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Bridging the Gaps: Using Agent-Based Modeling to Reconcile Data and Theory in Computational Communication Science

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In various branches of the social sciences, agent-based models (ABMs) have long been applied to enhance researchers' understanding of complex systems and processes. However, in communication science, this approach is rarely used. In this article, we argue that ABMs have the potential to advance communication research in general, and computational communication science (CCS) in particular, by helping scholars address two major gaps. First, by generating emergent global phenomena from individual interactions, ABMs make it possible to explicitly link micro and macro perspectives in communication research. Second, by formalizing theories, ABMs offer mechanism-based explanations for observed empirical patterns in data. To familiarize more communication scholars with this approach, this article provides a systematic overview of the potentials, applications, and challenges of ABMs in communication science. Special attention is paid to the criteria of reliability and validity.

Keywords: agent-based model, computational communication science, data science, communication theory, reliability, validity, social simulation

Recent accounts of computational communication science (CCS) focus on harvesting and analyzing big digital trace data (Choi, 2018; Shah, Cappella, & Neuman, 2015; van Atteveldt & Peng, 2018) rather than on theory development with computational modeling. However, agent-based modeling (ABM) and simulation is a computational social science tool that has been applied for decades to enhance researchers' understanding of complex social systems and processes (Miller & Page, 2007) and to predict behavior over time (Hassan, Arroyo, Galán, Antunes, & Pavón, 2013). It has been used to model and simulate the emergence of human cooperation (Axelrod, 1997b) and social norms (Conte, Andrighetto, & Campenni, 2014), the dynamics of social influence and opinion (Flache et al., 2017), and the effects of policy interventions (Gilbert, Ahrweiler, Barbrook-Johnson, Narasimhan, & Wilkinson, 2018), to name a few areas of application.

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Agent-based models (ABMs) are object-oriented computer models simulating the behavior of a population of agents in a defined environment (Gilbert & Troitzsch, 2005; Macy & Willer, 2002). They consist of agents (e.g., individuals or organizations) with specific attributes that live and interact in a given environment (e.g., a network, geography, or abstract Euclidian space). The agents act according to predefined rules specifying how they process and react to information from their environment. Through the aggregation of these individual actions and reactions, macrosocial phenomena such as opinion spirals or collective action may emerge.

We argue that this approach presents an opportunity to resolve two major issues in communication research in general and CCS in particular. First, it helps bridge the gap between micro and macro research perspectives. Research conducted from a macrosocial perspective describes long-term societal changes and developments taking place over weeks and months, while research completed from a microlevel perspective investigates immediate psychological and physiological media effects on individuals. Few theories integrate these perspectives to explain macrolevel developments as emergent phenomena from individual interactions. ABM offers a bottom-up approach to study how individual interactions cumulatively result in specific macrosocial patterns (Epstein, 2006).

Second, ABM addresses the gap between data and theory, which is becoming more pressing as communication scholars engage in the collection of massive amounts of digital trace data on media users and content. Analyses of these abundant data sets are often descriptive and atheoretical, ignoring the still-relevant theories of the field (Choi, 2018; Mahrt & Scharkow, 2013). If researchers integrate this data with ABM, mechanism-based explanations for observed empirical patterns may be developed and the applicability of theories to data may be critically assessed.

Although ABM has been used in other disciplines to work on closing the gaps between the micro and macro perspectives and to reconcile theory and data (Bruch & Atwell, 2015), little research on these issues has been completed in communication science. Reasons for the hesitant approach toward this method may include concerns about the external validity of simulations and the programming and data analysis skills required as well as obliviousness to the specific applications of ABM in communication science. In this article, we seek to lower the threshold for the application of ABM in communication science by addressing all three potential obstacles: First, we discuss the potentials of ABM for CCS research by providing specific application examples in various fields. Second, we present two implementation examples of ABMs with reference to available tools. Third, we discuss the questions of ABMs' reliability and validity, further challenges, and future perspectives.

Potentials of ABM for CCS Research

In the social sciences, ABM has been used in a wide range of applications, from the simulation of artificial societies to the precise reconstruction of case-based dynamics (Squazzoni, 2012) and the prediction of dynamics resulting from policy decisions (Gilbert et al., 2018; see Bruch & Atwell, 2015, for a review of ABM applications in the social sciences). Many simulation studies touch on core research interests of communication science, such as opinion dynamics and social influence (Flache et al., 2017). Additionally, ABM has the potential to address specific issues in communication science, most notably the gap between micro and macro perspectives in media effects research (Scheufele, 2008) and the call for more theoretical grounding of data-intensive computational analyses (Mahrt & Scharkow, 2013).

