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Agent-Based Modeling: A New Approach for Theory Building in Social Psychology

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Most social and psychological phenomena occur not as the result of isolated decisions by individuals but rather as the result of repeated interactions between multiple individuals over time. Yet the theory-building and modeling techniques most commonly used in social psychology are less than ideal for understanding such dynamic and interactive processes. This article describes an alternative approach to theory building, agent-based modeling (ABM), which involves simulation of large numbers of autonomous agents that interact with each other and with a simulated environment and the observation of emergent patterns from their interactions. The authors believe that the ABM approach is better able than prevailing approaches in the field, variable-based modeling (VBM) techniques such as causal modeling, to capture types of complex, dynamic, interactive processes so important in the social world. The article elaborates several important contrasts between ABM and VBM and offers specific recommendations for learning more and applying the ABM approach.

Keywords: *evolutionary psychology; metatheory; research methods*

Most social and psychological phenomena—from attitude polarization in group discussion, to escalation of intergroup conflicts, to stereotype formation, to large-scale social trends in aggression or unhealthy behavior—occur not as the result of explicit choices by isolated individuals but rather as the result of repeated interactions between multiple individuals over time. In fact, in many cases, the overall collective outcome is vastly different from what any party expects or desires (Flache & Macy, 2004). This paradox can occur in an escalating interpersonal or intergroup conflict, where

each party is confident that its own incremental escalation will cause the other to back down and give up, but the dynamics of the situation mean that conflict instead spirals to an extreme. It can also occur in situations of bystander intervention, where everyone assumes that someone else will offer help, but the outcome is that nobody does. And it can occur when people “free ride” or use a freely available resource (such as public radio) without paying for it, which can destroy the desirable resource.

For social psychologists, the goal of characterizing and theoretically understanding social and psychological phenomena requires a detailed understanding of such dynamic and interactive processes. Yet as we argue, the most commonly used theory-building and modeling techniques in our field are less than ideal for this type of task. This article describes an alternative approach to theory building, termed agent-based modeling (ABM; also called multiagent modeling). We believe that the ABM approach is better able than prevailing approaches to capture the types of complex, dynamic, and interactive processes that are so important in the social world. The ABM approach is not new in social psychology or in the social sciences more generally; well-known and

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important contributions by Axelrod and Hamilton (1981) and by Nowak, Szamrej, and Latané (1990), among others, exemplify the approach. But we believe that it deserves to be more widely applied in our field.

This article has several goals. First, we introduce the ABM approach in general terms and with concrete examples. We then draw out several important contrasts between ABM and the typical approach used in theoretical modeling within our field, variable-based modeling (VBM). We describe examples of ABM in social psychology as well as related fields to convey a sense of the range of topics to which it can be applied and to suggest how ABM can both build on the results of empirical studies and inspire and guide new research. Finally, we discuss some limitations of the ABM approach and obstacles to its adoption, together with some specific recommendations for overcoming those obstacles and going further in understanding and applying the ABM approach.

INTRODUCING ABM

Definitions

The term *agent* is used in a variety of ways in cognitive science and computer engineering. As the term is used in modeling, an agent tends to have a number of characteristics, although a range of variability exists on many of these dimensions (Macal & North, 2005; Flache & Macy, 2004):

Discrete. An agent is a self-contained individual with identifiable boundaries.

Situated. An agent exists in and interacts with an environment that generally includes other agents and may include other (nonagent) resources, dangers, and so forth.

Embodied. An agent may be embodied (robotic) or a purely software-simulated entity; the latter is more common.

Active. An agent not only is affected by the environment but also is assumed to have a behavioral repertoire that it can use proactively.

Limited information. An agent is usually assumed not to be omniscient but to be able to gather information only from its own local environment—for example, agents can see only their neighboring agents (not all agents) and only their behaviors (not their internal states, goals, etc.).

Autonomous goals. An agent has its own internal goals and is self-directed in choosing behaviors to pursue those goals, rather than being simply a pawn under the command of some centralized authority.

Bounded rationality. Agents ordinarily are assumed to gather information and generate behaviors by the use of relatively simple rules, rather than being capable of extensive computations such as maximizing expected utility.

Adaptation. Some models assume that agents use fixed, pre-specified rules to generate their behavior; others use agents that can learn or adapt, changing their rules based on experience.

A simple example is a simulated agent that moves around in a simulated environment seeking food and consuming the food when it finds it. In most models of concern to social psychology, an agent is a simplified, abstract version of a human being. However, other levels of agents are also possible; an agent could represent a neuron in a simulated neural network or a large-scale economic actor such as a corporation. We briefly discuss these possibilities at the end of the article.

A multiagent system, then, is a system that contains multiple agents interacting with each other and/or with their environments over time. Thus, many simple food-seeking agents may coexist, interacting with each other either indirectly (by competitively consuming the food resource) or directly (e.g., by fighting for control of food sources or by cooperating to increase the availability of food). It is important that these forms of interaction mean that the outcomes of individual agents' behaviors are interdependent: Each agent's ability to achieve its goals depends on not only what it does but also what other agents do.

An ABM is a simulated multiagent system constructed with a particular goal: to capture key theoretical elements of some social or psychological process (for a review of simulation approaches in social psychology generally, see Hastie & Stasser, 2000). In such a system, each agent typically represents an individual human acting according to a set of theoretically postulated behavioral rules. These may involve simple heuristics or more complicated mechanisms that may involve learning, constructing internal representations of the world, and so forth. In an ABM, many simulated agents interact with each other and with a simulated environment over time. This approach allows for the observation of the large-scale consequences of the theoretical assumptions about agent behavior when the behaviors are carried out in the context of many other agents and iterated dynamically over an extended period of time.

In essence, ABM is a tool to conceptually bridge between the micro level of assumptions regarding individual agent behaviors, interagent interactions, and so forth and the macro level of the overall patterns that result in the agent population. As we illustrate repeatedly, the value of such a tool is based on the fact that in many cases, and even for extremely simple behavioral rules, the consequences of multiple-agent interactions over time fail to match what might be expected based on the properties of an individual agent (Epstein, 1999; Macy & Willer, 2002; Resnick, 1994). Recall the examples of conflict escalation, failures of bystander intervention, and free riding introduced at the beginning of this article. This quality of defying intuitions is true of complex dynamic systems in general (Holland, 1992; Wolfram, 2002).

Social Psychological ABM: Segregation

To concretize these definitions, we begin by presenting two particularly simple examples of ABM. The economist Thomas Schelling (1971), in one of the earliest multiagent investigations in the social sciences, explored how segregation can arise in diverse populations through the actions of individual agents even when no agent specifically desires segregation. Schelling distributed agents of two different types (red and green) randomly in a lattice. His model assumed that each agent used a single, simple rule: Do not be in the minority in your local neighborhood. Agents moved to empty spaces if the proportion of same-color agents surrounding them (e.g., in the eight squares surrounding each square in the lattice) fell below a threshold, such as 30% or 50%. This rule was repeatedly applied until all agents stopped moving. The final result (under a wide range of assumptions, such as the particular values of agent thresholds) generally was a pattern of near-complete segregation, with clear boundaries between groups and virtually no mixed neighborhoods.

Schelling's (1971) model demonstrates that even when no agents specifically desire extreme segregation—instead, each has a moderate and understandable desire not to be in a minority in its own neighborhood—extreme segregation still arises as an all-but-inevitable outcome. As Epstein (2005) has observed, the importance of this demonstration is not that the model is right in all its details—it certainly does not claim to be, and humans obviously have a far more complex set of race-related attitudes, motives, behaviors, and so on. “It’s important because—even though highly idealized—it offers a powerful and counter-intuitive insight” (Epstein, 2005, pp. 12-13). The insight allows us to understand, first, that segregation does not force the inference that the individuals involved actually hate out-groups and want to completely avoid them. Second, it makes clear that a highly organized spatial pattern of segregation need not be a product of a central, directing body (such as “steering” by housing authorities or real estate agents) but can arise in self-organized fashion from agent-level goals. Third, the model calls attention to a variable whose importance might not otherwise be recognized: the spatial scope of an agent’s definition of *neighborhood*. When agents care about a small, local neighborhood, segregated patterns robustly emerge. But if agents care about a more spatially extended neighborhood, or about the composition of the population as a whole, segregation is much less inevitable. To see this, consider that if each agent wanted to avoid being in a minority in the whole population (rather than in a local neighborhood), all agents would always be satisfied with a 50-50 mix and none would move. The initial randomly intermixed (completely integrated) pattern

would prevail, rather than segregation. As Epstein observed, the power of the Schelling model to provoke such insights stems from its great simplicity, rather than from a detailed match to real-world data (which the model obviously cannot claim).

