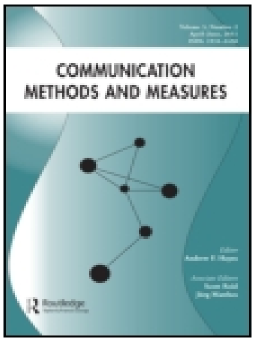


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# Worlds of Agents: Prospects of Agent-Based Modeling for Communication Research

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# Worlds of Agents: Prospects of Agent-Based Modeling for Communication Research

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**ABSTRACT**

Agent-based computational models create virtual laboratories in which to formalize and simulate dynamic, multi-level theories of communication. They allow the systematic development of thought experiments, and they improve our understanding of the generative mechanisms that underlie patterns observed in empirical data. Simulation models help explore hypothetical and unprecedented scenarios, serving as powerful hypothesis generators for future theoretical and empirical research. This Special Issue showcases a collection of studies that demonstrate the analytical potential and methodological contribution of agent-based modeling (ABM) for media and communication research. In this introduction, we highlight five major benefits of this modeling approach to communication scholarship: (1) formalization, (2) understanding, (3) explanation, (4) prediction, and (5) exploration. We then present the four studies of this special issue, which contribute methodologically and theoretically to diverse key areas of communication: the emergence of meanings; political deliberation; information diffusion; and media use and social influence. We conclude with outlining future perspectives of ABM in communication research.

## Introduction

During the COVID-19 pandemic, mathematical models have become highly visible, and the value of their computational implementation has become very tangible. Predictive modeling quickly became essential to forecast the evolution of the pandemic, e.g., the numbers of infections and hospitalizations, and the impact of specific policy measures such as curfews or wearing masks (Poletto et al., 2020). Among these modeling efforts, a subset of approaches relied on simulation, showcasing the strengths of formalizing social dynamics to understand, explain, predict, and explore their complex interactions and consequences.

Computational agent-based models have been used to understand basic mechanisms in viral spreading, and to explain the outcomes of interventions, such as mask-wearing, in highly visible, general-public outlets (McMillan, 2020; Stevens, 2020) or in schools (Lasser et al., 2021). These models (and their epistemic goals, which we outline below) have allowed policymakers and the general public all over the world to make quick decisions on far-reaching measures to mitigate the pandemic's impact on public health, the economy, and well-being.

Communication science has been at the heart of many of the challenges confronted by researchers modeling epidemic spreading. As the "infodemic" metaphor suggests, the spread of misinformation runs in parallel to the spread of the virus (Gallotti et al., 2020). The dynamics of social contagion have been extensively studied for decades (for comprehensive reviews cf. Centola, 2018;

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González-Bailón, 2017). Social influence is a prominent mechanism underlying spreading phenomena, for example, when memes go viral on social media or people mobilize for protests (Aral, 2020; Jackson et al., 2020). Many long-standing research problems in communication science focus on such emergent macro phenomena, and simulation models help us unpack their emergence, including in domains like waves of public attention (Waldherr, 2014), echo chambers and polarization (Flache & Macy, 2011; Geschke et al., 2019; McKeown & Sheehy, 2006), or digital divides (Lim et al., 2014).

The *emergence* of such collective macro phenomena is a typical feature of complex systems, along with *nonlinearity, heterogeneity, interconnectedness, and self-organization* (Miller & Page, 2007; Sherry, 2015; Waldherr, 2017). Emergent phenomena often show *nonlinear* dynamics such as tipping points (when a system changes drastically after long periods of stability) or butterfly effects (when very small impulses are enough to lead to such drastic changes) (Miller & Page, 2007). They arise from interactions of *heterogeneous* and *interconnected* actors which adapt to each other's behavior, leading to feedback loops and to *self-organization* in the absence of centralized planners. In real-world social systems, these bottom-up dynamics co-exist with top-down dynamics such as policy interventions (Conte, 2009) or other exogenous forces, like marketing campaigns (Van den Bulte & Lilien, 2001).

The modeling of these phenomena in complex systems science challenges the classic social sciences toolbox traditionally used in communication research. The traditional statistical methods of today's mainstream rely on several assumptions, such as the independence of the units of analysis or the prevalence of linear correlative relationships. These assumptions run counter to the nonlinear behavior of complex systems and their interconnectedness (Doran & Gilbert, 1995; Hedström, 2005; Waldherr et al., in press). Linear regression methods cannot capture the interactive dynamics of complex systems and network effects, which means that their estimates will be biased and misleading (Miller & Page, 2007; Wettstein, 2020). The restrictive assumptions of many statistical models make it difficult to analyze the interactions between individual, group, and aggregate dynamics in social behavior (González-Bailón, 2017; Waldherr & Wettstein, 2019).

