and social filters. *International Journal of Public Opinion Research*, *19*, 287-312. doi:10.1093/ijpor/edm014

Huckfeldt, R., Mendez, J. M., & Osborn, T. (2004). Disagreement, ambivalence, and engagement: The political consequences of heterogeneous networks. *Political Psychology*, *25*, 65-95. doi:10.1111/j.1467-9221.2004.00357.x

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263-291. doi:10.2307/1914185

Katz, D., & Allport, F. H. (1931). *Student Attitudes*. Syracuse, NY: Craftsman

Katz, E., & Fialkoff, Y. (2017). Six concepts in search of retirement. *Annals of the International Communication Association*, *41*, 86-91. doi:10.1080/23808985.2017.1291280

Katz, E., & Lazarsfeld, P. E. (1955). *Personal influence: The part played by people in the flow of mass communications*. New York, NY: The Free Press.

Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London Series A*, *115*, 700-721. doi:10.1098/rspa.1927.0118

Knobloch-Westerwick, S., & Johnson, B. K. (2014). Selective exposure for better or worse: Its mediating role for online news' impact on political participation. *Journal of Computer-Mediated Communication*, *19*, 184-196. doi:10.1111/jcc4.12036

Lang, K., & Lang, G. E. (2012). What is this thing we call public opinion? Reflections on the spiral of silence. *International Journal of Public Opinion Research*, *24*, 368-386. doi:10.1093/ijpor/eds014

Lasorsa, D. L. (1991). Political outspokenness: Factors working against the spiral of silence. *Journalism Quarterly*, *68*, 131-139. doi:10.1177/107769909106800114

Lazer, D., Rubineau, B., Chetkovich, C., Katz, N., & Neblo, M. (2010). The coevolution of networks and political attitudes. *Political Communication*, *27*, 248-274. doi:10.1080/10584609.2010.500187

Leckenby, J. D., & Rice, M. D. (2013). A beta-binomial network TV exposure model using limited data. *Journal of Advertising*, *14*(3), 25-31. doi:10.1080/00913367.1985.10672954

Lee, C. (2009). The interplay between media use and interpersonal communication in the context of healthy lifestyle behaviors: Reinforcing or substituting? *Mass Communication and Society*, *13*, 48-66. doi:10.1080/15205430802694869

Liang, H. (2018). Broadcast versus viral spreading: The structure of diffusion cascades and selective sharing in social media. *Journal of Communication*, *68*, 525-546. doi:10.1093/joc/jqy006

Lippmann, W. (1922). *Public opinion*. New York, NY: Harcourt, Brace.

Macy, M. W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, *28*, 143-166. doi:10.1146/annurev.soc.28.110601.141117

Matthes, J. (2015). Observing the "spiral" in the spiral of silence. *International Journal of Public Opinion Research*, *27*, 155-176. doi:10.1093/ijpor/edu032

Matthes, J., Knoll, J., & Sikorski, C. (2018). The "spiral of silence" revisited: A meta-analysis on the relationship between perceptions of opinion support and political opinion expression. *Communication Research*, *45*, 3-33. doi:10.1177/0093650215593145

Matthes, J., Morrison, K. R., & Schemer, C. (2010). A spiral of silence for some: Attitude certainty and the expression of political minority opinions. *Communication Research*, *37*, 774-800. doi:10.1177/0093650210362685

McDonald, D. G., Glynn, C., Kim, S., & Ostman, R. E. (2001). The spiral of silence in the 1948 presidential election. *Communication Research*, *28*, 139-155. doi:10.1177/009365001028002001

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*, 415-444. doi:10.1146/annurev.soc.27.1.415

McQuail, D. (2014). Paradigm shift in the study of media effects. In W. Donsbach, C. Salmon & Y. Tsfati (Eds.), *The spiral of silence: New perspectives on communication and public opinion* (pp. 35-43). New York, NY: Routledge.

Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: An introduction to computational models of social life*. Princeton, NJ: Princeton University Press.

Moy, P., Domke, D., & Stamm, K. (2001). The spiral of silence and public opinion on affirmative action. *Journalism & Mass Communication Quarterly*, *78*, 7-25. doi:10.1177/107769900107800102

Moy, P., & Hussain, M. M. (2014). Media and public opinion in a fragmented society. In W. Donsbach, C. T. Salmon & Y. Tsfati (Eds.), *The spiral of silence: New perspectives on communication and public opinion* (pp. 92-100). New York, NY: Routledge.

