



# Modeling Affect and Cognition

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## Modeling Affect and Cognition: Opportunities and Challenges for Managerial and Organizational Cognition

Mark P. Healey, Mercedes Bleda and Adrien Querbes

### ABSTRACT

In this chapter we examine some possibilities of using computer simulation methods to model the interaction of affect and cognition in organizations, with a particular focus on agent-based modeling (ABM) techniques. Our chapter has two main aims. First, we take stock of methodological progress in this area, highlighting important developments in the modeling of affect and cognition in other fields, including psychology and economics. Second, we outline how ABM in particular can help to advance managerial and organizational cognition by building and testing theoretical models predicated on the interaction of affect and cognition. We argue that using ABM for this purpose can improve the level of specificity of cognitive and affective concepts and their interrelationships in organizational theories, yield more behaviorally plausible models of behavior in and of organizations, and deepen understanding of the generative behavioral mechanisms of multi-level organizational phenomena. We highlight possibilities for using ABM to model -affect–cognition interactions in studies of mental models, collective cognition, diversity in work groups and teams, and organizational decision-making.

Keywords: Affect; agent-based modeling; behavioral -strategy; cognition and emotion; computer simulation; managerial and organizational cognition

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## Introduction

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The origins of the field of managerial and organizational cognition (MOC) are in the Carnegie School of Organization Theory (March & Simon, 1958; Simon, 1947). The study of cognitive processes in organizations pioneered by the Carnegie School scholars was strongly influenced by another line of work in which these scholars were engaged; namely, the study of human problem solving (Newell & Simon, 1972). Through their analyses of skilled performance in chess and other intellectual problems, these scholars advanced theories that described human cognition in terms of information-processing activities that were “amenable for use in a digital computer” (Newell, Shaw, & Simon, 1958, p. 151). The Carnegie scholars built computer simulation models to emulate memory and related information processes in individual learning (Simon & Feigenbaum, 1964) and organiza-

tional decision-making (Cyert, Feigenbaum, & March, 1959). One characteristic of these theories and models was that they largely described human cognition in terms of “cold” cognition, that is, cognitive processes that are free of affect<sup>1</sup> and emotion. The functions and limitations of memory, the role of symbolic representations, and the features of human information processing systems became the hallmarks of human cognition and by extension human behavior. Affect rarely entered the picture.

In later work, however, Simon’s (1967) exploration of how emotion controls information processing led him to conclude that “in order to have anything like a complete theory of human rationality, we have to understand what role emotion plays in it” (Simon, 1983, p. 29). Despite this exhortation, the neglect of affect came to characterize not only the study of problem-solving and decision-making but also the analysis of cognition in organizations (for reviews of the latter, see Hodgkinson & Healey, 2008; Lant & Shapira, 2000; Walsh, 1995; Weick, 1979).

Around the turn of the 21st century, however, the behavioral sciences witnessed an affective revolution, as advances in social neuroscience and neuroeconomics demonstrated that human behavior reflects the interplay of cognition and emotion (Camerer, Loewenstein, & Prelec, 2005; Damasio, 1994; LeDoux, 1998). At this juncture, MOC scholars also sought to afford a more prominent role to emotion (e.g., Fisher & Ashkanasy, 2000; Hodgkinson & Healey, 2011; Huy, 1999; Weick, 1995). However, this endeavor has proven to be challenging for MOC scholars. Hodgkinson and Healey (2008) argued that the challenge of emotion for MOC is whether to augment existing (primarily cold) cognitive theories and models by incorporating affective variables or to develop new models and theories built from first principles regarding the role of affect and emotion in organizational life. It seems fair to say that progress via either route has been piecemeal. Similarly, although researchers have made great strides with formal modeling of bounded rationality in organizations (Puranam, Stieglitz, Osman, & Pillutla, 2015), progress has also been slow in incorporating a role for affect and emotion, despite calls for such integration (Gavetti, Levinthal, & Ocasio, 2007).

In this chapter, we consider how agent-based modeling (ABM) can help MOC scholars understand better the interaction of affect and cognition in organizations. ABM is a simulation technique. Davis, Eisenhardt, and Bingham (2007, p. 481) define simulation as:

a method for using computer software to model the operation of “real-world” processes, systems, or events ... This definition is consistent with other definitions that describe simulation models as virtual experiments ... or as simplified pictures of the world having some, but not all, of the characteristics of that world ... In particular, simulation involves creating a computational representation of the underlying theoretical logic that links constructs together within these simplified worlds. These representations are then coded into software that is run repeatedly under varying experimental conditions (e.g., alternative assumptions, varied construct values) in order to obtain results.

According to Davis et al. (2007, p. 480), the advantage of simulation is that it occupies a “sweet spot” between theory-creating methods (e.g., inductive case studies and formal modeling) and theory-testing methods (e.g., statistical analyses of empirical data). Relatedly, Chang and Harrington (2006, p. 1277) suggest that computational models of organizations achieve a middle ground between the two traditional types of organization theory: theories that are “broad, institutionally rich and vague while using informal arguments articulated in a narrative” and those that are “narrow, simplistic, and mathematically precise while using formal logic articulated in a set of assumptions, a statement of a theorem, and a proof.” According to Chang and Harrington (2006), computational models provide the precision of formal models but can handle the richness of informal theories, trading off universality of results for richness and rigor.

ABM has become the main form of computational simulation used across the social sciences (for overviews, see Axelrod, 1997; Bonabeau, 2002; Epstein, 1999, 2006; Miller & Page, 2007; Smith & Conrey, 2007; Squazzoni, Jager, & Edmonds, 2014). Perhaps the defining feature of ABM is that it models a system “as a collection of autonomous decision making entities called agents” (Bonabeau, 2002, p. 7280). Previous reviews have outlined the advantages of using ABM for studying organizations and organizational behavior in general (Fioretti, 2013; Harrison, Lin, Carroll, & Carley, 2007; Hughes, Clegg, Robinson, & Crowder, 2012; Miller, 2015; Neumann & Secchi, 2016). In contrast to these more general reviews, this chapter focuses specifically on the opportunities for using ABM to understand the interaction of affect and cognition in MOC. The theme of our chapter is that using ABM for this purpose offers three distinct advantages: it can improve the level of specificity of cognitive and affective concepts and their interrelationships in organizational theories, yield more behaviorally plausible models of behavior in and of organizations, and deepen understanding of the generative behavioral mechanisms of multi-level organizational phenomena.