Over the past decade, the computational turn in the social sciences has brought a range of methodological advancements tackling some of these challenges, among them advanced statistical methods for modeling large-scale, nested, and constantly streaming data such as languages, locations, networks, and images (Lazer et al., 2020). In the field of communication, as in broader social sciences, the adoption of these advancements has been mostly driven by the availability and relevance of digital trace data (Freelon, 2014; Jungherr et al., 2017; Peng et al., 2020). For example, network science techniques have been developed and applied to the study of communication networks (Monge & Contractor, 2003) that were, in the past, out of reach (e.g., Jackson et al., 2020; Kenneth et al., 2020; Yang et al., 2020). Major efforts have also been invested in developing and validating techniques for automated text analysis (Guo et al., 2016; Maier et al., 2018; Scharkow, 2013; Van Atteveldt et al., 2021; Watanabe, 2021), and more recently, of computer vision (Araujo et al., 2020; Casas & Williams, 2020; Chen et al., 2021).

These methods are central to the rise of computational communication science (Van Atteveldt & Peng, 2018), and they are largely data-driven: they are used to model and analyze empirical data. In this Special Issue, we spotlight agent-based modeling (ABM) as the complementary, theory-driven computational approach of the computational paradigm (Hilbert et al., 2019). ABM is a method for modeling and simulating complex systems based on theoretical principles that uses data for calibration purposes and conceptual validation. The focus of agent-based models (ABMs) is on the individual micro processes that generate aggregated data and patterns observed on the macro level. The main goal of ABM is to offer mechanism-based explanations of empirical observations (Waldherr & Wettstein, 2019).

In this introductory article, we explain the basic principles and benefits of ABM, before we present the four studies that form this Special Issue and conclude with future perspectives of ABM in communication research.

## Why model in communication research?

ABM is a method of object-oriented computer modeling and simulation especially suited to model complex systems (Conte et al., 2012; Gilbert & Troitzsch, 2005; Wilensky & Rand, 2015). An ABM consists of a number of agents which interact with each other in a given environment (Cioffi-Revilla, 2014; Epstein & Axtell, 1996). This can be a separate space or topography in which the agents move, but the environment can also consist of networks of interconnected agents. These agents are designed to have certain attributes, which enables researchers to add actor-level heterogeneity, and they follow rules that encode behavioral mechanisms. Following these rules, agents are able to react to their environment and to adapt their behavior as the system evolves. The experimental part of these simulations relies on defining key parameters that are systematically tuned to determine how much the changes alter the results; for instance, population size or behavioral rules can be systematically varied to analyze how much they determine the overall dynamics. Agent-based models can be implemented with any object-oriented computer language. User-friendly ABM platforms such as NetLogo or Repast are also popular among social scientists.

Applications of ABM in the social sciences date back to the 1990s (Epstein & Axtell, 1996; Gilbert & Doran, 1994). Yet, in communication research, it is a still marginal, and we think, underused, and undertaught method. In the following, we highlight five major features that, in our view, make this approach beneficial for communication scholarship: (1) formalization, (2) understanding, (3) explanation, (4) prediction, and (5) exploration.[1]

### *Formalization*

ABMs are formalized theories (Gilbert & Troitzsch, 2005). In order to make sense of the world around us, we all constantly create models in our mind: "If I do A then B happens." "I think A is because of B." In communication research, we usually make these models explicit in some verbal or visual form, by sketching out the way we think several independent and moderating/mediating variables interact to influence some dependent variable(s). These models are the basis for statistical hypothesis testing. Classical linear models such as linear regressions entail a range of assumptions that are typically challenged in complex systems, e.g., that observations in a sample are independent and normally distributed. If we run these models, we are formalizing a linear relationship for our data.

