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COEVOLUTIONARY DYNAMICS AND AGENT-BASED MODELS IN ORGANIZATION SCIENCE

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ABSTRACT

This paper provides empirical and theoretical support for the application of coevolutionary dynamics and agent-based models in organization science. The support stems from the following logical progression: (a) organization science theorists have explored, and in many instances, acknowledged the applicability of complexity theory to organization science research; (b) much of the acceptance for complexity science applications follows from the conceptualization of an organization as a Complex Adaptive System (CAS); (c) complexity science offers a robust explanation of order in natural and social systems; (d) coevolutionary dynamics provide the mechanisms with the highest explanatory power for describing order-creation in social systems. This paper provides an overview of the literature for each element of the preceding logical progression and concludes with a discussion of the applications of agent-based models to instantiate coevolutionary dynamics.

1 APPLICATIONS OF COMPLEXITY THEORY TO ORGANIZATION SCIENCE

As complexity theory extends the scientific frontiers in many other disciplines such as physics, chemistry, biology and other natural sciences; the concept of the applicability of complexity theory to organization science has recently generated much debate. Specifically, many theorists (for example, Anderson (1999), Brown and Eisenhardt (1997), Carley and Prietula (1994), Gell-Mann (1994), Gersick (1991), Lissack (1999), Mainzer (1997), McKelvey (1997; 1999b), Stacey (1995), and Thietart and Forgues (1995)) have argued convincingly in support of the applicability of complexity theory to organization science. In addition to this support for the theoretical efficacy of complexity science applications to organization science, other theorists (Kauffman and Macready 1995, Carley and Svoboda 1996, Carley 1997, Dooley 1997, Levinthal 1997, Sorensen 1997, Levinthal and Warglien 1999, Siggelkow 2001, McKelvey 2002b, Siggelkow 2002) have detailed the non-linear adaptive capacity of organizations and the non-linear complexity of organizational dynamics (Dooley and Van de Ven 1999).

1.1 An Organization as a CAS

Central to the research exploring the non-linear adaptive capacity of organizations and the non-linear complexity of organizational dynamics lays the conceptualization of an organization as a Complex Adaptive System (CAS). Other considerations of an organization as a CAS (e.g., Dooley (1997) and Anderson (1999)) describe an organization as a system: (a) consisting of many interacting components, (b) constituting more than the sum of these interacting components and (c) possessing some capacity to adapt to its external environment. To facilitate a more comprehensive analysis, the subsequent discussion first describes Holland's (1995) widely held definition of CAS in greater detail and then identifies the direct correlation between his definition and relevant theories in organization science.

1.2 Holland's Complex Adaptive System

Holland (1995) describes a CAS according to what he refers to as the "seven basics" - four properties and three mechanisms; when simultaneously occurring, this set of seven basics constitutes the necessary and sufficient conditions of all CAS. The four properties consist of (a) aggregation, (b) nonlinearity, (c) flows, and (d) diversity. The three mechanisms consist of (a) tagging, (b) internal models, and (c) building blocks. More than their distinction as properties or mechanisms, Holland emphasizes the importance of the interrelations between the seven basics.

Aggregation represents both the standard process in modeling of focusing on the salient issues and simplifying all other aspects of the system, as well as, the behavior of CAS: namely, the emergence of large-scale behaviors from the aggregate interactions of less complex agents. Tagging, the mechanism for aggregation and boundary formation in CAS, facilitates selective interaction among agents which ultimately leads to hierarchical organization. CAS possess nonlinear properties, in that agent interactions make the behaviors of the aggregate more complex than can be predicted by summing "typical" agent behavior (i.e., a linear assumption would hold if system behavior was fully deducible from summing or averaging the behavior of the system's components). Flows describe CAS as a network representation of processing nodes (i.e., agents) and connectors (i.e., possible interactions). Two properties of economic flows are important to all CAS: (a) a multiplicative effect – if an agent injects additional resources at a particular node and (b) a recycling effect – the effect of cycles in the network, especially those that extend the utility of resources.

Diversity describes the many different types of agents within a CAS. Each type of agent is intended to fill a unique niche which is defined by the interactions centering on that focal agent. Diversity also arises from the emergence of a new niche to be exploited by adaptations of competing agents. Agents that increase recycling flows discover and exploit new niches, which therefore enhances diversity and leads to perpetual novelty - the hallmark of all CAS.

