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Agent-Based Modeling: A Guide for Social Psychologists

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Abstract

Agent-based modeling is a long-standing but underused method that allows researchers to simulate artificial worlds for hypothesis testing and theory building. Agent-based models (ABMs) offer unprecedented control and statistical power by allowing researchers to precisely specify the behavior of any number of agents and observe their interactions over time. ABMs are especially useful when investigating group behavior or evolutionary processes and can uniquely reveal nonlinear dynamics and *emergence*—the process whereby local interactions aggregate into often-surprising collective phenomena such as spatial segregation and relational homophily. We review several illustrative ABMs, describe the strengths and limitations of this method, and address two misconceptions about ABMs: reductionism and "you get out what you put in." We also offer maxims for good and bad ABMs, give practical tips for beginner modelers, and include a list of resources and other models. We conclude with a seven-step guide to creating your own model.

Keywords

agent-based modeling, computational social science, social dynamics, social psychologies

From Detroit to El Paso, New York to Los Angeles, urban environments are divided by race and ethnicity. The pernicious consequences of segregation lead us to infer pernicious causes: People must live in homogenous neighborhoods because they are racist. This explanation for segregation seems plausible, as prejudiced individuals do avoid people of other races—but it assumes that the collective behavior of neighborhoods can be explained similarly to the behavior of individuals. Almost 40 years ago, Thomas Schelling (1971) challenged this assumption, asking whether segregated neighborhoods would form even when individuals had no prejudice, and only wanted a few neighbors similar to themselves.

Schelling placed red and green pennies on a chessboard to represent people in neighborhoods. People were happy—and remained in their square—if they were surrounded by at least 30% of their "color"; if this number dropped below 30%, however, people became unhappy and moved to a new square. Schelling played out this model by moving pennies one by one until each person on the board was happy, by which time the board was highly color segregated. At higher (75%) or lower (15%) thresholds of similarity, segregation was more or less pronounced (see Figure 1 for an illustration of these effects), but the key is that even individuals who embraced high diversity could still end up segregated.

Schelling's work is an elegant testament to how simple and innocent individual preferences can produce surprising societal outcomes over time. His model also serves as a prototypical—if low-tech—example of the power of agent-based modeling (ABM)[1] in understanding emergent social behavior.

Agent-Based Modeling

Agent-based models (ABMs) are computational simulations in which artificial entities interact over time within customized environments. These entities (agents) are programmed to represent humans who behave in precisely specified ways. As summarized by Macy and Flache (2009, p. 247), agents are adaptive in that they respond to their environment through learning and evolution and are autonomous in that they control their own goals, states, and behaviors. They are also intentionally simplified, usually following only one or two basic rules

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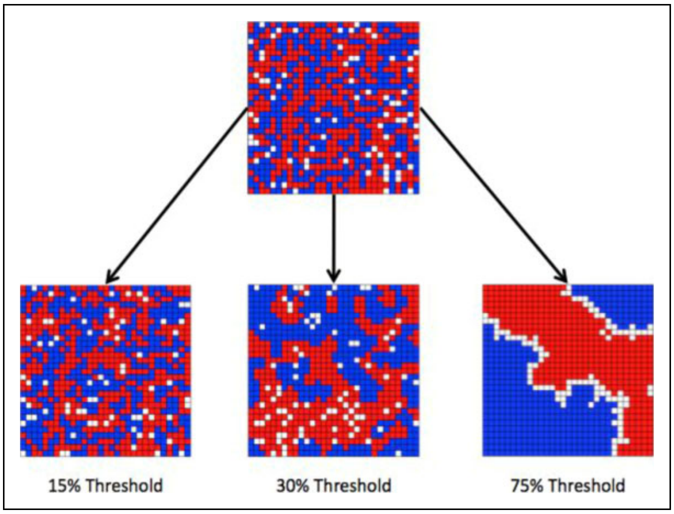

Figure 1. Visualization of Thomas Schelling's (1971) segregation model at its commencement (top panel) and conclusion (bottom panels). When agents have a 15% threshold for similarity (left panel), only minimal segregation occurs. However, 30% (middle panel) and 75% (right panel) thresholds produce striking segregation. Retrieved from http://nifty.stanford.edu/2014/mccown-schelling-model-segregation/

(representing habits, norms, or preferences) throughout the simulation.

The outcomes of ABMs, however, are anything but simple. A well-programmed model offers insight into how local interactions between agents can lead to complex group- and system-level phenomena. Consider how a single bird's tendency to align and remain close (but not too close) to her peers can create a swirling flock that appears to be moving with a collective mind (Reynolds, 1987) or how predator–prey interdependence can explain animal species' resurgence following near extinction (Borschev & Filippov, 2004). ABMs are uniquely equipped to shed light on such phenomena and countless other applications involving interacting individuals.