Mutz, D. C. (2006). How the mass media divide us. In P. S. Nivola & D. W. Brady (Eds.), *Red and blue nation? Characteristics and causes of America's polarized politics* (Vol. 1, pp. 223-263). Washington, DC: Brookings Institution Press.

Mutz, D. C., & Martin, P. S. (2001). Facilitating communication across lines of political difference: The role of the mass media. *American Political Science Review*, *95*, 97-114.

Neiheisel, J. R., & Niebler, S. (2015). On the limits of persuasion: Campaign ads and the structure of voters' interpersonal discussion networks. *Political Communication*, *32*, 434-452. doi:10.1080/10584609.2014.958258

Neuwirth, K., Frederick, E., & Mayo, C. (2007). The spiral of silence and fear of isolation. *Journal of Communication*, *57*, 450-468. doi:10.1111/j.1460-2466.2007.00352.x

Newman, M. (2010). *Networks: An introduction*. New York, NY: Oxford University Press.

Newman, M., Strogatz, S., & Watts, D. (2001). Random graphs with arbitrary degree distributions and their applications. *Physical Review E*, *64*, 026118. doi:10.1103/PhysRevE.64.026118

Noelle-Neumann, E. (1974). The spiral of silence: A theory of public opinion. *Journal of Communication*, *24*, 43-51. doi:10.1111/j.1460-2466.1974.tb00367.x

Noelle-Neumann, E. (1993). *The spiral of silence: Public opinion—Our social skin*. Chicago, IL: University of Chicago Press.

Nowak, A., Szamrej, J., & Latane, B. (1990). From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, *97*, 362-376. doi:10.1037/0033-295X.97.3.362

Oshagan, H. (1997). Reference group influence on opinion expression. *International Journal of Public Opinion Research*, *8*, 335-354. doi:10.1093/ijpor/8.4.335

Page, S. E. (2015). What sociologists should know about complexity. *Annual Review of Sociology*, *41*, 21-41. doi:10.1146/annurev-soc-073014-112230

Price, V., & Roberts, D. F. (1987). Public opinion processes. In C. Berger & S. Chaffee (Eds.), *Handbook of communication science* (pp. 781-816). Newbury Park, CA: SAGE.

Rogers, E. M. (2003). *Diffusion of innovations*. New York, NY: Free Press.

Rolfe, M. (2014). Social networks and agent-based modeling. In G. Manzo (Ed.), *Analytical sociology* (pp. 233-260). Chichester, UK: John Wiley.

Ross, B., Pilz, L., Cabrera, B., Brachten, F., Neubaum, G., & Stieglitz, S. (2019). Are social bots a real threat? An agent-based model of the spiral of silence to analyse the impact of manipulative actors in social networks. *European Journal of Information Systems*. Advance online publication. doi:10.1080/0960085X.2018.1560920

Ross, L., Greene, D., & House, P. (1977). The "false consensus effect": An ego-centric bias in social perception and attribution processes. *Journal of Experimental Social Psychology*, *13*, 279-301. doi:10.1016/0022-1031(77)90049-X

Salmon, C. T., & Neuwirth, K. (1990). Perceptions of opinion 'climates' and willingness to discuss the issue of abortion. *Journalism & Mass Communication Quarterly*, *67*, 567-577. doi:10.1177/107769909006700312

Sassenberg, K., & Jonas, K. J. (2007). Attitude change and social influence on the net. In A. Joinson, K. McKenna, T. Postmes & U.-D. Reips (Eds.), *The Oxford handbook of internet psychology* (pp. 273-288). New York, NY: Oxford University Press.

Schelling, T. C. (1978). *Micromotives and macrobehavior*. New York, NY: W. W. Norton.

Scheufele, D. A. (2008). Spiral of silence theory. In W. Donsbach & M. W. Traugott (Eds.), *The SAGE handbook of public opinion research* (pp. 175-183). London, England: SAGE.

