Coevolution of Decision-Making and Social Environments

ELIZABETH BRUCH, ROSS A. HAMMOND, and PETER M. TODD

Abstract

Social scientists have a longstanding theoretical interest in the relationship between individual behavior and social dynamics. A growing body of work demonstrates that, when human behavior is interdependent—that is, what one person does depends on the past, present, or anticipated future actions of others—there is not a simple or linear relationship between the choices of individuals and their collective consequences. Outside of the academy, policy makers are increasingly aware that well-intentioned interventions can backfire if they fail to account for how people change their behavior in response to the intervention. This type of problem requires a systematic modeling approach. Our entry provides a brief introduction to a growing body of research that brings together two disparate literatures—studies of decision-making and studies of the interplay between individuals' decisions and features of the social environment—through dynamic computational modeling. Cognitive scientists characterize human decision-making under uncertainty using *heuristics*, rules-of-thumb that produce satisfactory choices quickly and with limited information. The heuristics we use and information samples we gather have profound consequences for the choices we make. At the same time, the social context defined by the choices of others feeds back to affect individual decision-making. In recent years, there has been growing interest in methods such as agent-based modeling and systems dynamics that can capture the dynamic interplay between individuals' choices and features of the environment. However, historically these approaches have not been grounded in cognitively plausible models of human behavior. We identify areas of high potential for future research, and lay out a preliminary framework to help guide understanding of the decision-making process and its consequences in different social domains.

INTRODUCTION

The leading causes of death and disease in the United States are attributed to behavioral factors such as tobacco use, poor diet and inactivity, alcohol consumption, risky sexual behavior, and avoidable injuries (Danaei *et al.*, 2009; Mokdad, Marks, Stroup, & Gerberding, 2004). Behavior is thus central to the prevention, treatment, and management of diseases and health

Emerging Trends in the Social and Behavioral Sciences. Edited by Robert Scott and Stephen Kosslyn.
 ISBN 978-1-118-90077-2.

care, and many interventions are aimed at changing behavior in healthier directions. However, these interventions are often based on models of human decision-making that lack empirical support, are difficult to quantify, or largely ignore the bi-directional feedback between the individual and the social (for a review of the behavioral theories guiding interventions, see Glanz & Bishop, 2010). Research that ignores the processes by which people actually make decisions in real settings or the interdependence of those decisions may result in mis-specified behavioral models that lead to incorrect predictions and ineffective policy recommendations.

There is also growing recognition that policy interventions are most likely to be effective if they adopt ecological or systems perspectives (Huang & Glass, 2008; Nader *et al.*, 2012; Mabry, Olster, Morgan, & Abrams, 2008; Sallis, Owen, & Fisher, 2008). The ecological perspective emphasizes that multiple levels of influence shape behavior (e.g., individual, interpersonal, organizational, community, and public policy), and the systems perspective emphasizes the interconnectedness of these levels (including dynamic feedback between individuals' actions and their social environment). A major challenge in solving pernicious social problems is accounting for this bidirectional feedback between individuals and their environment (Sterman, 2006). In recent years, studies have identified "systems science" methods such as agent-based modeling (ABM) as a potentially transformative tool for capturing feedback across multiple levels of analysis (Hammond, 2009; Luke & Stamatakis, 2012; Mabry, Marcus, Clark, Leischow, & Méndez, 2010). However, the ability of systems science approaches to reach their full potential in offering new insights about behavior has been limited by the unmet need for empirically valid models of individual behavior that can be operationalized computationally and incorporated into the systems analysis.

Below, we draw on insights from cognitive science and decision theory to outline an initial framework to help guide the development of more cognitively sophisticated computational models. We identify both key features of individuals' choices (and the contexts in which those choices take place) that may shape the process of decision-making, and also how those decisions impinge on the current and future decisions of others. We view these as an initial set of important structural features that determine both what strategies are available for individuals to use in navigating the choice environment, and also the ways in which the decisions of individuals feed back to shape the choice environment. We begin with a brief overview of agent-based models aimed at capturing feedback between individuals' choices and the social environment. We then review some of the state-of-the-art literature on decision strategies, and how they rely on features of the environment. In the final section, we outline a framework for exploring the aggregate implications of "cognitively plausible" decision models as individuals simultaneously react to and change their social environment.