In an ABM, we model actors and their interactions, which goes beyond the mere modeling of general factors and their aggregate variables (Macy & Willer, 2002). When designing and implementing an ABM, we have to carefully think about the rules we encode in the agents and be very precise in their definition – ambiguous or incomplete commands will not execute. For example, if we wanted to operationalize the assumption "The more journalists report an issue today, the more they report this issue tomorrow," we would need to first answer the question: How many *more* reports do we expect journalists to produce in the next temporal iteration? Does their coverage grow linearly from one time step to the next, or exponentially, or logistically? And what is the right temporal resolution to assume for each iteration step? Next, we might wonder if the same rule applies for growth and decay of attention. A literature review of empirical studies will probably reveal this is a blind spot in agenda-setting research. Formalizing theories thus helps us identify rules and assumptions that have not been explicitly postulated in existing theories but which are needed to build a complete and functioning model. This is one way in which ABMs can help identify gaps in existing research as well as inconsistencies in theoretical systems that went unnoticed prior to the attempt to formalize them. Finally, formalizing also forces us to simplify a theory in the sense of reducing it to the major assumptions needed to describe and explain a phenomenon, or as Smaldino (2017, p. 319) puts it: formal models allow "systematizing our stupidity, and ensuring that we are all talking about the same thing."

[1]For more reasons for "Why model?", see Epstein's seminal lecture (2008).

ABMs focus on formalizing mechanisms at the micro level (as opposed to other modeling techniques that rely more on mathematical formalization of system dynamics). In an ABM, the macro dynamics emerge from the interactions happening on the micro level. One example comes from an attempt to model the self-reinforcing spirals between selective media use and media effects (Song & Boomgaarden, 2017). This model allowed the authors to dynamically simulate individual feedback processes between partisan selective exposure and attitude polarization across a much longer time scale than empirical research typically covers. The model facilitates the analysis of macro patterns of polarization or stabilization under specific micro conditions – thus extending the original framework.

## Understanding

ABMs offer an analytical approach to hypothesize about and understand the mechanisms bringing about emergent patterns at the group and population level. With the help of computer simulations, we can observe how micro interactions lead to macro patterns. Running simulation experiments with varying micro conditions, ABMs can help us illuminate the macro implications of the individual-level assumptions, contributing to our understanding of basic core dynamics and relationships in complex systems (Epstein, 2008). This is one way in which ABM can contribute to theory development, in ways for which classical empirical methods would be more limited. Even very simple models implementing thought experiments – such as Schelling's (1971) seminal segregation model – can be very illuminating of how emerging patterns often result as an unintended consequence of individual action.

Building on a long tradition of formal models of collective action (Granovetter, 1978; Oliver, 1993), researchers have used ABMs to analyze mobilization dynamics (Centola, 2013) and opinion spreading (Alvarez-Galvez, 2016) – shedding light on the interplay of strong and weak ties, the role of a critical mass, homophily, and network topology. For example, Piedrahita et al. (2018) developed an ABM to analyze large-scale contagion dynamics combining classic models of coordination with different network topologies. This model allows them to specify the conditions under which large-scale contagion is more likely to emerge and offers an explanation for why large-scale contagion fails to emerge more often than not, bringing us directly to our next point.

## Explanation

Finding which micro mechanisms are able to generate certain – empirically observed – macro phenomena is already an important step toward explaining these phenomena (Ball, 2007). Epstein (2006) called this bottom-up approach to explanation "generative social science." Explaining social phenomena in terms of ABM means letting heterogeneous agents interact in a simulated environment according to simple rules to assess how those interactions generate, from the bottom up, the regularities that we can observe at the collective level. In an approach of pattern-oriented modeling (Railsback & Grimm, 2012), we refine the model in several iterations until we have a model that sufficiently reconstructs the empirically observed patterns, or at least highly abstracted "stylized facts" (p. 228) which are qualitatively capturing the essential characteristics of a pattern.

For example, Waldherr (2014) created an ABM which is able to generate the stylized patterns of issue-attention cycles in news coverage that have been observed repeatedly in empirical studies. She found that adaptive co-orientation among journalists in reaction to events kicking off a self-reinforcing cascade of coverage is the main driver for the emergence of news waves. Strategic actors promoting specific issues were not necessary to create such waves, but changed and extended their typical temporal patterns.

In a similar approach, Geschke et al. (2019) contributed to the explanation of echo chambers with an ABM. They simulated twelve different information filtering scenarios allowing them to specify the conditions under which social media and recommender algorithms contribute to fragmentation. They showed that selection biases and global propagation of information are enough to foster the emergence of echo chambers, even without any social or technological filters added. However, such filters tend to reinforce the emerging patterns of fragmentation.

Being able to explain a dynamic is not only important for scientists, but is essential in order to sway the public. A clear example is the unprecedented success with which ABMs were used to explain the dynamics of social distancing and mask-wearing to the general public (McMillan, 2020; Smaldino, 2020; Stevens, 2020).