Linking Micro- and Macrosocial Processes

Especially in media effects research, scholars have identified a substantial gap between the micro perspective—focusing on the immediate, individual effects of communication—and the macro perspective, which focuses on long-term societal dynamics (Scheufele, 2008). Studies investigating psychological effects at an individual level only include aggregate social dynamics and long-term effects in their argumentation for the social relevance and implications of the research. At the same time, theories on media effects at a societal level (e.g., knowledge gap theory and opinion dynamics) use aggregate data from surveys or content analyses and largely neglect the individual psychological processes that may explain the observed effects. Only a few theories, such as the spiral of silence (Noelle-Neumann, 1984) and cultivation theory (Gerbner, 1969), integrate societal and psychological media effects to explain emergent macro phenomena through an accumulation of individual interactions with media and society. However, comprehensive empirical tests of these theories are difficult to accomplish because they require long-term observations of the individual media use, social interaction, and attitudes of a large sample of respondents.

This gap is not unique to media effects research; it is one of the oldest puzzles in the social sciences (Coleman, 1990). In the last few decades, scholars of sociology in particular have leveraged ABM’s potential for bridging micro and macro research (e.g., Hedström, 2005; Sawyer, 2003), but this effort has gone largely unnoticed in communication science. Thus, we see integrating micro and macro perspectives on media effects as one of the most promising venues for ABM in communication science.

By virtue of their structure, ABMs may serve to both deconstruct societal phenomena to identify the individual processes underlying them and extrapolate individual effects to a societal level to observe emergent effects in a virtual environment (Epstein, 2006). Though all rules of an ABM are defined at an individual level, societal and organizational contexts are not ignored. They can be incorporated as additional corporate agents or environmental properties of the model (Conte, 2009; Sawyer, 2013). This enables researchers to directly realize Coleman’s (1990) macro-micro-macro model (see Figure 1).

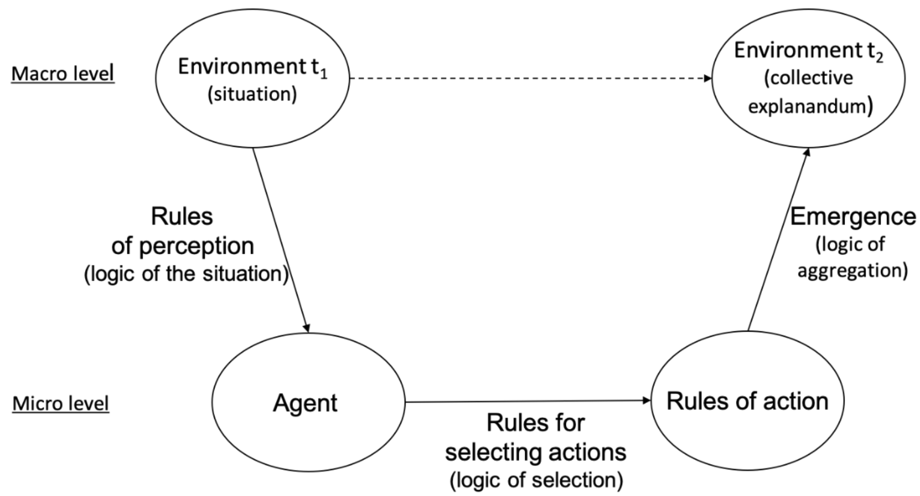

Figure 1. Macro-micro-macro model of agent-based modeling. Adapted from Waldherr and Bachl (2011, p. 239).

Once specified, an ABM that includes the individual actor's ability to observe its society and environment can be used to perform systematic thought experiments by simulating the outcomes of social processes based on different initial states and parameters. In this respect, a simulation study resembles a controlled experiment in which the effect of alterations of initial parameters on the outcome may be studied. In these virtual experiments, hypotheses based on specific theories may be tested to prove their internal consistency or to explore the macro implications of basic model assumptions (Rand & Rust, 2011). Because weeks and months may be simulated in mere seconds and parameters may be set to values hardly observable in the real world (Axelrod, 1997a), a wide range of parameters may be tested in a relatively short time to increase understanding of boundary conditions and limiting factors of emergent phenomena (Gilbert & Troitzsch, 2005).

In communication science, this approach has been used to formalize theories on spiral processes and explore the boundary conditions for related macro phenomena to emerge. For example, Sohn and Geidner (2016) explored the connection between locally perceived opinion climates and the likelihood of the emergence of a spiral of silence as hypothesized by Noelle-Neumann (1984), stating that individuals perceiving their opinion to be in the minority will remain silent. Specifically, Sohn and Geidner (2016) investigated in an ABM how the spiraling process is affected by varying the distribution of individuals' network sizes, which influences their accuracy in estimating the overall opinion climate. Simulation results indicate that the global spiral process is more likely to occur when the population is less polarized in its perception of the overall opinion climate.

Song and Boomgaarden (2017) investigated another spiral process, formalizing Slater's (2007) theory of self-reinforcing spirals between selective media use and media effects and integrating it with the filter-hypothesis framework (Schmitt-Beck, 2003). They developed an ABM that simulates feedback processes between partisan selective exposure and attitude polarization and found that the spiral process is highly contingent on the configurations of interpersonal discussion networks and other contextual factors. Depending on the specific conditions, media exposure caused attitudes to stabilize or polarize.

ABM has also proven useful for refining theories on diffusion processes and social contagion. For example, Liu (2007) modeled the two-step flow of communication based on the core assumptions of Katz and Lazarsfeld (1964) to simulate the role of opinion leaders in elections. Simulation experiments revealed that opinion leader influence is unlikely to diffuse beyond the leader's closest followers.