We begin by arguing the case for studying the interaction of affect and cognition in organizations, before reviewing briefly the limitations of alternative methods that have been applied to this purpose. We then outline some of the general advantages of the ABM approach. Next, we review prominent examples of simulations in psychology and economics that model the affect–cognition interaction, which provide important theoretical and methodological pointers for MOC scholars. Finally, we discuss the specific challenges and opportunities pre-

sented by using ABM to study emotion and cognition in MOC, highlighting possibilities for studies of mental models, collective cognition, diversity in work groups and teams, and organizational decision-making.

## Why Affect–Cognition Interactions Matter to MOC

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At heart, the field of MOC is concerned with the study of thinking; thinking within organizations, by organizations, and between organizations (Eden, Spender, & Spender, 1998; Hodgkinson & Healey, 2008; Hodgkinson & Thomas, 1997; Lant & Shapira, 2000; Meindl, Stubbart, & Porac, 1994). By thinking, we mean the mental work that produces impressions, ideas, judgments, inferences, and the like, which enables people to take purposive action (Kahneman, 2011). For Walsh (1995), the key aspect of thinking in organizations is the knowledge structures (e.g., schemas, frames, categories, mental models) that individuals and groups use to interpret and act upon complex, ambiguous, and munificent information environments. Other scholars emphasize the constructive aspects of how people make sense of novel or ambiguous events in organizations, focusing on how managers “construct, rearrange, single out and demolish many of the objective features of their surroundings” (Weick, 1979, p. 164).

In his essay on how organizations think, Ocasio (2001) identified the building blocks of a theory of organizational cognition at individual, social, and organizational levels of analysis. Individual-level building blocks concern the individual capacities that shape thinking, including bounded rationality constraints (e.g., limited attention and memory). Social building blocks concern the influence of the situation on thinking. Organizational building blocks concern how thinking is embedded in the wider social, cultural, and economic systems of the organization.

However, the foundational works of MOC tend to overlook the fact that thinking in organizations is carried out by human beings with physical bodies (Healey & Hodgkinson, 2014, 2015). Thinking is embodied; it is embedded in the body and in bodily states, bodily actions, and bodily meanings (Barsalou, 1999, 2008; Clark, 1997; Wilson, 2002). Perhaps the most profound consequence of such embodiment is that biologically rooted affect exerts a strong influence on thinking. This influence is profound because affect exerts fundamental constraints on our goals, what we attend to, what we think about, how we think about it, and how much we think (Damasio, 2000a; LeDoux, 1998; Loewenstein, 2007b). For instance, emotions shape decisions by influencing the content of thought, depth of thought, implicit and explicit processing goals, and interpersonal interactions (Lerner, Li, Valdesolo, & Kassam, 2015). From a biosocial perspective, emotions are building blocks for biological and social functions that are essential for adaptive behavior (Izard, 1992; Tooby & Cosmides, 1990). For all of these reasons, a complete understanding of thinking in organizations is untenable without affect – MOC needs an additional building block.

## Theorizing and Measuring -Affect–Cognition Interactions

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To add this building block, research requires methods suitable for examining the interaction between affect and cognition. By interaction, we mean how affect and cognition influence one another and how they combine to influence behavior. Before we review alternative methods for capturing this interaction, it is important to be clear about what is being measured; that is, to be clear about the theoretical assumptions being made about the nature of affect–cognition interactions.

In the psychological sciences there has been considerable debate over the relative primacy of affect and cognition, that is, whether cognition precedes affect or vice versa (see the “preferences need inferences” debate: Frijda, Kuipers, & Ter Schure, 1989; Oatley & Johnson-Laird, 1987; Zajonc, 1980, 1984). For MOC scholars who have built an impressive and valuable body of theory and research on “cold” cognitive foundations, these debates are highly pertinent. On one hand, it is possible that affective mechanisms might provide explanations of organizational action that are rivals of cold cognitive explanations.

For instance, in the study of decision-making, some of the effects commonly attributed to pre-decisional deliberation can be accounted for by non-deliberative affective mechanisms (March, 1994; Loewenstein, 1996; Loewenstein, Weber, Hsee, & Welch, 2001; Slovic, Finucane, Peters, & MacGregor, 2007). Hence, one possible approach is to model affect and cognition as competing influences, each dominating behavior at different points through distinct mechanisms (cf., Healey, Vuori, & Hodgkinson, 2015; Hodgkinson & Healey, 2011).

On the other hand, the interaction between affect and cognition can be conceived in terms of how they influence each other and how they combine to influence behavior. For instance, some theories assume that emotion acts as a feedback system but does not influence action only indirectly, its effects being mediated by cognitive processes such as reflection, inference, and anticipation (Baumeister, Vohs, Nathan DeWall, & Zhang, 2007).

Dual-process theories in cognitive and social psychology have proven helpful for understanding the interaction between affect and cognition (Chaiken & Trope, 1999; Evans, 2008; Smith & DeCoster, 2000). Common to most

dual-process theories is the idea that action occurs through two main routes: a “reflective” route that is deliberative, cognitively effortful, and cold (i.e., emotionally neutral) and a more “reflexive” route that is fast operating, cognitively undemanding, and hot; that is, affectively charged (Epstein, 1994; Lieberman, 2007; Loewenstein & O’Donoghue, 2004). Evans (2007) suggests that the interaction between the two systems can be modeled as default-interventionist or parallel-competitive. In default-interventionist models, intuitive and reflexive reactions (including emotions) arise quickly in response to stimuli; they are the default response. But, effortful cognitive processes intervene upon these responses, using and regulating them to generate more deliberative reactions. In contrast, parallel-competitive models hold that reflective and reflexive responses co-occur (i.e., they occur simultaneously) and exert distinct effects on action, variously competing with or complementing each other. In these models, cognitive processes can regulate emotional ones but the intervention of the cognitive system is effortful and not always sufficient to dampen down emotional responses; hence, emotional responses often override more reasoned cognitive ones (Epstein, 1994; Loewenstein, 1996).

MOC research has frequently drawn on dual-process ideas, with varying degrees of explicitness. For instance, researchers have used parallel-competitive ideas to theorize the interaction of affect and cognition in strategic management (Healey & Hodgkinson, 2017; Hodgkinson & Healey, 2011, 2014), strategy-making teams (Hodgkinson & Clarke, 2007), and intra-team coordination (Healey et al., 2015). In contrast, sense-making research has tended to take more of a default-interventionist approach, conceiving emotion as an interruption that triggers sensemaking (Maitlis, Vogus, & Lawrence, 2013; Weick, 1995), although, some sensemaking studies have adopted a more reciprocal view of the relationship between sensemaking and emotion (Liu & Maitlis, 2014; Rafaeli, Ravid, & Cheshin, 2009). Overall, theory building has outstripped theory testing, perhaps in part due to the limitations of existing methods for incorporating affect.