LINKING INDIVIDUAL BEHAVIOR WITH THE SOCIAL ENVIRONMENT

Social science has a longstanding interest in the relationship between individuals' motivations and decisions and large-scale patterns of social organization and change. The "micro–macro problem" concerns how to explicitly account for the ways in which actions of individuals give rise to social organization and dynamics, rather than assuming that macrolevel phenomena are simply aggregates of individual characteristics and behavior (Coleman, 1994, p. 197; Granovetter, 1978, p. 1421). The connection between individuals' actions and their collective consequences would be simple if one could simply sum over individuals' intentions or behavior to generate expected population-level attributes. The problem is that much of human behavior is interdependent; individuals' actions often depend on what others are doing. For example, individuals may directly influence one another through social norms, peer effects, and other expectations for behavior. Even in situations where direct social influence plays a minimal role, the alternatives available to people at any given moment may nonetheless depend on the past, present, or future choices of others. For example, the availability of a job is often dependent on the decision of its prior occupant to vacate it (Chase, 1991), individuals' decisions about who to date or marry typically require reciprocity of affections by the potential mate (Roth & Sotomayor, 1992), and both require that the options have not already been taken by other searchers (Todd, 2007).

ABM is a relatively new computational simulation approach specifically designed to yield insight into how the behavior of decentralized autonomous actors generate macro-level outcomes of interest, explicitly incorporating dynamic feedback from macro back to micro. Agent-based models have been used to study the macro–micro-dynamics governing a host of social processes, ranging from segregation to civil unrest to the outbreak and spread of disease (Bruch & Mare, 2006; Cioffi-Revilla & Rouleau, 2010; Epstein, 2006; Schelling, 1971). Until recently, however, behavior of individual agents in an ABM has rarely been grounded in cognitively or neurobiologically "plausible" rules.[1] Typically, agents have been programmed with stylized rules for behavior, or in some cases with a psychologically unrealistic statistical model that relates features of the environment to the probability of

1. Exceptions include the work of Todd and colleagues, who explore how heuristics interact with and create features of the social environment (Todd, Billari, & Simão, 2005; Davis, Todd, & Bullock, 1999); as well as work by Hammond and Ornstein (2014) and Epstein (2014).

the agent taking one set of actions or another. The potential has thus largely been missed for psychologically grounded agent-based models to provide new insights about how individuals' choices shape and are shaped by their social and physical environment. Combining advances in cognitive science with those in complex systems science can yield a new generation of models that shed light on both individual behavior and its instantiation in social environments.

MODELS OF DECISION-MAKING

How do people make decisions? The classical model of decision-making is the rational actor model endemic to neoclassical economics, which assumes a fully informed, forward-looking rational actor with unlimited time for information processing (Becker, 1993; Von Neumann & Morgenstern, 2007). However, over the past 40 years, a large body of work has demonstrated that real people make decisions under conditions of limited time, bounded cognitive resources, and uncertainty. As a result, people often use heuristics—simple rules for making a choice or inference—that serve to keep the processing demands of a decision within the environmental and cognitive limits.

Heuristics are "problem-solving methods that tend to produce efficient solutions to difficult problems by restricting the search through the space of possible solutions, on the basis of some evaluation of the structure of the problem" (Braunstein, 1972, p. 520). While early work from the "heuristics and biases" school often emphasized the fallibility of human decision-making (Kahneman, Slovic, & Tversky, 1982), more recent research on "ecological rationality" shows how individuals' simple decision strategies can capitalize on systematic structure in the decision-making environment (Todd, Gigerenzer, & The ABC Research Group, 2012). In other words, while people do have limited knowledge and constraints on their ability to process information, they can nonetheless make good decisions using heuristics that match (by learning or evolution) to the ways that information is organized in their environment. Such well-matched heuristics are designed to capitalize on key features of the decision environment, and so can get away with using limited information processed in a quick manner.

Heuristics are often composed of building blocks that underlie decision-making, including: *search rules* that specify how to seek out information on available choice alternatives; *stopping rules* that specify when a search should be ended; and *decision rules* that specify how the final choice is reached (Gigerenzer & Gaissmaier, 2011, p. 456). For example, some marriage market models consider how people choose a marriage partner when potential mates can only be explored one at a time, and there is uncertainty about whether the next person to be encountered will be better than a currently available partner. One commonly studied heuristic approach for such challenging sequential choices is to use a "satisficing" mechanism incorporating building blocks whereby people initially spend some period of time searching for available options and learning about them, stop that search after a reasonable amount of time and set an aspiration level based on what they have experienced, and then decide on the next available partner encountered who meets that aspiration level (Todd & Miller, 1999; Todd, Billari, & Simão, 2005).