That social diffusion processes are more complex than simple viral contagion has been shown in an agent-based simulation study by Centola (2013) examining the emergence of critical masses in social movements in networks. Challenging Granovetter's (1977) study on "the strength of weak ties," simulation results indicate that weak ties may hinder mobilization, whereas homophily in close network clusters might be critical for stabilizing a social movement and reaching a critical mass. Similarly, Alvarez-Galvez (2016) found that densely connected networks facilitated the spread of minority opinions, and Piedrahita, Borge-Holthoefer, Moreno, and González-Bailón (2018) discovered that the structure of communication networks essentially affected actors' ability to coordinate in collective action scenarios. Further examples include works modeling individual interpersonal and computer-mediated communication to simulate the digital divide (Lim, Lee, Zo, & Ciganek, 2014), the privacy paradox in social media (Tubaro, Casilli, & Sarabi, 2014), transactive memory systems in team communication (Palazzolo, Serb, She, Su, & Contractor, 2006), and the emergence of echo chambers (Geschke, Lorenz, & Holtz, 2019).

While these examples demonstrate that some communication scholars have fruitfully applied ABM to bridge the micro-macro gap, the approach is far from established in this discipline; we see much more potential for applying it to a broader range of research questions in communication theory.

Linking Data and Theory

Current trends in computational social science focus on the increasing amount of data available on any kind of human interaction and communication (Lazer et al., 2009; Shah et al., 2015; Tinati, Halford, Carr, & Pope, 2014) and neglect theories that might explain the dynamics and patterns observed therein (Hedström, 2005). Here, too, ABM may prove valuable for communication research because these models allow researchers to explicitly link theories to new data to understand the emergence of unintended patterns (Gonzalez-Bailón, 2017) and develop causal explanations (Bruch & Atwell, 2015). Of course, ABM is not the only means to this end, but it is a viable strategy to develop models with explicit and analyzable causal assumptions and implications (Smaldino, 2017). Although also statistical methods exist for establishing causal inferences, such as those summarized by Pearl (2009), ABM has proven particularly useful for modeling complex systems' behavior (Miller & Page, 2007).

The following sections outline three basic ways in which empirical data may be included in ABMs to both increase the models' external validity and develop causal explanations for the empirical data. These strategies are not mutually exclusive and are often combined. Also, they are rarely used only once; rather, theory development and empirical validation reciprocally inform each other in an iterative process that may lead the researcher down unexpected paths.

Empirical Data as Output Reference

Empirical data may be used as a benchmark for simulation outputs. In this approach, also called pattern-oriented modeling (Railsback & Grimm, 2012, p. 225), ABMs are developed to simulate specific empirical phenomena, which can have any level of abstraction, from highly stylized facts to specific case-based time series or outcome distribution patterns. The final state of the simulation, its progression, and the state of the agents are then compared with empirical data on these phenomena.

Comparing simulation results with empirical data is a common technique to assess the validity of an ABM and its underlying assumptions (Liu, 2011), but tailoring a model to achieve specific outcomes may also prove valuable in theory development in communication science. For example, Mosler, Schwarz, Ammann and Gutscher (2001) implemented theories on information processing in an ABM to perform virtual experiments and then compared the results with the outcomes of actual experiments. Waldherr (2014) modeled the allocation of public attention to events and compared the progression of attention with empirical data on issue-attention cycles. In doing so, scholars not only validate the model on empirical data but also gain valuable insights on the boundary conditions for emergent phenomena to occur.

Likewise, recent simulation studies of online news use and discussion tried to mimic the dynamics in chat rooms (Tadić, Gligorijević, Mitrović, & Šuvakov, 2013) and reactions to online debates (Chmiel et al., 2011). Like the examples above, these studies not only modeled observed phenomena but also furthered scholars' understanding of emotions and predispositions concerning positive and negative phenomena in online communication and the effects of interventions.

Thus, by providing valuable insights into processes leading to observed phenomena, pattern-oriented modeling often leads to new hypotheses and theory development. If, in the iterative process of matching ABMs with reality, new rules and environmental conditions must be imposed to fit the empirical data, these amendments may be translated to hypotheses for future research. In this way, ABMs help researchers ask the right questions (Epstein, 2008), create better empirical research designs, and allocate resources wisely by focusing only on factors that proved consequential in simulation experiments.

Eberlen, Scholz, and Gagliolo (2017) go a step further by noting that the output reference may also be the desired result of an experiment or previous results from similar studies. Thereby, researchers may learn in virtual experiments how many respondents may be required to achieve specific results, which moderating effects should be taken into account, and what probability of alpha and beta errors should be expected. This may aid in the process of formulating specific hypotheses for preregistration and the optimization of experimental settings.