Another source of diversity within a CAS stems from the idiosyncrasy of agent's internal models. Virtually synonymous with Gell-Mann's (1994) "schema," internal models provide the CAS with a mechanism for anticipation. By eliminating details so that selected patterns are emphasized, internal models provide an agent with a mechanism with which it can detect and then "select patterns in the torrent of input which it receives and then convert those patterns into changes in its internal structure (Holland 1995, p. 31)."

But an agent develops its internal model based only upon its unique experience in a "perpetually novel environment (p. 34)." Therefore, an agent reduces the complexity of a given situation by searching for familiar elements that it is has learned through experience or by natural selection to be effective in similar situations. Holland refers to these familiar elements as building blocks and argues that "this use of building blocks to generate internal models is a pervasive feature of CAS (p. 37)."

1.3 Holland's CAS and Relevant Theories of Organization Science

The discussion now briefly addresses the convergence between Holland's (1995) CAS and some foundational literature in organization science research (see Hazy, Tivnan and Schwandt (2003) for a comprehensive review of this convergence). Schwandt's (1997) definition of an organization as a system comprised of subcomponents (e.g., actions, actors, symbols and processes) correlates directly to the aggregation property of a CAS. Certainly tagging as the mechanism for aggregation and boundary formation in a CAS relates closely to the notion of an organizational boundary and the Environmental Interface subsystem in Schwandt's Organizational Learning Systems Model (OLSM). The nonlinear characteristics of organizational dynamics are well-supported throughout the literature as well as organizations as networks of resource-processing nodes (Krackhardt and Carley 1998). The diversity of a CAS is directly analogous to the idiosyncratic microstates of organizations (McKelvey 1997). And finally, an agent's internal model and its experiential nature relate very closely to the OLSM; where the building blocks of the internal model correspond to the Sensemaking interchange media of the OLSM.

2 COMPLEXITY SCIENCE AS ORDER CREATION SCIENCE

The research of the pioneers in complexity theory has led to the modern understanding of order as an emergent phenomena stemming from complex, seemingly random events (Prigogine and Stengers 1984, Kauffman 1993, Holland 1995). Building on the conceptualization of an organization as a CAS, several organization scientists (Stacey 1993, Mainzer 1997, McKelvey 2001b, McKelvey Forthcoming) have explored the emergence of order within as well as between organizations. Most notably, McKelvey (2001b, p. 137) argues that complexity theory is "really order-creation science" by first recounting the literary perspectives and definitions of order and then detailing the recent scientific advances in understanding order and its root causes. The discussion of complexity theory as order-creation science continues with a brief summary of McKelvey's (2001b, Forthcoming) analysis.

Following in the Darwin-Wallace model (Darwin 1859) of natural selection and its explanation of speciation in the biological world, order first came to be understood as the emergence of differentiated entities (Durkheim 1893, Spencer 1898). More than half of a century later, Ashby (1956) extends the understanding of order with his concept of requisite variety.

Ashby (1956) does not define order as the emergence of entities but in terms of the *connections* between those entities. He describes his "law of requisite variety" in terms of the connection between two entities (e.g., A and B). Order exists between A and B, if and only if, the connection between A and B is "conditioned" by a third entity, C, which is external to the connection between A and B. Therefore, an entity can only adapt effectively when the variety of its internal order matches the variety of its environmental constraints (Ashby 1956). Of particular note, Ashby's description of order as a function of environmental context fits with Prigogine's (1955) research and the work of other physicists to be described below.

But as McKelvey (2001b, Forthcoming) highlights, Ashby (1956) describes the phenomenon of order but says nothing about what causes order to emerge. McKelvey (Forthcoming, p. 3) describes mature science, "Orthodoxy," as being founded on the equilibrium principle at the core of the 1st Law of Thermodynamics. The 1st Law states that energy itself cannot be created nor destroyed; though its forms may change, the sum of all energy remains fixed (Chaisson 2001). McKelvey (Forthcoming) asserts that since "normal science [or Orthodoxy] accepts order as a given in the universe…this leaves the thermodynamics of order translation as the defining dynamic of science (p. 3)." However, the Nobel-Laureate, Ilya Prigogine, has shown that the 1st and 2nd Laws of Thermodynamics differ on the aspect of reversibility (Prigogine 1955, Prigogine and Stengers 1984).