## Alternative Methods for Studying Affect and Cognition

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MOC is a broad church when it comes to research methods. Common methods include knowledge elicitation techniques (Huff, 1990; Huff & Jenkins, 2002), surveys (Hodgkinson, 2005; Lewis, 2003), case studies (e.g., Kaplan, 2008), field (Mitchell, Shepherd, & Sharfman, 2011) and laboratory (Hodgkinson, Bown, Maule, Glaister, & Pearman, 1999) experiments, observation (Liu & Maitlis, 2014), ethnography (Huy, 2002), and methods for analyzing language and text (Nadkarni & Naryanan, 2005, 2007). However, each of these methods faces considerable limitations for studying the interaction between affect and cognition.

One particular limitation concerns the ability to ascribe causality to affect and/or cognition. Understanding whether a given behavior or set of behaviors is driven by affective factors, cognitive factors, or a combination of both would seem desirable for MOC theory, research, and practice. However, naturalistic methods (i.e., methods that seek to analyze behavior as it happens, without artificial intervention), such as field observation, text analysis, and case studies, lack the ability to isolate specific causes from background factors; that is, they suffer from low internal validity (Campbell & Stanley, 1971). For instance, if, when observing a management team meeting, a manager looks angry, categorizes a colleague as a change resistor, and then storms from the room, it would be difficult for the observer to specify reliably whether the manager’s feelings caused his/her thoughts or vice versa and to discern which of these factors was most responsible for the manager’s behavior. While ethnography and discourse

analysis are proving valuable for acknowledging the recursive relationship between affect and cognition in organizations

(Maitlis & Christianson, 2014), such techniques are, in our view, less useful for disentangling this fundamental relationship. Although experimental control is often seen as the key to internal validity, disentangling the effects of affect and cognition has also proven difficult for experimenters, even when conducting studies with contrived tasks in highly controlled environments (see, e.g., Murphy & Zajonc, 1993).

Methods that rely on the analysis of language or text may struggle to detect or capture accurately actors’ emotions. Especially in work organizations, where language is monitored and regulated and discourse is politicized, people may not always express their feelings in language and may choose words that are emotionally neutral rather than expressive (Alvesson & Kärreman, 2000; Sturdy, 2003). Such effects can obscure the influence of affect on cognition and action. Similarly, employees and managers often hide their feelings from others to comply with cultural norms (Hochschild, 2003; Huy, 2005), making it difficult to observe emotion.

A final challenge for conventional methods concerns capturing the dynamic interplay between affect and cognition. In many organizational settings and tasks, affective and cognitive processes operate in a dynamic interplay, each influencing the other and combining to influence behavior in complex ways (Elfenbein, 2007). In such situations, the idea of disentangling the two processes seems artificial and undesirable (Damasio, 1994). Rather, the goal should be to capture this dynamism, without losing sight of the distinct features, contributions, and generative mechanisms of the two types of influence (Hodgkinson & Healey, 2011). Controlled methods such as laboratory and

field experiments struggle to capture the naturalistic aspects of this interplay (Lipshitz, Klein, Orasanu, & Salas, 2001). Equally, elicitation methods, surveys, and interviews are ill-equipped to capture its temporal dynamics. Although case studies, observation, and discourse analysis methods allow the researcher to examine changes in processes over time, as noted above, they lack the specificity required to capture how affect and cognition combine to generate distinctive patterns of behavior. Fortunately, the ability to specify and analyze the effects of such generative mechanisms is one of the strengths of ABM simulation techniques.

## Advantages Of ABM for MOC

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In this section, we describe three features of ABM that address methodological concerns that lie at the heart of MOC, namely the ability to: (i) specify the cognitive capabilities and processes of agents while also examining the influence of higher (i.e., social and organizational) levels of analysis; (ii) examine complex and dynamic phenomena, including the generative mechanisms of social and organizational processes; and (iii) analyze the behavior of systems comprising heterogeneous interacting individuals.

At a basic level, ABM involves specifying the characteristics and behaviors of autonomous individuals. This essential feature enables researchers to create cognitive agents able to perform cognitive work (e.g., representing, remembering, learning, evaluating, deciding) in multi-domain tasks (e.g., economic, social, affective). Using the individual as its main element, an agent-based model is typically an artificial world in which a set of interacting objects follow instructions (Fioretti, 2013). The nature of the objects and their interactions is decided entirely by the modeler. By specifying the features of the agents *and* the features of their environment (i.e., the physical and/or social environment and the tasks to be performed), the modeler is able to examine not only how agents influence the environment but also how the environment influences the agents. Hence, behavior can be both bottom-up (i.e., agentic) and top-down (i.e., environmentally constrained). ABM thus provides a means of developing a more agentic view of the microfoundations of organizational activity, while also analyzing the top-down influence of social and organizational actors on individuals. As Felin and Foss (2005) observe, the fact that organizations are made up of individuals is often lost in the increasing focus in organizational research on structure, routines, culture, institutions, and capabilities. Moreover, ABM can examine different levels of analysis across varying tasks and environments (e.g., social relations, natural resources, strategic decisions), providing a more integrative view of human activity (Hughes et al., 2012).

By enabling the modeler to move from the individual to the collective, ABM is dynamic and complex – it allows complex patterns to emerge at the aggregate level from simple rules at the individual (agent) level (Epstein, 2006). However, the ABM approach is not only bottom-up; individual agents can also be influenced by the results of collective action (Miller, 2015). The level of complexity of these artificial systems can almost match the complexity of real organizations, but unlike real organizations there are fewer constraints in the data that can be collected and measured. This is particularly relevant for studying patterns that emerge longitudinally, such as the development of social relationships or the formation of inter-organizational networks (e.g., Provan, Fish, & Sydow, 2007), which require a close monitoring to fully grasp their ongoing dynamics (Querbes & Frenken, 2017).

ABM embraces the characteristics of diversity and heterogeneity. These characteristics can result from stochastic processes (e.g., the random allocation of traits) but they can also emerge by adaptation and evolution, for instance as the product of reinforcing mechanisms or positive feedback. Whereas experimental and regression methods tend to erase outliers and emphasize central tendencies, ABM brings individual specificities and small events to the foreground; that is, it accentuates the “microscopicness” of social reality (Squazzoni et al., 2014, p. 281). In addition to the diversity that can emerge across individuals, ABM can also capture the subtleties of their interactions and relations (Fioretti, 2013). It is particularly powerful as a means of analyzing “tensions” or “trade-offs” (Davis et al., 2007). For example, Ethiraj and Levinthal (2009) modeled the trade-offs faced by complex organizations pursuing multiple goals and tested the efficacy of various strategies that can help to avoid the tendency toward freezing on the status quo when multiple goals cannot be reconciled.