Empirical Data as Input Reference

Empirical data also may be used early in the modeling process to specify the rules of a model. Based on experiments and meta-analyses of individual responses to media or interpersonal message content, researchers can infer expectable effect sizes and response latencies to construct such rules. Likewise, content analyses, surveys, and qualitative studies may provide reasonable indicators for the setup of the agent's attributes, environment, and contexts (Edmonds, 2015). For example, in a study of online helping behavior, Tsvetkova and Macy (2015) used survey data from Amazon Mechanical Turk to calibrate an ABM that was then used to predict helping behavior in online discussions.

Because studies following this approach use empirical findings in the setup of the ABM but do not strive to reach a specific final state, the approach is mostly used for the exploration of counterfactual or future what-if scenarios for which rich empirical data are unavailable (Hilbert, 2015). Although the approach has not traditionally been employed in communication science, it has been used in policy-modeling approaches that seek to explore the consequences of policy decisions (Gilbert et al., 2018). The ability to model various possible consequences has made this approach valuable in participatory processes in which multiple stakeholders are included in strategic planning (Voinov et al., 2016). Simulation experiments then are used to study the cumulative and long-term effects of the established rules at a system level. In communication science, using empirical data as an input reference may be useful in fields such as public relations, health communication, algorithm research, and media governance.

Empirical Data as Input-Output Reference

Empirical data may be used for both the initial and final states of the model to test different sets of rules. Using this approach, the applicability of different theories to an observed empirical development may be tested directly with an ABM. It must be noted, however, that this method necessitates fitting models closely to the empirical case providing the data. To generalize the model and counter overfitting, it may be wise to test the model on other data sets once it fits one case.

Muis (2010), for example, was interested in how Dutch populist politician Pim Fortuyn was able to maximize votes in only a few years. Muis implemented an ABM of party competition with media effects for the Dutch case by using empirical data on party positions, public opinion polls, and election outcomes from May 1998 to May 2002 for calibration. In a follow-up study, Muis and Scholte (2013) were able to reproduce the rise of the Dutch Party for Freedom with the model. Based on this work, the researchers observed that the key mechanism for populists winning ground was their flexibility in finding winning positions, while established parties often stuck to their ideological stances.

In another example by Wettstein (2018)—described in more detail in the next section—an ABM was calibrated with panel survey data and then optimized to simulate the unobserved period between panel waves and reach a final state similar to the next panel wave.

Real-world data can be incorporated at various stages of model development (see Figure 2) to ensure that a theoretically derived model can appropriately reconstruct and eventually even forecast empirical patterns. For modelers and empirical researchers, integrating empirical data and ABM means going the extra mile to gather the data or to specify the model, respectively. However, we hope that our account makes it clear that it is worth the effort.

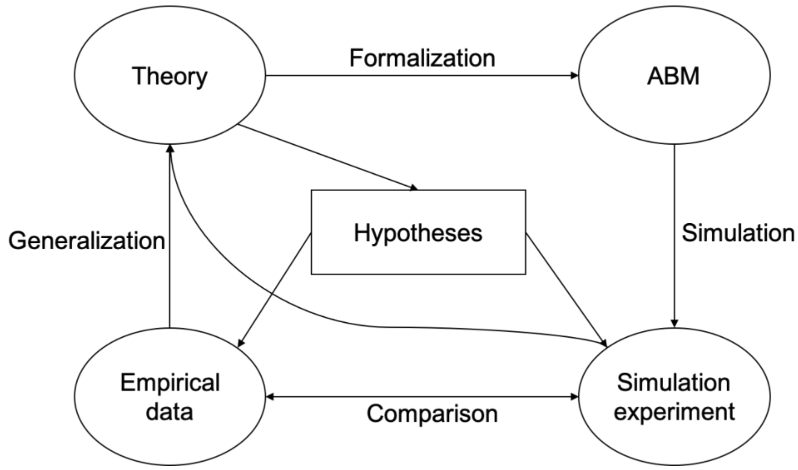

Figure 2. Agent-based modeling and the empirical research process.

Two Implementation Examples

One reason that ABM has not often been applied in communication research might be the fact that it is not a method readily included in statistical software. Each model needs to be tailored to a specific research interest, and the researcher is required to refine the simulation's rules and environment. To clear this hurdle, in this section, we present two sample models in two different programming environments. In the first example, a prototype simulation generating initial results was implemented in a few weeks, while the second example took only days. The iterative process of model specification, analysis, and adjustment, however, amounted to more than half a year in both cases.

Issue-Attention Cycle in NetLogo

NetLogo is a free programming platform specifically tailored for ABM that features many built-in tools for visualizing and parametrizing models. The programming language is quite easy to grasp, even for scholars without programming skills. Many tutorials and a few textbooks (Railsback & Grimm, 2012; Wilensky & Rand, 2015) facilitate self-teaching the language.

The agent-based model of the media arena (AMMA) (Waldherr, 2014) was implemented in NetLogo. This model integrates the main drivers of news waves as identified by empirical research in agenda setting and building. An overview of the basic code structure is presented in Figure 3.

```
to setup; procedure for initialization of the model
   clear-all
       ...
   setup-topics
   setup-journalists
   reset-ticks
end

to go; rules for the simulation
   produce-events
   ask journalists [report-event]
   update-topic-values
   calculate-outputs
   tick
   do-plots
   ask links [die]
   ask events [die]
   if ticks > 7000 [stop]
end
...

; here, the specific sub-procedures follow...
```

Note. NetLogo can be downloaded at http://ccl.northwestern.edu/netlogo. The documented NetLogo model of the AMMA is available at http://www.openabm.org/model/4110.