Perhaps because of their ability to simulate large-scale dynamics with bottom-up processes, ABMs are popular in economics (e.g., Tesfatsion & Judd, 2006), sociology (Bruch & Atwell, 2015; Macy & Willer, 2002), political science (Cederman, 2005; Johnson, 1999), and some applied sciences (e.g., artificial intelligence; Beer, 1995; Gasser, Braganza, & Herman, 1987; Wooldridge, 2003). In psychology, however, ABMs continue to exist at the field's margins (see Goldstone & Janssen, 2005; Smith & Conrey, 2007) perhaps because psychologists view them as difficult to implement and see their results as only reflecting the assumptions of their programmers (you get out what you put in).

This article aims to address these concerns and to pique social psychologists' interest in ABMs. We provide examples of classic and recent ABMs that illuminate social behavior, compare modeling to other methods in social psychology, and give concrete advice to social psychologists wishing to implement their own ABMs. Although there are ABMs that simulate nonsocial events (e.g., weather patterns or artificial intelligence), we focus on models of social processes. We hope to provide an in-depth but accessible introduction to ABM for social psychologists.

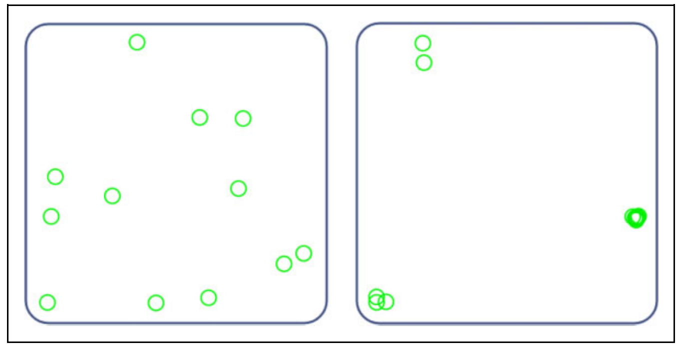

Figure 2. Visualization of Gray and colleagues' (2014) model displayed at Round 1 (left panel) and Round 300 (right panel). Retrieved from online simulation at http://www.mpmlab.org/groups/

Social Psychological Questions Addressed by ABMs

Schelling's (1971) model of segregation addresses one of social psychology's core questions: Why do individuals segregate based on race? ABMs also address other important questions: What is the basis of group formation? What is the best strategy for maintaining cooperation? Why do couples pair off in terms of attractiveness? These questions are well suited to ABM because they involve individual behaviors interacting to produce surprising collective phenomena.

What Is the Basis of Group Formation?

Social identity is the dominant framework for understanding why people split into "us" versus "them": People with similar race, religion, or culture form groups, which then square off against each other (Tajfel, 1982). However, these social identities can only emerge once people separate into groups. This logic creates a regress in which groups require identity but identity requires groups. To escape this chicken–egg dilemma, Gray and colleagues (2014) examined whether groups could form in a completely homogeneous population without any identities. The authors programmed agents with only two simple characteristics: reciprocity (the tendency to cooperate with those who have previously cooperated with you) and transitivity (the tendency to share your network's social preferences)—each of which was a well-established social tendency (Holland & Leinhardt, 1971; Levine, 1998). The model's results revealed robust group formation even though agents had no sense of us or them, suggesting that groups can form even without identity (see Figure 2).

What Is the Best Strategy for Maintaining Cooperation?

Real-world questions of cooperation are captured by the "prisoner's dilemma," in which two people each have the choice to cooperate or defect. The *group* payoff is maximized when both people cooperate, but each player is made better off *individually* by defecting—capturing the essential tension of social dilemmas. Political scientist Robert Axelrod asked people to program agents with different strategies for repeated prisoner dilemma games (e.g., always cooperate, always defect, copy your partner's past behavior) and then paired these agents with each other in a round-robin design (Axelrod, 1980; Axelrod & Hamilton, 1981). As long as the agents engaged in repeated interactions, the winner was a very simple agent—"tit-for-tat"—which began with cooperation and then copied its partner's previous decision. Axelrod's ABM was important because it revealed a simple route for the emergence of cooperation, even in complex societies.

More recently, Bear and Rand (2016) developed an ABM to explore the psychological basis of cooperation. Agents played either one-shot or repeated prisoner's dilemmas. They could engage in two different kinds of cognition: a low-cost generalized intuitive response or a higher cost calculated response that could tailor its choice to whether the game was one-shot or repeated. The results showed that—given a high likelihood of repeated interaction—the best strategy was to intuitively cooperate and deliberatively defect when the game was one-shot. This ABM therefore offered an evolutionary explanation for why people sometimes cooperate when they can get away with defection.

Do Couples Seek Out Similarly Attractive Partners?