Prigogine demonstrated that the 1st Law is time-reversible (i.e., the Newtonian processes of classical physics are bi-directional and thus reversible), while also demonstrating the irreversibility of the 2nd Law. The 2nd Law states that any system not in a state of equilibrium will expend energy in an attempt to move toward equilibrium and this loss of energy is called entropy production (Bar-Yam 1997). Prigogine along with his colleagues (1984, 1989; 1997) argues that entropy production is an irreversible process. The foundation of Prigogine's argument rests on Eddington's (1930) "arrow of time" - that nowhere in the Universe can we observe randomness dissipate into order; whereas, we frequently observe order dissipate into randomness.

3 COEVOLUTION AS THE MECHANISM OF ORDER-CREATION

As the concept of coevolution continues to draw more and more attention from organization scientists as evidenced by a dedicated issue in *Organization Science* (Lewin and Volberda 1999), several leading researchers consider coevolution as a principal mechanism of order-creation in organizational ecology (e.g., Baum and Singh (1994), Lewin and Volberda (1999), and McKelvey (1997, 1999a, 2002b)). This discussion of coevolution as the mechanism for order-creation in organizations continues with a description of the properties, types and damping mechanisms of coevolution.

3.1 Essential Properties of Coevolution

While arguing for coevolution as a unifying framework for research in strategy and organization science, Lewin and Volberda (1999) list the essential properties of coevolution as: (a) multi-levelness / embeddedness, (b) multi-directional causality, (c) nonlinearity, (d) positive feedback, (e) path and history dependence. A brief summary of these properties follows.

McKelvey (1997, 1999a, 2002b) asserts that coevolutionary dynamics occur at multiple levels of analysis; within an organization (i.e., microcoevolution) and between organizations and their respective environments (i.e., macrocoevolution) which is similar to Granovetter's (1985) notion of embeddedness. McKelvey (2002b, p. 3) asserts that an organization's ability to macrocoevolve with its competitors depends on its microcoevolutionary processes. An excellent example of this multi-level nature is March's (1991) study of environmental turbulence and the corresponding adaptation at the levels of the organization and the organizational microstate.

Because organizations coevolve with each other and with a perpetually altering environment (Holland 1995, Kauffman 1995, McKelvey 1997), the distinction between dependent and independent variables becomes problematic since variables are sensitive to endogenous effects (i.e., multi-directional causality). Consistent with Holland's (1995) description of the nonlinear properties of CAS, Lewin and Volberda (1999) describe the nonlinear properties of coevolution as producing counter-intuitive changes in one variable from presumably insignificant changes in another variable. Similar to Weick's (1979) concept of enactment, an organization influences its environment and is influenced by its environment; these recursive interactions and the resulting interdependency are summarized as positive feedback. Unlike the population ecologists (e.g., Hannan and Freeman (1984)) who point to variations in the environment, coevolutionary theorists (e.g., McKelvey (2002b) and Lewin and Volberda (1999)) point to an initial heterogeneity between the organizations to explain the varying effectiveness of organizational adaptability (i.e., path dependence).

3.2 Types of Coevolution

After describing the similar properties of all coevolutionary processes, the discussion now briefly shifts to a description of the kinds of coevolutionary dynamics. Maruyama (1963) described four kinds; namely, (a) mutation rate and the environment, (b) predator / prey, (c) supernormal, and (d) inbreeding and population size. McKelvey (2002b) offers another kind of coevolution: symbiotic.

The coevolution of mutation rate and the environment addresses the interdependence between the rates of change of an organism and its environment. Similarly, predator / prey coevolution describes the respective rates of change of competing populations. Supernormal coevolution describes the "snowballing" (i.e., nonlinear) effect of a favored characteristic as a tag governing the interaction of agents within a population (e.g., McKelvey (2002b) relates this to the propensity for good-looking, intelligent people to attract other good-looking, intelligent people and produce still more good-looking, intelligent people). Inbreeding within a small population rapidly leads to the isolation of the small population from other populations (i.e., diminished embeddedness and few, if any, structural holes); the more isolated the population, the more likely inbreeding will occur and lead to further differentiation. Symbiotic coevolution describes the cooperative and mutually beneficial interdependence of two dissimilar agents.