Decision Tasks and Decision Environments

Many decision theories emphasize that the heuristics used successfully in decision-making depend on particular features of the task environment (Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1993; Simon, 1990; Todd & Gigerenzer, 2012), so to know what heuristics to build into psychologically realistic models we must first assess the relevant features of that environment that shape decision strategies. These features include attributes of the decision task as well as characteristics of the social and physical environment in which the decision occurs.[2]

Key features of *decision tasks* include:

1. The expected *time horizon* over which the decision will play out. This includes the anticipated consequences of the decision as well as the number of decisions made over a day, year, or lifetime. For example, decisions about what to eat are made on a daily basis, whereas decisions about where to live are made on average once every 3–5 years. It follows that repeated decisions are likely to be governed more by habits and learning over time than infrequent decisions (Scheibehenne, Mata, & Todd, 2011). Another dimension of time horizons is the extent to which decision consequences are immediate or cumulative. For example, the effects of food choices and physical activity decisions cumulate gradually over time, with feedback via biological outcomes often occurring only after a substantial time lag.
2. The extent to which the decision is subject to *social influence*. This depends on how much individuals can observe the preferences, strategies, or decision outcomes of others (e.g., exercise choices made in public vs sleep behaviors done in private). Another aspect of social influence is the degree to which the successful outcome of a decision is under the control of the decision maker alone or is affected by others.

2. In this essay, we make an analytical distinction between attributes of decision tasks and attributes of decision environments. But in practice, because tasks, decisions, and social environments are strongly intertwined, this distinction may be blurred.

For example, the successful implementation of a young woman's decision to use condoms depends on the cooperation of her partner, but her choice to take the stairs or the elevator is more individually determined, both of which will affect her selection of appropriate decision mechanisms.

3. The decision's valence in terms of *reward seeking versus harm avoidance*. It is well established that human beings are more sensitive to negative change in their environment than positive change; this is sometimes referred to as the *positive–negative asymmetry effect*. In reward-seeking situations, people are typically more tolerant of uncertainty and willing to take risks (Kahneman & Tversky, 1979). In contrast, when the environment is difficult and dangerous, it is likely that people's time horizons will become considerably shorter, changing the heuristics they use.

Key features of *decision environments* include:

1. The *number of alternatives* to choose among. When there are only a few alternatives, decisions are often made through a comparison process that considers the most important features one at a time until a choice can be made (e.g., the take-the-best heuristic and others—see Payne *et al*., 1993; Rieskamp & Hoffrage, 1999). With more alternatives, a multi-stage process can be used where each stage reduces the number of options remaining under consideration. For example, the elimination by aspects heuristic systematically reduces the number of alternatives by first eliminating all those that are not good enough on the most important aspect (e.g., all those restaurants in town that cost more than $50 per person), then eliminating all those left that are not good enough on the second aspect (e.g., all those remaining restaurants that are over ten miles away), and so on until only one option is left (Tversky, 1972).
2. The *distribution of alternatives.* When satisfactory alternatives are plentiful, the decision maker requires little search or information to decide among them, as most choices will be good. When good choices are rare, strategies that search for longer are more appropriate (Fasolo, Hertwig, Huber, & Ludwig, 2009). The distribution of cue values (which is related to how informative the cues are) also influences what strategies will work well (Reimer & Hoffrage, 2012).
3. The extent to which *available options depend on the choices of others*, and the degree to which scarce items are replenished. For example, food options may be sold out at the grocery story, but this could imply high demand, which usually results in a resupply, calling for choice strategies that revisit resource locations periodically. In contrast, when two people marry they are removed from the list of possibilities available to others

for an extended period (Todd, 2007). People may also be sensitive to the rate of change in their choice environment, as well as the direction of change (i.e., whether the change is perceived as positive vs negative), which can favor different heuristics (Dudey & Todd, 2002; Hey, 1982).

4. The *redundancy in the environment* in terms of the correlation among feature dimensions of choice alternatives. When there is a high degree of redundancy, knowing one attribute of a particular alternative tells the chooser something about its other attributes, so that heuristics that focus on "one good reason" for making a choice will work well with a quick information search (Rieskamp & Dieckmann, 2012). In situations with multiple orthogonal attributes that are important for choice (e.g., in social settings as when children select friends based on family background, sex, and mutual interests), heuristics that tally all those features may be more effective (Fasolo, McClelland, & Todd, 2007).

These components of task environment structure can be used to identify shared properties of seemingly disparate choice applications, which may help in the design of more effective policies aimed at changing behavior. Because features of the decision environment determine what heuristics will be most efficacious, interventions that succeed in one domain may be fruitfully applied to another that shares structural features.