Members of a romantic couple tend to be similarly attractive, but it is not immediately clear why. Although some believed that people intentionally search for their attractiveness "match" (Huston, 1973; White, 1980), Kalick and Hamilton (1986) used an ABM to test whether matching could occur even if all people preferred maximally attractive partners. Heterosexual male and female agents were assigned an attractiveness score from 1 to 10 and were repeatedly paired up. Pairs asked each other on "dates," and if both agreed, they left the pool, otherwise they were paired up with new agents. Kalick and Hamilton ran two variations of the model: one in which people wanted maximally attractive partners (motivated for supermodels) and another where people wanted similarly attractive partners (motivated for matching). In the "motivated for matching" condition, agents' attractiveness was *very* highly correlated ($r = .85$) with their partners'—significantly higher than what actually occurs in real life. In contrast, agents who were "motivated for supermodels" had their attractiveness moderately correlated ($r = .5$) with their partners'—nearly the same correlation as in real life (Critelli & Waid, 1980). This moderate matching occurred because when everyone preferred the prettiest people, the prettiest ended up together first, and the less pretty were left to pair up afterward. As with many ABMs, people's individual preferences (for attractive partners) led to unexpected collective patterns (attractiveness matching).

Emergence

Agents in the previous examples were not programmed to segregate, to form social groups, to maintain stable cooperation, or to find partners of a similar attractiveness. Instead, these group phenomena arose via *emergence*—when the aggregation of small-scale *individual* behavior yields qualitatively different *collective* behavior. Emergence lies at the heart of almost any complex phenomenon, from traffic jams, to the wetness of water, to the neural basis of consciousness (Bassett & Gazzaniga, 2011; Tononi, Sporns, & Edelman, 1994). For example, while no individual neuron is conscious, their collective interactions yield human consciousness. Likewise, Schelling's model revealed that segregation could arise from the innocent decisions of relatively egalitarian individuals.

Historically, the impact of ABMs has been proportional to the amount of emergence they reveal—the apparent disconnect between individual and collective behavior. For example, the models from the previous section feature large-scale phenomena that are difficult to predict from individuals' behavior. Importantly, in explaining complex group-level phenomena with simple individual-level rules (see Smaldino, 2014), good ABMs typically reduce complexity—leading to these two complementary maxims for research with ABM:

Maxim for good ABMs: Reduce complexity by revealing how higher level phenomena emerge from the repeated interaction of simple rules.

Maxim for bad ABMs: Introduce complexity by taking a simple phenomenon and inventing complicated rules to explain it.

These maxims serve as useful criteria in evaluating whether ABMs add to or detract from a paper. The very best ABMs are explainable in plain prose and should reveal the emergence of complex or surprising phenomena using simple principles. Conversely, bad ABMs take a straightforward, intuitive phenomenon and complicate it with unjustified assumptions and abstruse mathematics. These maxims also help to address two traditional criticisms of ABMs.

Reductionism

ABMs are often seen to be reductionist, destroying the specialness of psychological processes by explaining them with simple agent behaviors. For example, claims of reductionism have been leveled against research linking love to hormones—if hormones are involved in love, is love "just" hormones? But fears of reductionism ignore the possibility of emergence, and the fact that all phenomena are embedded in a chain of lower and higher level events. Even if love can be "reduced" to hormones, there is still an undeniably powerful *feeling* of love, a higher level emergent experience that motivates people to write sonnets and run through the airport at the last minute. Emergence also provides a defense against claims of reductionism in ABMs. Even if reciprocity and transitivity

Table 1. Comparing Agent-Based Modeling to Other Methods.

Research Aspect	Field Studies	Lab Experiment	Archival Studies	ABMs
Control and realism	Low control; high realism	Medium control; medium realism	Low control; medium realism	High control; low realism
Scale	Medium to high scale	Low to medium scale	High scale	High scale
Nonlinear dynamics	Medium visibility	Low visibility	Medium visibility	High visibility
Mechanism	Medium clarity	High clarity	Low clarity	High clarity

Note. ABMs = agent-based models.

are sufficient conditions for group genesis (Gray et al., 2014), groups themselves prompt powerful feelings of solidarity and important behaviors—from war to religious movements—which cannot be reduced to these lower level processes.

You Get Out What You Put In

Critics of ABM have also claimed that the results of ABMs are closely tied to researchers' decisions in setting their models' parameters. In some sense, this is a strength of ABMs: Unlike in the laboratory or the field, the behavior of agents can be isolated and specified with precision—which forces researchers to explicitly formulate their theories. ABM-derived hypotheses are therefore decidedly falsifiable, with no ambiguity about what a model should predict. Of course, this level of experimenter control has the potential to make the final outcome seem obvious—but again, this criticism holds primarily with models that fail to show emergence. In Schelling (1971), there is nothing obvious about a slight preference for similarity causing rampant segregation, and in Gray and colleagues (2014), there is nothing obvious about two simple rules of interaction—reciprocity and transitivity—leading to stable grouping within homogenous populations.