The type of coevolution that offers the most relevance to organization science research is the coevolution of mutation rate and the environment. All the more applicable in high-velocity environments (Eisenhardt 1989) and hypercompetitive contexts (D'Aveni 1994), what an organization has learned (Schwandt and Marquardt 1999) and the rate at which it learns (McKelvey 2002b) offer the organization its best source of sustainable, competitive advantage (McKelvey 2001a). That is, an organization must learn faster and more effectively than its competitors to establish an initial competitive advantage, and then that same organization must continue to learn faster still if it is to sustain its competitive advantage. This dynamic is known as an “arms race” or the “Red Queen effect”, adopted from Carroll’s (1946) Red Queen when she says to Alice, “[i]t takes all the running you can do, to keep in the same place.”

3.3 Boiled Frogs and Damping Mechanisms

With a better understanding of the properties and types of coevolution, this section of the paper concludes with a brief discussion of the “boiled-frog effect” and damping mechanisms. The “boiled-frog effect” stems from the finding that a frog placed in a pot of cold water will not attempt to escape if you slowly bring the pot to a boil, but a frog will instantly leap from a pot of already boiling water. This relates to the notion that an initiating event stimulates the onset of coevolutionary dynamics and how significant the event needs to be.

Some complexity scientists (e.g., Prigogine (1997) and Mainzer (1997)) require a significant initiating event; whereas, other complexity scientists believe the initiating event can be almost trivial (Bak 1996, Brunk 2000). McKelvey (2002b) asserts that if the latter was true and trivial events stimulate effective organizational adaptation then virtually no failing organizations would exist, but failing organizations are commonplace (Meyer and Zucker 1989). Conversely, the nonlinear aspects of coevolution could lead to unexpectedly significant outcomes from indiscernibly small events (Kauffman 1995, Lewin and Volberda 1999). McKelvey (2002b) offers another explanation for when coevolution occurs and when it does not: damping mechanisms.

A damping mechanism provides a method for influencing the rate of coevolution (McKelvey 2002b). The practical implications of damping mechanisms lie in the realization that managers will likely desire to weaken damping mechanisms when coevolution is leading to effective adaptation or to strengthen them when coevolution leads to dysfunction.

Three of McKelvey’s (2002b) damping mechanisms have particular relevance to organization science research: (a) loss of agent heterogeneity, (b) loss of weak-ties, and (c) failing human capital. Fundamental to Ashby’s (1956) Law of Requisite Variety, agent heterogeneity needs to constantly be increased so as to provide an organization with flexibility and responsiveness (i.e., Law of Excess Diversity (Allen 2001)). Loss of weak-ties occurs when strong cliques emerge to diminish the innovation and entrepreneurship that results from information sharing and interaction among heterogeneous agents. Failing human capital occurs when agents decrease their absorptive capacity (Cohen and Levinthal 1990) and thus diminish their ability to learn and adapt.

This discussion of damping mechanisms concludes the argument supporting the coevolutionary assumption underlying this research. Damping mechanisms both bring the subject of coevolution to the practical implications for managers as well as tie directly into the following discussion of the two overarching constructs. Human and social capital (i.e., the connectedness of the agents (Burt 1992, 1997)) as well as agent heterogeneity relate strongly to organizational learning and interorganizational collaboration as the subsequent discussion demonstrates.

4 SIMULATION AS METHOD IN ORGANIZATION SCIENCE

To explore complex dynamics such as those of coevolution, simulation often represents the method of choice for organization scientists (e.g., Carley and Svoboda (1996), Epstein and Axtell (1996), Levinthal (1997), March (1991) and McKelvey (1999a, 1999c) among others). The subsequent discussion of simulation as method begins with a general overview and then briefly describes some landmark, simulation-based studies that influential to organization science research. This discussion continues with the call for a specific class of simulation for organization science research, namely simulation with agent-based models (McKelvey 1999a, 1999c, 2002c) followed by a brief description of some influential agent-based models in organization science. This section concludes with a brief epistemological discussion of a model-centered, organization science with agent-based models at its core.

