# Complex Adaptive Systems in the Behavioral and Social Sciences

Roy J. Eidelson
Bala Cynwyd, Pennsylvania

This article examines applications of complexity theory within the behavioral and social sciences. Specific attention is given to the fundamental characteristics of complex adaptive systems (CAS)—such as individuals, groups, and societies—including the underlying structure of CAS, the internal dynamics of evolving CAS, and how CAS respond to their environment. Examples drawn from psychology, sociology, economics, and political science include attitude formation, majority–minority relations, social networks, family systems, psychotherapy, norm formation, organizational development, coalition formation, economic instabilities, urban development, the electoral process, political transitions, international relations, social movements, drug policy, and criminal behavior. The discussion also addresses the obstacles to implementing the CAS perspective in the behavioral and social sciences and implications for research methodology.

Over the past decade, investigators in many fields have increasingly directed their attention toward the dynamic processes and global patterns that emerge from the collective interactions of a system's individual components (e.g., Cowan, Pines, & Meltzer, 1994; Holland, 1995). Using theoretical models and research strategies that focus on nonlinear effects and temporal change, complexity theory researchers have discovered that a system's evolution and behavior often defy many commonly held assumptions about the world. For example, their findings reveal that randomness and determinism often coexist, that the whole cannot always be understood by reducing it to simpler parts, that instability is commonplace, and that change is frequently abrupt and discontinuous (e.g., Casti, 1994).

Although most of the principles of complexity theory have originated in the physical and natural sciences, Gell-Mann (1995) is among those who see the potential for a much broader impact: "Even more exciting is the possibility of useful contributions to the life sciences, the social and behavioral sciences, and even matters of policy for human society" (p. 322). Indeed, many areas of the behavioral and social sciences have already attracted the attention of complexity investigators; among these fields are attitude formation, majority–minority relations, social networks, family systems, psychotherapy, norm formation, organizational development, coalition formation, economic instabilities, urban development, the electoral process, political transitions, international relations, social movements, drug policy, and criminal behavior.

But despite the enthusiasm of its interdisciplinary proponents, the study of nonlinear dynamical systems has thus far failed to generate widespread interest and application within the community of behavioral and social scientists. A number of interrelated factors have contributed to this situation. First, there is currently much confusion over the concepts and definitions central to this relatively new area of scientific inquiry. The term *complexity* itself is burdened with a multitude of different technical meanings, including the amount of thermodynamic entropy in a system, the degree to which information is shared by a system's components, and the diversity displayed by the hierarchical levels of a system (Horgan, 1995). When researchers in diverse fields use their own particular translations of fundamental terminology, the resultant "interdisciplinary Tower of Babel" (Scott, 1991) serves only to further muddy the scientific waters. Vague distinctions between rigorous and metaphorical implementations, such as with the notion of chaos, also beset complexity theory at the present time (e.g., Abraham, 1995; Barton, 1994).

Certain basic assumptions in the social sci-

Correspondence concerning this article should be addressed to Roy J. Eidelson, 413 Pembroke Road, Bala Cynwyd, Pennsylvania 19004.

ences create another obstacle to broader application of complexity models in these disciplines. Heylighen and Campbell (1995) have termed one of these assumptions *methodological individualism,* which they described as the view that "all social processes are to be explained by laws of individual behavior, that social systems have no separate ontological reality, and that all references to social systems are merely convenient summaries for patterns of individual behavior" (p. 2). Similarly, Leydesdorff (1993) noted that in most approaches to modern sociology "social change has to be explained in terms of, or at least with reference to, individual human impact" (p. 331). In sharp contrast, Cowan (1994) raised the possibility that "societal behavior cannot be adequately described by any practically achievable integration across the behavior of individuals" (p. 4).

A second pervasive assumption in the behavioral and social sciences is that human systems are driven toward a stable equilibrium, and that only one such equilibrium-state exists for a given system. The presence of unstable dynamics is interpreted as being a consequence of "social disorganization, faulty design, malfunctioning or deviancy" (Young, 1991, p. 292). Such a perspective inevitably minimizes the recognition of and significance accorded to self-organized, far-from-equilibrium dynamical systems—the very heart of the complex-systems perspective.

It is not surprising that efforts to adopt a new paradigm for studying individuals and societies, such as that provided by complexity theory, have met with resistance (e.g., Kuhn, 1970). Such conflict, however, can ultimately prove constructive. As Kac (1969) noted, the main role of competing models is twofold—to polarize thinking and to pose sharp questions. However, because there is not yet a "unified theory of complex systems" (Horgan, 1995), there appears to be the predictable polarization of sides, but not an organized set of definitive, testable propositions for researchers to evaluate.

At this point, then, it is important for experts in the behavioral and social science disciplines without allegiance to complexity theory to give careful consideration to this growing field and determine whether and where its perspective may be useful for them. Such a step is clearly more modest than constructing (or evaluating) a unified theory of complex systems, but it may

well serve to establish the groundwork for such an undertaking. As a contribution to the process, this paper offers an overview of one particular arena in the realm of complexity theory— complex adaptive systems (CAS). Throughout the discussion that follows, links are made between key concepts and theoretical and empirical work by investigators in the fields of psychology, sociology, economics, and political science.

What, then, is a complex adaptive system? Most generally, a *CAS* is a large collection of diverse parts interconnected in a hierarchical manner such that organization persists or grows over time without centralized control. The brain (e.g., Haken, 1996; Kelso, 1995), the immune system (e.g., Bremermann, 1994; Holland, 1995; Varela, Sanchez-Leighton, & Coutinho, 1992), an ant colony (e.g., Kelly, 1994; Sole, Miramontes, & Goodwin, 1993), and human society (e.g., Mainzer, 1993; Weidlich & Haag, 1983) are often presented as examples.

Through a dynamical, continuously unfolding process, individual units within the system actively (but imperfectly) gather information from neighboring units and from the external environment. This information is subjected to local internal rules, and responses are formulated; these responses then work their way through the web of interconnected components. Within the CAS, competition operates to maintain or strengthen certain properties while constraining or eliminating others. Entirely new properties can also emerge spontaneously and unexpectedly. Configured in this manner, the complex adaptive system is poised for potential change and adaptation either through alteration of its rules, connections, and responses or through modification of the external environment. In fact, the external stimulus impacting a CAS is often one or more other complex adaptive systems. The resulting coevolution is itself an extremely complicated process.

Given the breadth of the topic, the framework for this paper is necessarily arbitrary and incomplete. Nevertheless, four important subject areas have been selected for particular attention: (a) the principles underlying the structure of complex adaptive systems; that is, how CAS are put together; (b) the evolution of CAS over time, with a focus on self-organization and non-linear change; (c) the relationship between the complex adaptive

system and its environment, including adaptation and coevolution; and (d) an analysis of the theoretical and empirical issues central to effectively evaluating or implementing the CAS paradigm in the behavioral and social sciences.

## The Underlying Structure of CAS

### Hierarchical Arrangements With Distributed Control

The numerous and diverse interacting units that constitute a complex adaptive system are typically arranged in a hierarchical structure. Simon (1995) described the arrangement as "sets of boxes nesting within sets of boxes" (1995, p. 26) through several repetitions. Similarly, Holland (1995) has explained that new hierarchical levels are created whenever individual units, or *agents*, are aggregated. Indeed, he views this process of aggregation as one of the most basic elements of complex adaptive systems. In turn, each aggregate can connect with other aggregates to form *meta-agents*, which can then combine to form *meta-metaagents*, and so on. In this way, the aggregation of business firms forms an economy, the combination of antibodies creates an immune system, and a network of neurons forms the nervous system. Simon (1995) has noted, however, that some aggregations, such as human society, involve an especially complex network structure because each agent may belong within a number of different boxes at the same hierarchical level (e.g., an individual may simultaneously be a member of a family, a professional organization, and a therapy group).