Comparing ABM to Other Methods

In addition to the theoretical framework of emergence, ABMs offer several methodological advantages that complement other methods. In comparison to laboratory experiments, field studies, or archival investigations (including "big data" analysis), ABMs offer a unique combination of experimental control and massive scale, along with the ability to capture nonlinearities and underlying mechanisms. However, like any tool in a social psychologist's toolbox, ABMs come with limitations, of which external validity is most notable. This drawback is mitigated by supplementing ABMs with other tools—such as laboratory or field experiments—in multimethod investigations. Table 1 shows a comparison of the relative advantages and disadvantages of ABMs compared to other methods.

Control and Realism

In psychology, maximum control is often ascribed to experimental lab paradigms featuring random assignment, but even experiments have their limits. Participants may respond differently to experimental manipulations based on their cultural background (Hong et al., 2003), their religious upbringing (Shariff, Willard, Anderson, & Norenzayan, 2016), or even their transient mood (Forgas, 1995). Despite the flexibility of experiments, they are also limited by questions of ethics and feasibility—there is only so much that participants can do (or be asked to do) in the lab. In contrast, ABMs offer exceptional control: Agents in computational models can be instructed to perform almost any initial behaviors and will follow their instructions with complete uniformity. This control also remains high over indefinitely large samples and infinitely long simulations.

The trade-off to ABMs' high control is a low degree of external validity. For example, the agents in Schelling's model moved neighborhoods without incurring the financial or social costs inherent in relocation. Kalick and Hamilton's date choice model similarly assumed that individuals who accept dates permanently leave the dating pool, which seldom occurs in real life. Because of these shortcomings, ABMs are most effective when used in conjunction with laboratory or field experiments, which can use human subjects to validate an ABM's parameters (as in Luhmann & Rajaram, 2015) or its causal pathways (see Bear & Rand, 2016; Kalick & Hamilton, 1986).

Scale

One clear advantage of ABMs over other methods is statistical power. Obtaining sufficient *N* can prove difficult, as researchers struggle against a subject pool deadline or limited funding for participants. Even in field studies, researchers may obtain large sample sizes, but these samples may be incomplete or feature troublesome attrition. In ABMs, sample size is simply a parameter specified in the model. ABMs can also operate over any amount of time and sample at any rate. Of course, large *N*, long-term and high sampling-rate ABMs may take longer to run, but this typically means extras days and not years (and computing superclusters can substantially reduce this time). The critical point is that by analyzing large samples over an extended time, ABMs can reveal large-scale societal emergence (e.g., segregation and homophily), which is often impossible to observe with more traditional paradigms (and even with "big data" analyses; Lewis, 2015).

Nonlinear Dynamics

Most social psychology paradigms often only assess the behavior of one group at one specific time point, but social processes unfold dynamically across time and individuals.

Considering conformity, People generally follow behaviors more as they become more common (Asch, 1956; Boyd & Richerson, 1985; Henrich & McElreath, 2003), except for nonconformists who follow the behavior less (Efferson, Lalive, Richerson, McElreath, & Lubell, 2008). As a result, conformity follows an oscillating pattern of increases, decreases, and stability, which is difficult to fully capture with static experiments (Jarman et al., 2015). The spread of social attitudes (Nowak, Szamrej, & Latane, 1990) and stereotypes (Kashima, 2000) and the process of group formation (Halberstadt et al., 2016; Jackson, Halberstadt, Jong, & Feldman, 2015) also follow nonlinear patterns. In fact, there are few social phenomena that behave truly linearly over time, given the dynamic nature of social–cultural interactions and the unpredictable impacts of initial conditions (Vallacher & Nowak, 1999). ABMs are an ideal method for modeling these nonlinear processes, as they can include millions of time points and multiple runs (Abbott, 1988).

Mechanism

With their high controllability, ABMs are often able to isolate and directly manipulate the discrete psychological processes underlying complex social phenomena. Of course, psychological mechanisms can take many forms and can exist on many levels of analysis. ABMs are best suited to study how manifestations of individual (or dyadic) behavior influence larger scale group-level phenomena, such as when a slight individual desire for similarity catalyzes neighborhood segregation (Schelling, 1971). One question is whether the mechanism provided by ABM is the same in real life: Just because a mechanism sufficiently generates some outcome does not mean this mechanism necessarily or always generates the outcome. However, revealing even likely mechanisms is valuable for both basic research and policy decisions.