4.1 Overview of Simulation in Organization Science

While simulation research in organization science first occurred as much as forty years ago (e.g., Cyert and March (1963)), only recently has it begun to generate a broader acceptance (Dooley 2002). Not only special issues but entire journals are now dedicated to simulation and its application to organization science (e.g., Carley (1995), Lissack (1999) and Gilbert (1998)). This acceptance stems from two critical aspects of simulation research: (a) simulation allows researchers to explore the inherent complex dynamics of organizations (Dooley and Van de Ven 1999, Dooley 2002), hence (b) simulation research allows for the conduct of experiments that would typically be impossible or impractical in the physical world (Gilbert and Troitzsch 1999).

Stressing the value of simulations for theorizing (Weick 1995), Axelrod (1997, p. 23-24) believes that simulation offers a new vehicle for conducting scientific research that differs from induction (i.e., the "discovery of patterns in empirical data") and deduction (i.e., "specifying a set of axioms and proving consequences that can be derived from those assumptions"). On the one hand, simulation research resembles deduction in that simulations start with a set of assumptions. On the other hand, the simulation generates data to be inductively analyzed. Axelrod (1997, p. 24) refers to simulation research as "thought experiments" since the assumptions might seem simple but the results are often counter-intuitive (i.e., the nonlinear, macro-level effects of interacting agents known as emergent properties).

Axelrod (1997) provides further support for simulation as an alternative to the rational actor / choice assumptions. Because the rational actor / choice assumption allows for deduction, researchers are willing to overlook the boundedly rational limitations of their actors (Simon 1976). The primary alternative to the rational actor / choice assumption lies in some form of adaptive behavior. Due to the complex effects of social interactions, Axelrod (1997) asserts that simulation offers the only vehicle to study sets of actors who possess an adaptive capacity.

Recognizing these inherent strengths of simulation, James March proved to be one of the earliest pioneers of simulation in organization science and consequently has produced some of the most influential research in the field. As one of the first simulation-based studies in organization science, Cyert and March (1963) advance the organizational theories of Barnard (1938) and Simon (1955) to demonstrate that managers are rational in their pursuit of their personal goals while attempting to satisfy various stakeholders and avoid uncertainty. Cohen, March and Olsen's (1972) Garbage Can Model demonstrated the path dependent nature of organizational issues and structure as well as their effect on organizational performance. As described earlier as being particularly relevant to organization science research, March's (1991) multi-level research linking individual learning and adaptation in the organization code supports the assertion that microcoevolutionary order within an organization emerges in the context of macrocoevolutionary selection and competitive pressure (McKelvey 1997, p. 361). As two of the first studies in organization science to use an agent-based model, Cohen, March and Olsen's (1972) and March's (1991) studies proved to be watershed events for simulation-based research.

4.2 A Call for Agents in Organization Science

With the growing acceptance of simulation in organization science due in no small part to March's research, several leading scholars have called for the formal use of agent-based models (e.g., Anderson (1999), Axelrod(1997), Dooley (2002) and McKelvey (1999a, 1999b, 1999c)). As the primary tool of complexity theorists, agent-based models assume that agents behave in a stochastic, nonlinear manner and that agents possess a nonlinear capacity to adapt over time.

This stochastic, nonlinear behavior of agents is consistent with the stochastic, idiosyncratic microstates of organizations. That is, despite institutional influences (Zucker 1988, Scott 1995), strong forces remain to idiosyncratically steer both the behaviors of organizational members and the conduct of organizational processes (McKelvey 1997). Among others, such forces might include unique organizational cultures, the unique set of organizational suppliers and customers (i.e., organizations are each embedded within a unique social network) and the unique interaction network of different individuals each with his/her own personal history in different contexts. Therefore, agent activity in an agent-based model can offer an excellent representation of the adaptive and idiosyncratic behavior of an organization and that of its members.

4.3 Noteworthy Agent-Based Models in Organization Science

Some of the most commonly occurring agent-based models in organization science research include cellular automata (Toffoli and Margolus 1987), the NK model (Kauffman 1993), simulated annealing (Aarts and Korst 1989), and genetic algorithms (Holland 1995). Cellular automata consist of identical cells, usually arranged in a grid pattern, that interact locally according to some homogeneous rules (see Epstein and Axtell's (1996) extension of the cellular automata model to explore the emergence of social networks, markets, and cultural differentiation). The NK model uses the concept of rugged landscapes where ruggedness is determined by the number of components in a system, N, and the interdependence between those components, K (see Levinthal (1997, 1999), McKelvey (1999a, 1999c), Rivkin (2000), and Sorensen (1997) for applications of the NK model). Analogous to the physical process of annealing a solid, simulated annealing provides a heuristic solution to combinatorial, optimization problems (see Carley and Svoboda's (1996) microcoevolution study linking agent learning and organizational adaptation). Analogous to evolutionary theory and natural selection, genetic algorithms consider the fitness of each agent in a population and 'breed' the agents with the highest fitness (see Axelrod's (1997) seminal research on cooperation in the Prisoner's Dilemma).