Social Psychological ABM: Date Choice

A model by Kalick and Hamilton (1986) is another early example of the ABM approach. Their simulation was motivated by a simple and well-replicated empirical fact: When the attractiveness of members of heterosexual dating or married couples is measured, the partners’ attractiveness levels tend to correlate. Attractive people tend to pair up with other attractive people, and less attractive people also tend to pair with their counterparts, with r typically in the .5 to .6 range (e.g., Critelli & Waid, 1980). To explain this observation, theorists in the 1980s often assumed that people actively sought partners with relatively similar levels of attractiveness to their own. This was assumed to result either from a fear of rejection if they made offers to far more attractive others (Berscheid, Dion, Walster, & Walster, 1971) or from a simple preference for partners with similar levels of attractiveness—after all, similarity in many other domains (e.g., social background, attitudes) is well known to lead to liking. However, repeated studies find no evidence for this hypothesized preference for others with matching attractiveness levels but rather a strong preference for the most attractive potential partners (e.g., Curran & Lippold, 1975).

Kalick and Hamilton (1986) constructed a multiagent simulation in an attempt to resolve this paradox. Their model aimed to shed light on how the individual-level psychological processes of a number of agents interact to generate the aggregate-level correlation. They created a simulated population of 1,000 individual agents, 500 males and 500 females, each with a randomly assigned attractiveness level ranging from 1 to 10. At each time step, a male and a female agent were randomly selected, and each assessed the other’s attractiveness and decided whether to extend the other an offer to date. If both made offers, they formed a couple and were removed from the dating pool. The process continued for many time steps, until all agents were matched. The researchers ran two versions of this simulation. In one, agents followed a similarity-matching rule in selecting potential mates, being most likely to make offers to another agent with attractiveness close to their own. In the other version, agents followed an attractiveness-seeking rule (making an offer with probability 1.0 to a partner with attractiveness 10, 0.9 to a partner with attractiveness 9, and so forth).

Two main results emerged from Kalick and Hamilton's (1986) model runs. If each agent was assumed to seek a partner similar to its own attractiveness level, the resulting couples showed an unrealistically high correlation in the .8 to .9 range. However, if each agent was assumed to seek highly attractive partners, the resulting couples matched the empirically observed level of correlation (.5 to .6). How does this correlation come about? In the model, the most attractive agents tend to pair up early and, thus, to be removed from the population. As time passes, the average attractiveness of the remaining dating pool (and, thus, the attractiveness of the couples that are formed) decreases. This over-time trend constitutes a new and empirically testable prediction from Kalick and Hamilton's model.

In short, Kalick and Hamilton (1986) demonstrated that a particular postulated rule for an agent's behavior (e.g., seeking the most attractive possible partner) can have strikingly counterintuitive consequences when it is (a) implemented in the context of multiple interdependent agents simultaneously following their own behavioral rules and (b) iterated over time. As with the Schelling (1971) segregation model, the power of this demonstration does not require that the model be a fully realistic reproduction of human mate preferences—in fact, the elegance of the demonstration depends on the model's very abstractness and simplicity.

Summary

These two simple examples illustrate key properties of the multiagent approach (Macy & Willer, 2002). First, agents are autonomous. Schelling's (1971) agents seek to avoid being in a local minority, and Kalick and Hamilton's (1986) agents seek attractive partners; they independently pursue those individual goals based on their own local information. There is no central authority, controller, or planner—for example, nobody explicitly assigns attractive individuals to pair up with other attractive ones. This property means that population-scale patterns or structures that emerge from a multiagent system are because of processes of self-organization rather than centralized design and planning (Kauffman, 1995; Resnick, 1994).

Second, agents are interdependent. The actions of each agent influence the others, whether directly (by accepting or rejecting another's offer to form a couple) or indirectly (by altering the group composition of a new neighborhood by moving there; by altering the pool of available partners that remain for other agents).

Third, agents in these models follow extremely simple rules. One frequent goal of ABM is to identify the simplest and best supported assumptions about individual agent behavior (such as the motive to seek the most

attractive partner) that will generate the overall pattern or outcome of interest. One hallmark of ABM is that it typically assumes that the overall system's complexity emerges from the interaction of many very simple components, rather than from great complexity in the behavior of individual agents (Kauffman, 1995). In other models illustrated later in the article, we will see somewhat more complex assumptions about agent behaviors, such as agents that learn and adapt over time. For instance, one might modify the Kalick and Hamilton (1986) model by assuming that an agent who has been refused several times when making offers to attractive partners might "lower its sights" and start making offers to less attractive partners (cf. Todd, 1997).

Finally, in each case, the interest value of the model is in the surprising nature of the results that are obtained. Perhaps the key lesson from ABM in general is that individual agent behavioral rules do not allow direct or simple predictions of large-scale outcomes: "We get macro-surprises despite complete micro-level knowledge" (Epstein, 1999, p. 48). The term *emergence* is frequently applied to this sort of surprising, unpredicted, or counterintuitive outcome from multiagent simulations (Kauffman, 1995; Resnick, 1994; Wilensky & Resnick, 1999). However, one caution regarding this term is essential: If *emergent* means essentially *surprising*, we must remember that what is surprising may change from one observer to another or may change with time as theories in a topic area become more sophisticated and comprehensive (see Epstein, 1999).

History of ABM

To put the ABM approach in context, we briefly describe its history and relationships to other concepts and techniques. One intellectual ancestor is the "complex adaptive systems" approach (Gell-Mann, 1994; Holland, 1992; Kauffman, 1995). This approach focused initially on biological rather than psychological or social systems and emphasized the role of adaptation and the "bottom-up" rather than "top-down" construction of complex systems. A paradigm example is the way termites build large, elaborately structured nests out of hardened mud—obviously, there is no "architect" termite giving orders and overseeing the construction; thus, researchers and theorists sought to describe simple behavioral rules (simple enough to be implemented by insect brains) that could account for such large and complex structures. The complex adaptive systems approach, like the more recent ABM approach, emphasizes the ways dynamic and nonlinear combinations of simple behaviors can result in the construction of emergent, complex patterns.

A related development is "cellular automata," which can be viewed as a simple, restricted form of ABM

(Wolfram, 2002). Cellular automata were developed in computer science and popularized by John Conway's Game of Life (Gardner, 1970). A cellular automaton is a gridlike arrangement of simple agents that are fixed in place and can change their state from one discrete value to another (e.g., alive or dead in the Game of Life) using a simple rule based on the states of their neighbors. Wolfram (2002) has demonstrated that even in the simplest possible form of cellular automaton, where the agents are fixed along a single line (rather than a two-dimensional grid), specific rules can produce a remarkable range of complex, patterned behavior. Some ABM approaches in the social sciences are essentially instances of cellular automata (e.g., Nowak et al., 1990; Stauffer, 2001).

A third important precursor of ABM is the field of "distributed artificial intelligence" within cognitive science (e.g., Gasser, Braganza, & Herman, 1987). Workers in this field sought to build computational agents (whether robotic or software implemented) that could work together cooperatively to perform significant tasks (Beer, 1990; Wooldridge, 2002). An example is the "swarm intelligence" model (Eberhart, Shi, & Kennedy, 2001) in which many simple agents explore potential solutions to a particular problem and communicate with each other about the quality of the solutions they have identified. The communication enables the entire set of agents to converge rapidly on high-quality solutions. Related research in cognitive science also examines how communication can aid multiple agents in solving problems (Mason, Jones, & Goldstone, in press).