Scheufele, D. A., & Moy, P. (2000). Twenty-five years of the spiral of silence: A conceptual review and empirical outlook. *International Journal of Public Opinion Research*, *12*, 3-28. doi:10.1093/ijpor/12.1.3

Scheufele, D. A., Shanahan, J., & Lee, E. (2001). Manipulating the dependent variable in the spiral of silence research. *Communication Research*, *28*, 304-324. doi:10.1177/009365001028003003

Shah, D. V., Cho, J., Nah, S., Gotlieb, M. R., Hwang, H., Lee, N., & Scholl, R. M. (2007). Campaign ads, online messaging, and participation: Extending the communication mediation model. *Journal of Communication*, *57*, 676-703. doi:10.1111/j.1460-2466.2007.00363.x

Shanahan, J., Glynn, C., & Hayes, A. F. (2007). The spiral of silence: A meta-analysis and its impact. In R. W. Preiss, B. M. Gayle, N. Burrell, M. Allen & J. Bryant (Eds.), *Mass media effects research: Advances through meta-analysis* (pp. 415-427). Mahwah, NJ: Lawrence Erlbaum.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*, 623-656. doi:10.1002/j.1538-7305.1948.tb01338.x

Slater, M. D. (2007). Reinforcing spirals: The mutual influence of media selectivity and media effects and their impact on individual behavior and social identity. *Communication Theory*, *17*, 281-303. doi:10.1111/j.1468-2885.2007.00296.x

Smith, E. R., & Conrey, F. R. (2007). Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review*, *11*, 87-104. doi:10.1177/1088868306294789

Sohn, D., & Geidner, N. (2016). Collective dynamics of the spiral of silence: The role of ego-network size. *International Journal of Public Opinion Research*, *28*, 25-45.

Song, H., & Boomgaarden, H. G. (2017). Dynamic spirals put to test: An agent-based model of reinforcing spirals between selective exposure, interpersonal networks, and attitude polarization. *Journal of Communication*, *67*, 256-281. doi:10.1111/jcom.12288

Southwell, B. G., & Yzer, C. (2007). The roles of interpersonal communication in mass media campaigns. *Communication Yearbook*, *31*, 419-462. doi:10.1080/23808985.2007.11679072

Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating parameter estimation and sensitivity analysis of agent-based models: A cookbook using NetLogo and R. *Journal of Artificial Societies and Social Simulation*, *17*(3), 11-56. doi:10.18564/jasss.2503

Valente, T. W. (1995). *Network models of the diffusion of innovations*. Cresskill, NJ: Hampton Press.

Visser, P. S., & Cooper, J. (2007). Attitude change. In M. A. Hogg & J. Cooper (Eds.), *The SAGE handbook of social psychology* (pp. 197-218). London, England: SAGE.

Visser, P. S., & Mirabile, R. R. (2004). Attitudes in the social context: The impact of social network composition on individual-level attitude strength. *Journal of Personality and Social Psychology*, *87*, 779-795. doi:10.1037/0022-3514.87.6.779

Wang, N., Guo, Z., & Shen, F. (2011). Message, perception, and the Beijing Olympics: Impact of differential media exposure on perceived opinion diversity. *Communication Research*, *38*, 422-445. doi:10.1177/0093650210384985

Watts, D. (2004). The "new" science of networks. *Annual Review of Sociology*, *30*, 243-270. doi:10.1146/annurev.soc.30.020404.104342

Watts, D. & Strogatz, S. (1998). Collective dynamics of 'small world' networks. *Nature*, *393*(6684), 440-442. doi:10.1038/30918

Weaver, W. (1948). Science and complexity. *American Scientist*, *36*, 536-544. doi:10.1007/978-3-642-24672-2_3

Wilensky, U. (1999). *NetLogo*. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. http://ccl.northwestern.edu/netlogo/

Wojcieszak, M. (2008). False consensus goes online: Impact of ideologically homogeneous groups on false consensus. *Public Opinion Quarterly*, *72*, 781-791. doi:10.1093/poq/nfn056

Wojcieszak, M., & Rojas, H. (2011). Communication diversity and the projection of personal opinions onto others. *Journal of Broadcasting & Electronic Media*, *55*, 543-562. doi:10.1080/08838151.2011.620665

Author Biography

Dongyoung Sohn is a professor in the Department of Media & Communication at Hanyang University, Seoul, Korea. His research interests include media psychology and computational approaches to studying communication networks and social dynamics.