### Prediction

Besides explanation, prediction may be the goal of modeling efforts (Hassan et al., 2013). In this case, ABMs are applied "like a calculator" (Heath et al., 2009, para 2.17) to provide estimates about a system's behavior. In social systems, however, there may be inherent limits to predictability, because the phenomenon of interest itself is unpredictable (Hofman et al., 2017). Complex systems may show chaotic behavior: even in a system following simple and deterministic rules, small variations in the starting conditions can lead to completely different outcomes (Mitchell, 2009, p. 38). This is why the use of ABMs for prediction is partly disputed in the social simulation community.

Troitzsch (2009), for instance, stresses that "not all explanations predict satisfactorily, and not all good predictions explain" (p. 1). We might have a perfect understanding of the basic mechanisms at work, but in a system showing chaotic behavior we are not able to predict how exactly the system will behave. Earthquakes, lightning, or epidemics are the usual examples cited to illustrate this (Epstein, 2008), but the social world is also full of examples where prediction is difficult if not impossible, e.g., online diffusion cascades or success in cultural markets (Hofman et al., 2017). On the other hand, we may be able to correctly predict the trajectory of a system without much insight into the mechanisms at work.

However, while often not being able to exactly predict which state a target system will reach in the near future, ABMs can be used to generate ensembles of predictions, or possible futures, in the sense that they tell us "which kinds of behavior can be expected" (Troitzsch, 2009). ABMs in policy contexts, for example, are especially useful to identify dynamics to be expected under certain policy interventions (Gilbert et al., 2018). This approach is particularly promising for exploring possible futures in the sense of what-if scenarios or scenarios for which observational data are not available (Hilbert, 2015; Hilbert et al., 2019).

While there is huge potential for such approaches in communication research, actual applications are still few. Zhang et al. (2015) built an agent-based network model simulating the prevalence of obesity and calibrated it with data from a longitudinal study of adolescent health in the United States. Using this model, they were able to predict how a range of interventions might affect health outcomes. Ross et al. (2019) explored what-if scenarios in an ABM of the spiral of silence to estimate the potential influence of social bots in tipping over opinion trends. Likewise, Schieb and Preuss (2018) used ABM simulations to assess the effectiveness of counter speech strategies in a Facebook setting. They found moderate counter speech to achieve the highest impact on the opinions of interaction partners. Such insights can be translated into policy recommendations for platform governance and strategic communication. A big advantage compared to directly testing interventions in the real-world (as with large-scale A/B testing) is that there are almost no limitations to the number and types of interventions that can be tested. This is particularly relevant for ethically sensitive interventions in areas like misinformation, hate speech, or discrimination bias, where treatments might backfire.

### Exploration

Systematic model exploration with the help of simulation experiments is also a powerful tool for generating hypotheses for further empirical research. ABMs are "artificial laboratories" (Epstein & Axtell, 1996, p. 4), in which all processes of interest can be made observable. This allows conducting experiments that are not possible in physical lab or field experiments with human subjects. The systematic modification of parameters allows analyzing system behavior under a vast range of possible conditions. This way, researchers can find out how sensitive or robust the observed behaviors are to varying conditions and identify critical thresholds, such as tipping points, where the system dramatically changes from one state to another, e.g., a collapse of an ecosystem or regime. Also, the potential effects of interventions can be tested and counter-intuitive or unintended consequences identified (González-Bailón, 2017).

Sohn and Geidner (2016), for example, implemented an ABM of the spiral of silence and explored how varying the distribution of individuals' network sizes and locally perceived opinion climates (i.e., the perceived shares of voices taking pro vs. contra positions on an issue as defined by Noelle-Neumann, 1984) affects the global spiraling process. They found that spirals of silence are more likely to occur in populations with less polarized perceptions of the overall opinion climate.

Such insights help develop and refine hypotheses that can then be tested with empirical data and additional methods. Modeling eventually guides data collection and helps optimize experimental settings for empirical studies (Eberlen et al., 2017), which is particularly relevant as more and more communication researchers pre-register their studies to foster open science practices (Dienlin et al., 2020).

In sum, the computer simulations of ABMs are virtual laboratories that help formalize and explore dynamic, multi-level theories of communication. They allow the systematic development of thought experiments, thereby contributing to the understanding of generative mechanisms, offering explanations for empirically observed patterns in (big or small) data sets, as well as predictions for hypothetical and unprecedented scenarios. ABMs, in other words, serve as powerful hypothesis generators that allow us to develop theories and further empirical research.