Paralleling all these developments, interest in ABM began to grow in the 1980s in the social and behavioral sciences. As noted above, Schelling (1971) provided a very early example of agent-based thinking in the social sciences, and other early models are those of Axelrod and Hamilton (1981) on the emergence of cooperation, Kalick and Hamilton (1986) on mate choice, and Nowak et al. (1990) on social influence in groups. The economists Epstein and Axtell (1996) developed the influential Sugarscape model, which is profoundly interdisciplinary, involving agents that engage in mate selection, sex, and reproduction; group formation, war, and conflict; and trade and the accumulation of wealth. Some of these and other examples of the ABM approach in areas close to social psychology are described below.

CONTRASTING ABM WITH VBM

ABM, with its emphasis on dynamic interactions among agents over time, contrasts with the dominant approach to theory building in social psychology: VBM. There are two major types of VBM. The first is the

dynamical systems approach, which uses differential equations to describe changes in variable values over time. This approach has been uncommon in social psychology (see Vallacher, Read, & Nowak, 2002) but is influential in other scientific fields. We will illustrate its central ideas below. The second is the popular causal modeling approach, represented by path diagrams showing causal flows among variables, which can be estimated by multiple regression or related techniques. In all VBM approaches, the focus is on relations among variables, not on interactions among agents.

Contrasting Conceptions of "Explanation" in ABM Versus VBM

The ABM approach differs from VBM approaches in several ways, but one is the most fundamental: The models are associated with basically different ways of thinking about causality and explanation.

Most psychologists, indeed most social scientists in general, endorse a positivist "covering-law" or "statistical regularity" notion of causation and explanation, broadly deriving from David Hume (Bechtel & Richardson, 1993; Cederman, 2005; Doreian, 2001). Causation is identified with a consistent covariation between two variables (i.e., whenever the cause occurs, the effect does as well). Thus, in their search for causal explanations, scientists seek such regular covariations between variables, usually through the application of statistical analyses. In physics, for example, one might discover that all massive bodies attract each other with a force that is proportional to the product of their masses and inversely proportional to the squared distance between them. Then one might explain the orbit of the moon around the earth, or the trajectory of a cannonball, by demonstrating that they mathematically follow as consequences of that universal law.

However, despite the lip service paid to the physicslike covering-law model of explanation by most social and behavioral scientists, laws of such precision and regularity are found only rarely within our fields (among the few examples might be laws relating to sensory transduction). And there is a deeper issue. Following the covering-law model of explanation, one might observe that attractiveness correlates at about .50 in a sample of couples and explain that observation by noting that it is subsumed under the general law that such correlations are generally in that range (cf. Kalick & Hamilton, 1986). But this would seem to be a profoundly unsatisfying type of explanation that gives no real insight into the phenomenon, despite its formal resemblance to the covering-law explanations used in physics and other fields. Bechtel (1998) observed that in fact, most research in the behavioral and cognitive sciences does not actually seek to

subsume specific phenomena under universal laws but instead aims to uncover the specific processes that account for the observed behavior of a system.

This second goal reflects a completely different conception of explanation, which is being advanced by philosophers of science as an alternative to the covering-law conception (e.g., Bechtel & Richardson, 1993). “Generative” or “mechanistic” explanations seek to explain an observed phenomenon by postulating a process or set of mechanisms that generate the phenomenon. In other words, the phenomenon is explained as emerging from the ongoing interaction of assumed (and in psychology, often unobserved) underlying processes. This focus on mechanisms and processes is congenial to most social psychologists. As shown below, the generative explanations offered by ABM provide a deeper understanding of the phenomenon than do statistical explanations that simply observe that in general, across a large number of empirical investigations, a particular regularity (e.g., a correlation) is found.

To further clarify the distinction between the statistical regularity and generative approaches to explanation, consider the example of group polarization. This is the tendency of people’s attitudes in a group discussion to move further in the direction of the initial majority position over time. A variable-based, statistical approach to group polarization would seek to discover a general law describing the pattern of change in an initial majority over time. Such a law might be expressed as an equation that could yield the prediction, for example, that an initial majority of 8 in a group of 12 would end up as an increased majority of 10 out of 12 after *N* minutes of discussion. But such a statistical regularity (even if one could be identified) would not provide much insight into the underlying reasons the initial majority increases—other than to summarize the fact that in a large number of studies it has been found to do so. In contrast, an agent-based generative approach to explaining this phenomenon might involve assumptions about how one individual’s expressions of opinion affect others through conformity processes and how members of a majority exert more influence on others than do members of a minority (cf. Nowak et al., 1990). This could occur simply because of their larger numbers or because for various reasons, majority opinions exert more persuasive impact (e.g., people may assume that replication of an opinion indicates its validity). Overall, a generative explanation would demonstrate that group polarization emerges as a higher level consequence of processes assumed to occur within individual agents and in agent-to-agent interactions.

As all these examples illustrate, the generative approach explains phenomena by postulating processes of interaction among agents or other entities, whereas the statistical or regularity approach does so by identifying

patterns of covariation among variables (Epstein, 1999; Wilensky & Reisman, 2006; Wilensky & Resnick, 1999). Doreian (2001) wrote that “one [approach] tries to capture the generative mechanism of social phenomena while the other seeks a numerical summary in the form of a set of linked equations and their estimated parameters” (pp. 95-96). Generative explanations, of course, acknowledge the existence of covariational regularities, but “even in those cases where they can be said to exist, process theorists would regard them as insufficient and superficial substitutes for the deeper understanding yielded by a generative explanation” (Cederman, 2005, p. 868). Cederman (2005) traced the generative approach to explanation back a century to the sociologist and philosopher Georg Simmel and noted that it is widespread in the natural sciences (McMullin, 1984).

We believe that the generative approach to explanation, which is highly congenial with ABM, comports well with current empirical and theoretical practices in social psychology. Based on their behavior, it is fair to say that researchers generally find it more satisfying to understand how underlying entities interact to produce some phenomenon of interest than to account for the phenomenon by showing that it is an example of some more general statistical regularity expressed as a typical relationship between variables. The generative mode of explanation enabled by ABM is also consistent with our typical styles of theoretical thinking in social psychology. We are used to thinking conceptually about the underlying cognitive and affective processes that give rise to a particular judgment or behavior or the interpersonal processes that give rise to phenomena such as group polarization or correlations between romantic partners in their attractiveness. For this reason, it seems unnatural that social psychologists generally express our theories in terms of relations among variables rather than processes of interaction among entities.

Contrasting Roles for ABM and VBM

Besides the fundamental difference in the conceptions of explanation that they support, there are a number of other contrasts between ABM and VBM approaches. In most cases, the contrasts are actually complementarities, which means that each approach is particularly suitable for a specific set of goals and objectives. To describe these contrasts, we use a simple example of a predator-prey system, which (although it is not a social psychological example) has the advantage that it is conceptually well understood and can be easily modeled using both ABM and VBM (dynamical systems) approaches (Epstein, 1999; Wilensky & Reisman, 2006; Wilensky & Resnick, 1999).

An ABM approach would involve numerous individual agents of two types, predators and prey (let us call

them wolves and sheep, for concreteness). There are behavioral rules for the agents: Sheep move around, eat grass to gain energy, reproduce if they gain enough energy, and die if they do not have sufficient energy. Wolves move around, eat sheep to gain energy, reproduce and die, and so forth. It is interesting that even this simple model exhibits counterintuitive properties. For example, under some parameter values, starting the model with a larger sheep population leads to the extinction of sheep at an earlier time compared to starting with a smaller sheep population.

The VBM approach summarizes the predator/prey dynamics in two quantitative variables: the sizes of the wolf and sheep populations. A pair of coupled differential equations describes the rates of change in wolf and sheep population sizes as a function of the current population sizes. In such a model, the effect of one population (e.g., wolves) on another (e.g., sheep) is summarized and represented as a numerical coefficient, without reference to the details of the underlying interactions that contribute to that effect (wolves eat sheep). One standard version of such a differential equation model, termed the Lotka–Volterra equations, is the following, where s and w are the variables representing the population sizes of sheep and wolves, respectively, and A , B , C , and D are model parameters:

$$\begin{aligned} ds/dt &= As - Bsw \\ dw/dt &= Csw - Dw \end{aligned}$$

The left side of each equation (e.g., ds/dt) is the rate of change over time of the respective population size. The first term of the first equation says that the sheep population will naturally increase exponentially (because of births) with parameter A if there is no predation. The second term says that the sheep population will decrease as a function of the number of encounters between wolves and sheep (which is proportional to the product of the two population sizes) with predation parameter B . (This version of the equation does not provide for natural death of sheep; their population size is limited solely by predation.) The second equation says that the wolf population increases in proportion to the number of encounters between wolves and sheep with a different parameter C because the more sheep the wolves eat, the faster the wolves can reproduce. And the second term describes exponential decline of the wolf population through natural death.