## Modeling the Interaction of Affect and Cognition: Illustrative Examples

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To illustrate the specific advantages of simulation, and ABM in particular, for studying the interaction of affect and cognition, in this section we review four extant simulation models that capture variously this interaction and how it affects decision-making and action. Table 1 provides a comparative overview of the four models. Our selection of models is illustrative rather than exhaustive. The first two models we review are not multi-agent models but rather intra-personal models that simulate how affect and cognition operate *within* the individual. These are Abelson’s (1963) influential model of hot cognition, which is the first computational model of affect and cognition,

and a more recent formal model by Loewenstein, O'Donoghue, and Bhatia (2015). Although these two models lack a social component and thus do not incorporate the social complexity and inter-agent heterogeneity that are hallmarks of the ABM approach, they do provide important insights into how affective and cognitive processes can be simulated within the individual, that is, how agents function when endowed with affective *and* cognitive capabilities. The second two models we review are examples of ABM by Thagard and Kroon (2006) and Epstein (2014). These models also imbue agents with affective and cognitive capabilities but in addition they incorporate a role for social influences on individual and collective behavior. As we will see, this ability to generate behavior by specifying affective and cognitive characteristics and rules at multiple levels of analysis offers significant potential to MOC researchers.

#### ABELSON'S "HOT" COGNITION MODEL

Abelson's (1963) "hot" cognition model is an artificial intelligence model that uses symbolic representations (cognitive elements, predicates, sentences, and beliefs) to simulate attitude change within the individual. Affect is incorporated in the form of evaluations pertaining to attitude objects and has both a sign (quality) and a magnitude (quantity). Evaluations summarize affective consequences; that is, the evaluation of an object is the net positive or negative affect aroused by the object. Inputs are sentences (a representation of something just heard or read). After they enter thought, such sentences are sent for an emotional balance test: if they are emotionally unbalanced (i.e., have both an element that arouses positive affect and an element arousing negative effect) the individual makes changes (termed evaluative transfer) until balance is achieved and the sentences in question are stored in memory. Evaluative transfer toward emotional consistency requires time and cognitive effort. The model incorporates a certain level of resistance to changing the received input (sentence); otherwise, given repeated application of evaluative transfer, "...the individual would find himself [sic.] adrift in a sea of neutrality" (*ibid.*, p. 280).

#### LOEWENSTEIN, O'DONOGHUE, AND BHATIA'S MODEL OF AFFECT AND DELIBERATION

Loewenstein et al.'s (2015) model is also a model of how affect and cognition interact within the individual, but in this case represented in a formal mathematical model. This model builds on dual-process theory to model individual behavior as the joint product of a deliberative system that assesses options according to utility-related goals and a more reflexive, affective system driven by emotions and other motivational states. The model represents an individual choosing an option from a choice set according to two "objective functions": the motivational function depends on the intensity of affective reactions (which are a function of temporal and non-temporal proximity of rewards and costs and the vividness of stimuli) and the utility function. If the affective system alone were in charge of behavior, the individual would choose the option that maximizes his motivational function, that is, the *affective optimum*. If the deliberative system alone were in charge of behavior, the individual would choose the option that maximizes utility; that is, the *deliberative optimum*. In the model, neither system is completely in charge of behavior; both systems interact to generate behavioral outcomes. However, the affective system has default control of behavior and the deliberative system can step in to exert its influence. When the two systems are in conflict, exercising deliberative control requires willpower or an expenditure of effort (a cost in utility units). The further the deliberative system moves behavior away from the affective optimum, the more willpower is required to induce a given deviation from it.

The model makes two general predictions: if an individual faces a binary choice between the two optima then willpower depletion increases the cost of exerting willpower and makes it less likely that the person chooses the deliberative optimum. Facing the same choice, if affective intensity increases the affective preference for the affective optimum over the deliberative one, then affective intensity makes it less likely that the individual will choose the deliberative optimum. If, instead, affective intensity decreases the affective preference for the affective optimum over the deliberative one, then an increase in affective intensity makes it more likely that the individual will choose the deliberative optimum.

#### THAGARD AND KROON'S MODEL OF EMOTIONAL CONSENSUS IN GROUP DECISION-MAKING

Thagard and Kroon (2006) developed an agent-based model that simulates how consensus is reached in decision-making groups of interacting "emotional" agents. In particular, it focuses on the social mechanisms that lead to emotional consensus, understood as the individuals in the group sharing similar positive and negative feelings about particular actions and goals. In this model, each agent first makes a preliminary individual decision about what action to take. If all group members agree about what action to take, the process stops because consensus has been reached. If there is no consensus, however, agents meet to exchange factual and emotional information and then reevaluate their individual decisions, based on the extent of their emotional (in)coherence. If, after re-evaluation, there is consensus, the process stops; if not, emotional communication takes place again.

The process continues until consensus is reached or stops if it cannot be reached after repeated interactions have taken place.

Individual decision-making is modeled using Thagard's (2000) approach to emotional coherence at the intra-personal level. Specifically, the elements of an individual decision are representations of competing actions and goals and the individual uses internal rules for evaluating their coherence and accepting or rejecting those elements. Much like the Loewenstein et al. (2015) model, these individual foundations provide sufficient fidelity to plausibly represent intrapersonal processes.

The key part of this model, however, is the process of information exchange that facilitates emotional consensus at the group level. Once the agents have individually made their preliminary decisions, they interchange emotional information, in an attempt to influence the preliminary decisions of other agents via social mechanisms such as means-ends and analogical arguments, emotional contagion, and altruism. These mechanisms allow the positive or negative valence of the source to spread to the target, increasing or decreasing its valence, as necessary, and making the target action more or less emotionally attractive. Means-ends and analogical argument are verbal means by which senders attempt to modify the emotional reactions of receivers, while in emotional contagion, the sender provides non-verbal inputs such as bodily states. In altruistic transmission the receiver cares for the sender, so receiving (verbal or non-verbal) inputs about the sender's goals changes the receiver's emotional state and individual decisions.

Thagard and Kroon's model effectively simulates simple cases of group decision-making. In the first case (a decision about which movie to see) contagion and altruism mechanisms do not lead to consensus when used separately; however, the group reaches consensus after only a few meetings when both mechanisms are combined. In the second case (a university department making a hiring decision) reaching consensus depends on the order in which the members of the group meet. Although these are quite simplified cases, the model shows that small groups can exhibit hitherto unrecognized decision-making behavior as the result of simple rules of interaction and emotional transmission.