## Overview on the models in this special issue

The articles in this Special Issue demonstrate the analytical potential and methodological contribution of ABMs for media and communication research.

The study of Poong Oh and Soojong Kim is a prime example of how ABMs can be used for theory development and formalization in order to understand and explain emergent phenomena from a set of micro assumptions. The authors tackle one of the most basic problems of communication: the emergence of meanings in natural languages. How do individuals coordinate their signals in a way that everyone associates the same meaning, or – in the words of the authors – how do they "collectively produce common and stable signaling systems" without any central authority? In this context, Oh and Kim are especially interested in the conditions under which stable, but suboptimal signaling systems emerge, manifested, for example, in synonyms and homonyms. Building on previous signaling games, the authors develop an ABM and implement reinforcement learning as the main evolutionary coordination mechanism. In a series of simulation experiments, this mechanism proved sufficient to generate common and stable signaling systems. Varying several key parameters and observing their consequences on the evolutionary process, Oh and Kim were able to identify finite memory as a critical parameter for the emergence of meanings. Shorter memory of the agents accelerated the evolutionary coordination process, but also resulted in suboptimal, highly redundant signaling systems more often. Thus, the authors propose finite memory as a major explanation for redundancy in natural languages, because it enables communicators to achieve coordination quickly and effectively under cognitive constraints.

Sarah Shugars applies the ABM method to shed new theoretical insight into complex deliberative exchanges in group discussions. Inspired by Kaufman's NK model framework, which has long been adopted by communication scholars (Monge & Contractor, 2003), she models how individuals with varying opinions, experience, and information attempt to collaborate and make decisions through a game of giving and asking for reasons. Following our above discussion, there might be other ways to formalize deliberative exchanges, but the general framework of Shugars' model makes it widely applicable, including in political, cultural, and organizational communication. In a typical use-case of understanding the macro-behaviors from micro-motives, agents share beliefs around possible policy initiatives and attempt to enact "good" policies through a process of mutual exchange and consideration. The model considers an interconnected policy landscape in which implementing or not implementing a policy mediates the value of other policies. While empirical evidence suggests that collaborative reasoning often leads to good decisions, there are several "canonical failures of deliberation," which her model seeks to explain, namely the roles of limited cognitive capacity, group factions, and tendencies to make poor judgments when accepting or rejecting others' views. Among other insights, her model predicts that the limiting role of cognitive capacity of a group to reach a good decision can be mitigated by having groups of opposing factions. In other words, while polarization has gotten a bad reputation, as of recent, simulation results show that polarized groups do surprisingly well at identifying optimal policy solutions. This shows that heterogeneity, combined with good deliberation practices of mutual listening and learning, are essential contributors to achieve good outcomes. As usual for ABMs, the setup is much broader than a single paper is able to handle, and Shugars ends by discussing some of the ways models like hers could be used to further explore deliberative spaces.

The next study is situated in one of the classic application areas of ABMs and network models: information diffusion (e.g., Hui et al., 2010). Reed M. Reynolds contributes to this strand of research by formalizing the process of information-seeking in networks with an ABM. In his model, information only diffuses if agents are interested in it and specifically ask for it as is typical, for example, for advice-seeking behavior in healthcare or organizational contexts. Reynold uses the model to explore the effects of two structural network parameters on the diffusion process: network hierarchy and fluidity. In a series of simulation experiments, he compares the diffusion rates in networks with random versus exponential degree distributions, the first showing an equal and the latter a strongly hierarchical network structure. Additionally, he allows the agents to deviate randomly from this set network structure in addressing their information requests. Introducing this "structural fluidity" into the model, yields interesting interaction effects. In line with previous research, Reynold finds that hierarchical networks substantially increase the variance of diffusion rates. They make both rapid diffusion and diffusion failure more likely. This effect is moderated by structural fluidity in a nonlinear way such that the likelihood of rapid diffusion in hierarchical networks is further increased by only moderate levels of fluidity. Additionally, Reynolds explores the relevance of initial seeds for the diffusion process, showing that especially hierarchical networks are sensitive to initial conditions.