With these two approaches to this simple example in mind, here are several respects in which the approaches may be contrasted:

1. *Variable-based equations often offer concise, quantitative descriptions of phenomena.* If one's goal is to predict

the population sizes at any time point, the differential equations offer a much more compact and precise way to make such predictions, compared to ABM.

2. *ABM offers insights into generative processes.* If the variable-based equations excel in making numerical predictions, ABM seems to be superior in offering an accounting of the underlying processes that generate the changes in population sizes (e.g., wolves eat sheep).
3. *Equations may allow formal proofs of important properties.* In some cases, capturing the behavior of a system in variable-based equations allows for mathematical and logical proofs of significant properties (Epstein, 1999)—for example, it might be possible to prove that the sheep population will inevitably go to extinction or that the populations will oscillate within a given range forever. An ABM approach cannot offer the logical certainty of such proofs; at best, one can run the model numerous times with random starting points and observe that in $x\%$ of cases, a particular outcome occurs.
4. *VBM often requires simplifying assumptions of rationality.* Economic modeling techniques generally require the assumption that economic agents (individuals or firms) are rational profit maximizers. These assumptions are required to make the models analytically tractable (solvable by mathematical techniques; Doreian, 2001; Sawyer, 2003). Many models in the social sciences beyond economics have adopted comparable assumptions: that individuals are self-interested, rational utility maximizers. But these assumptions are becoming less defensible as knowledge advances, and ABM approaches generally do not require such simplifying assumptions. Instead, they can assume that agents are smart or stupid, self-interested or altruistic, in accordance with whatever theory is guiding model construction.
5. *Causal models often require strict causal-ordering assumptions.* The types of causal models generally used in social psychology require the assumption that causality is unidirectional—that if X causes Y , Y does not cause X (even indirectly through other variables).¹ Of course, real-world systems rarely match this assumption (Clogg & Haritou, 1997). In contrast, multiagent models as well as dynamical system approaches can readily incorporate multiple causal directions. For example, wolf and sheep population sizes influence each other, although with different time scales. If the numbers of wolves increase, they eat more sheep, reducing the sheep population in days or weeks. If the numbers of sheep increase, more wolf reproduction results over a period of a year.
6. *ABM allows incorporation of nonlinear, conditional, or qualitative effects.* ABMs can easily incorporate all sorts of nonlinear effects, which are technically difficult to handle within VBM approaches. An example is a threshold effect, specifying that an agent will adopt a new attitude only when at least half of its neighbors have done so, rather than assuming that the probability of adoption is a linear function of the number of adopting neighbors. The ABM approach also makes it easy to incorporate conditional effects, for example, to assume that an agent might either assimilate to or contrast away from a social norm, depending on certain factors such as its current motivational state. In a similar manner, agents can be assumed to make random decisions among qualitatively different

alternatives (e.g., pick 1 of 10 available products). In contrast, although nonlinear specifications of effects are possible in regression or other VBM approaches, they are rarely used within psychology.

7. *VBM and ABM focus on different levels of abstraction.* ABM focuses on a more concrete level than does the VBM approach. In our example, ABM specifies particular interactions among agents (e.g., a wolf eats a sheep at a particular point in time and space), rather than abstract relations among highly aggregated variables such as population sizes. ABM can also generate predictions for relations among aggregate-level variables as part of its output, of course. But the reverse is not true: VBM is inherently highly aggregated and cannot predict details of individual agent behaviors and interactions.
8. *Causal modeling can offer insight into relations of variables within a specific data set.* As typically used in social psychology, causal modeling is not a theory development tool but rather a data-analytic approach used to estimate causal parameters (path coefficients) based on a specific data set. As noted above, this can be done only with the aid of stringent *a priori* assumptions about the causal ordering of the variables involved, the linear and additive nature of relationships, and so forth. But even with these restrictions, the technique has proven useful, and many researchers have learned many interesting things by applying it. ABM is not well suited for this goal; it is a technique for developing theory and gaining general insights into the implications of postulated theoretical processes, rather than a technique for understanding what happened in one particular data set.

In summary, the respective strengths and weaknesses of the dynamical systems approach, the causal modeling approach, and the ABM approach tend to be generally complementary, as the techniques are aimed at different (although related) goals. Dynamical systems analyses should appeal to researchers seeking concise, quantitative descriptions of system behavior and the possibility of mathematical proofs about that behavior; they are applicable even to systems with multidirectional causation. Causal modeling is valuable to researchers seeking to understand variable relationships within a particular set of data, if they are willing to endorse the required assumptions. ABM is particularly suited for those who seek to explain how a system's behavior is generated by underlying processes or mechanisms, with a special focus on the linkage between micro and macro or aggregate levels, and who wish to avoid having to make simplifying assumptions such as that agents are rational or causation is unidirectional.

ABM FOR SOCIAL PSYCHOLOGY

The ABM approach offers, we argue, a good match for the theoretical concerns of social psychology. In our field, usually an agent will be assumed to represent an

individual person. Multiagent simulation provides a natural vehicle for incorporating all of the diverse types of processes that social psychologists study. These include intrapersonal processes (accessibility, decision making, heuristics, memory effects, schema-based interpretation, personality differences, etc.), interpersonal processes (reciprocity in dyadic interchange, interpersonal liking and mate choice, social influence, emotional contagion, etc.), group processes (norm formation, leadership, status differentiation, etc.), intergroup processes (intergroup bias, discrimination, intergroup anxiety, etc.), and social and cultural processes (allocation of groups to social roles, cultural transmission of concepts, innovation diffusion, etc.).

This is one of the key advantages of ABM, that it does not restrict a theorist to a single level of analysis. In many cases, the whole point of a multiagent model is to bridge theoretical levels. A study of interpersonal attraction might discover what factors make one individual prefer one potential mate as opposed to another. But only multiagent modeling (e.g., Kalick & Hamilton, 1986; Todd, 1997; Todd, Billari, & Simao, 2005) can put attraction in its context to determine the patterns that will emerge when many individuals in a population simultaneously evaluate each other. A successful model explains the aggregate patterns as resulting from a process of emergence and self-organization; the patterns come into existence without any central controller or executive in a way that is not known, anticipated, or sometimes even desired by the individual agents.

Social psychology is, by definition, concerned with both the psychology of the individual and the individual's relationships to the social environment. But these levels interact in complex ways that call into question any simple analysis in terms of unidirectional causal paths. Recognizing this fact, relationship researchers (Reis, Collins, & Berscheid, 2000) have recently called for a reexamination of the traditional approach to explaining relationship outcomes in terms of properties of individuals. Based on the complex adaptive systems perspective (Capra, 1996), Reis et al. (2000) observed that from the time of conception, individuals are nested within relationships, those relationships are in turn nested within social systems, and all these systems evolve and influence each other over time, making the use of causal analyses dubious. For example, it may seem straightforward to assume that innate brain systems (e.g., systems governing affective responding) exert a causal influence on relationships, but the causal pattern is actually "transactional" (Reis et al., 2000, p. 852), with reciprocal influences at every moment during the entire course of development. ABMs are, in principle, capable of describing the properties of such multilevel interactive systems and lending insights into their implications for the phenomena under study.

The key feature of multiagent simulation is that it allows the examination of outcomes when, as in real social life, multiple interdependent agents engage in dynamic, reciprocal interaction over time. Each agent is affected by its environment, which is made up largely of other agents' behaviors. The environment acts as a source of both constraints and opportunities for that individual. But at the same time, each agent's actions affect its environment and other agents. Thus, instead of decontextualizing a single aspect of agent interaction, such as how one agent responds when it sees another agent consuming a desired resource, multiagent models permit assessment of the outcomes when multiple interdependent agents, each serving both as perceiver and perceived, behave in interactions that extend over time.