Each component part in the CAS is relatively autonomous in function and generally capable of individualized responses to local events (e.g., Holland, 1992, 1994; Kelly, 1994; Langton, 1995). This phenomenon is illustrated, for example, in the connectionism of neural networks (parallel distributed processing systems with applications ranging from financial-market prediction to patient classification). Rather than relying on a central processing unit as most supercomputers do, input information in a neural network is only exchanged locally among neighboring nodes. Through summation processes based on nonlinear threshold functions, the actions of interacting components produce the network's response even without the imposi-

tion of any overarching organization (Tryon, 1995).

Freeman's (1991, 1995) neurophysiology research offers intriguing evidence that the brain itself—from which neural networks derive their inspiration—demonstrates distributed control. Whereas the individual neuron's membrane provides it with considerable local autonomy, each neuron's activity impacts the other neurons in its vicinity. These interactive masses are simultaneously and reciprocally linked to other local and more distant neural masses. As an example, Freeman reports data indicating that every neuron in a rat's olfactory bulb responds to the stimulation provided by a discriminable odor. He concludes that "the neural information that correlates with the behavior of animals exists in the cooperative activity of many millions of neurons and not in the favored few" (1995, p. 22).

Social systems also demonstrate decentralized control in a variety of ways. In animals, for example, the "intelligent" behavior of a swarm of bees selecting a new hive site or a colony of ants locating a food source unfolds despite the absence of an executive agent (Kelly, 1994). Similarly, Huberman and Hogg (1995) have observed that *communities of practice*—informal networks of people ranging from chemists in competing pharmaceutical firms to the foreign affairs personnel of adversarial countries to gangs in schools and prisons—develop interaction structures that do not rely on central controls. Indeed, the investigators' mathematical models indicate that dynamical instabilities in these interaction patterns often produce spontaneous adaptive realignments among the members without the intervention of a central planner.

Regarding human society more broadly, Brown (1995) has analyzed the social conventions that frequently become powerful influences on behavior. Forming lines at a banking machine or a fast-food drive-through window and the unplanned coordinated activity of strangers confronted with an emergency situation are instances of organization dependent on distributed control. In a like manner, Axelrod (1986) has concluded that norms often serve as mechanisms to coordinate behaviors and regulate conflicts without the intervention of a central authority. He has pointed out that societal norms in fact often precede the

formulation or enactment of laws. Interestingly, in computer simulations of the evolution of norms under conditions of limited rationality, Axelrod found that metanorms, such as the expectation that an individual will punish someone who fails to punish a norm-violator, can play important roles in establishing and protecting group norms.

When efforts are made to impose some degree of centralized control on social, political, and economic systems, the outcomes are often disappointing and unanticipated. Heylighen and Campbell (1995), for example, have cited two reasons why consolidating the control of an organization in a subgroup or individual can be problematic. First, important knowledge is likely to be farther removed from the local site or situation where it is most needed. Second, the transfer of information—in both directions—is highly susceptible to delays and degradation. Furthermore, they noted that "the capacity of the control system for anticipation, which normally compensates for the loss of information, is notably poor for social systems, which are inherently difficult to predict" (p. 16). Goerner (1994) has echoed these admonitions, and emphasized that *dominator hierarchies*, characterized by the upward flow of information and the downward exercise of control, can stifle creativity and the development of greater efficiencies.

Jacobs' (1984) analysis of the problems encountered by large nation-states governing their cities through centralized control and centralized problem-solving also supports these conclusions. In particular, she argued that "national or imperial currencies give faulty and destructive feedback to city economies and that this in turn leads to profound structural economic flaws, some of which cannot be overcome no matter how hard we try" (p. 158). Jacobs has suggested that broad national economic policies are flawed because they ignore the unique features and needs of individual cities and thereby interfere with locally informed efforts at self-correction and stable growth. She has compared this common circumstance to an imaginary one in which an elephant, three sheep, two puppy dogs, and a rabbit are all connected to the same brain-stem breathing center—not all are likely to survive. Among the real-life examples Jacobs has provided is the Volta Dam in Ghana, which displaced 80,000

villagers; she stresses that the dam was economically pointless because there simply were no solvent city markets or industries to use its power.

It is important to note, however, that the distributed control of CAS is not without its potential drawbacks. Hardin's (1968) "tragedy of the commons" describes one of them very effectively. Imagine a situation in which a common resource (e.g., land for grazing cattle) is available for shared use by all members of a community (e.g., a group of herdsmen). As each individual increasingly uses the commons in an effort to maximize his own benefit, the collective consequence may well be the destruction of the resource from excessive exploitation. In short, localizing control at the level of each agent or component can prove catastrophic if competing demands go unrecognized or unresolved. More speculatively, multiple personality disorder may be an even more striking instance in which distributed control, in this case within the human brain, produces extraordinary outcomes (e.g., Putnam, 1989).

## Interconnections Among CAS Components

Another important structural feature of a complex adaptive system is the nature of the connections among its components. Simon (1981) described the typical configuration as "near decomposability." That is, intracomponent linkages tend to be stronger than intercomponent linkages, and neighboring components tend to have stronger connections than distant components. Huberman (1992) explained that this method of organization allows for "an effective isolation of a given level from both the rapid fluctuations of the lower echelons and the quasi-static constraints of the higher ones" (p. 129).

Both the absolute number of connections between units and the strength (or frequency) of these linkages can play consequential roles. Kelly (1994) has speculated that in nature connectance is conserved by a trade-off between these two particular measures; changes in one dimension will likely lead to compensating changes in the other. Similarly, interaction patterns among members of an organization, such as coworkers, typically range from infrequent contacts with all fellow members to very frequent contacts with just a few colleagues

(Huberman & Hogg, 1995). Adding the dimension of linkage quality in his discussion of social systems, Merry (1995) also has emphasized the importance of matching the degree of interdependence among individuals with the quality of their relationships. He has hypothesized, for example, that when interdependence is high and relationship quality is low, the participants (e.g., work-team members or nations) are likely to endure an uncertain period of conflict and crisis.

A related issue is whether there is an ideal level of connectivity within a CAS. On the one hand, inadequate connections can make it difficult for the system to coordinate adaptive responses to internal or external changes. For example, if messages fail to reach their targeted destinations in a timely manner, disruptive influences may attain a secure foothold before countervailing forces can be activated. In this regard, Varela (1995; Varela, Sanchez-Leighton, & Coutinho, 1992) has proposed that both autoimmune diseases and drug addiciton are disturbances caused by insufficient connectedness throughout the afflicted system. From his perspective, in the first instance the body's immune system suffers from inadequate internal regulation, causing vaccination to be ineffective as a treatment; in the second case, healthy connections between the addicts and the larger society have been severed.