Figure 3. Generalized Structure of the Agent-Based Model of the Media Arena in NetLogo.

The basic model features an abstract and limited public space of 33 patches by 33 patches in which 100 randomly distributed agents (journalists), called turtles in NetLogo, interact with one another, three topics, and a random number of events. Communication in this space is global (i.e., everything that happens can be perceived by everybody).

In each time step, a random number of events happen and are randomly attributed to a topic. Then the journalists move around, each choosing one interesting event and reporting it. The rules for choosing the events are based on news value, a value between 0 and 1 signifying how interesting each event is. The news value partly consists of the event value (i.e., how interesting the specific event is to the public) and the related topic value (i.e., how interesting the topic in general is to the public). The higher the news value of an event, the higher the probability of a journalist reporting it. Also, the news value must exceed the basic attention threshold of the journalist for the related topic, and journalists slightly prefer reporting topics that are physically closer to them, representing publication bias.

Topic values and attention thresholds change dynamically during the simulation. The more (less) journalists report a topic, the more the related topic value increases (decreases) and journalists' attention thresholds for the topic increase (decrease) with each day (not) reporting it. This combination of positive and negative feedback leads to journalists flocking around one topic after another, generating recurring news waves in the simulated time series plot (see Figure 4).

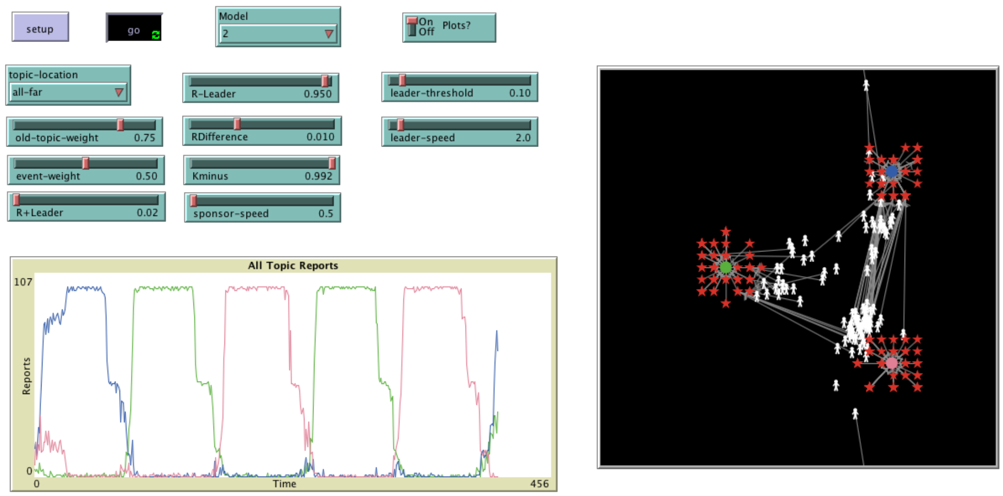

Figure 4. Modeling interface of the agent-based model of the media arena as developed by Waldherr (2014). Circles represent topics, and stars represent events. Links signify topic attribution and reports.

To generate a pattern closely resembling the stylized issue-attention cycle, it is necessary to distinguish various types of journalists differing in their adoption speed of rising topics and thus triggering chain reactions of leading and following in the media system.

Social Impact Theory in Python

An ABM with empirical data as an input-output reference was implemented in Python to model the unobserved processes between panel waves of an opinion survey. Object-oriented programming languages (e.g., Python, Java, and C++), while not specifically designed for simulations, provide a suitable programming environment for ABM because they allow for the definition of complex objects, such as agents and environmental factors.

The study used data from three panel waves in the run-up of a referendum to define the input and output of agents and employed a parallel media content analysis to define the agents' environment. The rules that governed agent behavior were derived from social impact theory (Latané, 1981), which holds that the impact of an individual's surroundings leads to minute changes in the individual's attitudes. By aggregating these influences, individuals adjust to align with their peers.

The simulation was implemented as a Python script with a series of objects. First, for each respondent in the panel, an agent was defined as a dictionary holding all survey responses. These responses included sociodemographic variables, place of residence, attitudes, attitude certainty, media reliance, and self-reported frequency of media use for all media outlets in the content analysis. Second, an object was defined for the environment, holding the media content for each medium on each day between the panel waves, including the slant toward the referendum. Finally, a set of rules was defined as functions that, for each point in time and for each actor, evaluated the personally encountered media bias and the opinion climate of agents nearby. The generalized structure of the Python code is shown in Figure 5.

```
agents = initiate_agents(survey_data)
media = initiate_media(content_analysis)
for d in days:
        for a in agents:
        used_media = agents[a]['media']
        m_bias = compute_media_impact(media,d,used_media)
        o_bias = compute_social_impact(agents, a)
        impact = m_weight * m_bias + s_weight * o_bias
        agents[a]['Attitude'] += impact
```

Note. The full documented code of the program is provided at https://github.com/Tarlanc/ABM_PanelWaves

Figure 5. Generalized structure of the simulation of social impact in Python.