Unlike real social life, however, the values of parameters in a multiagent model can be set to arbitrary values. We can test the consequences of varying the ratio of males to females, the time to agent maturity, or the variance in food acquisition over time. There are no ethical or practical concerns to constrain how we explore our simulated worlds, and this exploration in turn allows us to approach testing our theories in the real world with a much better understanding of what we are looking for and how to interpret our findings.

To illustrate the particular suitability of the ABM approach for social psychology, we present brief descriptions of several such models in related areas.

Stasser's model of the common knowledge effect in group discussion. Stasser (1988) introduced a simulation model to help make sense of the common knowledge effect in group discussion. Stasser and Titus (1985) provided group members with a mixture of uniquely held and shared information about the discussion topic. Discussion tended to focus on the shared information, despite the fact that depending on the initial distribution of information, this focus might lead to suboptimal outcomes for the group decision. Stasser's DISCUSS model simulates several stages in the group discussion process, beginning with memory for the provided information, proceeding through listening to others and making one's own contributions to the discussion, and ending at the eventual group decision. Work with the model has provided information about which features of the discussion environment are most important for producing the common knowledge effect.

DISCUSS represents a valuable early example of an ABM with several of the key features we have discussed here. First, it can be and has been employed in conjunction with empirical work to shed light on a complex process. Second, it crosses levels of analysis, mapping out processes both within individual minds (memory, cuing by others' statements, inferences of validity from

repetitions of a statement) and simultaneously, in the group as a whole. Finally, Stasser and his colleagues (Stasser, 1988; Stasser, Kerr, & Davis, 1989; Stasser & Vaughan, 1996) have explored the model by systematically varying parameters to determine which features are most important and how they affect the simulated discussion outcomes.

Nowak, Szamrej, and Latané's model of group polarization. Social influence is a core social psychological topic that has received a substantial amount of attention from ABM theorists in several disciplines including sociology, economics, and even physics (Friedkin, 1999; Hegselmann & Krause, 2002; Janssen & Jager, 2001). In one influential multiagent simulation of social influence, Nowak et al. (1990) formalized Latané's (1981) theory of social impact. This work was intended to address a failing in theories of social influence and persuasion that had been noted by Abelson and Bernstein (1963) years before but had gone unaddressed: Almost all conventional theories of social influence assume purely linear, assimilative influence. That is, any persuasion that occurs produces a shift in the direction of the delivered message. Abelson and Bernstein pointed out that if such a rule is applied in a social group and allowed to iterate, the group inevitably converges on the group mean position—dissent cannot persist.

Nowak et al. (1990) built a model in which agents located on a fixed grid begin with a random position on an issue. Each agent receives attitudinal support from nearby others who share their attitude and persuasive force from nearby others who take the opposite side. The authors demonstrated that given only a few assumptions, it was possible to maintain attitudinal diversity in the population over time. Specifically, they found that (a) an initial majority tends to increase in size over time (i.e., group polarization occurs under their assumptions) but (b) agents holding the minority opinion persist indefinitely in self-organized spatial clusters that help protect the minority agents from being converted by the global majority.

Kenrick's evolutionary models. Evolutionary psychology is another domain in which ABM has proven useful. The evolutionary psychology perspective is fundamentally dynamic and situated; its theories concern how humans think and act as a result of multiple generations interacting with other humans and with an environment during long periods of time. Evolutionary psychology is also limited in its ability to employ traditional methods such as experimentation. These features have led some evolutionary psychologists to explore the potential contribution of ABM to the field. Kenrick, Li, and Butner (2003) presented several cellular automaton models,

including analyses of human aggression and mating strategies. In these models, agents determine their own strategies by observing the strategies of their immediate geographical neighbors. If many other agents in a given agent's neighborhood are engaging in aggressive behavior, for instance, it may be adaptive for the agent to engage in aggressive behavior of its own. These models allow us to explore the relationship between overt behavior (e.g., a current aggressive state) and underlying psychological decision rules (e.g., a rule that if there are three aggressive neighbors, go into an aggressive state).

Axelrod's model of the evolution of cooperation. Psychologists and representatives of many other social science disciplines have been interested in understanding how autonomous, self-interested individuals can come to cooperate when cooperation offers potential advantages but also leaves one open to exploitation by an uncooperative other. The Prisoner's Dilemma, perhaps the most studied game in the field of game theory, has often been used to formalize this general issue. In this game, mutual cooperation by two players gives a high pay-off, but cooperating when the partner defects has the lowest pay-off. In a single game, defection is always the most rational strategy, but when the game is played repeatedly, other strategies become more adaptive.

Axelrod (1984; Axelrod & Hamilton, 1981) employed ABM to determine the most successful strategy in the iterated Prisoner's Dilemma. He solicited strategies from expert game theorists and added a few obvious ones (always cooperate; always defect; play randomly) and pitted all the strategies against each other in a round-robin computer tournament. It is surprising that the simplest submitted strategy won. This strategy—dubbed tit-for-tat—begins by cooperating and after that, copies the previous move of its partner. Tit-for-Tat succeeds because it is responsive to a partner's defection (punishing the partner by defecting on the next trial) and, therefore, is not indefinitely exploitable, but tit-for-tat will never initiate defection. ABM approaches allowed Axelrod (1984) to offer informed speculation about how cooperation could evolve through agents cooperating with their kin, or interacting repeatedly with their geographic neighbors, even when surrounded by a sea of noncooperative agents.

Other Areas of Recent Models Relevant to Social Psychology

Besides the classic contributions described in the previous section, and in many cases building on them, ABMs are being actively developed in many areas of great interest to social psychologists (although in most cases the modelers themselves are from other fields).

Emergence and maintenance of cooperation. Building on Axelrod's seminal work, many modelers are examining the conditions under which autonomous, self-interested agents can manage to cooperate (see Gotts, Polhill, & Law, 2003). For example, what if in a "noisy" environment, an agent's move might sometimes be misperceived—a cooperative move misread as a defection, for instance? With some strategies, this can lead to a long spiral of attacks and retaliations, and researchers have studied strategies that are more robust in the presence of noise (e.g., Macy, 1996). Another recent focus is on situations where an agent has the option to exit the situation rather than continuing to play with a specific partner. This allows for additional strategies, such as sticking with a partner until he or she defects, then leaving to seek an alternative, perhaps more cooperative, partner (Schüssler & Sandten, 2000). Finally, an interesting model by Takahashi (2000) examines the emergence of what he termed "generalized exchange"—cooperation directed at anonymous other agents (similar to a donation to charity that will be used to help unspecified individuals) rather than cooperation with a specific, individual other.

Evolutionary analyses. A significant proportion of ABMs incorporate evolutionary assumptions, and there have been great recent advances in the depth and sophistication of these assumptions. "Evolutionary game theory" (Gintis, 2000; Maynard Smith, 1982) examines the outcomes as a changing and adapting population of agents interacts with each other and with an environment over many simulated generations and analyzes the agent strategies that fare best in such competition. A key concept is an "evolutionarily stable strategy." A strategy X is an evolutionarily stable strategy if a population all using strategy X can outcompete a small number of "invading" individuals using any other strategy. If this is true, then strategy X, once it has evolved, will remain stable. In some cases, logical proofs can be used to demonstrate that a particular strategy is an evolutionarily stable strategy; in other cases, researchers apply evolutionary multi-agent simulations. Models using such evolutionary analyses include investigations of cooperation in large groups (Liebrand & Messick, 1995) and the emergence of norms favoring communal sharing of resources, including an analysis of the issue of who will enforce such a norm when enforcement carries costs to the enforcer (Kameda, Takezawa, & Hastie, 2003).