Finally, Thomas Friemel models the dynamics of media use with a specific type of ABM designed to analyze evolving social networks – a family of statistical models known as *Stochastic Actor-Oriented Models for Network Dynamics* (SAOMs; Snijders, 2017). His analytical approach is a good example of how ABMs can be combined with empirical data. Friemel takes as input to the model a three-wave panel tracking data on friendship ties and media use, and offers estimates on the effects that friendship has on media use and vice versa, i.e., whether media use also helps explain the formation and maintenance of friendship ties. Disentangling these dynamics is challenging given the clustered nature of the data, and the confluence of exogenous and endogenous forces driving the evolution of the network. The analyses reveal empirical support for the social influence hypothesis, especially regarding TV programs and YouTube channels, but they do not support the social selection hypothesis. More generally, this article is a good illustration of how ABMs allow us to identify the individual-level mechanisms that underlie aggregated phenomena (like network evolution).

## Conclusion and future perspectives

Altogether, the ABMs presented and discussed in this Special Issue contribute methodologically and theoretically to research in diverse key areas of communication, namely the emergence of meanings, political deliberation, information diffusion, and media use and social influence. The studies demonstrate how ABMs can be applied to tackle key methodological challenges in communication research, such as the formalization and understanding of multi-level dynamics, the identification of explanatory mechanisms underlying macro phenomena, and the systematic exploration and prediction of what-if scenarios.

The studies show how ABMs are particularly instrumental for formalizing and experimenting with theories and how this helps advance theory development in communication research. ABM allows us to (re-)formulate communication theories in a way that accounts for the complexity of communication systems, particularly their multi-level dynamics, and puts theories to the test of logical rigor: are the assumptions complete, consistent, and sufficient to generate the system-level behavior of interest? The studies introduced here focus on different mid-range theories and are good examples of finding the right balance between generalization and specificity, which is one of the biggest challenges in modeling. Models that are too abstract and general may offer interesting simplifications but do not offer many empirical lessons. Models tailored to a very specific case are hard to generalize (akin to the problem with statistical overfitting in empirical research). ABMs with the appropriate level of abstraction can serve as hypotheses generators for future empirical research, mutually complementing each other.

The article by Friemel is a good example how ABMs can be especially insightful when combined with empirical methods. On the one hand, empirical data serve as a reality check, ensuring that model rules and parameters are aligned with observed phenomena. On the other hand, ABMs offer explanations for observed effects by disentangling the specific dynamics going on under the surface of aggregated behavior and probing the specific conditions leading to those aggregations (Hedström, 2005). As Wettstein (2020) shows in a study linking panel data with ABMs this is also helpful to explain missing, minimal, or seemingly contradictory effects. While early research in the computational paradigm has largely focused on either empirical data science (Lazer et al., 2009; Watts, 2007), or simulations-based theory building (Cioffi-Revilla, 2014; Conte et al., 2012) these recent developments show an exiting level of maturity in the symbiosis of empirical and theoretical approaches (Hilbert et al., 2019).

Given these benefits and challenges, we think that the potentials of ABM are far from fully exploited in our discipline. However, we are optimistic that ABM can play a larger role in communication for three reasons. First, it can help consolidate stronger theoretical foundations adapted to the complexities of communication in the digital era. Second, more and more communication programs incorporate in their syllabi coding skills, which will open up more entry points to these modeling techniques. And third, computational power is constantly expanding, which makes it possible to simulate more and more complex systems, including networks with hundreds of thousands of nodes. This allows, for instance, simulating social media networks at real scales and exploring the large-scale consequences of possible interventions, e.g., to counter misinformation, hate speech, or radicalization.

This opens up perspectives to make stronger use of explanatory as well as predictive modeling in communication research, e.g., in the fields of media governance, political communication, public relations and advertising, or health communication. Such large-scale endeavors will likely require collaborative efforts in multidisciplinary teams. However, communication should not delegate computational modeling to computer scientists, mathematicians, or physicists. Much of the work of modeling is theoretical work, for which we need communication scientists to translate communication theories.

We hope that this collection of articles will spark further interest in ABM as a viable addition to the toolbox of communication research. With this Special Issue, we aim to inspire more communication researchers to engage in modeling efforts and enrich this growing area of research. [2]

[2]A good start for beginners are online courses and more comprehensive textboooks that have become popular in recent years, especially around NetLogo (https://ccl.northwestern.edu/netlogo). Its designer, Uri Wilensky, offers a 500 page textbook (Wilensky & Rand, 2015), accompanied by an online course (Rand, 2018). The MOOC platform Coursera offers an online course with exercises (Hilbert, 2020) as well as project tutorials in NetLogo (Vaz, 2020).

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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