## EPSTEIN'S AGENT\_ZERO MODEL

Epstein's (2014) model is an agent-based model that generates collective behavior from individually grounded mechanisms. The basic idea of this model is that emotional, cognitive, and social factors shape the behavior of individuals in groups and hence constitute the basis of emergent social dynamics. The model demonstrates that these simple and rational components can, when operating concurrently, produce a variety of non-rational collective behaviors, from genocide to financial panic.

The model seeks to "generate ... social dynamics in social networks of neurocognitively plausible individuals" (Epstein, 2014, p. xiii). That is, the model defines individual behavior with reference to neural and cognitive mechanisms that are consistent with contemporary neuroscience, theories of associative learning, and bounded rationality. To represent individual behavior Epstein introduces a hypothetical entity, *Agent\_Zero*, endowed with emotional/affective, cognitive/deliberative, and social modules or components. In the basic version of the model, an agent's deliberative, affective, and social components work in parallel (i.e., they do not influence each other directly) to influence the disposition of the agent to perform an action. The agent's disposition to act is the sum of the three components. Hence, unlike other theories and models that afford primacy to affective, cognitive, or social mechanisms, all three components simultaneously influence behavior.

The *affective* component is defined according to a model of classical conditioning that is consistent with the neural mechanisms of fear conditioning. It uses a Pavlovian theory of associative learning; specifically, a generalization of the Rescorla and Wagner (1972) model of classical conditioning. Building on this model, the individual's emotional component is not represented as a balancing process as in Thagard and Kroon's model, but as time trajectories, that is, the acquisition and extinction of conditioned responses over time. The *deliberative* component involves the agent using local sampling of attributes in the environment to form probabilities representing how prevalent those attributes are. The agent's deliberative component is boundedly rational; it samples selectively from local parts of the environment and can only remember a limited proportion of the attributes it samples. As a result, the estimation of probabilities is systematically biased. To define the *social* component the model uses a network contagion model. Agents belong to social networks experiencing contagion mechanisms. Specifically, agents catch one another's affective and deliberative states, such that each agent's disposition is partially transmitted to its neighbors. In the model only the disposition is transmitted (dispositional contagion). Agents

do not observe their neighbors' actions and so cannot imitate them. Thus, the model includes no mechanisms for direct social (i.e., imitative) learning (cf. Bandura, 1977).

In the model, the affective, deliberative, and social components each provide the agent with a disposition to act, which the agents sum to form an overall disposition. When this overall disposition exceeds a given threshold, the agent acts. The threshold to act can be heterogeneous across agents, meaning that behavior varies greatly among individuals within the network.

While Epstein's objective is to improve the neurocognitive foundations of human behavior in social contexts,



the modeling approach he follows for the basic version of the model is minimalist: it explores the social behaviors that can be expected from the model (its generative properties) and provides empirical arguments supporting them, as well as many different extensions of the basic model predicated on varying assumptions, which are designed to answer fundamental questions in fields as diverse as social conflict, psychology, public health, law, and economics.

## CRITICAL EVALUATION OF THE FOUR MODELS

Our review of the above models shows that affect can be incorporated into simulation models in two main ways: by incorporating affect exclusively at the intra-personal level of the individual—as in the models of Abelson (1963) and Loewenstein et al. (2015)—or by adding it at the social and/or organizational levels in order to represent its interpersonal and collective influence—as in the agent-based models of Thagard and Kroon (2006) and Epstein (2014). In single agent models like Abelson (1963) and Loewenstein et al. (2015), the focus is on how interactions between affective and deliberative processes within the person affect individual decision-making and choice. In both of these models, individuals receive inputs from the environment to update attitudes or make a choice; however, these processes are not affected by the actions or motivational states of significant others with whom they might be interacting. In contrast, the two agent-based models place individuals in a context and represent emotional influence through collective processes. One advantage of this more social approach is that it is consistent with empirical evidence from organizational settings demonstrating interpersonal emotional contagion (Barsade, 2002) and the emergence of group affect (Barsade & Gibson, 2012; Huy, 2002).

It is clear that the ability to specify detailed affective and cognitive characteristics and capabilities at the agent level while simultaneously incorporating a role for collective influence is a significant advantage for MOC researchers interested in multi-level cognitive and affective phenomena. This ability provides a clear advantage of ABM over formal and simulation models that focus on one (individual or organizational) level of analysis. The key element in the models of Thagard and Kroon (2006) and Epstein (2014) is the transmission – via social mechanisms in Thagard and Kroon’s model and contagion in a social network in Epstein’s model – of environmental and interpersonal information among interacting individuals. However, as noted above, intra-individual models can be informative for ABM when it comes to specifying precisely how affect and cognition operate within the person; that is, specifying agent characteristics and behavioral rules. For instance, whereas Epstein’s (2014) model does not allow affect and cognition to influence one another, Loewenstein et al.’s (2015) model demonstrates the flexibility and explanatory power of a system where agents are able to regulate their affective responses. This latter approach not only provides a more behaviorally plausible view of the interaction of affect and cognition but might prove useful for MOC researchers who study emotion regulation in individuals (Grandey, 2000) and work groups and teams (Healey et al., 2015).

In addition, by incorporating the characteristics of individuals and their interactions at the micro-level, ABM can be used to examine how affect can influence the emergence of collective behavior from the bottom up. The models of Thagard and Kroon (2006) and Epstein (2014) explicitly represent autonomous cognitive agents who operate across multiple tasks in varying social contexts (e.g., a decision about which movie to see within a group, or about who to hire within an organization, a decision within a jury process as part of a group, or a decision to join a mob). In so doing, ABM strikes an appealing balance between detailed specification of the cognitive and affective capabilities of agents and the generalizability of those capabilities across tasks and settings. Moreover, applied to the analysis of organizations, allowing researchers to represent (albeit in a simplified manner) rich social and organizational dynamics from the bottom up provides a significant advantage for studying affective and cognitive microfoundations of collective organizational activity.

## Opportunities and Challenges for using ABM to Model Affect and Cognition in Organizations

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Building on the general advantages of ABM and exemplar models that unite affect and cognition, as reviewed above, in this section we focus on three distinct benefits of ABM for modeling affect and cognition in organizations. These advantages are (i) increased behavioral specificity (Fioretti, 2013), (ii) greater behavioral plausibility (cf. Puranam et al., 2015), and (iii) the ability to simulate with greater precision the generative mechanisms underpinning the dynamic relationships between affect and cognition (Epstein, 2006). We illustrate how MOC researchers can capitalize on these advantages. Table 2 provides an overview of the types of research opportunities we envisage, including examples of how ABM can improve specificity, plausibility, and emergence in MOC research.