THE COEVOLUTION OF DECISION-MAKING AND THE SOCIAL ENVIRONMENT

In most decision contexts, there is feedback between the choices that individuals make and the environment in which they make them. For example, there are well-documented peer effects on eating, smoking, medication compliance, exercise, and mate choice in which one's current choices influence and are influenced by the witnessed choices of others (Bowers, Place, Todd, Penke, & Asendorpf, 2012; Crandall, 1988; Lazev, Herzog, & Brandon, 1999; Todd & Minard, 2014). In addition, the choices of individuals at one time point can shape what options are available for future individuals. The classic example from social science is neighborhood tipping: Each individual who leaves a neighborhood because she cannot tolerate its racial composition changes its composition and that of the neighborhood she moves into (Schelling, 1978). Over time, the neighborhood choices available to others evolve as a product of previous mobility decisions. This phenomenon can also be seen in what food products are available for purchase in different areas, which reflects aggregate demand. Finally, the success of a decision may depend on the behavior of another person. For example, children are subject

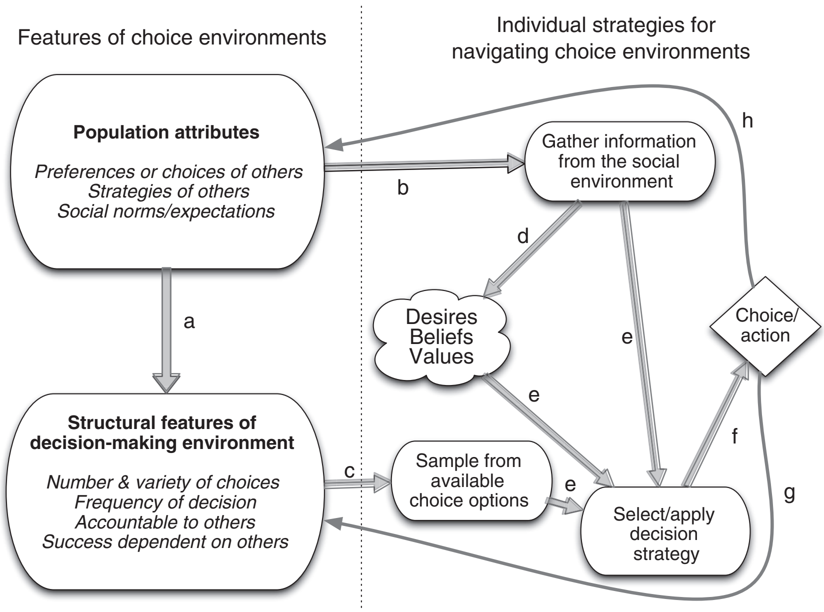

Figure 1 Interaction between individuals and environment.

to the food consumption decisions of their parents and people are more likely to exercise if they are accountable to a workout partner (Dishman, Sallis, & Orenstein, 1985; Wardle, Guthrie, Sanderson, Birch, & Plomin, 2001).

Figure 1 illustrates how individual strategies for decision-making interact with features of the environment. The left hand side represents features of both the social environment (e.g., the demographic make-up of the population, the behaviors of others, and social norms and other expectations) and the choice domain. The social context (in particular, the choices of others) influences the number and type of options available (*a*). Individuals will observe some subset of the social environment (*b*); these observations of the social environment may influence their preferences, beliefs, and/or expectations (*d*). For a particular choice domain, the individual will sample some set of options from the environment (*c*) which will—in conjunction with preferences and in some cases observing the decisions of others—determine their decision-making strategy (*e*). This strategy results in a particular action outcome (*f*). Individuals' choices may affect the choices available to others; for example in the case of mate choice, a pairing will eliminate those two people as options for others (*g*). Feedback to the social environment occurs both because the individual's choice may change his or her other attributes as a member of the population (e.g., weight and location) and also because his or her choice may be observed by others (e.g., eating in a group) (*h*).

Agent-based models that incorporate realistic decision heuristics to predict individual-environment interactions have begun to appear in the literature. For example, psychologically plausible satisficing heuristics have been used in models of mate choice, where individual agents first engage in an adolescent "dating" period where they meet a succession of potential mates of varying levels of quality, learn how well they can do at attracting those potential mates, adjust their own aspiration level for the kind of long-term mate they should seek in the future on the basis of those initial dates (raising their aspirations after successful interactions and lowering them after unsuccessful ones), and then enter the true mate-choice phase where they make marriage offers to individuals they encounter who meet their aspirations and get married and removed from the population when the offer is mutual—thereby changing the choice environment for all those agents still remaining in the mating market (Todd & Miller, 1999). This model predicts observed demographic patterns of the ages at which people get married (Todd *et al.*, 2005) and demonstrates the strength of the effect of others' decisions on one's own best choice strategy (Todd, 2007); other models have shown how the social norms that guide individuals' choices of an appropriately aged spouse can evolve (Billari, Prskawetz, & Fürnkranz, 2003). A similar model in different domain shows related effects on the best strategy to use for searching for a parking space (another type of sequential choice) when the choices made by other earlier parkers creates the environment—here the spatial layout of available spaces—for later drivers (Hutchinson, Fanselow, & Todd, 2012). In the context of food choice, recent work using agent-based models grounded in neurobiology describes the influence of food environments on preferences (Hall, Hammond, & Rahmandad, 2014; Hammond *et al.*, 2012) and the bi-directional coevolution of body weight and social norms (Hammond & Ornstein, 2014).