Building an ABM

After being inspired by ABM's rich history and unique methodology, readers might want to try their hand at model building. While training in ABMs is absent from most PhD programs in social psychology, many articles have linked ABMs to specific research questions (e.g., Axelrod, 1997; Carley, 2002; Schelling, 1971) with others providing more detailed, technical guides (e.g., Smith & Conrey, 2007). An edited volume by Tesfatsion and Judd (2006) includes chapters on ABM's history and its applications in economics as well as an introductory appendix with extensive practical tips for newcomers. Gilbert and Troitzsch (2005) provide a broader overview of ABM in the social sciences. Epstein (2008) includes a discussion of ABM's benefits over other methodologies, and Nowak (2004) gives an in-depth overview of emergence in ABM and the utility of simple models for simulating complex processes. Journal issues focusing on ABMs have included *American Behavioral Scientist* (Vol. 42, August 1999), *Science* (Vol. 284, April 1999), and the *Proceedings of the National Academy of Sciences* (Vol. 99, Supplement 3, 2002). Finally, websites like "OpenABM" (www.openabm.org) and "Agent-Based Models" (www.agent-based-models.com) provide courses, videos, and code libraries of previous models from which researchers can adapt code.

Aspiring ABMers must develop some level of computer programming. Python, MATLAB, R, and C have often been previously used to program ABMs. However, there are also more accessible tools available for those who do not have time to master a traditional programming language. The software package *Netlogo* (http://ccl.northwestern.edu/netlogo/; Tisue & Wilensky, 2004) is free and relatively simple and provides the code and explanation behind several of the models in this article, such as the predator–prey model, the flocking model, and Schelling's segregation model. Netlogo also comes with an extensive manual for researchers to learn the programming language as well as practical tips for building an ABM. Other tools that offer ABM training include "Swarm" (Minar, Burkhart, Langton, & Askenazi, 1996), which requires some programming ability (C or Java) but comes with a tutorial and example code to get new users started, and "Flexible Large-Scale Agent Modeling Environment," which is a more accessible computational environment, since models are specified in XML. "Cellular Automaton Explorer" offers a manageable interface to program simple ABMs and is particularly well suited for demonstration purposes (see, e.g., a popular Wolfram demonstration: http://demonstrations.wolfram.com/CellularAutomatonExplorer/).

To augment these resources, we provide a seven-step conceptual ABM algorithm, with each step illustrated by Schelling's (1971) segregation model and Gray and colleagues' (2014) grouping model. For more examples of the seven steps, we also provide a substantial (though not exhaustive) supplemental table with 35 additional ABMs on social–psychology topics ranging from the dynamics of online chatting to decisions about expressing pain. This collection offers insight into how other researchers have translated their research question into simulations.

Some of these steps do not apply to all models or all research questions, and so researchers should feel free to adapt them to their own needs. Nevertheless, the steps provide a useful guide for exploring social processes and for creating simulated worlds with the potential for collective emergence.

Step 1: What are your world's dimensions? Is your world flat or multidimensional? Schelling's segregation model is two dimensional (2-D)—like land—but group formation models are often multidimensional to represent complex social spheres (although these models often still involve 2-D visualizations to present data). In choosing the dimensionality, researchers must consider if the actions of one agent necessarily constrain the behavior of other agents—the more the mutual constraints, the lower the degrees of freedom and the lower the dimensionality (e.g., if I move across town from you, I not only move further from you but also your neighbor). Note that dimensions only apply to models where interactions between agents are

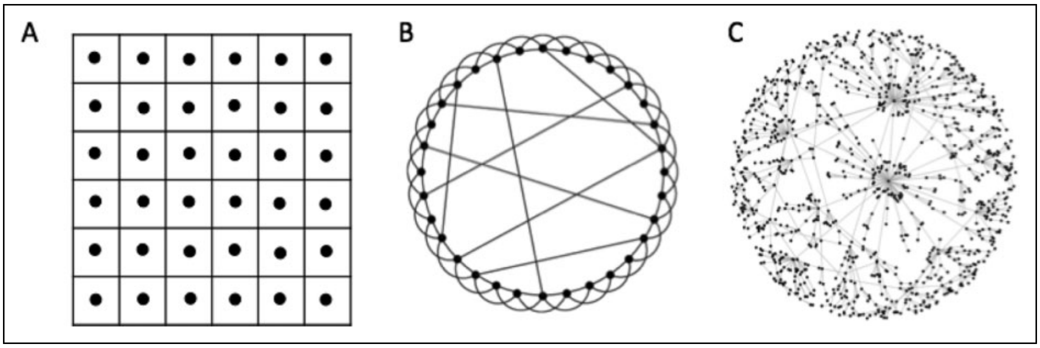

Figure 3. In the lattice network (A), agents only interact with their neighbors (applicable to residential models). In the small-world network (B), cross-network connections compliment neighboring connections, so that any two agents are connected by only a few degrees of separation (applicable to almost any social network). In the scale-free network (C), densely connected agents are more likely to generate new connections compared to sparsely connected agents (applicable to the Internet and citation networks).

governed by space. In network models, for example, there are no dimensions.