Other investigators, however, have discovered that excessive connectivity can also endanger a system. Kauffman (1993) investigated this phenomenon using randomly assembled Boolean networks in his computer simulations of genetic systems. In such arrangements, each element's current binary "on/off" state is regulated by its logical switching rule and the states of specific neighboring elements at the preceding time interval. For example, a particular node may be on only if all surrounding nodes were previously off. Kauffman discovered that his networks suffered paralysis when the number of connections per node exceeded a threshold value, which suggests that an individual component of a CAS may simply be unable to devise an adaptive response when faced with an overload of conflicting inputs.

In reviewing Kauffman's findings, Kelly (1994) concluded that system evolution can proceed most rapidly by adding members while holding the average number of links per node constant. However, there is evidence from other areas suggesting that adding members to a system can prove costly. Based on computer simulations of information-processing organizations, Miller (1995) has noted that additional nodes (e.g., workers) can be a mixed blessing. Although they may potentially increase the organization's processing power, they also extend and elaborate the pathways through which the information must flow. Similarly, in an exploration of simulated ecosystems, May (1973) found that combining too many different species tended to destabilize the system and produce higher extinction rates. Interestingly, May hypothesizes that diversity and stability can perhaps coexist most comfortably when subsystems develop to control cross-species interaction (i.e., by limiting connections per species).

Excessive numbers can also prove to be a liability when a group is faced with a social dilemma requiring collective action (e.g., environmental protection). Computer simulations reveal that overall cooperation tends to be unsustainable when group size exceeds a critical threshold (Glance & Huberman, 1994; Huberman & Glance, 1993). As the authors explained, beyond that threshold "the likelihood of bad consequences from an individual's defection becomes so small, whereas the potential gain stays so large, that the disincentive to defect vanishes" (Glance & Huberman, 1994, p. 78). They noted, however, that creating subsystems within an organization may produce "pockets of collaboration" that can spread throughout the entire system.

## Flexibility, Redundancy, and Error Management

Within a complex adaptive system, the weblike network of interconnections can also enhance error management capabilities. In this regard, von Neumann (1966) observed that the structures of both natural and human-made automata are greatly influenced by the precautionary arrangements designed to minimize the likelihood that any failure will prove lethal. The CAS typically limits system-threatening mistakes in several ways. First, its hierarchical "boxes-in-boxes" structure often confines the ripples caused by any single error. Second, an elaborate network of feedback loops reduces the likelihood of a similar mistake being repeated.

And third, the system incorporates a significant degree of redundancy in its components so that "replacement" parts or pathways are frequently available when a failure does occur (e.g., Kelly, 1994).

In examining this last phenomenon, Minsky (1986, 1995; Minsky & Papert, 1987) has explored how a person learns which methods are generally most effective for solving particular problems. He has stressed that people are more adaptable than computers because in fact they usually know several ways to accomplish the same thing. Whereas the typical computer program is paralyzed by any error of any size, the brain almost always finds some alternative method to tackle a problem when one particular approach has proven fruitless. By continuously devising new, seemingly redundant ways to accomplish currently manageable tasks a person is better prepared if or when the old ways cease to work. Indeed, Minsky (1995) described the human brain as, basically, a "collection of kludges" (p. 158) in which bits of machinery are added whenever necessary to meet a specific need without an underlying global plan. He suggested that, instead of having a few underlying basic principles, the brain is "a great jury-rigged combination of many gadgets to do different things, with additional gadgets to correct their deficiencies, and yet more accessories to intercept their various bugs and undesirable interactions" (p. 159).

Similarly, Holland (1994) has explained that if one of the components of a CAS is removed or disabled, the others often successfully reorganize themselves and compensate for the loss with changes that may even create niches where none had previously existed. In this regard, Kelso (1995) has reported experimental evidence that a variety of human behavior patterns reveal "invariance of function" even when key connections among component parts are reconfigured. As a specific instance, he and his colleagues (Kelso, Tuller, Vatikiotis-Bateson, & Fowler, 1984) devised a prosthesis so that they could instantaneously perturb a volunteer's jaw movements during speech. They discovered that, without any practice whatsoever, the participant's lips or tongue would spontaneously compensate when the jaw was suddenly disabled and thereby enable the vocalization of the intended sounds.

Such findings highlight the remarkable flexibility inherent in a system composed of many smaller, independently functional units. Kelly (1994) has advised, however, that the network structure of a CAS also places constraints on its malleability and the range of adaptations accessible to it. The CAS can change only by means of a step-by-step process operating through its component parts; modification of these parts, in turn, is limited by the structure of their own subcomponents, and so on. As a result, change occurs in discontinuous steps rather than continuously. Goodwin (1994a, 1994b) has described similar limitations when discussing the contrasting roles of natural selection and morphogenesis in the evolution of species. Although natural selection may underlie the persistence of particular forms, it does not aid in our understanding of why these forms ever existed in the first place. Goodwin has stressed that issues of morphology alone place significant limitations on possible biological forms, long before survival of the fittest enters into the equation. In short, some complex systems may not exist in a particular form because the parts simply cannot be assembled that way.

## The Internal Dynamics of the Evolving CAS

### Self-Organization

A hallmark of complex adaptive systems is their capacity for self-organization. Barton (1994) describes self-organization as "a process by which a structure or pattern emerges in an open system without specifications from the outside environment" (p. 7). Similarly, Farmer (1995) depicts self-organization as the way CAS "naturally progress from chaotic, disorganized, undifferentiated, independent states to organized, highly differentiated, and highly interdependent states" (p. 368). Central to the phenomenon is the interplay between constancy and change as the system maintains its essential identity while undergoing self-induced, nonlinear transformations.

Many of the major principles of self-organization have emerged from Prigogine's work on far-from-equilibrium thermodynamics (e.g., Nicolis & Prigogine, 1977; Prigogine & Stengers, 1984) and from Haken's theory of synergetics (e.g., Haken, 1983a, 1983b, 1988). According to the latter's perspective, the collec-

tive interactions among a system's individual components produce macroscopic properties referred to as *order parameters*. These order parameters, such as the roll patterns of fluids and the light waves of lasers, thereafter "enslave" the actions of the elementary units in a top-down manner. At the same time, the constituent parts continue to operate in a bottom-up fashion to support and reinforce the order parameters. Once established, this pattern of circular causality serves to stabilize the CAS, unless perturbed by external influences.

Order parameters have been used to describe the important features of a variety of CAS in the behavioral and social sciences. In regard to human cognition, for example, Stadler and Kruse (1995) have identified *meaning* as an order parameter for high-level brain processes; in many experiments, meaning serves as the organizational basis for the memory of complex verbal chains. Within the economic realm, a business firm's profits can act as an order parameter for the company's diverse activities; in the larger society, the difference in the number of citizens supporting two opposing solutions can operate as an order parameter for the community's response to an important problem (Wishcert & Wunderlin, 1993). Finally, Haken (1993, 1994) speculates that all of the following can emerge as order parameters within a particular CAS: language, national character, ritual, form of government, public opinion, corporate identity, and social climate.

Using simulation techniques, investigators have documented self-organizing transformations across a broad spectrum of social and economic systems. Schelling (1978), for example, developed a self-forming neighborhood model to explain the collective impact of individual preferences in regard to community racial composition. He devised a hypothetical checkerboard neighborhood in which each resident was assigned to a square, and his or her degree of discontent was based solely on the number of same-colored versus different-colored neighbors occupying the immediately adjacent squares. Importantly, whenever a person moved from a current site to a vacant square, the color ratios were altered in both the abandoned neighborhood and the new one. As each resident sought out a square of contentment, individual actions combined to create global patterns. In these simulations, Schelling

discovered that patterns of segregation emerged that frequently overstated the actual minimal preferences of the individuals involved. That is, even a limited desire to avoid being part of a small minority tended to alter a reasonably well integrated neighborhood and create a highly segregated one instead.