FUTURE DIRECTIONS AND CHALLENGES

Agent-based simulation models that put agents with realistic psychological decision mechanisms into social environments can be very useful in enabling researchers to learn about aspects of cognition and behavior that are otherwise difficult to study (Todd, 1996). First, such models can provide existence proofs, showing that particular hypothesized cognitive mechanisms can lead to particular observed patterns of behavior in specific environments. Second, they can elucidate the dynamics of an interacting population over time, helping us to understand what mechanisms and conditions can lead to the appearance or disappearance of particular behaviors or environment structures. And third, as "runnable thought experiments," they can help us explore complex interactions for which our intuitions are usually inadequate, and thereby come up with predictions—including for effective interventions to change behavior—that can be tested with empirical research.

A key challenge for future researchers interested in seeding their dynamic models with realistic human behavior is identifying what decision rules people are using, and how those rules depend on features of both the decision task and the social environment. The classic approach for studying how people make decisions is experiments that systematically vary features of both the decision task and the environment and observe outcomes. Commonly, computer-based choice situations are created in which people are presented with two options to choose between, and they can examine different pieces of evidence for each option (e.g., by clicking on a "show price" or "show mileage" button for choosing a car) until they have seen enough to decide, at which point their search, stopping, and decision rules can be assessed (Bröder, 2012; Payne *et al.*, 1993; Rieskamp & Hoffrage, 1999).

One promising source of information on choice processes is the behavioral data produced through activities online. Dating websites, housing search sites, job search sites, Facebook, and other electronic venues provide a detailed look at how people navigate these decision processes. However, an open question is the degree to which decision strategies observed online can be generalized to the same behaviors in other settings. For example, people visiting online dating sites may be confronted with thousands of potential mates over a short time period, while in their day-to-day lives they only encounter potential mates sporadically over an extended period. These task and environment differences may result in differences in strategy and selectivity as well (Lenton, Fasolo, & Todd, 2010).

There is a growing demand and opportunity for behaviorally sophisticated models of individual behavior that can also capture bi-directional feedback with social dynamics. We believe that advances in computational simulation and in cognitive science mean the time is ripe for rapid progress in connecting these two fields (to mutual benefit). This "emerging trend" is already underway, and offers the promise of both new insights into complex human behavior, and the design of more effective and efficient policies and interventions.

REFERENCES

Becker, G. (1993). Nobel lecture: The economic way of looking at behavior. *Journal of Political Economy*, *101*, 385–409.

Billari, F. C., Prskawetz, A., & Fürnkranz, J. (2003). On the cultural evolution of age-at-marriage norms. In F. C. Billari & A. Prskawetz (Eds.), *Agent-based computational demography: Using simulation to improve our understanding of demographic behavior* (pp. 139–157). Heidelberg, Germany: Physica Verlag.

Bowers, R. I., Place, S. S., Todd, P. M., Penke, L., & Asendorpf, J. B. (2012). Generalization in mate choice copying in humans. *Behavioral Ecology*, *23*, 112–124.

Braunstein, M. L. (1972). Perception of rotation in depth: A process model. *Psychological Review*, *79*(6), 510–524.

Bröder, A. (2012). The quest for take-the-best: Insights and outlooks from experimental research. In P. M. Todd, G. Gigerenzer & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 216–240). New York, NY: Oxford University Press.

Bruch, E., & Mare, R. (2006). Neighborhood choice and neighborhood change. *American Journal of Sociology*, *3*, 667–709.

Chase, I. D. (1991). Vacancy chains. *Annual Review of Sociology*, *1*, 133–154.

Cioffi-Revilla, C., & Rouleau, M. (2010). MASON RebeLand: An agent-based model of politics, environment, and insurgency. *International Studies Review*, *1*, 31–52.

Coleman, J. S. (1994). *Foundations of social theory*. Cambridge, MA: Harvard University Press.

Crandall, C. S. (1988). Social contagion of binge eating. *Journal of Personality and Social Psychology*, *55*(4), 588.