### GREATER BEHAVIORAL SPECIFICITY OF AFFECTIVE AND COGNITIVE MECHANISMS

Using ABM promises to yield more precise specifications of the nature of affect and its relationship with cognition through the construction of computational models with tightly specified parameters and dynamics. The advantage of specificity stems directly from the technical framework of ABM, that is, the ability to code, with almost any degree of simplicity or complexity, the behavioral characteristics, and rules of agents in a computational environment. With this capability, ABM is not limited to theory building via the design of abstract computational constructs. Moreover, in comparison with laboratory and field experiments, ABM has the advantage of providing perfect control, nearly unlimited sample sizes, tasks of greater complexity, and the ability to track with much greater precision the behavioral and cognitive processes of focal concern (Harrison et al., 2007).

In discussing the advantage of specificity, Neumann and Secchi (2016) distinguish two approaches in ABM: (i) one is following the KISS principle (Keep It Simple, Stupid), which is more suited for thought experiments in theoretical research;

(ii) the other follows the KIDS principle (Keep It Descriptive, Stupid), where models are more closely related to empirical data. Carley and Gasser (1999) connect the degree of specificity in a model with the quality of predictions derived from it. While simple models are adapted to theory building, the most complex models are adapted to simulate specific organizations and produce idiosyncratic results. Although the KISS approach has contributed to the success of ABM, the cognitive components of extant models are still very limited (Conte & Paolucci, 2011; Sun, 2008). Consequently, using ABM can enable MOC research to find a valuable niche in the middle; that is, specifying individual (i.e., affective and cognitive), social, and organizational characteristics for agents and systems that are sufficiently simple that they generalize to a variety of organizational tasks and problems, while enabling researchers to reproduce stylized facts (i.e., observed regularities, see Janssen & Ostrom, 2006) that accurately characterize the known behavior of individuals and groups in organizational settings.

ABM is particularly well suited to modeling projects interested in building a richer depiction of cognitive systems, either in terms of a richer set of properties for agents or a richer task environment (Chang & Harrington, 2006). As outlined above, Epstein's (2014) Agent\_Zero demonstrates the possibilities for using ABM to equip agents with rich affective and cognitive capabilities. Agent\_Zero's affective capabilities are grounded in a precise mathematical theory of classical conditioning and linked to contemporary neuroscience, whereas its cognitive capabilities draw on bounded rationality principles concerning the capacity and biases of human memory. Uniting these capabilities within a single agent constitutes a significant advance in specificity beyond most MOC research, even that which explicitly discusses the interaction of affect and cognition within organizational decision-makers (e.g., Healey et al., 2015; Hodgkinson & Healey, 2011, 2014). However, as Epstein notes, the ability to make simple modifications to and extensions of these capabilities means that researchers can further increase the specificity of future models, depending on the behavior to be simulated. Similarly, the mechanisms by which agents develop emotional consensus in Thagard and Kroon's (2006) model illustrate that formalizing even relatively simple rules for transmitting emotions among agents results in a highly specified description of interpersonal influence.

Table 2 provides examples of how building ABMs predicated on the affect-cognition interaction can provide greater specificity to existing research in MOC. For instance, ABM can augment existing research on mental models of strategic issues by specifying distinct affective and cognitive dimensions of such representations, enabling researchers to examine the potential consequences of being caught in two minds, that is, to believe that an issue is beneficial while also feeling that it is undesirable (see Healey, 2016; Healey et al., 2015). The models of Loewenstein et al. (2015) and Epstein (2014) provide important insights about how such conflict arises in agents and how they handle it. Similarly, equipping individuals with affective states and traits promises to enrich models of collective cognition. Although researchers have theorized that empathy and other emotions are important enablers of detecting and aligning with significant others' mental states (Gibson, 2001), studying this effect has proven challenging. By specifying behavioral rules concerning how empathy can affect interpersonal learning, ABM might shed new light on how collective cognition emerges and when it fails to emerge. In a related vein, by varying the degree of affective homogeneity/heterogeneity relative to belief diversity in a work group, ABM can enable researchers to examine the complementary effects of affective and cognitive diversity (Barsade, Ward, Turner, & Sonnenfeld, 2000; Kilduff, Angelmar, & Mehra, 2000).

One challenge concerning specificity is too much specificity. Some behavioral models in computational social science that address phenomena central to MOC are highly complex in their architecture and operations (e.g., connectionist architectures, see Rumelhart et al., 1986). Boero (2015) describes such models as cognitively rich, in the sense that their cognitive structure is irreducible. A problem with models containing an extreme level of affective and/or cognitive specificity is that it may be difficult to connect them to the broad, higher level concepts and problems typically studied in organizational research. Models that are too cognitively and/or emotionally rich may miss the middle ground, described above, which connects broad organizational theories/problems with precise but relatively parsimonious formal models.

Another way in which ABM can add value to MOC research is by increasing the behavioral plausibility of its theories and models. Puranam et al. (2015, p. 339) suggest that behavioral plausibility concerns “whether models of organizations that assume boundedly rational agents make psychologically ‘correct’ assumptions about humans” (see also Gavetti et al., 2007; Hodgkinson & Healey, 2011, 2014). On the one hand, existing formal models of organizations make assumptions following different traditions (e.g., the Carnegie School, evolutionary theory) that are not always grounded in the empirical and experimental literature on affect and cognition; formal representations of the affect–cognition interaction seem to be a logical extension of these models. On the other hand, ABM provides a platform for theoretical constructs encompassing every aspect of organizations (e.g., individuals, structures, collective behaviors) and, therefore, it helps formalize the agenda for empirical research.

As illustrated in the exemplar models reviewed above, incorporating affect promises to increase the behavioral plausibility of organizational models by allowing researchers to understand the effects of cognition and emotion at the micro-level and how they influence collective behavior at the organization level. Table 2 illustrates several ways that ABM can increase behavioral plausibility. In each example, the basic idea is that affective processes are incorporated as influences on behavior, alongside the cognitive processes specified in extant MOC theories. Plausibility in these examples does not mean making everything emotional. Rather, it simply means acknowledging that affect plays a role in thinking and action, in some cases shaping behavior strongly (e.g., emotions in high stakes strategic decisions; see Hodgkinson & Healey, 2011), in others cases influencing it more subtly (e.g., the competition between reflexion and reflection in coordination; see Healey et al., 2015), and in yet other cases requiring emotion regulation in order for cognitive processes to prevail (e.g., the deliberative control of affect in Loewenstein et al.’s (2015) model).