Latane and his colleagues have examined similar emergent phenomena in the processes underlying group attitude change (e.g., Nowak, Szamrej, & Latane, 1990). Based on the view that important attitudes act as categories rather than dimensions (Latane & Nowak, 1994), Latane, Nowak, and Liu (1994) designed computer simulations in which each agent maintained an opinion as long as the balance of social influence pressures from other agents did not favor the opposing point of view. In such a model, the combined pressures to switch opinions and pressures to stay with one's opinion (which include the strength of the agent's own opinion) are nonlinear in their impact; incremental changes in influence produce no effect until they reach a sufficient level, at which point the individual reverses his or her position.

Using a square grid in which each randomly assigned cell corresponded to an individual with either of two opposing attitudes, Latane, Nowak, and Liu (1994) found that over time the simulations produced significant changes from the initial configurations in reference to two order parameters. In regard to the first parameter—the polarization of opinions—incomplete polarization emerged; that is, the number of minority-view members diminished but did not disappear entirely. As for the second global variable—the clustering of opinions—clustering increased so that agents with shared opinions became more spatially segregated from those with the opposing viewpoint. Latane and Nowak (1994) describe the resulting self-organized equilibrium as one of "clustered groups in which minority members are shielded from the prevailing majority influence, finding themselves in local neighborhoods wherein their view is in the majority" (p. 244). They further suggest that strong-willed people around the edge of a minority-cluster (i.e., those least likely to change to the majority viewpoint) can enable the less committed within to actually believe they are part of a majority.

As another example, Glance and Huberman (1994) examined how and whether group

cooperation arises in situations requiring collective action. They discovered that their systems tended to evolve toward either of two stable but contrasting conditions: widespread defection among the agents or widespread cooperation. Regardless of where the group started, random perturbations caused by the agents' uncertainties regarding each other's behaviors and inclinations eventually caused the system to move rapidly to the more stable of these two states. Glance and Huberman have interpreted their findings as indicating that a cooperative resolution is most likely when a particular social group is relatively small, hetergeneous, and focuses on long-term consequences.

Self-organizing patterns in the economic arena have also been investigated (e.g., Allen, 1982; Krugman, 1994). Allen (1982), for example, analyzed the evolution of urban centers. The decision an individual, family, or business makes in selecting a home site is influenced by a multitude of interacting, nonlinear factors. These include the availability and quality of local employment and housing, and the competing opportunities offered by neighboring communities. Such selections need not be permanent. Depending on the relative costs involved, agents may choose to relocate as circumstances change with the passage of time. The collective impact of many such individual decisions became apparent in Allen's computer simulations. Over time an urbanization process unfolded as an initial network of equally populated cells transformed itself into a geographical space with a few high-density centers surrounded by satellite cities and more distant low-density cells.

*Positive Feedback*

The course of self-organization in complex adaptive systems is often influenced by positive feedback. Rather than relying on negative feedback controls only (e.g., the thermostat that keeps temperature within a narrow range), the CAS uses the nonlinear interactions among its parts to generate snowballing effects. The dynamics of the positive feedback cycle are self-reinforcing, and potentially amplify the impact of a small change or adjustment. Of course, the runaway effects do not always appear to be constructive (such as a chain reaction of stock market crashes around the

world). It should be kept in mind, however, that successful self-organization for a particular system as a whole can produce undesirable consequences for some of its individual parts and for other CAS.

A common instance of positive feedback is the *competency trap* (March, 1994). In this particular situation, successful learning drives an individual, organization, or society to a stable but suboptimal solution. For example, once an individual has developed a skill and derived positive outcomes from its use, he or she will have little incentive to learn an alternative method, even if it would potentially provide superior returns. Such a change not only would entail the costs in time and energy of learning a new approach, but could also expose the person to a diminished success rate until proficiency improves. Furthermore, with each successful implementation of the old skill, the reinforcement increases the disincentive to switch.

Arthur's (1988, 1990) analysis of increasing returns (i.e., positive feedback) in economic systems is also instructive. Conventional economic theory emphasizes the role of diminishing returns (negative feedback) in establishing a single and best equilibrium for prices and market shares. Arthur has pointed out, however, that there are many parts of the economy, especially those driven by technological innovation, in which positive feedback dominates. In these situations, expensive initial investments in research and design are typically followed by relatively low incremental production costs. When companies compete in such an arena, an early sales lead—even if caused by nothing more than a lucky break—can lead to a "locked-in" situation as the small advantage feeds on itself and ultimately eliminates the competition.

The history of the VHS–Beta battle in the VCR industry is a prime example of this phenomenon (Arthur, 1990). Despite the possible technical superiority of the Beta system, once the VHS system gained a slight edge in market share, the video outlets responded by stocking more VHS-format tapes, which further served to make VHS the recorder of choice among new consumers, and so on. Arthur suggests that a similar positive feedback loop can determine the location of a country's economic centers. If business enterprises benefit from being in close proximity to other firms,

then a self-reinforcing process will lead to industrial concentration in particular areas. These areas need not even have any inherent merit over geographic regions that ultimately fail to thrive.

## Intrinsic Dynamics

The self-organization process does not inevitably lead the CAS to a single fixed or static state. Indeed, many theorists and investigators have concluded that complex adaptive systems often exhibit internally generated fluctuations beneath their macroscopic stability. For example, Kelso et al. (1995) have reported that the dynamics of brain functioning in general and visual perception in particular are intrinsically metastable. In one study using a computer-screen depiction of the classic Necker cube, participants were asked to press a mouse button whenever their perception of the figure changed. The investigators found "bursts of switching . . . interspersed with prolonged periods during which no perceptual change takes place" (Kelso et al., 1995, p. 75).

From the synergetics perspective, the multistability produced by such oscillations is the means by which the brain resolves ambiguity because it cannot recognize both interpretations of a percept simultaneously (Haken, 1995). In this regard, Kruse and Stadler (1993) conducted several studies that revealed contextual and semantic influences on participants' perceptual stability when exposed to multistable patterns. Similarly, Wildgen (1995) has documented numerous instances in which linguistic ambiguity (e.g., the phrase "some more convincing evidence") is tied to multistability in language perception. Stadler and Kruse (1995) have concluded that multistability in perception is actually quite common, and that higher cognitive processes in the form of meaning contribute to the intermittent or permanent resolution of these ambiguities.

In another area, Vallacher and his colleagues (e.g., Vallacher & Nowak, 1994; Vallacher, Nowak, & Kaufman, 1994) have investigated the intrinsic dynamics of social judgment. Their findings contradict the commonly held assumption that evaluation of another person, once formed, changes only in response to external influences such as new information or pressure from others. The researchers used a *mouse*

*paradigm* in which a participant's positioning of a cursor in relation to a fixed point on a computer screen represented his or her moment-to-moment feelings about an acquaintance who was perceived either positively, negatively, or ambivalently. While participants in the positive and negative valence conditions gravitated over the 2-minute experimental session toward a position a fixed distance from the target point (the former-selecting a close location and the latter a distant one), those in the mixed-valence condition exhibited irregular oscillations in cursor positioning, suggesting that their evaluative judgments never stabilized on one fixed point.