Danaei, G., Ding, E. L., Mozaffarian, D., Taylor, B., Rehm, J., Murray, C. J. L., & Ezzati, M. (2009). The preventable causes of death in the united states: Comparative risk assessment of dietary, lifestyle, and metabolic risk factors. *PLoS Medicine*, *6*(4), e1000058.

Davis, J. N., Todd, P. M., & Bullock, S. (1999). Environment quality predicts parental provisioning decisions. *Proceedings of the Royal Society of London B: Biological Sciences*, *266*, 1791–1797.

Dishman, R. K., Sallis, J. F., & Orenstein, D. R. (1985). The determinants of physical activity and exercise. *Public Health Reports*, *100*, 158.

Dudey, T., & Todd, P. M. (2002). Making good decisions with minimal information: Simultaneous and sequential choice. *Journal of Bioeconomics*, *3*, 195–215.

Epstein, J. M. (2014). *Agent_Zero: Toward Neurocognitive Foundations for Generative Social Science*. Princeton, NJ: Princeton University Press.

Fasolo, B., Hertwig, R., Huber, M., & Ludwig, M. (2009). Size, entropy, and density: What is the difference that makes the difference between small and large real-world assortments? *Psychology & Marketing*, *26*, 254–279.

Fasolo, B., McClelland, G. H., & Todd, P. M. (2007). Escaping the tyranny of choice: When fewer attributes make choice easier. *Marketing Theory*, *7*, 13–26.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*, 451–82.

Glanz, K., & Bishop, D. B. (2010). The role of behavioral science theory in development and implementation of public health interventions. *Annual Review of Public Health*, *31*, 399–418.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology*, *83*(6), 1420–1443.

Hall, K. D., Hammond, R. A., & Rahmandad, H. (2014). Dynamic interplay among homeostatic, hedonic, and cognitive feedback circuits regulating body weight. *American Journal of Public Health*, e1–e7.

Hammond, R. A. (2009). "Complex systems modeling for obesity research". *Preventing Chronic Disease* 6(3), A97.

Hammond, R. A., & Ornstein, J. T. (2014). A model of social influence on body mass index. *Annals of the New York Academy of Science*, *1331*, 34–42.

Hammond, R. A., Ornstein, J. T., Fellows, L. K., Dube, L., Levitan, R., & Dagher, A. (2012). A model of food reward learning with dynamic reward exposure. *Frontiers in Computational Neuroscience*, *6*, 82.

Hey, J. D. (1982). Search for rules for search. *Journal of Economic Behavior and Organization*, *3*, 65–81.

Huang, T. T. K., & Glass, T. A. (2008). Transforming research strategies for understanding and preventing obesity. *JAMA*, *300*(15), 1811–1813.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292.

Lazev, A. B., Herzog, T. A., & Brandon, T. H. (1999). Classical conditioning of environmental cues to cigarette smoking. *Experimental and Clinical Psychopharmacology*, *7*, 56.

Lenton, A. P., Fasolo, B., & Todd, P. M. (2010). Who is in your shopping cart? Expected and experienced effects of choice abundance in the online dating context. In N. Kock (Ed.), *Evolutionary psychology and information systems research: A new approach to studying the effects of modern technologies on human behavior* (pp. 149–167). New York, NY: Springer.

Mabry, P. L., Marcus, S. E., Clark, P. I., Leischow, S. J., & Méndez, D. (2010). Systems science: a revolution in public health policy research. *American Journal of Public Health*, *100*, 1161–1163.

Mokdad, A. H., Marks, J. S., Stroup, D. F., & Gerberding, J. L. (2004). Actual causes of death in the United States, 2000. *Journal of the American Medical Association*, *10*, 1238–1245.

Nader, P. R., Huang, T. T. K., Gahagan, S., Kumanyika, S., Hammond, R. A., & Christoffel, K. K. (2012). Next steps in obesity prevention: Altering early life systems to support healthy parents, infants, and toddlers. *Childhood Obesity*, *8*(3), 195–204.

Reimer, T., & Hoffrage, U. (2012). Ecological rationality for teams and committees: Heuristics in group decision making. In P. M. Todd, G. Gigerenzer & the ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 335–359). New York, NY: Oxford University Press.

Rieskamp, J., & Dieckmann, A. (2012). Redundancy: Environment structure that simple heuristics can exploit. In P. M. Todd, G. Gigerenzer & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 187–215). New York, NY: Oxford University Press.

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell?. In G. Gigerenzer, P. M. Todd & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 141–167). New York, NY: Oxford University Press.

Roth, A. E., & Sotomayor, M. A. O. (1992). *Two-sided matching: A study in game-theoretic modeling and analysis*. Cambridge, England: Cambridge University Press.