As the simulation progressed through the periods between panel waves, the bias in the personally used media was queried from the environment object, and the local opinion climate was computed as the mean opinion of other agents, weighted by the inverted geographical distance to the agent. From the media bias and local opinion climate, a total impact was computed. Once the social impact for all agents was computed, it was added to their attitudes before the next time step.

By varying the weight of the media bias and opinion climate in the computation of the overall impact—both generally and depending on the media reliance and attitude certainty of individual agents—the model could be changed to yield different results. Using an evolutionary algorithm and bootstrapping to avoid overfitting, the weights were adjusted to match the simulation result with the empirical data of subsequent panel waves used as output reference. An interpretation of the optimal weights indicates that media bias became more important as the referendum drew near, but it was outweighed by the local opinion climate (Wettstein, 2018).

Reliability and Validity of ABM

Some reservations about ABM in communication science likely arise from concerns about the models' reliability and validity. Even complex and elaborate simulations are abstractions of reality and may not perfectly represent real interactions. Since the validity of simulations is an issue not only in communication science, it has been the focus of discussion for years in various disciplines applying ABM. Consequently, researchers have proposed various guidelines and tests to ensure the reliability and validity of ABMs (Gräbner, 2018; Kleijnen, Sanchez, Lucas, & Cioppa, 2005; Liu, 2011; Rand & Rust, 2011; Sargent, 2013; Thomsen, Levitt, Kunz, Nass, & Fridsma, 1999).

The nomenclature of criteria for the reliability and validity of ABM is, therefore, not always coherent and varies according to the tradition from which the guidelines emerge. The following sections outline the central points for ABM use in communication science. For reasons of compatibility with ongoing debates on the quality and applicability of experiments in communication science and psychology, the criteria are categorized using a threefold distinction between reliability and internal and external validity. The following paragraphs may be read as a catalog of strategies to ensure the model meets these quality criteria (see Table 1). However, the chosen strategies may vary with each modeling project and depend to a great extent on the modeling purpose.

Table 1. List of Criteria in the Quality Assessment of Agent-Based Modeling.

Level	Criterion	Test
Reliability	Verification	- Comparison of implemented rules and theory (e.g., by retranslation) - Proofreading of code by a different programmer
	Replication	- Reimplementation in another language, on a different platform, by a different programmer, etc.
Internal validity	Consistency	- Inspection of time series data on individual actors and the overall system - Comparison of agent attributes with real attributes
	Robustness	- Simulation using different initial settings of parameters with low expected influence
External validity	Conceptual validity	- Documentation of empirical findings and theories underlying all rules in the model - All rules must be justified - Compare results to possible end states deduced from the theory applied
	Realism	- Comparison of simulated and real data - Inclusion of real data as initial state of the model - Participatory modeling with external experts
	Reproducibility	- Comparison of results with comparable simulations
	Sensitivity	- Investigation of effects of parameters by systematic variation - Evaluation of system behavior under extreme circumstances
	Face validity	- Present simulation or simulated data to experts - Check whether it is discernible from empirical data (Turing test)

Reliability

The fundamental criterion for model quality concerns the model's reliability or methodological validity (Bharathy & Silverman, 2010). In ABM, this means that the model must be specified in a way that allows the replication of the simulation with the same model and others based on the same theoretical assumptions.

Verification

The central factor in ensuring model reliability is the rigorous testing of implemented rules (Rand & Rust, 2011; Thomsen et al., 1999). These rules are deduced from theories and translated to commands in a given programming language. The translation should be both accurate (i.e., representing the theoretical assumption) and correct (i.e., devoid of programming errors) to generate valid simulations. Errors in the implementation of rules may lead to unexpected and inexplicable outcomes.

One strategy is to use back-translation of programmed rules to compare the rules with the theory. Preferably, a person not involved in the programming should translate the ABM's rules to natural language. The result may then be compared with the model assumptions and theoretical background specified by the researcher. More strategies for testing and documenting code are given by Railsback and Grimm (2012, pp. 75–93).

Replication

A more effective test of model reliability is secondary implementation in a different programming language or using other hardware, modeling tool kits, or algorithms (e.g., Wilensky & Rand, 2015, pp. 336–346). The results may then be checked for congruence. A replication is successful if the new implementation creates model outputs similar to those of the original model. However, if the ABM contains random elements, perfect convergence of a single simulation is not to be expected. Multiple iterations of the same simulation should be performed to determine their average outcome.

Internal Validity

The internal validity of experiments is provided when interactions, reactions, and results may be understood and explained (Guala, 2003, p. 1198). In ABM, this means that the model should behave in an explicable manner on all levels, including agents' actions, the range of parameters and attributes, the reaction of the simulation to change, and the consistency of outcomes.