Finally, the analytical and simulation work of Youssefmir and Huberman (1995) highlight the intrinsic dynamics of large multiagent systems such as human society. The investigators designed models in which agents with incomplete information about the environment, or *bounded rationality* (e.g., Arrow, 1991; Arthur, 1994; Sargent, 1993; Simon, 1957), competed for limited resources. In efforts to optimize their individual outcomes, the adaptive agents were capable of switching strategies as the entire system continued to evolve. Under these general conditions, Youssefmir and Huberman found that even when resource use reached a stable equilibrium state for the system as a whole, the agents continued to switch strategies in pursuit of greater individual returns. These persistent internal fluctuations intermittently produced bursts of momentary instability and volatility before relaxing to equilibrium once again.

## Bifurcations

Although a complex adaptive system generates its own patterned evolution through intrinsic dynamics and self-organizational tendencies, the CAS can also exhibit abrupt, nonlinear, and often dramatic transformations from one reference state to a qualitatively different one when sufficiently perturbed by internal or external forces. From the dynamical systems perspective, this discontinuity is called a *bifurcation* or *phase transition* (e.g., Prigogine & Stengers, 1984) and has long been recognized in physical systems (e.g., Nicolis & Prigogine, 1989). Examples include a substance's change from liquid to solid (in response to the lowering of temperature), the thermal convection patterns of

Benard cells (caused by an increase in temperature differential), and an earthquake or volcanic eruption (due to increasing subsurface stresses). A more readily observable instance is the sudden shift in a horse's gait as with increasing speed it switches from walking to trotting to galloping (Goerner, 1995).

A critical variable measuring the forces that push the system toward bifurcation is often referred to as a *control parameter* (e.g., Haken 1983b; Nicolis & Prigogine, 1989; Nowak & Lewenstein, 1994). In general, a bifurcation occurs at a specific point along the continuum of this parameter's values. Depending on the particular system under consideration, the control parameter could be, for example, the temperature differential between two locations, the concentration of a chemical in a solution, the number of members in an organization, or the degree of social pressure applied to an individual. For parameter values below the bifurcation point, the system will typically remain relatively stable; that is, small changes in the control parameter will have little impact on the system's behavior. When the control parameter approaches the bifurcation point, however, the system becomes increasingly unstable and begins to display critical fluctuations (Haken, 1983a, 1983b). At the critical value itself, the system reorganizes and assumes a significantly different form.

There are many different types of bifurcations (Abraham, 1995; Nowak & Lewenstein, 1994). In what is perhaps the simplest case, the system has only one stable state available to it once beyond the bifurcation point. By comparison, with the *pitchfork bifurcation* the system selects either of two divergent paths at the point of bifurcation. Although incremental change in the control parameter's values pushes the system toward bifurcation, at the critical point the slightest random perturbation or intentional influence may determine which particular course is chosen. Both alternatives lead to renewed stability, although a secondary bifurcation point may subsequently be reached. Prigogine and Stengers (1984) described this nonlinear process as "a delicate interplay between chance and necessity, between fluctuations and deterministic laws. We expect that near a bifurcation, fluctuations or random elements would play an important role, while between bifurcations the

deterministic aspects would become dominant" (p. 176).

This notion of discontinuous change and bifurcation has received both theoretical and empirical attention from a variety of behavioral and social scientists. For example, Merry (1995) has suggested as a general proposition that the successive stages of human history alternate between periods of relative stability and predictability on the one hand, and sharply contrasting intervals of instability and extreme sensitivity to small chance events on the other. Shermer (1995) has referred to this latter process as contingent necessity and provided an extensive cataloging of fluctuations or triggers of change that may precipitate a society's abrupt reorganization; they include inventions, discoveries, famine, invasions, population explosions, and natural disasters. Similarly, Wiedlich and Haag (1983) have stated that even a few influential individuals can determine a society's direction by triggering a revolution, but only if their actions come at an opportune time.

Within the realm of political science, Lustick's (1993) model of state-building and state-contraction provides a detailed example of discontinuous change in a CAS. Comparing the historical relationships between Britain and Ireland and between France and Algeria with the current turmoil surrounding Israel and the West Bank–Gaza territories, he has proposed that the political institutionalization of new territories—and the disengagement from them—consistently proceeds through three predictable stages: struggles over incumbency, conflicts over regime integrity, and finally contention over ideological hegemony. Most noteworthy here are the two distinct thresholds that must be crossed to move from one stage to the next in either direction. Lustick refers to the threshold points between stages as "discontinuities in the process of institutionalization" and adds that "moving from one stage to another entails a shift in the order of magnitude of political conflict that would surround efforts to change a particular institution" (p. 37). In short, these thresholds represent bifurcation points which abruptly transport the political system to a qualitatively different, reorganized state.

Bifurcations are also common phenomena in the economic arena, where the gradual accumulation of destablizing stresses often leads to discontinuities. Jacobs (1984) has provided two

examples: (a) the combined toll of rising costs and increasingly inadequate facilities inducing a growing local business to relocate to another city, and (b) rising demand for public transportation coupled with only limited capacity for additional surface traffic leading to the construction of a new subway. Young (1991) has offered a somewhat different illustration, suggesting that a widening gap between an individual's desire for goods and the financial resources to acquire them may cause the abrupt adoption of a criminal lifestyle.

Some of Kelso's (1981, 1984, 1995) earliest experimental work on bifurcations in human behavior involved phase transitions in hand movements. Participants were first asked to move their index fingers rhythmically back and forth in a parallel alignment with each other. They were then instructed to progressively increase the speed of movement. When the speed (i.e., the control parameter) reached a critical level, the index fingers involuntarily switched from parallel to symmetrical patterning.

Tuller and Kelso (1990) documented a similar phenomenon in human speech. When research participants repetitively vocalized the syllable *eep* while progressively increasing their speaking rate (the control parameter), a phase transition occurred and subjects spontaneously began reciting *pee* instead. Kelso (1995) also has reported more recent findings derived from the experimental analysis of magnetic fields and spatiotemporal patterning in the brain. He concluded that "nonequilibrium phase transitions offer a new mechanism for the collective action of neurons, they provide the brain with a switching mechanism, essential for rapidly entering and exiting various coherent states. Thus phase transitions confer on the brain the hallmark of flexibility" (p. 284).

From a more theoretical perspective, other researchers have identified directed discontinuous transformations as an important factor in psychological change. For example, many psychotherapists view bifurcation points as critical opportunities for positive change (Abraham, 1995). That is, a client experiencing increasing discomfort may be ideally situated to discard worn-out, maladaptive behaviors and adopt new, more promising ones instead. Similarly, in an analysis of academic competence in college settings, Torre (1995) has

emphasized that the educational interventions of counselors should induce sufficient tension to cause a bifurcation, while not creating so much instability as to preclude constructive change. Along the same lines, Guastello, Dooley, and Goldstein (1995) have noted that facilitators attempting to promote organizational change must foster an environment in which workers unleash their "inherent propensity toward bifurcation" (p. 269). This often involves encouraging the recognition of discontent and amplifying rather than dampening any areas of intraorganization disagreement.

Bifurcation points have also been employed in the study of close relationships. Baron, Amazeen, and Beek (1994) adopted a dynamical systems perspective in their analysis of Levinger's (1980) ABCDE model of long-term dyadic relations. In this five-stage model, Stage A refers to *attraction* and is followed by Stage B, *building a relationship*. Of particular interest here is Stage C, which begins at a bifurcation point culminating in one of three forms of relationship continuation: *growing–satisfying, placid–static*, or *unstable–conflictful*. Both of the latter two forms lead to Stage D—*deterioration*—and then Stage E, *ending through separation*. The growing–satisfying path, on the other hand, skips Stage D and instead continues until Stage E, *ending through death*.