Sallis, J., Owen, N., & Fisher, E. (2008). Ecological models of health behavior. In Glanz, K., B. K. Rimer, and K. Viswanath (Eds.), *Health behavior and health education: Theory, research, and practice*, (pp. 465–486). San Francisco, CA: John Wiley & Sons, Inc.

Scheibehenne, B., Mata, J., & Todd, P. M. (2011). Older but not wiser—Predicting spouse's preferences gets worse with age. *Journal of Consumer Psychology*, *21*, 184–191.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *2*, 143–186.

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

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology*, *41*(1), 1–20.

Sterman, J. D. (2006). Learning from evidence in a complex world. *American Journal of Public Health*, *3*, 505–514.

Todd, P. M. (1996). The causes and effects of evolutionary simulation in the behavioral sciences. In R. Belew & M. Mitchell (Eds.), *Adaptive individuals in evolving populations: Models and algorithms* (pp. 211–224). Reading, MA: Addison-Wesley.

Todd, P. M. (2007). Coevolved cognitive mechanisms in mate search: Making decisions in a decision-shaped world. In J. P. Forgas, M. G. Haselton & W. von Hippel (Eds.), *Evolution and the social mind: Evolutionary psychology and social cognition* (pp. 145–159 (Sydney Symposium of Social Psychology series)). New York, NY: Psychology Press.

Todd, P. M., Billari, F. C., & Simão, J. (2005). Aggregate age-at-marriage patterns from individual mate-search heuristics. *Demography*, *42*, 559–574.

Todd, P. M., & Gigerenzer, G. (2012). *Ecological Rationality: Intelligence in the World*. Oxford, England: Oxford University Press.

Todd, P. M., & Miller, G. F. (1999). From pride and prejudice to persuasion: Satisficing in mate search. In G. Gigerenzer, P. M. Todd & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 287–308). New York, NY: Oxford University Press.

Todd, P. M., & Minard, S. L. (2014). Simple heuristics for deciding what to eat. In S. D. Preston, B. Knutson & M. Kringelbach (Eds.), *The interdisciplinary science of consumption*. Cambridge, MA: MIT Press.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, *79*(4), 281–299.

Von Neumann, J., & Morgenstern, O. (2007). *Theory of games and economic behavior* (Commemorative ed.). Princeton, NJ: Princeton University Press.

Wardle, J., Guthrie, C., Sanderson, S., Birch, L., & Plomin, R. (2001). Food and activity preferences in children of lean and obese parents. *International Journal of Obesity & Related Metabolic Disorders*, *25*(7), 971–977.

FURTHER READING

Agent-Based Modeling

Epstein, J. (2006). *Generative social science: Studies in agent-based computational modeling*. Princeton, NJ: Princeton University Press.

Macy, M., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, *28*, 143–166.
Miller, J., & Page, S. (2009). *Complex adaptive systems: An introduction to computational models of social life: An introduction to computational models of social life*. Princeton, NJ: Princeton University Press.

Systems Science and Public Policy

Luke, D. A., & Stamatakis, K. A. (2012). Systems science methods in public health: Dynamics, networks, and agents. *Annual Review of Public Health*, *33*, 357–376.
Mabry, P. L., Marcus, S. E., Clark, P. I., Leischow, S. J., & Mendez, D. (2010). Systems science: a revolution in public health policy research. *American Journal of Public Health*, *100*, 1161–1163.
Mabry, P. L., Olster, D. H., Morgan, G. D., & Abrams, D. B. (2008). Interdiciplinarity and systems science to improve population health: a view from the NIH Office of Behavioral and Social Sciences Research. *American Journal of Preventive Medicine*, *35*(S2), 11–24.

Heuristic Decision-Making

Gigerenzer, G., Hertwig, R., & Pachur, T. (2011). *Heuristics: The foundations of Adaptive Behavior*. New York, NY: Oxford University Press.
Gigerenzer, G., Todd, P. M., & The ABC Research Group (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.
Kahneman, D., Slovic, P., & Tversky, A. (Eds.) (1982). *Judgment under uncertainty: heuristics and biases*. Cambridge, England: Cambridge University Press.
Payne, J., Bettman, J., & Johnson, E. (1993). *The adaptive decision maker*. Cambridge, England: Cambridge University Press.

Co-Evolution of Heuristic Strategies and Social Environments

Hammond, R. & Ornstein, J. (2014). A model of social influence on body weight. *Annals of the New York Academy of Science.* Forthcoming.
Hutchinson, J. M. C., Fanselow, C., & Todd, P. M. (2012). Car parking as a game between simple heuristics. In P. M. Todd, G. Gigerenzer & The ABC Research Group (Eds.), *Ecological rationality: Intelligence in the world* (pp. 454–484). New York, NY: Oxford University Press.
Todd, P. M., Billari, F. C., & Simão, J. (2005). Aggregate age-at-marriage patterns from individual mate-search heuristics. *Demography*, *42*(3), 559–574.