"Cognitive agents." Several modelers (Sallach, 2003; Sun, 2001) have argued that ABM of human behavior needs to go beyond simple rules to incorporate relatively sophisticated models of individual agent cognition. Sun's (2001) model, CLARION, contains a neural network model of the mind of each agent, with learning rules that

allow the agent to adapt and change its behavior with time. Cognitive scientists have been developing agent languages that permit agents to communicate statements, requests, negotiating demands, and so forth (Wooldridge, 2002). It is obvious that such agents have behavioral potential far beyond that of agents who follow simple and fixed behavioral rules (e.g., the tit-for-tat strategy in a cooperation game). However, two points must be raised. First, the question of whether the increased complexity actually furthers or impedes a deep conceptual understanding of a model's behavior must always be kept in mind. Second, serious arguments can be made that adaptive human behavior actually results from the application of cognitive simple heuristics rather than extensive, resource-demanding cognitive processes (e.g., Gigerenzer, Todd, & the ABC Research Group, 1999).

In a related vein, studies by Macy (1996) compared the effects of individual-level adaptation (learning) and population-level adaptation (evolution) in studies of the emergence of cooperation. It is interesting that under the assumptions Macy implemented, evolution was more powerful than adaptation in that "smart" individual agents were unable to learn a class of powerful strategies that could emerge through evolution.

Communication and cognition. As noted above, multiagent models of interagent communication in group problem solving have been developed (Eberhart et al., 2001; Mason et al., in press; Stasser, 1988). Social psychologists have recently been interested in other ways communication interacts with social cognition, for example, in the effects of communication on the stereotypes or other mental representations that individuals hold (Brauer, Judd, & Jacquelin, 2001; Lyons & Kashima, 2003; Ruscher, 1998). The empirical findings from such studies could be modeled by multiagent systems in which individuals construct and maintain mental representations that are affected by communications from other agents. Indeed, models of this sort have been developed to explain other types of communication-cognition interaction, notably the development of language (Hazlehurst & Hutchins, 1998; Steels & Belpaeme, 2005)—a theoretically central issue because it touches on both individual psychological processes (e.g., syntax acquisition, vocabulary learning) and processes of social coordination (e.g., developing shared names for objects).

In considering the effect of communication on individual cognition, how much reliance should an agent place on information communicated by a specific other agent? The sender might be misinformed or ignorant or might even be a competitor and provide intentionally misleading information. The general solution seems to be for agents to adaptively change the weights they give to information from others based on their experience, and

van Overwalle and Heylighen (2006) developed a model of this. Agents maintain and update "trust" weights for each other agent, for each potential topic of knowledge (i.e., one might trust Jim's opinions about baseball but not about fine wines). The trust weights are increased (or decreased) as the other agent communicates information that is similar (or dissimilar) to what one already knows. Thus, trust is in a sense "earned" by providing apparently truthful communications. van Overwalle and Heylighen demonstrated that their model accurately reproduces the results of several social psychological experiments on group discussion, social influence, and related topics.

Obstacles and Limitations

Our purpose in this article is to highlight the value and potential utility of ABM for social psychologists, but we would be remiss if we did not also discuss some obstacles to its adoption and potential limitations to the approach.

Is modeling just unconstrained game playing? One activity that people can engage in with a multiagent model is to "play around," unsystematically trying different parameter values to see what happens. This approach can lead to important insights (e.g., when changing a parameter has an unexpected, counterintuitive effect on the outcome; see, e.g., Axelrod, 1997), but the activity itself is easily dismissed as game playing rather than doing science. For ABM to be a scientific tool (specifically, a theory-building tool) it must, of course, be subject to empirical validation. As Epstein (1999) noted, the key question is

Does the hypothesized microspecification suffice to generate the observed phenomenon . . . ? The answer may be yes and, crucially, it may be no. Indeed, it is precisely the latter possibility—empirical falsifiability—that qualifies the agent-based computational model as a *scientific* instrument. (pp. 45-46)

Of course, social psychology's familiar empirical methods, especially laboratory experimentation, will be essential in testing and perhaps falsifying hypotheses deriving from ABM.

Lack of training in modeling. Our students learn ANOVA, regression, and causal modeling as a precondition for entry to the field and, almost without exception, do not learn computational modeling techniques. Indeed, in most cases, they have no access to such training even if they want it. Patterns of professional training inevitably are a source of conservatism in any field, for they encourage the continued exploitation of techniques that have proven useful in the past and hold back the adoption of

conceptual or methodological innovations (not only ABM but also other techniques such as fMRI imaging). This is, of course, a real and meaningful obstacle to one who is interested in exploring the potential of ABM for his or her own research. All we can say is that ABM (in contrast to dynamical systems modeling, for example) is quite accessible for researchers with no background in high-level mathematics. Some level of computer programming skill is essential for constructing an ABM, but a system such as NetLogo (described below; Wilensky, 1999) makes programming quite simple and painless. In fact, NetLogo is used in elementary and middle school classrooms. In addition, the conceptual discipline of programming agent behaviors is closely akin to thinking in terms of theoretical processes and mechanisms, which is common in social psychology. Overall, we believe that ABM, aside from its relative unfamiliarity, is less demanding of technical and mathematical skills than are multiple regression and causal modeling, which virtually every social psychologist successfully masters.

Difficulty of identifying the correct balance between simplicity and complexity. Perhaps the most fundamental issue in fruitfully applying ABM is that of finding the right level of complexity at which to specify a model. Let us once again take Kalick and Hamilton (1986) as our example. The first reaction of many people on learning about the model is to want to add complexities: What if some percentage of agents want same-sex rather than opposite-sex partners? What if mating is not permanent and, thus, some couples break up and reenter the dating pool? What if the sexes differ in the importance they attach to a partner's attractiveness? Obviously empirically or conceptually motivated complexities such as these could be multiplied almost indefinitely. Should Kalick and Hamilton be criticized for not incorporating these "refinements" into their model? Our answer is no; we think that the modelers got it precisely right. Adding complexities such as these might be reasonable in a model whose goal is a close match to a specific set of empirical data. But closer fit to data comes at a cost: Additional processes obscure the fundamental elements of the generative theory, while adding nothing that is conceptually critical. In the case of the Kalick and Hamilton model, their goal was not to closely fit a data set but to provide a compelling, crystal clear demonstration of a counterintuitive principle (that individual agent preferences can generate population patterns that superficially look quite different). Adding more theoretical components to the model, however well each one could be empirically justified, would only have interfered with that goal.

But how is a modeler (especially a novice modeler) to make these judgments? Our best advice is KISS (keep it simple, stupid). The logic behind this advice is that an

ABM is a representation of a theory about social behavior, not a representation of some slice of complicated social reality. Our best (most insightful, generative, compelling, etc.) theories in social psychology tend to relate two, three, or four highly abstract constructs: Negative affect increases aggression; self-esteem indicates how our relationships are faring; identification with a group increases adoption of the group's goals; and behavioral intention is a function of attitude and subjective norm. It is notable that our best theories are not collections of 15 or 20 "factors" that are empirically known to affect some phenomenon. In a similar manner, the most elegant experiments that our field offers as classics and inspiring exemplars tend to involve manipulations of 2, 3, or 4 factors—not 15 or 20. An ABM should be more like a theory or an elegant experiment than like a long list of "relevant factors." Thus, we suggest as a guideline that one should strive to include no more than 2, 3, or 4 fundamental theoretical principles in a model. More than that runs the risk of obfuscating what is really going on.

Resistance to expressing human behavior in computer code. Finally, some may feel that programming theories about human behavior into computer-simulated agents implicitly likens humans to computers (logical, emotionless, etc.). The premise is mistaken; simulating human behavior on a computer does not restrict the assumptions we can make about that behavior. If we can describe an agent's emotional responses with simple rules, those can be simulated by a computer. The overall goal of psychology is to describe human behavior using relatively simple theoretical assumptions, and computer code is just an alternative way to express those assumptions—with advantages in some respects, such as precision and the ability to run and show us the consequences of our assumptions, and disadvantages in others, such as the easy (if imprecise) understanding afforded by traditional verbal formulations of theory.

HOW TO GET STARTED WITH ABM

Tool Kits and Resources

General conceptual introductions and broad reviews of the ABM approach that are particularly likely to be accessible for social psychologists include Flache and Macy (2004), Wilensky and Resnick (1999), Epstein (1999), Resnick (1994), and Epstein and Axtell (1996).