One challenge regarding behavioral plausibility concerns the absence of a unified or agreed upon theory of emotion. Whereas bounded rationality has provided precise conceptual building blocks for simulation modelers, we do not have an equivalent simple yet powerful and generalizable model of emotion. Simon (1990) argued that human cognitive limitations, such as the number of information chunks that can be held in short-term memory, constitute invariants of human behavior – i.e., universal system constraints on human thinking. It is difficult to point to equivalent invariants for emotions and there are marked variations across even the most consensually supported theories of emotion (see, e.g., Barrett, Lewis, & Haviland-Jones, 2016; Cornelius, 1996). Hence, choosing which emotional characteristics with which to imbue individual agents requires careful judgment. Starting with basic motivational principles, such as avoiding pain and seeking pleasure, has proven beneficial for behavioral economists (e.g., Loewenstein et al., 2015). Thagard and Kroon’s (2006) model of emotional coherence also starts from emotional first principles, although those principles are more complex. A further option for MOC scholars is to start with models of affect that are common in organizational research, such as the affective circumplex (Barsade & Gibson, 2007; Healey & Hodgkinson, 2017; Hodgkinson et al., 2015) or the affect-infusion model (Forgas, 1995).

A further challenge is how to evaluate whether a given model is behaviorally plausible. This can be achieved through informal comparisons of model characteristics with empirical data (e.g., Puranam et al., 2015). Indeed, the empirical validity of ABM can be assessed by the empirical consistency of the results (e.g., the accuracy of the predictions), the process (e.g., the calibration of the model parameters using real data) or both. The choice of the validation method depends on the purpose of the model. However, ABM is often used to build new theories or examine theories that are incomplete or not yet well understood (Davis et al., 2007). When working close to the knowledge frontier, it may be difficult to find empirical data for validation. In such situations, researchers may be restricted to evaluating the behavioral plausibility of a given model by reference to its internal consistency or consistency with more general observations of behavior (cf. Miller, 2015).

## REPRESENTING GENERATIVE MECHANISMS WITH GREATER PRECISION

Epstein (2006, p. 4) contends that a key advantage of ABM is that it enables researchers to represent and understand with greater precision generative mechanisms underlying social behavior by studying “how rules of individual behavior give rise – or ‘map up’ – to macroscopic regularities and organizations.” Although MOC scholars frequently allude to the generative mechanisms that underpin the emergence of higher-level cognitive -phenomena (see, e.g., Healey & Hodgkinson, 2014, 2015; Kozlowski & Klein, 2000), such mechanisms are difficult to study with conventional methods. Table 2 illustrates how the emergent ability of ABM can be applied to different topics in MOC.

For instance, by specifying distinctive rules to represent how affect influences cognition at the intra-personal level of individuals and their particular interactions in varying social/organizational contexts, ABM can simulate behavioral patterns in which collective cognition emerges and others in which it does not, thereby helping to ascertain which generative mechanisms lead to one aggregated pattern or another. Similarly, ABM enables researchers to specify intra- and inter-agent rules regarding how trust, empathy, and anxiety shape individual contributions to processes of collective decision making in an organization; that is, rules about how affective responses influence individual and group evaluations of strategic opportunities.

ABM provides a fully flexible platform for building and testing MOC theories based on emergent<sup>2</sup> principles. ABM is particularly useful for the process of building theories to explain phenomena that are not well understood or where extant theories are incomplete (Davis et al., 2007; Miller, 2015). The behavioral and cognitive sciences have an excellent record of establishing empirically sound facts concerning macroscopic regularities but often lack theories for the underlying principles (Marchiori & Aharon, 2015; Strube, 2000). ABM can help, for instance, to compare competing explanations of the interplay between emotion and cognition using comparable agent-based computational experiments. The ability to fully repeat, recover, and observe these artificial experiments gives the theorist many opportunities to improve understanding of the problem space (Miller & Page, 2007). Harrison et al. (2007) maintain that “the entire simulation process constitutes a methodology for theory development, starting with assumptions and model construction and ending with predictions of theory (findings)” (p. 1233). Miller (2015) describes this process as one of *abduction*, whereby theory is built through repeated adjustments of a given model, refining its causal mechanisms to experiment with alternative explanations that can yield results consistent with observed dynamics. For instance, in an ABM of how affect influences the emergence of collective cognition the modeler can find that the specified affect-related intra- and inter-agent rules give rise to plausible or empirically relevant aggregated patterns of collective cognition that were not anticipated by the hypotheses used to build the model, thus contributing to the refinement of theory.

In more general terms, Axelrod (1997) describes ABM as a third way for theory building, situated between *deduction* (based on assumptions) and *induction* (based on observations). Specifically, ABM enables scholars to connect empirical and theoretical investigation by using real-world data to calibrate a model's inputs or to corroborate its outputs. Such empirical connection is not limited to quantitative data. ABM can “close the circle” between quantitative and qualitative data (Neumann & Secchi, 2016), as, for instance, when qualitative data are used to discover the generative mechanisms of a simulation model, which can then be tested with quantitative data.

In terms of level of analysis, Epstein (2014) shows how agents generate and respond to behaviors and affects from different levels in a nested hierarchy of interactions. This approach is particularly valuable for MOC, because ABM makes it possible to represent neural networks, individuals, teams, or organizations as agents, which, as noted earlier, is valuable for understanding the interaction of affect and cognition as an embodied and social phenomenon (Healey & Hodgkinson, 2014, 2015). ABM can be used in conjunction with other formal methods, for instance by representing physical properties (e.g., neurological, biological, and environmental) through mathematical equations or by representing social structures in terms of the characteristics of social networks (e.g., homophily, power; see Helbing, 2012). With its roots in complexity theory, ABM is particularly suitable for addressing the complexity of dynamic organizations, where cognitive and emotional mechanisms at the individual and group levels can generate change at the organizational level, while being themselves influenced by the outcomes of collective behavior and processes occurring at the organizational level.

## Conclusions

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We have argued for the value of simulation modeling, and ABM in particular, for meeting some of the most pressing challenges of contemporary MOC research. By enabling scholars to specify the micro-processes by which affect and cognition interact and simultaneously examine how those interactions scale up to the collective level (Powell, Lovallo, & Fox, 2011), we have sought to illustrate how ABM can open up new lines of enquiry for MOC that would not be possible using conventional methods. To that end, we hope that this chapter will stimulate greater use of these techniques within the MOC community.

## Notes

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1. Following convention in the psychological and decision sciences, we use the term *affect* as an umbrella term to refer to a range of affective states that carry thought and action tendencies, including emotions, moods, and basic drive/motivational states such as pain (Barsade & Gibson, 2012; Lerner et al., 2015; Loewenstein, 2007a).
2. In line with Epstein and Axtell (1996, p. 35), we use the term emergent to denote “stable macroscopic patterns arising from the local interaction of agents.” This meaning of emergence differs from its meaning in classical emergence, where it is used to denote the position that the higher-level properties of a system cannot be fully explained with reference to its lower-level components. For details of the distinction, see Epstein (1999). For a recent discussion of emergence and cognition in organizations, see Healey and Hodgkinson (2014, 2015).