ELIZABETH BRUCH SHORT BIOGRAPHY

Elizabeth Bruch, PhD is an Assistant Professor in sociology and complex systems, and Affiliate of the Population Studies Center at the Institute for

Social Research. Much of her work blends statistical and agent-based methods to examine the relationship between individuals' decisions about where to live and patterns of residential segregation. She is also working on a project exploring how individuals' mate search strategies and willingness to settle intersect with demographic constraints to generate dating or marriage market dynamics in US metro areas. She has served as a consulting editor for the American Journal of Sociology, and on the editorial board for Sociological Methodology. Her work has received the Gould Prize from the American Journal of Sociology, as well as best article prizes from the Mathematical and Urban Sociology sections of American Sociological Association. She is a member of the National Institute of Health's Network on Inequality, Complexity, and Health.

ROSS A. HAMMOND SHORT BIOGRAPHY

Ross A. Hammond, PhD is a Senior Fellow in Economic Studies at the Brookings Institution, where he is also the Director of the Center on Social Dynamics & Policy. His primary area of expertise is modeling complex dynamics in economic, social, and public health systems using methods from complexity science. His current research topics include obesity etiology and prevention, food systems, tobacco control, behavioral epidemiology, crime, corruption, segregation, and decision-making. Hammond received his BA from Williams College and his PhD from the University of Michigan. He has authored numerous scientific articles, and his work has been featured in *New Scientist*, *Salon*, *The Atlantic Monthly*, *Scientific American*, and major news media. Hammond was recently appointed to the Institute of Medicine/National Research Council committee *Framework for Assessing the Health*, *Environmental*, *and Social Effects of the Food System*, and is both a Public Health Advisor at the National Cancer Institute and an Advisory Special Government Employee at the FDA Center for Tobacco Products. He serves on the editorial boards of the journals *Behavioral Science & Policy* and *Childhood Obesity*, and has been a member of the NIH-funded research networks MIDAS (Models of Infectious Disease Agent Study), ENVISION (part of the National Collaborative on Childhood Obesity Research), and NICH (Network on Inequality, Complexity, and Health). Hammond currently holds appointments at the Harvard School of Public Health, Washington University, and University of Michigan. He has been a consultant to the World Bank, the Asian Development Bank, the Food and Drug Administration, the Institute of Medicine, and the National Institutes of Health. He has taught computational modeling at Harvard, the University of Michigan, Washington University, the National Cancer Institute, and the NIH/CDC Institute on Systems Science and Health.

PETER M. TODD SHORT BIOGRAPHY

Peter M. Todd grew up in Silicon Valley, studied mathematics and electronic music at Oberlin College, received an MPhil in computer speech and language processing from Cambridge University, and developed neural network models of the evolution of learning for his PhD in psychology at Stanford University. In 1995, he moved to Germany to help found the Center for Adaptive Behavior and Cognition (ABC), based at the Max Planck Institute for Human Development in Berlin. The Center's work was captured in the book *Simple Heuristics That Make Us Smart* (Gigerenzer, Todd, and The ABC Research Group; Oxford, 1999); the sequel, *Ecological Rationality: Intelligence in the World*, covering information-environment structures and their impact on decision-making, came out in 2012, along with a book on search behavior, *Cognitive Search: Evolution, Algorithms, and the Brain* (Todd, Hills, and Robbins, eds.; MIT Press). Todd moved to Indiana University in Bloomington as Professor of Cognitive Science, Psychology, and Informatics in 2005 and set up the ABC-West lab there (http://www.indiana.edu/~abcwest/). His ongoing research interests cover the interactions between and coevolution of decision-making and decision environments, focusing on the ways that people and other animals search for resources—including mates, information, and food—in space and time.

RELATED ESSAYS

Models of Revealed Preference *(Economics)*, Abi Adams and Ian Crawford
Choice Architecture *(Psychology)*, Adrian R. Camilleri and Rick P. Larrick
Behavioral Economics *(Sociology)*, Guy Hochman and Dan Ariely
Emotion and Decision Making *(Psychology)*, Jeff R. Huntsinger and Cara Ray
Against Game Theory *(Political Science)*, Gale M. Lucas *et al*.
From Individual Rationality to Socially Embedded Self-Regulation *(Sociology)*, Siegwart Lindenberg
Event Processing as an Executive Enterprise *(Psychology)*, Robbie A. Ross and Dare A. Baldwin