## Cusp Catastrophes

An important subgroup of bifurcations in complex adaptive systems are those categorized as *cusp catastrophes*. The general framework of catastrophe theory translates discontinuous changes into mathematically complex topological forms (e.g., Thom, 1975; Zeeman, 1976, 1977); the approach has proven controversial primarily due to imprecision in some of its applications and the overzealousness of some of its proponents (Casti, 1994; Guastello, 1995). Nevertheless, Casti (1994) has noted that catastrophe theory does provide a useful template for understanding many processes. Similarly, Latane and Nowak (1994) emphasized that "despite these criticisms, catastrophe theory provides a convenient geometrical description of how a continuous function may change into a discontinuous one and allows us to predict a number of associated phenomena" (p. 229).

In a cusp catastrophe, the interaction between

two control parameters determines whether the system experiences gradual or discontinuous change. Guastello (1995) has referred to these paired parameters as *asymmetry* and *bifurcation controls*. As long as the value of the bifurcation variable remains low, macroscopic system change occurs gradually in response to changes in the asymmetry parameter. If the bifurcation control value is sufficiently high, however, the system abruptly destabilizes as the asymmetry control crosses a threshold point, jumping from one stable state to a qualitatively different stable state.

Tesser and Achee (1994) have proposed that this cusp catastrophe model has broad explanatory value for understanding human behavior whenever an individual's disposition to act in a certain way conflicts with social pressures against doing so. They presented romantic behavior as an example. When social pressures (the bifurcation control) against a young, unmarried couple's involvement are minimal, dating activities are likely to increase gradually as mutual attraction grows (the asymmetry control). On the other hand, when social pressures act as strong inhibitors, attraction may grow with little behavioral manifestation until a critical point is reached at which romantic behavior abruptly leaps to high levels.

Latane and Nowak (1994) have used a cusp catastrophe model of attitude change (e.g., Zeeman, 1976, 1977) to generate the hypothesis that attitudes tend to be distributed bimodally (i.e., as categories) when an issue is important to a group, and tend to be normally distributed (i.e., as dimensions) when the issue itself is relatively unimportant. Within this framework, the importance of the issue to the individual can be viewed as the bifurcation control, and the degree to which he or she receives negative versus positive information regarding the topic operates as the asymmetry control.

For an uninvolving issue, the favorability of the individual's attitude should be a smooth, continuous function of the valence of the information about the topic. If the issue is an involving one, however, changes along the asymmetry control (i.e., *information valence*) that cross a threshold point should produce a dramatic, nonlinear shift in the individual's attitude. Furthermore, this region of instability should prevent a highly involved person from maintaining a noncommittal, "middle-of-the-

road" attitude on the issue. In two separate studies of college students' attitudes toward political propositions, and in a reanalysis of attitude data collected from U.S. soldiers during World War II, Latane and Nowak (1994) found strong support for the model's prediction that greater involvement with an issue is associated with the adoption of more extreme attitudes.

Another application of the cusp catastrophe to a CAS is as a model of organizational change (e.g., Bigelow, 1982; Guastello, 1995). In Bigelow's conceptualization, organizational practice—the sanctioned activities carried out by the organization's members—is influenced by two control parameters. The bifurcation control is the degree of resistance to change, most frequently expressed as support for the organization's initial practice. The asymmetry control is the amount of pressure for change.

According to the model, when resistance to change is low, increasing pressure to change will produce a gradual transition or evolution in organizational practice away from the initial conditions. On the other hand, if resistance to change is high, when growing pressure to change reaches a critical threshold, a dramatic, revolutionary alteration in organizational practice results. Bigelow noted that despite the model's limitations and qualitative nature, its predictions are consistent with actual accounts of organizational process and change. In particular, he emphasized that the model provides insight into how different developmental paths may result from attempts to influence the two control parameters. "It may be possible to prevent change from occurring by keeping pressure for change low. Smooth change may be brought about by keeping resistance to change low while increasing pressure for change. Abrupt change may be brought about by increasing resistance to change before pressure for change becomes very great" (p. 38).

While many bifurcation models of complex adaptive systems thus far remain speculative and must await validation, Guastello (e.g., 1991, 1995) has employed catastrophe models extensively in his empirical studies of the workplace. In an investigation of accident incidence among a sample of transit operators, Guastello (1991) found that a cusp model was superior to a linear model in fitting the data provided by the participants' survey responses. Transit hazards, such as violent passengers or riders who needed

to be reprimanded for rule infractions, operated as the asymmetry control; the bifurcation control included social stressors like job insecurity and role conflicts. Under conditions of high stress, relative safety abruptly changed to accident occurrence when transit hazards reach a critical threshold.

In a related investigation with the same sample of workers, Guastello (1992) determined that cusp models were also more effective than linear alternatives in explaining patterns of specific stress-related illnesses (e.g., nervousness, insomnia, high blood pressure, carpal tunnel syndrome). However, the relevant asymmetry and bifurcation variables differed, to some degree, from one illness to the next. In the case of ulcers, for example, age, experience, and physical stress were the asymmetry controls while social stressors were the bifurcation controls. For high blood pressure, on the other hand, anxiety was more important than physical stress as an asymmetry variable, and danger replaced social stress as the primary bifurcation variable.

## Hysteresis

An important identifying characteristic of all cusp catastrophes and many other forms of CAS bifurcation is *hysteresis* (e.g., Nicolis & Prigogine, 1989). A hysteresis effect appears in a dynamical system if the precise point of bifurcation along the control parameter (or asymmetry variable) depends on the direction of change in that parameter. In this situation, the system's history influences its current state. That is, for the same control parameter value, a system can be in either of two states depending on whether the control parameter was increasing or decreasing. Returning to the example of a horse's gait, with increasing speed a point is reached at which the animal abruptly shifts from a trot to a gallop. When the horse later slows down, however, the speed at which it returns to a trot may be slower than the shift point where the earlier discontinuity occurred. Similarly, under controlled conditions, the temperature at which water turns to vapor can be above the temperature at which the vapor returns to liquid form.

Each of the cusp catastrophes described earlier manifests hysteresis to some degree. For example, once Tesser and Achee's (1994) couple have firmly established their romantic involve-

ment, it may require a larger decline in attaction before their dating behavior diminishes appreciably. That is, for the same range of attraction, romantic activity will be higher during the dissolution of the relationship than it was during its creation. In regard to attitude formation (Latane & Nowak, 1994), once an individual has established a strong opinion regarding an issue of personal importance, he or she is likely to cling to that position even when later confronted with considerable negatively valenced information. In other words, the very same information on an issue may produce either a favorable or an unfavorable attitude, depending on how it compares in valence with previous information. Again, history matters.

Similarly, organizational practice may display hysteretic effects (Bigelow, 1982). If resistance to change is strong but pressure to change has been sufficient to produce a discontinuous alteration in practice, that new mode of operation will likely persist even if significant pressures to return to the old ways develop. Finally, once workplace accidents or stress-related illnesses have been triggered, they may remain high despite successful efforts at moderating their precipitating influences (Guastello, 1991, 1992).