4.4 Current Research to Model Coevolutionary Dynamics in Organization Science

At present, the author is developing an agent-based model to explore the coevolutionary dynamics between firms collaborating and competing within the same resource niche (Tivnan 2004). This research extends the model of boundary-spanning activity of a single organization (Hazy, Tivnan, and Schwandt 2003) to a model that will permit the exploration of the collaborative efforts of organizations in a competitive, coevolutionary context; namely, the emergence of strategic networks. This new model is called the **C**oevolutionary model of **B**oundary-spanning **A**gents and **S**trategic **N**etworks (C-BASN; pronounced "Sea Basin"). C-BASN incorporates the previously described type of coevolution deemed most relevant to organization science research; namely, the coevolution of organizational mutation rate and its environment.

4.5 A Model-Centered, Organization Science

Inspired by the merits of agent-based models to capture the stochastic idiosyncrasy of organizations, McKelvey (1999b, 2002c) calls for a model-centered, organization science. That is, he supports the use of stylized models to further organization science by adhering to the semantic conception for scientific inquiry.

The semantic conception, first introduced by Beth (1961) and later advanced by Suppe (1989), is a normal science, post-positivist epistemology. It contends that "scientific theories relate to models of idealized systems, not the complexity of real-world phenomena and not necessarily to self-evidently true, root axioms (McKelvey 1999b, p. 12)." Fundamental to the semantic conception is a model-centered view of science which uses models as an intermediary between theory and phenomena to both represent theoretical relationships and predict fundamental, phenomenonological behavior. This model-centered view provides "a useful bridge between scientific realism and the use of computational experiments as a basis of truth-tests of complexity theory–rooted explanations in organization science" (McKelvey 1999b, p. 13).

Critical to this model-centered view, these tests of verisimilitude (i.e., "truth-tests") bifurcate all scientific inquiry into two related activities, analytical and ontological adequacy (McKelvey 2002c). Tests of analytical adequacy focus on the THEORY-MODEL link and encompass the coevolution of the THEORY and the MODEL until the MODEL produces the applicable effects predicted by and within the scope of the THEORY. Tests of ontological adequacy focus on the MODEL-PHENOMENA link and encompass the evolution of the MODEL and its substructures. Model-Substructures are "the components of a model that represent a usually causal element of complex real-world phenomena" (McKelvey 2002a, p. 893). Tests of ontological adequacy continue until each Model-Substructure sufficiently depicts its corresponding behavioral effect in the PHENOMENA.

McKelvey (2002c) identifies Contractor et al. (2000) as an exemplar of this model-centered approach to organization science. Using Giddens' (1984) structuration theory to predict self-organizing networks, Contractor et al. describe 10 Model Substructures and compare the results from their computational experiment with those from their quasi-experimental field research. Although not all Model Substructures are supported by their field research, McKelvey (2002c) recognizes the Contractor et al. research for its avoidance of making the "*direct* predictive leap from structuration-based hypotheses to real-world phenomena" (p. 766, his italics).

5 CONCLUSION

Extending the research on CAS and organizational adaptive capacity, many scholars now point to emergent order and coevolutionary dynamics as fundamental tenets for advancing organization science (Lewin and Volberda 1999, McKelvey 1999c, 2002b). Indicative of emergent order, the largely-uncoordinated microstate activities of boundary spanning give rise to macrostate properties of enhancements to the adaptive capacity of the focal organization (Hazy, Tivnan and Schwandt 2003) and, in some instances, strategic networks between collaborating organizations (Tivnan 2004). Indicative of coevolution, the emergence of strategic networks represents the adaptation activities of a focal organization and the subsequent adaptation activities undertaken by cooperating and competing organizations in the external environment of that focal organization. Agent-based models provide a promising research platform to explore these coevolutionary dynamics and therefore contribute to advancing this critical area of organization science research.

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