Consistency

A minimal requirement for the validity of a simulation is the consistency of agent behavior with reasonable expectations. Agents' attributes should remain within boundaries observed in the real world and take on similar distributions and developments (Sargent, 2013, p. 17). For example, if an attribute is expected to be normally distributed on a scale from 1 to 5, values above 5, uniform distribution, or convergence to a single value in the process of the simulation would be inconsistent with expectations.

Checking these inconsistencies may require descriptive analyses of parameter values for individual agents as well as the aggregate. Additionally, the development of variable attributes may be observed in time series analyses or visual confirmation of visualizations (Rand & Rust, 2011). If attributes change at an unexpected rate, the model may have been specified incorrectly.

Robustness

Especially if the goal of the simulation is outcome prediction, the model should be robust in the presence of irrelevant variance (Hassan et al., 2013). Although the theory may suggest that certain parameters can influence the dynamic and outcome of the emergent phenomenon, most parameters are assumed to have little or no effect. Consequently, alterations in these parameters may not be expected to exert strong influence on the simulation's final state. To test for robustness, some parameters of the environment may be changed systematically to demonstrate their effect on the model (Railsback & Grimm, 2012, pp. 302–306). If the variation of irrelevant parameters leads to unexpected changes in the result, the predictive quality of the model is questionable.

External Validity

The third aspect of model quality is the ABM's external validity. If ABMs are used to simulate human behavior, their dynamics and results should be comparable to phenomena witnessed in society (Guala, 2003, p. 1198). Due to abstractions and simplification of agents and rules in the definition of an ABM, their external validity is generally doubted (Bharathy & Silverman, 2010), and researchers should take care to address possible limitations to external validity.

Conceptual Validity

A major aspect of external validity is the model's compatibility with the world it represents (Louie & Carley, 2008). Primarily, this concerns the validity of the rules and assumptions made in the process of modeling. If the rules contradict empirical observations or violate the theoretical assumptions of the model itself, external validity may not be established (Sargent, 2013; Thomsen et al., 1999). Therefore, the researcher must ensure that the model is defined according to observed processes.

Realism

Because researchers are often criticized for not putting enough effort into the empirical validation of their models (Waldherr & Wijermans, 2013), another important aspect of external validity is a realistic setup of agents and environmental factors. Even if the agents are blunt abstractions of humans, their attributes should match those of the population they represent (Rand & Rust, 2011; Thomsen et al., 1999). Data from cross-sectional surveys of the population represented in the simulation may be used as input reference for the distribution and covariance of attributes. Likewise, experts may be included in the model development process to refine assumptions (Boero & Squazzoni, 2005). The more closely the agents match real humans, the higher the ABM's external validity.

Realism may also be tested by comparing the model's final state with empirical data. Using surveys or measurements produced under similar circumstances, the model's outcome can be tested for consistency (Galán et al., 2009; Kleijnen et al., 2005; Liu, 2011; Sargent, 2013). The more the model's final state resembles real data, the stronger the case is for external validity. Depending on the model's purpose, the comparison between simulated and empirical data can focus on qualitative patterns, stylized facts, or quantitative measures.

Reproducibility

If other studies have been completed with similar ABMs, their results may be compared with those of the model. The reference models need not have the same design as the ABM, but they should have similar assumptions and rules. The ABM may then be used to imitate the previous studies, and one can compare the outcomes (Macy & Willer, 2002). If the ABM can successfully reproduce results from similar models, this increases the external validity of the findings.

Sensitivity

Just as robustness is a criterion for internal validity, sensitivity to changing parameters may be tested to establish external validity. If the theory predicts that emergent phenomena will change under specific circumstances, these circumstances may be used to test the prediction (Sargent, 2013, p. 16). This is especially the case with ABMs simulating an experimental situation. Here, a change in the experiment's stimulus should lead to different outcomes (Macy & Willer, 2002, p. 163). Alternatively, extreme values of specific relevant parameters may be used to generate extreme results (Thomsen et al., 1999, p. 390). For example, if communication between agents is suspended completely, the resultant change should merely reflect their reactions to external influences. Any other dynamic would cast doubt on the external validity of the model.

Face Validity

Finally, external validity may be tested against the expectations and beliefs of the researcher and third parties. For this purpose, visualizations of the simulation are helpful because they are often intuitively interpretable (Kleijnen et al., 2005; Liu, 2011). For example, the distribution of an opinion climate may be represented by agents changing their color according to their opinions (Nowak & Latané, 1994, p. 81). Watching the development of the opinion climate as a moving picture informs the researcher on whether the agents behave as expected and often serves as a strategy for verification, as described above (Railsback & Grimm, 2012, p. 81). Oscillating agents, sudden outbursts of contrary opinions in a homogeneous group, and other unexpected developments may be spotted even by untrained eyes. The main question in the test of this criterion is whether the behavior of the system is plausible and consistent with expectations.

The ultimate test for face validity is a Turing test, in which the results are presented to experts as actual measurements in an experiment or survey (Bharathy & Silverman, 2010). If this claim is accepted by the experts after inspecting the data and comparing it to data from other sources, the outcome of the simulation may be considered plausible (Sargent, 2013, p. 17).