Application of Step 1. In Schelling's model, agents were paired in a 2-D space (as illustrated in Figure 1), while in Gray and colleagues' grouping model, agents interacted in a multidimensional space where one agent's position did not impede other agents' movement.

Step 2: How do agents meet? Behavior in ABMs is usually divided into rounds, and on each round, some number of agents interact with each other. One question is how to select which agents interact. Do they interact only with their neighbors, or can they be paired up with any other agent in the simulation? These choices stem in part from the dimensionality (see Step 1), but there are other choices within each of these sets. In some models, agents can avoid interactions entirely—perhaps because they are "unpopular"—while in others, agents can interact with more than one agent. In the latter case, what rules will govern interaction order? And will agents prioritize some interaction partners over others? Will interactions be governed randomly or according to a rule (or a bit of both)? The answers to these questions (along with your world's dimensionality) will determine the network you choose for your model. Three popular networks are displayed in Figure 3.

Application of Step 2. Since Schelling's segregation model focused on neighborhood dynamics, he programmed agents to only interact with their next-door neighbors. In contrast, Gray and colleagues' agents could interact with any other agent in the model, though they were more likely to interact with "friends" than with "enemies"—and they only interacted with one partner per round.

Step 3: How do agents behave? When agents meet, what do they do? Do they ask other agents on dates (Kalick & Hamilton, 1986)? Do they share food (Jahanbazi, Frantz, Purvis, Purvis, & Nowostawski, 2014)? In many social science ABMs, agents repeatedly play economic games, which allows for experimenters to mathematically approximate real social behavior (Perc & Szolnoski, 2010). For example, prisoner's dilemmas can represent people's decisions to either act selfishly or cooperatively. In any ABM, researchers should ensure that agents' behavior approximates the type of social behavior of interest, which often involves programming in a degree of randomness for variability.

Application of Step 3. In Schelling's model, agents decided whether to stay in their neighborhood or to move to another vacant space on the grid. Gray and colleagues' agents played a prisoner's dilemma game.

Step 4: What is the payoff? Payoffs correspond to what agents get out of an interaction and can represent money, happiness, or social bonds. In some ABMs, there is no payoff system, but in many ABMs that feature interactive decision-making, payoffs are determined by considering an agent's decisions and those of that agent's partner(s). In a prisoner's dilemma, for example, an agent's decision to cooperate yields a different payoff depending on whether their partner chooses to also cooperate or to defect.

Application of Step 4. Schelling's agents received no payoff, since there was no interactive decision-making. Gray and colleagues' agents, however, received a payoff that depended on their prisoner's dilemma decisions.

Step 5: How do agents change? Agents can change in a number of ways throughout the simulation. In many economic models, agents "remember" the way their counterpart treated them and adjust their behavior in future rounds. In evolutionary models, each round will end with some agents dying (often if they have received a low payoff) or reproducing (often if they have received a high payoff). In mating models, agents can pair up (or break up). In models where agents form groups, agents can become closer to some agents and move further from others.

Application of Step 5. Both Schelling's and Gray and colleagues' agents changed via movement, moving to a randomly selected grid space (Schelling) or closer to those who treated them nicely (i.e., their friends; Gray and colleagues).

Step 6: How long does your world last? As mentioned earlier, one of the major advantages of ABMs is their scale. Researchers can collect data for any specified amount of time, meaning that an ABM investigation will almost never be underpowered. However, researchers should set a theoretically meaningful length to their model. In some cases, models should run until they have reached some form of equilibrium. In other cases, models should run for a length that approximates some phenomenon of interest (e.g., Luhmann & Rajaram's, 2015, model of collective memory) but still allows the researcher to conduct analyses with adequate reliability. In either case, decisions are limited only by (practically unlimited) computer storage space and CPU speed.

Application of Step 6. Both Schelling's and Gray and colleagues' models ran until a point of equilibrium. In Schelling's model, this equilibrium was the point at which agents were no longer moving across neighborhoods. For Gray and colleagues, equilibrium represented the point at which agents had all formed groups or group formation was impossible.

Step 7: What do you want to learn from your world? At the end of the day, ABM is a theory testing and development paradigm (Smith & Conrey, 2007) with independent and dependent variables. In the case of ABMs, independent variables (or "parameters") are customized by the experimenter, while dependent variables are measured throughout the model or at the model's conclusion. If experimental hypotheses are confirmed, researchers should consider adding other independent variables into the model as moderators. Using new variables or situations to test the generalizability of a phenomenon is often called a "robustness analysis," and it can reveal surprising new effects or nonlinearities.

Application of Step 7. Schelling's central parameter was agents' desired similarity, while his dependent measures were agents' positions at the conclusion of the simulation. His finding was that a relatively low rate of similarity seeking ($\sim 30\%$) could produce relatively homophilous agent distributions at the conclusion of the simulation.