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Table 1: Selected Simulation Models and Formal Models of the Interplay of Affect and Cognition.

Model	Problem(s)	Model Type	Representation of Cognition	Representation of Affect	Representation of Affect–Cognition Interaction	Insight(s)
Abelson (1963)	Attitude change and resistance to attitude change	Process model imitating cognitive micro-processes involved in cognitive balance	Beliefs are “cold”; beliefs and belief systems as primitive cognitive elements	Objects are “affect laden”; they arouse specific emotions (e.g., anger, pride, fear, joy) that are cognitively summarized in attitudes	Cognition controls affect: cognitive processes summarize the net positive/negative affect of an object; cognition mediates the transfer of affect	To restore cognitive balance, micro-processes of denial and rationalization transfer affect across evaluative inconsistent elements
Loewenstein et al. (2015)	Intertemporal choice, risky decisions, and social preferences	Mathematical expression model of a dual-process model of behavior	Deliberative processes assess options in a consequentialist manner	Affective processes assess options based on emotions and motivational states	Deviating from affectively optimum choice requires cognitive control; affect can override cognition when affective reaction is strong or cognitive control (willpower) is weak	Increasing affective intensity relative to cognitive control increases myopia, the endowment effect, and concern for others
Thagard and Kroon (2006)	Role of emotions in group decision-making understood as emotional consensus	Multi-agent system with emotional communication and artificial neural networks	The elements in individuals’ decision include representations of competing actions and goals	The elements have positive and negative valences (emotional attitudes), such that the valence of one element can influence the valence of other elements	Emotional coherence affects the adoption and maintenance of beliefs and practices	Mechanisms such as emotional contagion, altruism, analogy, and empathy can transfer emotional attitudes across individuals and help to resolve conflicts
Epstein (2014)	Conflicts between passion, reason, and social forces	Mathematical and agent-based model of individual -actions	Myopic or partial sampling/ exploration of the environment	Experiences contribute to the acquisition and extinction of conditioned responses	Addition of the three components (cognition, affect, and social networks); refinements of the relationship between the components are possible	Individuals can generate group behaviors (e.g., collective violence) without reasons, triggers, or orders

Table 2: Using ABM to Study Affect–Cognition Interactions in Organizations: Illustrative Examples.

Problem	Use of ABM	Benefits of Using ABM
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Mental models in managerial thinking and action	Incorporating affective as well as cognitive components in the mental representation of organizational issues to model how these components interact to influence managers' judgments, decisions, and actions.	<p><i>Specificity: Provides the ability to specify the relationship (e.g., independent or interacting) between affective and cognitive components of representation, the mechanisms through which they influence behavior (e.g., parallel or competing) and the action tendencies of distinct emotions (e.g., fear, anger).</i></p> <p><i>Plausibility: The idea that individuals represent issues in affective as well as cognitive terms is consistent with basic evidence in neuroscience (Damasio, 2000b; LeDoux, 1989) and applied evidence from the field (Hodgkinson, Wright, &amp; Anderson, 2015).</i></p> <p><i>Emergence: Rules for when to act based on affective associations or cognitive associations can help explain collective patterns of approach/avoidance behavior, such as risk aversion and threat rigidity.</i></p>
Collective cognition	Examining the affective mechanisms that influence the development and functioning of collective cognition	<p><i>Specificity: Can be used to specify the affective mechanisms of collective cognition at the intra-agent (e.g., empathy enabling agents to detect and reason about other agents' cognitive states) and inter-agent (e.g., emotional contagion and group emotions influencing interpersonal information exchanges) levels.</i></p> <p><i>Plausibility: Although organizational theories and models of collective cognition rarely incorporate affect, basic evidence shows that emotions serve a vital function in binding social groups and motivating collective thinking and action (Fischer &amp; Manstead, 2008; Keltner &amp; Haidt, 1999).</i></p> <p><i>Emergence: Simulating how affect shapes the intra- and inter-agent mechanisms of collective cognition promises to provide a clearer understanding of when collective cognition emerges and when it does not.</i></p>
Cognitive and affective diversity in work groups and teams	Examining the relationship between diversity in terms of cognition (e.g., beliefs, goals) and affect (e.g., trait affect, mood, and emotion states) and their distinct and combined effects on group processes and performance.	<p><i>Specificity: Enables researchers to specify particular cognitive and affective characteristics for individual group members and specify rules for the consequences of combinations of group homogeneity/heterogeneity in those characteristics (e.g., belief diversity can aid decision quality while affective diversity can hinder cooperation). Examining the processes and performance consequences of interactions among different forms of diversity can shed light on complex dynamics such as thresholds for the level of cognitive and affective diversity required to produce varying outcomes.</i></p> <p><i>Plausibility: Evidence shows that group processes depend on the sharedness of cognitive and affective characteristics (Barsade &amp; Gibson, 2012; Healey et al., 2015), but their interaction is rarely considered.</i></p> <p><i>Emergence: Permits researchers to examine how group diversity can influence and be influenced by group processes by simulating how bottom-up (collective states and processes emerging from various combinations of individual cognitive and affective characteristics) and top-down (cognitive and affective norms and relations influencing individual cognitive and affective characteristics) mechanisms interact in complex dynamics.</i></p>
Organizational decision-making	Incorporating affect in models of the collective decision-making of autonomous interacting agents, including affective influences on information aggregation in the collective evaluation of opportunities and imperfections in decision networks.	<p><i>Specificity: Allows researchers to specify intra- and inter-agent mechanisms by which emotions contribute to collective decisions, such as how trust and anxiety shape individual contributions and how affective responses can yield false positives and negatives when evaluating opportunities.</i></p> <p><i>Plausibility: Affect exerts powerful effects on decision processes (Lerner et al., 2015), especially strategic decisions that involve high stakes and affectively charged issues (Healey &amp; Hodgkinson, 2017; Hodgkinson &amp; Healey, 2011, 2014), but this is rarely reflected in boundedly rational models of organizational decision-making.</i></p> <p><i>Emergence: Enables the simulation of how individual motivations and affective responses (e.g., motivated reasoning goals) can generate group decision rules and information aggregation structures that shape collective judgment and choice. Also it enables the simulation of how affective processes (e.g., trust, empathy, anxiety) can generate different forms of social decision networks that shape how agents share information in collective choice, including what information is shared and how much information is shared.</i></p>