It should be noted that no criterion listed above and summarized in Table 1 is considered necessary and sufficient to establish external validity, and a model does not necessarily have to satisfy all criteria to be useful (Gräbner, 2018). Depending on the model and the focus of the research, some criteria may not apply, while others may be vitally important. It is advisable to define a list of criteria and their weight in quality assessment before starting the assessment. This facilitates an honest and complete evaluation of the model.

Challenges and Future Perspectives

Modeling social phenomena using ABM implies conceptual as well as operational challenges. Some of these challenges have already been discussed with respect to reliability and validity. In this section, additional challenges in the preparation, definition, and analysis of ABMs are briefly outlined and discussed.

The first challenge may result from an incomplete theory—that is, one that does not suffice to define a model. This issue often arises with verbally formulated theories, which are standard in the communication discipline (Smaldino, 2017). In the specification of an ABM, the researcher is required to translate communication theories into precise and quantified rules for agents. While theories may remain vague in some areas, the rules of an ABM require exact parameters (e.g., effect sizes, latencies, and interactions) in the setup. In some cases, the researcher may refer to the results of experimental studies within and outside the current field of research. In many cases, however, educated guesses are the best method to define parameters, though they may not be entirely satisfactory (see Poile & Safayeni, 2016, for a thorough discussion of the implications). In these cases, we recommend a direct comparison between models with different guesses for each parameter. From this comparison, the researcher learns about the influences of each parameter and may update the initial theory with boundaries of realistic values.

A second challenge lies in the selection of the correct size and resolution of the model and its output. Using large numbers of agents, a multitude of steps, and a complete output of all individual data may seem appealing at first. This approach, however, leads to extensive data sets consisting mainly of irrelevant data for the research question in the current research process. Therefore, we recommend deliberately deciding on these points before implementing and running the model. If the data analysis method is decided on before designing the model, the data may be streamlined to match the requirements.

A third challenge in the specification of ABMs is finding an adequate complexity. In the effort to recognize all possible context effects on all agents, rules multiply rapidly and increase the complexity of the system—a problem called the "curse of dimensionality" (Eberlen et al., 2017, p. 157). If the model shows unpredictable effects, the identification of faulty rules, parameters, or conditions may become difficult. Following Railsback and Grimm (2012) as well as many other practicing modelers, we suggest the model be kept as simple as possible. The first design of the model should contain only the most central rules.

Gradually, additional mechanisms and conditions may be added to account for known context effects (Bharathy & Silverman, 2010).

A fourth challenge is determining the resolution and format of the output generated in the simulation. It pays to spend time on the preparation of aggregated outputs. Some tools for ABM offer preprocessed outputs, which are useful for reducing complexity. In programs written in object-oriented programming languages, the possibilities for data preparation are potentially unlimited. The most straightforward method for preprocessing is aggregating several runs of the simulation with random parameters to get robust mean values. Other approaches may include the automated calculation of correlations of attributes during the simulation to create time series data, pattern recognition, or automated comparisons of intermediate and final states with real data.

The output format may pose an additional challenge in data analysis because it is most likely to contain nonlinear elements. Due to interactions between the agents and emergent phenomena of the system, time series data pertaining to agents or the whole model are unlikely to satisfy the requirements for ordinary least squares regressions and analysis of variance. Complex time series and nonlinear changes in properties are to be expected. To prevent methodological artifacts, the data should be subjected to all required tests before performing statistical analyses. In some cases, nonlinear modeling may be required to handle simulation data.

As we have shown in this article, ABM has proven to be a powerful tool for bridging two major gaps in the field of communication science in the age of big data: the micro-macro gap and the data-theory gap. With its generative (Epstein, 2006) and mechanism-based (Hedström, 2005) approach to explanation, ABM can be a valuable contribution to the classic toolbox of communication scholars, which has so far been almost exclusively focused on explaining variance in variable measures. Many research phenomena of interest in this field exhibit exactly the features that ABMs are most suitable for: autonomous, heterogeneous actors interacting with one another in a dynamic environment and generating emergent macrosocial phenomena, such as waves of public mood and attention.

Thanks to free, advanced tools for model specification and available code snippets for object-oriented programming languages, ABM may be applied by researchers who lack advanced programming skills. This fact raises hopes that ABM will diffuse more widely among communication scholars in the near future. The relative ease of implementation must, however, not hide the fact that the method has strong conceptual, theoretical, and methodological requirements.

Depending on the research interest, ABM may be used to extrapolate individual effects to an aggregate level, perform virtual experiments, explain observed societal dynamics, reproduce emergent phenomena, or predict the consequences of policy decisions or interventions. It should be kept in mind, however, that these models remain strictly abstract and simplified representations of human behavior. Rigorous quality assessment at all stages of model design and analysis is indispensable to maintain external validity and achieve a better understanding of real social phenomena. When applied with due caution, we see great value and potential in more closely integrating ABM with empirical research, particularly digital trace data. This may be best achieved if modelers and data scientists join forces in interdisciplinary teams.

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