In Gray and colleagues' model of "us and them," the central parameters were agents' tendency to show reciprocity and transitivity, and the central-dependent variable was group clustering. Varying parameters and measuring clustering revealed how reciprocity and transitivity could produce stable grouping. Gray and colleagues also examined a moderating role for "trust"—the baseline tendency for cooperation or defection.

Conclusion

ABM is not a new technique, but its promise and power are often overlooked by social psychologists. We believe that there are two assumptions that have hindered their increased use. The first is that ABMs are difficult to learn or understand. However, good ABMs should be easy to conceptually understand, and the resources discussed above should make their implementation easier. The second assumption is that ABMs fail to generate new knowledge. As we suggest, good ABMs harness the power of emergence, in which higher level phenomena derive from the simple behavior of agents. As with any method, ABM is imperfect, but it does offer social psychologists a powerful way to implement precise hypotheses and to explore emergence. Not only can researchers build whole worlds to examine social processes, they also can sample from these worlds over thousands of generations to yield unprecedented insight into collective behavior. Whether studying relationships, stereotypes, culture, attitudes, emotions, religion, or the self, social psychologists should consider adding ABM to their methodological toolbox.

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Note

1. While we use the term "agent-based modeling" in this article, the terminology around agent-based model is diverse and potentially confusing. Alternative terms include "multiagent systems," "agent-based simulation," "agent-based computing," and "individual-based modeling."

References

Abbott, A. (1988). Transcending general linear reality. *Sociological Theory*, *6*, 169–186.

Asch, S. E. (1956). Studies of independence and conformity: I. A minority of one against a unanimous majority. *Psychological Monographs: General and Applied*, *70*, 1–70.

Axelrod, R. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton, NJ: Princeton University Press.

Axelrod, R. (1980). More effective choice in the prisoner's dilemma. *Journal of Conflict Resolution*, *24*, 379–403.

Axelrod, R., & Hamilton, W. D. (1981). The evolution of cooperation. *Science*, *211*, 1390–1396.

Bassett, D. S., & Gazzaniga, M. S. (2011). Understanding complexity in the human brain. *Trends in Cognitive Sciences*, *15*, 200–209.

Bear, A., & Rand, D. G. (2016). Intuition, deliberation, and the evolution of cooperation. *Proceedings of the National Academy of Sciences*, *113*, 936–941.

Beer, R. D. (1995). A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence*, *72*, 173–215.

Borshchev, A., & Filippov, A. (2004, July). *From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools*. Paper presented at the 22nd International

Conference of the System Dynamics Society, Oxford, UK. doi:10.1.1.511.9644

Boyd, R., & Richerson, P. J. (1985). *Culture and the evolutionary process*. Chicago, IL: University Chicago Press.

Bruch, E., & Atwell, J. (2015). Agent-based models in empirical social research. *Sociological Methods & Research*, *44*, 186–221.

Carley, K. M. (2002). Smart agents and organizations of the future. *The Handbook of New Media*, *12*, 206–220.

Cederman, L. E. (2005). Computational models of social forms: Advancing generative process theory. *American Journal of Sociology*, *110*, 864–893.

Critelli, J. W., & Waid, L. R. (1980). Physical attractiveness, romantic love, and equity restoration in dating relationships. *Journal of Personality Assessment*, *44*, 624–629.

Efferson, C., Lalive, R., Richerson, P. J., McElreath, R., & Lubell, M. (2008). Conformists and mavericks: The empirics of frequency-dependent cultural transmission. *Evolution and Human Behavior*, *29*, 56–64.

Epstein, J. M. (2008). Why model? *Journal of Artificial Societies and Social Simulation*, *11*, 12.

Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, *117*, 39.

Gasser, L., Braganza, C., & Herman, N. (1987). MACE: A flexible testbed for distributed AI research. In M. N. Huhn (Ed.), *Distributed AI* (Vol. *1*, pp. 119–152). London, England: Pitman.

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the social scientist*. New York, NY: McGraw-Hill Education (UK).

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in Cognitive Sciences*, *9*, 424–430.

Gray, K., Rand, D. G., Ert, E., Lewis, K., Hershman, S., & Norton, M. I. (2014). The Emergence of "us and them" in 80 lines of code modeling group genesis in homogeneous populations. *Psychological Science*, *25*, 982–990.

Halberstadt, J., Jackson, J. C., Bilkey, D., Jong, J., Whitehouse, H., McNaughton, C., & Zollmann, S. (2016). Incipient social groups: An analysis via in-vivo behavioral tracking. *PLoS One*, *11*, *e0149880*.

Henrich, J., & McElreath, R. (2003). The evolution of cultural evolution. *Evolutionary Anthropology: Issues, News, and Reviews*, *12*, 123–135.