## Self-Organized Criticality and the Edge of Chaos

The transition or bifurcation regions in which the dynamic instabilities of a CAS are greatest have received particular attention from some theorists and investigators. Bak and his colleagues (Bak, 1994; Bak & Chen, 1991; Bak, Tang, & Wiesenfeld, 1988), for example, have proposed that the self-organization process itself is governed by a principle called *self-organized criticality.* Self-organized criticality refers to the tendency of a large dynamical system to naturally evolve to a critical state between order and disorder, often also called the *edge of chaos* (e.g., Packard, 1988). The global features of such a system cannot be understood through an analysis of individual parts; at the point of self-criticality, either a large or small event can trigger a chain reaction of unpredictable magnitude (e.g., earthquakes, ecosystem extinctions, or financial market collapses).

The classic example of self-organized criticality is a pile of sand. As sand is slowly added

from above, the pile's height increases until the slope reaches a critical state. At that point, any additional grains of sand will cause an avalanche of unpredictable magnitude. In fact, the distribution of sandslides is best described by a power law, with a small slide far more likely than a large one. But perhaps most intriguing is the premise that the same conditions can produce dramatically different outcomes on different occasions. What remains relatively constant, however, is the critical state that the pile must return to before the next avalanche will occur. Bak (1994) also notes that once the pile is poised at the critical state, any analysis based on individual grains of sand ceases to be useful. At that point, the pile of sand must be viewed as a whole because even grains considerable distances apart are linked through an elaborate network.

Scheinkman and Woodford (1994) have applied the notion of self-organized criticality to the observed instability of economic aggregates. They propose that the significantly nonlinear and strongly localized nature of the interactions between different parts of the economy prevents the law of large numbers from dampening variations in demand or production. Because small changes in a particular unit's level of production can have large and nonuniform effects on the economic activities of its immediate neighbors, inventory dynamics can propagate across time and between sectors in a large economy. Assuming such a pattern of linkages and potential chain reactions, the authors concluded that final-goods demand (treated as an exogenous shock) can cause a production avalanche of any size, entirely unrelated to the size of the system.

Bak and Chen (1991) also suggested a more speculative example of self-organized criticality: "Throughout history, wars and peaceful interactions might have left the world in a critical state in which conflicts and social unrest spread like avalanches" (p. 53). In a similar vein, Shermer (1995) has offered a metaphorical analogy in the rise and fall of various social movements. Suggesting that "certain historical phenomena repeat themselves, not in specifics but in universals" (p. 77), he proposed that the witch crazes of past centuries have equivalents in modern day mass hysterias, moral panics, alien abduction claims, and fears of Satanic cults. Shermer has noted that the social condi-

tions underlying the emergence of all these phenomena have much in common (e.g., a feeling of loss of personal control and responsibility), and that each movement propagates through a rapidly growing network of information exchange. Once the critical peak has been reached, however, even a small event (e.g., the demonstrated falsity of one claim) reverberates through the system causing the collapse of the movement and a loss of interest by the general public.

Other investigators have focused on the edge of chaos notion, seeking theoretical or empirical support for the view that complex adaptive systems evolve toward a critical state between order and disorder. Langton (1990, 1992, 1995), for example, has proposed that this phase transition area is where a system has maximum adaptability and maximum effective information exchange. In the ordered regime, the system is too rigid and both information exchange among components and responsiveness to a changing environment are therefore limited. In the disordered regime, on the other hand, the system is too turbulent and its connections are too disorganized to allow it to function at peak effectiveness.

Langton further contends that a CAS will actually "slow down" when it reaches the phase transition state. Rather than moving quickly through this region, the system clings to the edge until pushed in one direction or the other. Indeed Kelly (1994) has proposed that in order to maintain itself in this poised state, the CAS will engage in a self-tuning process characterized by increasingly complex strategies and feedback mechanisms. Similarly, Kelso (1995) explained that complex adaptive systems often hover near bifurcation points. He suggests that the brain itself "is poised on the brink of instability where it can switch flexibly and quickly. By living near criticality, the brain is able to anticipate the future, not simply react to the present" (p. 26).

Using computer simulations, Kauffman (1991, 1993, 1995) has found that selection processes can drive simple Boolean networks (such as cellular automata) to this edge of chaos. He suggests that the same phenomenon likely operates with actual genetic regulatory systems. Along the same lines, Schuster (1994) reports that RNA viruses, faced with rapidly changing environments, do in fact appear to evolve near

the edge of disorder. For such viruses, stagnation enables the host organism to mount effective defenses, whereas runaway mutation can prove self-destructive to the virus. More speculatively, Kauffman (1995) raises the possibility that democratic forms of government provide the best opportunity to resolve difficult problems among conflicting interests because pluralism facilitates movement toward the phase transition region where optimal compromise solutions can be found.

## A Note on Chaos

In some complex adaptive systems, completely deterministic rules may nevertheless lead to unpredictable outcomes. This paradoxical phenomenon, initially identified in weather patterns and turbulent fluid flow, is caused by sensitive dependence on initial conditions and is the particular focus of chaos theory (e.g., Baker & Gollub, 1990; Cambel, 1993; Crutchfield, Farmer, Packard, & Shaw, 1986; Gleick, 1987; Stewart, 1989). With chaotic behavior, exceedingly small, perhaps even unmeasurable differences in parameter values at one point in time lead to large and ultimately unpredictable differences in observed behavior at some later point in the future.

The classic summarization of this particular disproportionality between cause and effect is the so-called *butterfly effect* (Lorenz, 1993), which suggests, for example, that the flap of a butterfly's wings in Brazil can cause a tornado in Texas. Merry (1995) provides two additional hypothetical instances. First, neighboring nations developing under virtually identical economic and political conditions may subsequently display dramatically different national cultures. Second, two brothers subjected to the same poverty-stricken childhood in an inner-city ghetto may grow up to be quite different from each other—one a renowned scientist and the other an incarcerated criminal.

Sensitivity to initial conditions results from the inherently nonlinear nature of the equations underlying chaotic processes. Repeated iterations, in which values from calculations at preceding time points are "fed back" into the system of equations to determine the values at the next time point, lead to a dramatic amplification in differences as the time horizon lengthens. The ultimate result is the appearance

of randomness in a system governed by deterministic rules.

Crutchfield (1994) describes this phenomenon in the following way:

> Where in the determinism did the randomness come from? The answer is that the effective dynamic, which maps from initial conditions to states at a later time, becomes so complicated that an observer can neither measure the system accurately enough nor compute with sufficient power to predict the future behavior when given an initial condition. (p. 516)

Casti (1994) also points out that even when observing quite simple nonlinear behavior, it may still be impossible to know the system's initial state precisely. And to further complicate matters, investigators note that chaotic systems may exhibit nonchaotic behavior over much of their domain (Gregersen & Sailer, 1993; Nicolis & Prigogine, 1989).

Inherent in the process underlying chaotic behavior, however, lies the opportunity for surprisingly accurate short-term predictions. That is, there may be pockets of predictability even though long-term prediction is unattainable. Kelly (1994) summarizes the situation this way: "The character of chaos carries both good news and bad news. The bad news is that very little, if anything, is predictable far into the future. The good news is that in the short term, more may be more predictable than it first seems" (p. 424). Mandell and Selz (1994) also note that even chaotic behavior may exhibit stability when viewed from the perspective of deep characteristics. For example, they describe the circumstances of a compulsive hand-washer. Although it may be impossible to anticipate precisely when he or she will engage in this intermittent behavior, one can nevertheless be confident that washing will occur with higher-than-normal frquency over any given period of time.