Several programming languages and tool kits have been developed to facilitate constructing an ABM. Swarm (Minar, Burkhart, Langton, & Askenazi, 1996), Repast (North & Macal, 2005), MASON (Luke, Cioffi-Revilla,

Panait, & Sullivan, 2004), and NetLogo (Wilensky, 1999) are prominent examples. We focus on NetLogo for one simple reason: Its originators explicitly maintain a philosophy of “low threshold” for starting to use the system. In practice, this means that with NetLogo, a social psychologist modeler can construct and interact with the model himself or herself, rather than through the mediation of a hired professional programmer (which is the more likely scenario with the other tool kits mentioned).

Our single most heartfelt recommendation for anyone interested in ABM is to download the NetLogo system from <http://ccl.northwestern.edu/netlogo/> and to spend some time interacting with it. This free software system runs on Windows, Mac OS X, or Linux and includes extensive documentation and a library of hundreds of ready-to-run models illustrating different types of multi-agent systems. Specific library models, including Wolf-Sheep Predation, Party (Schelling’s [1971] segregation model), and Prisoner’s Dilemma, illustrate points discussed in this article. NetLogo is not only easy and engaging to experiment with (e.g., it contains clear visual depictions of the model as well as numerical plots and graphs summarizing results) but also offers advanced users the ability to modify existing models and to construct new models by programming them from scratch.

Step-by-Step Recommendations for Modeling Practices

For social psychologists who may be motivated by our arguments to explore ABM, we offer step-by-step recommendations and advice (see Flache & Macy, 2004, for a similar viewpoint):

1. *Think theoretically in terms of entities and interactions, not in terms of variables.* The ABM approach encourages theorists to think in terms of entities and their interactions over time, rather than in terms of statistical relationships among variables. In some sense, this approach should be natural for social psychologists, who typically work with process-oriented theories. However, it may require some unlearning because we have long taught ourselves to express process-oriented theoretical conceptions in the somewhat incompatible language of variable-oriented models. Thus, the first step in producing an ABM is to identify the relevant entities (depending on the theory), which will usually but not always be individual people.
2. *Formulate the model using the chosen tool kit.* Next, based on theory from social psychology or other disciplines, specify the behavior of the agents as simple rules, which can be translated into computer code within NetLogo or whatever programming environment is being used. It is obvious that the more precise the theory, the easier the model development process will be. ABM encourages us to think especially about two aspects of a model: the behavioral rules for individual agents and the nature and patterning of agent-to-agent interactions. Various assumptions can be made about the latter, including (a) agents occupy fixed positions and interact only with their neighbors (e.g., Nowak et al., 1990), (b) agents can interact with any others, without geographical or other restrictions (e.g., Axelrod’s Prisoner’s Dilemma tournament; wolf-sheep predation), and (c) agents have enduring connections to specific other agents, constituting a social network, and can interact with other agents to whom they are linked. The latter is probably the most realistic if one is modeling real human social behavior.
3. *Keep it simple.* In the model development process, the overriding goal should be simplicity and elegance. In VBM, the general approach to understanding complex psychological systems has been to increase the complexity of causal models—to add more variables. But that approach sometimes leads in unproductive directions—to the generation of unwieldy catalogs of variables that explain small amounts of variance without promoting satisfying conceptual understanding of the phenomena. In developing an ABM, elegance and simplicity should be the chief goals. In many cases, apparent complexity in a large-scale system may be found to arise as an emergent result of extremely simple underlying behaviors and interactions—just as, in mathematics, the supremely complex Mandelbrot Set object emerges from iteration of a simple algebraic equation. In other words, if a phenomenon examined at a particular level of analysis seems so complex that it seems to require 24 variables to explain it, one should consider the possibility that it is actually an emergent result of much simpler processes operating at a lower level (Resnick, 1994; Wolfram, 2002). As we have said, it is crucial to keep in mind that ABM is a representation of a theory (typically with fewer than a half dozen fundamental principles), not a representation of messy social reality. As Flache and Macy (2004) commented, “Analysis of very simple and unrealistic models can reveal new theoretical ideas that have broad applicability, beyond the stylized models that produced them” (p. 295).
4. *Debug the model.* Any significant piece of computer code is likely to contain bugs. Because ABMs often produce “emergent” or unexpected results, it becomes even more important to check and recheck the code to be sure that the result does not simply reflect a bug (Gilbert & Terna, 2000). It can be valuable to have a second programmer generate an independent implementation of the same model—which is unlikely to contain the same bugs, and, thus, convergence of results between the two implementations offers good reassurance. In some actual cases, independent reimplementations have demonstrated that originally published results depended on a highly specific detail of the original implementation and changed dramatically when that detail was altered; see the case study by Galan and Izquierdo (2005).
5. *Explore the model systematically.* An ABM should be an object of systematic investigation, a means to investigate the space of possible outcomes generated by varying theoretical assumptions. As we have repeatedly emphasized, ABMs are often too complex, and too likely to produce

surprising or emergent behavior, for their implications to be grasped intuitively. Therefore, developing a picture of a model's implications is very much a matter of experimentation, of systematically and rigorously testing different assumptions within a plausible range (Epstein, 1999; Flache & Macy, 2004). The Behaviorspace facility of NetLogo facilitates this process, conducting automatic runs with all combinations of a specified set of parameter values and recording the results. In this way, a simulation model becomes the subject of focused investigation, with the ultimate goals of (a) understanding the consequences of different theoretical assumptions and, hence, (b) ultimately identifying the simplest and most empirically validated assumptions that generate the overall patterns of observed behavior.

6. *Validate the model by matching results to data.* Validation of ABMs can be done at both the micro and macro levels (Moss & Edmonds, 2005), so their falsifiability is really of two separate kinds. Using the Kalick and Hamilton (1986) model as a simple example, one can ask both (a) Does their assumption about individual agent preferences match what is known about human mate preferences? (Answer: Yes; many studies show that people do prefer highly attractive partners.) and (b) Does their model's generated outcome match what is observed in human populations? (Answer: Yes; correlations in attractiveness between partners are generally found in real populations.). Virtually all of the ABMs described in this article similarly can be validated or compared to data at both of these levels. Of course, a match at both levels increases confidence in the validity of the model. Validation of the micro rules describing individual agent behavior is a task that is especially well suited for social psychology's most familiar and powerful research technique, lab-based experimental studies.

The tightness or looseness of the model–data comparisons involved in validation (at either the micro or macro level) is a more difficult issue. A model may be asked to match what Epstein (1999, p. 46) called “stylized facts” or qualitative, generic empirical regularities, such as that residential segregation exists (Schelling, 1971) or that partner attractiveness correlates (Kalick & Hamilton, 1986). These are the kinds of broad empirical generalizations that might be the chief results of a meta-analysis of a research area—general summaries of what is empirically known rather than detailed results of a single, specific study. We believe that in many cases, this level of empirical validation is sufficient for the main purposes of ABM: the attaining of basic insights such as those offered by the models just mentioned (or many other examples in this article). But in other cases, a much tighter and more precise match to data is demanded. Epstein cited several examples of economic ABMs that have been developed to explain highly specific patterns in data, such as the distribution of firm sizes in the economy. Whether one seeks to validate relatively general, qualitative patterns or to match data in exact quantitative detail depends on the overall goals of a model and on the availability of suitable data sets.

7. *Test hypotheses within the model.* ABM allows for the familiar (to social psychologists) activity of testing hypotheses in a direct way. Say a model has several

distinct principles, such as a set of rules for generating behavior and a learning rule, which changes the behavior-generating rules based on feedback. If the model as it stands fits data adequately, it is possible to test the hypothesis, for instance, that the learning rule contributed to that success. The modeler would do this by “turning off” the learning component and determining whether the resulting limited model could also fit data. It is clear that this approach offers a way to test the conceptual hypothesis that the learning rule contributes to the model's success in a particular domain. Conversely, models can also provide a test of the hypothesis that a particular process is not necessary for the model's success. If a model lacking process X can fit data (especially data that had previously been thought to require process X for an adequate explanation), that counts as a powerful demonstration that X is in fact unnecessary. The Kalick and Hamilton (1986) model is an example, showing that the assumption of preference for partners similar to oneself in attractiveness is not necessary to account for partner correlations in attractiveness.