Hong, Z., Bednarek, S. Y., Blumwald, E., Hwang, I., Jurgens, G., Menzel, D., . . . Verma, D. P. S. (2003). A unified nomenclature for Arabidopsis dynamin-related large GTPases based on homology and possible functions. *Plant Molecular Biology*, *53*, 261–265.

Holland, P. W., & Leinhardt, S. (1971). Transitivity in structural models of small groups. *Comparative Group Studies*, *2*, 107–124.

Huston, T. L. (1973). Ambiguity of acceptance, social desirability, and dating choice. *Journal of Experimental Social Psychology*, *9*, 32–42.

Jackson, J., Halberstadt, J., Jong, J., & Felman, H. (2015). Perceived openness to experience accounts for religious homogamy. *Social Psychological and Personality Science*, *6*, 630–638.

Jahanbazi, M., Frantz, C., Purvis, M., Purvis, M., & Nowostawski, M. (2014, August). Agent-based modelling of primitive human communities. *Proceedings of the Web Intelligence (WI) and Intelligent Agent Technologies (IAT) 2014 IEEE/WIC/ACM International Joint Conferences*, *3*, 64–71. doi:10.1109/WI-IAT.2014.151

Jarman, M., Nowak, A., Borkowski, W., Serfass, D., Wong, A., & Vallacher, R. (2015). The critical few: Anticonformists at the crossroads of minority opinion survival and collapse. *Journal of Artificial Societies and Social Simulation*, *18*, 6. doi:10.18564/jasss.2663

Johnson, P. E. (1999). Simulation modeling in political science. *American Behavioral Scientist*, *42*, 1509–1530.

Kalick, S. M., & Hamilton, T. E. (1986). The matching hypothesis reexamined. *Journal of Personality and Social Psychology*, *51*, 673–682.

Kashima, Y. (2000). Maintaining cultural stereotypes in the serial reproduction of narratives. *Personality and Social Psychology Bulletin*, *26*, 594–604.

Levine, D. K. (1998). Modeling altruism and spitefulness in experiments. *Review of Economic Dynamics*, *1*, 593–622.

Lewis, K. (2015). Three fallacies of digital footprints. *Big Data & Society*, *2*, 1–4.

Luhmann, C. C., & Rajaram, S. (2015). Memory transmission in small groups and large networks an agent-based model. *Psychological Science*, *26*, 1909–1917.

Macy, M., & Flache, A. (2009). Social dynamics from the bottom up: Agent-based models of social interaction. In P. Hedström & P. Bearman (Eds.), *The Oxford handbook of analytical sociology* (pp. 245–268). New York, NY: Oxford University Press.

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

Minar, N., Burkhart, R., Langton, C., & Askenazi, M. (1996). *The swarm simulation system: A toolkit for building multi-agent simulations*. Retrieved from http://www.santafe.edu/media/workingpapers/96-06-042.pdf

Nowak, A. (2004). Dynamical minimalism: Why less is more in psychology. *Personality and Social Psychology Review*, *8*, 183–192.

Nowak, A., Szamrej, J., & Latané, B. (1990). From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, *97*, 362–376.

Perc, M., & Szolnoki, A. (2010). Coevolutionary games—A mini review. *BioSystems*, *99*, 109–125.

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH Computer Graphics*, *21*, 25–34.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*, 143–186.

Shariff, A. F., Willard, A. K., Andersen, T., & Norenzayan, A. (2016). Religious priming a meta-analysis with a focus on prosociality. *Personality and Social Psychology Review*, *20*, 27–48.

Smaldino, P. E. (2014). Group-level traits emerge. *Behavioral and Brain Sciences*, *37*, 281–295.

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.

Tajfel, H. (1982). Social psychology of intergroup relations. *Annual Review of Psychology*, *33*, 1–39.

Tesfatsion, L., & Judd, K. L. (Eds.). (2006). *Handbook of computational economics: Agent-based computational economics* (Vol. 2). Amsterdam, the Netherlands: Elsevier.

Tisue, S., & Wilensky, U. (2004, May). *Netlogo: A simple environment for modeling complexity*. Paper presented at the Fifth Proceedings of the International Conference on Complex Systems, Boston, MA.

Tononi, G., Sporns, O., & Edelman, G. M. (1994). A measure for brain complexity: Relating functional segregation and integration in the nervous system. *Proceedings of the National Academy of Sciences*, *91*, 5033–5037.

Vallacher, R. R., & Nowak, A. (1999). The dynamics of self-regulation. In R. S. Wyer Jr. (Ed.), *Perspectives on behavioral self-regulation* (pp. 241–259). Mahwah, NJ: Lawrence Erlbaum.

White, G. L. (1980). Physical attractiveness and courtship progress. *Journal of Personality and Social Psychology*, *39*, 660–668.

Wooldridge, J. M. (2003). Cluster-sample methods in applied econometrics. *The American Economic Review*, *93*, 133–138.

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