8. *Move back and forth between models and empirical investigations.* The relationship between model and empirical research is not one way. Models not only can be subject to empirical validation but also can suggest new hypotheses for empirical study. For example, Kalick and Hamilton's (1986) model predicts that the pairs that form will decline in attractiveness level with time, a hypothesis that would not be generated under the alternative theoretical idea that people seek partners with similar levels of attractiveness. Without a theory, one does not know what to look for, so ABM can heuristically guide empirical research in this way—especially research directed at the kinds of level-crossing phenomena (relating micro- and macro-level properties) that are the most characteristic domain of ABM.
9. *Use models to compare and integrate theories.* Finally, ABM can be used for “model alignment” (Axtell, Axelrod, Epstein, & Cohen, 1996), comparing competing theories of a particular effect. By implementing the theories in ways that are as closely parallel as possible, one can discover what differences in assumptions generate different behaviors in the model and what differences are immaterial. It may even be possible to incorporate the competing theories within a single, more general overall model. Flache and Macy (2002) provided a case study in using this process to compare and integrate two models of statistical learning, and Abrahamson and Wilensky (2005) took a similar approach in comparing “Piagetian” and “Vygotskian” conceptions of child development. Even when empirically based validation of a model is difficult or impossible (e.g., because appropriate data are not available), ABM can be valuable in this way for the goal of understanding, comparing, integrating, and ultimately improving theory.

FURTHER DIRECTIONS AND CONCLUSIONS

This article focuses on ABMs where agents represent individual persons, for this is a natural level for social

psychological theorizing. However, agents can be used to represent entities at other levels, whether lower level (neural networks) or higher (social groups, organizations, economic actors). We briefly discuss these possibilities.

Lower level agents: Agents as “cognitive elements.”

Some models in social cognition propose that psychological processes such as person perception, attitude formation and change, or stereotyping arise from the interaction of multiple simple “nodes” analogous to neurons and interconnected in simulated “neural networks” or “connectionist models” (Kunda & Thagard, 1996; Shoda & Mischel, 1998; Smith, 1998; van Overwalle, 1998). One simple class of such models implements parallel constraint satisfaction processes. Similar to some interpretations of dissonance theory, such models postulate that there are multiple simple cognitive elements (e.g., beliefs, attitudes, self-identities) interconnected with positive (excitatory) or negative (inhibitory) links. The elements mutually adjust to each other to achieve coherence or harmony. This means that if any one cognitive element changes, the others will in principle also change in response. In other words, causality goes in all directions, so such models are difficult to encompass within the causal VBM framework. But these are natural examples of multiagent models, where each agent is identified with a cognitive element that both influences and is influenced by other related elements on the basis of simple rules. Of course, agents representing neurons in a simulated connectionist network or cognitive elements (beliefs, attitudes, etc.) in a parallel constraint satisfaction system would be assumed to have much simpler behavioral rules than cognitive agents representing humans. On the other hand, connectionist models most often assume that the agents (nodes) can adapt and change their responses through time through the application of simple learning rules (see Smith, 1996, 1998).

The close connection between the multiagent approach and connectionist modeling is felicitously illustrated by Selfridge’s (1959/1988) fanciful “Pandemonium” model. Selfridge postulated a visually based letter recognizer composed of numerous “demons” of different types. Feature demons each examine the visual input for a specific visual feature (e.g., a horizontal bar) and yell if they see it. Letter demons listen to feature demons, and a specific letter demon (e.g., for *H*) yells in turn if it hears yelling from the feature demons for horizontal bar and vertical stroke (i.e., the components of that letter). Finally, a single decision demon listens to the yells of all the letter demons and issues as the final output of Pandemonium the name of the letter demon who is yelling loudest. It should be clear that Pandemonium is

(a) an instance of a multiagent model where agents (demons) behave and interact according to simple rules and whose overall behavior (letter recognition) is emergent from those simple interactions, as well as (b) capable of being straightforwardly translated into a standard neural network, where demons become nodes and yells become signals sent over connections between nodes.

Higher level agents: Agents as large-scale actors. A large-scale entity consisting of multiple individuals, such as an army, a corporation, or a terrorist cell, can also be considered an agent that is autonomous and seeks to accomplish its own goals—which may be at least potentially distinct from the goals of the individuals who make up the entity. Economic theory is a VBM approach that describes interactions among economic agents (which may be individuals or firms and are assumed to be rationally profit maximizing). ABM can equally well be used to describe interactions among such large-scale agents (see review in Flache & Macy, 2004). One important and interesting question is whether ABM can also account for the emergence or coming into existence of such agents (Cederman, 2005). In other words, similar to Axelrod’s (1984) discussion of the emergence of dyadic cooperation, can ABM account for the way people band together cooperatively to form a group/team/corporation that can then act as a unified autonomous agent to accomplish goals its individual members could not? This is an intriguing direction for future research.

Agent-based thinking and cross-disciplinary integration. One of the primary features of ABM is that it allows, even forces, theoretical thinking to cross levels, as modelers seek to understand high-level structures and processes as outcomes of low-level agent interactions. Thus, ABM provides a common framework for processes at multiple levels, making it a natural focus for cross-disciplinary integration. In fact, in disciplines related to social psychology, many sociologists (e.g., Cederman, 2005; Macy & Willer, 2002) have been using ABM, as have economists such as Epstein and Axtell (1996) and political scientists such as Axelrod (1984). The power of ABM to offer cross-disciplinary insights can be illustrated by Epstein and Axtell’s Sugarscape model. The model incorporates both a biological level (reproduction, evolution) and a cultural/institutional level, permitting the researchers to pose and answer questions such as Does a social mechanism of inheritance (passing wealth down from parents to offspring) alter the operation of biological evolution? Answer: Yes; the offspring of parents who themselves performed well are somewhat insulated by their inherited wealth from the rigors of evolutionary competition.

Turning from the social science interface of social psychology to its cognitive science interface, cognitive science in general has begun to recognize the importance of the interactions of multiple agents for the understanding of individual cognition as well as group performance and group problem solving (Eberhart et al., 2001; Mason et al., in press; Sun, 2001; Wooldridge, 2002). Productive contacts between social psychology and these disciplines will be facilitated by a common theoretical approach that emphasizes multiagent thinking. The result may be models that integrate all areas of social/personality psychology including intrapersonal processes (personality, cognition, attitudes) and interpersonal processes (relationships, group processes), as well as higher levels of populations, cultures, and social institutions.

Agent-based thinking, situated cognition, and emergence. A key message of ABM is that the implications of a given social or psychological process cannot be well understood if the process is studied in isolation, removed from its context, at a frozen moment in time. Instead, processes have effects that are often surprising and emergent when they operate in the context of other simultaneous and interdependent processes, in dynamic fashion over time. This understanding is the motivating force behind the “situated cognition” movement in psychology during the past couple of decades (Clancey, in press; Smith & Semin, 2004). Clancey (in press) noted that for situated cognition,

The one essential theoretical move is contextualization (perhaps stated as “antilocalization,” in terms of what must be rooted out): We cannot locate meaning in the text, life in the cell, the person in the body, knowledge in the brain, a memory in a neuron. Rather, these are all active, dynamic processes, existing only in interactive behaviors of cultural, social, biological, and physical environment systems.

As noted earlier, within social psychology, relationship researchers (Reis et al., 2000) are making similar appeals for viewing relationships as emergent outcomes of interactive forces (cognitive, affective, interpersonal, and cultural) that operate during a lifetime of development. Cultural psychologists are making a parallel argument regarding the mutually interdependent constitution of self and culture (Adams & Markus, 2004; Fiske, Kitayama, Markus, & Nisbett, 1998). ABM should ultimately allow us to conceptualize all the diverse phenomena of social psychology not as reflecting static relationships among variables but rather as emergent results of dynamically interactive processes taking place in their contexts.

NOTE

1. Nonhierarchical causal modeling techniques can relax the unidirectionality assumption, but they have restrictive requirements of their own and are little used in social psychology.

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