## How the CAS Responds to Its Environment

Although the focus thus far has been on the internal structure, dynamics, and self-organizational tendencies of CAS, these systems exist in a larger environment that typically confronts them with a multitude of challenges, including the actions of other coevolving complex adaptive systems. The survival or success of the CAS, then, often depends on its capacity to

effectively modify goal-oriented behavior in response to a changing environment. The adaptations are not necessarily passive; in many cases the system responds actively with behaviors designed to influence and perhaps even control the environment (Hubler & Pines, 1994). In this light, Huberman and Hogg (1986) observe that an important measure of adaptability is how well a system can function under varying conditions with only minimal changes in its structure.

*Fitness Landscapes*

Several investigators have found the concept of *fitness landscapes* useful in analyzing the adaptation and coevolution of complex adaptive systems (e.g., Gell-Mann, 1994b; Kauffman, 1993; Wright, 1986). In this metaphor, the agent is pictured as moving about on an imaginary topographical map. The landscape typically includes hills and valleys of varying degree, and the tallest peak represents the site of the agent's optimal fitness. Alternatively, the fitness landscape can be viewed upside-down; from this perspective, optimal fitness lies at the bottom of the deepest basin. In either case, it is important to note that not all agents climb identical landscapes, and that the landscape itself can change. In short, complex adaptive systems differ from each other in the paths and obstacles to optimization.

Heylighen and Campbell (1995) have used a fitness landscape approach in describing how systems evolve through the twin processes of variation and selection. Although such evolution typically proceeds with small adaptive steps gradually leading to higher ground, occasionally the transitions temporarily take the system to somewhat lower regions. If these latter locations are too low, the system risks elimination. But without some nonadaptive excursions, the CAS is likely to get "stuck" on a local fitness maximum and therefore never attain the more desirable global maximum. In other words, evolution would cease because there would be no direct path to increased fitness.

Kollman, Miller, and Page (1992, 1995) document just such risks in their computer simulations of electoral landscapes in which political parties are adaptive agents competing with each other for votes. In particular, they offer an explanation for why a challenging party

may fail to defeat an incumbent. Lacking full information about the preferences of the entire population, the challenger must rely on polls of randomly selected voters to refine its platform. This iterative process may result in the party becoming stuck on a local peak, committed to a platform that, although superior to all neighboring platforms, nevertheless lacks the broad-based appeal necessary for victory. In short, the challenger's search method can lead it to think it has identified a winning platform when, in fact, it has not. In a similar manner, it is common-place for a person undertaking psychotherapy to report feeling stuck in a particular life situation; in some instances, this experience likely results from adaptations that have "trapped" the individual on a local fitness peak from which higher peaks are not directly accessible.

This landscape perspective demonstrates how a complex adaptive system can sometimes benefit from errors or random behaviors if such actions inadvertently displace the agent from a local peak, thereby increasing the likelihood that the agent will reach the landscape's global maximum (Gell-Mann, 1994b). In fact, Kelly (1994, p. 470) views "honor your errors" as a guiding commandment for effective adaptation. He advises that by nurturing small failures, a system can make large failures less probable. That is, small cracks can prevent larger fractures. Indeed, errors are often renamed innovations when they lead to a better problem solution or a more adaptive path. Furthermore, tolerating minor mistakes instead of trying to correct or eliminate them also frees a system to focus on more important and more urgent functions.

Of course, system errors or random behaviors more often disrupt or prevent adaptive progress, especially when they are excessive in frequency or magnitude. Many small steps toward a fitness peak can be quickly undone by large, misdirected movements (e.g., Gell-Mann, 1994b). Especially in a constant, unchanging environment, such actions can prevent an agent from even maintaining fitness levels already achieved. External "noise" from the environment itself can also contribute to a system's failure to successfully adapt. A noisy environment not only complicates the system's task of sorting usable information from random signals, but it can also disrupt efforts to focus attention and effectively respond to any particular input (Hubler & Pines, 1994). Nor can the impact of a

sudden, catastrophic environmental event be overlooked. As Gould (1989) points out, such accidents permanently alter the course of history. Even the most fit can be undone by a random bolt of lightning.

Whenever the environment or landscape is populated by multiple adaptive entities, coevolutionary forces make the dynamics of adaptation increasingly complex. Indeed, the combined activities of the individual agents create a larger CAS that incorporates all of them (e.g., Gell-Mann, 1994a). In order to reach their own respective fitness peaks, these coevolving agents must simultaneously adapt to one another. As a result, their optima are no longer fixed and independent; the agents experience their shared environment as a landscape that constantly shifts and deforms (e.g., Kauffman, 1993, 1995; Kauffman & Johnsen, 1992; Kollman, Miller, & Page, 1995).

## Internal Models

Many theorists and researchers have examined the basic mechanisms that some complex adaptive systems, such as human beings, make use of in formulating actions intended to yield positive consequences and greater fitness. Gell-Mann (1994a, 1994b, 1995), for example, has explained that a complex adaptive system actively searches for regularities in its own behavior and in the environment and then compresses incoming information into an organized collection of schemata. The use of particular schemata in actual situations produces consequences that, by means of feedback loops, serve as input information for the modification of the schemata. This competitive cycle ultimately leads to adaptation and learning. Gell-Mann has pointed out, however, that this process is imperfect and that a maladaptive schema can persist uncorrected for a long time. For example, a person may perceive regularities where in fact there is only randomness (e.g., superstition), or vice versa (e.g., denial). In this regard, Goertzel (1994) likens belief systems to immune systems, suggesting that a set of faulty but mutually supporting beliefs can act to "protect" an individual from the inputs of external reality.

Holland (e.g., 1992, 1994, 1995) provides a particularly detailed and rigorous analysis of the processes that govern CAS responses to the environment. From his perspective, the system uses a hierarchical set of rules—from the most global to the very specific—to anticipate the consequences of its own actions. If this *look-ahead* indicates negative consequences on the horizon, the system can alter its current actions accordingly. However, this internal model is a truly effective predictive mechanism only if the system can analyze a situation and execute the appropriate rules more quickly than the environment changes—an especially challenging task in coevolutionary environments.

Holland views the capacity to modify an internal model as critical to the complex adaptive system's effective functioning. Only in a perpetually static environment can the same rules always work, and even then fine tuning may be advantageous. Furthermore, most CAS derive their rules from only a limited sampling of the environment. As with Gell-Mann's schemata, Holland's rules undergo constant review by the system, competing with each other in an evolutionary process designed to maximize the CAS's adaptability and chances of survival. The complex adaptive system also forms plausible new rules from the component parts of tested rules. This process of recombination is a crucial element in the system's delicate balancing of *exploitation* and *exploration*. Exploitation here refers to the use of actions that have produced beneficial outcomes in the past. Exploration, on the other hand, refers to experimentation with new behaviors; these behaviors may prove to be extremely valuable or quite costly. Although there are attendant risks, without such exploration the CAS will eventually encounter a situation for which it has no appropriate or effective response.

Kauffman (1994) has proposed a speculative framework for how the internal models of interacting individuals coevolve. Consistent with Holland's focus on look-ahead, Kauffman's central premise is that adaptive agents strive to maximize the accuracy of their predictions about each other. Through ongoing interactions, each agent develops a finite model of the other agent that will sooner or later prove inaccurate. When a particular prediction fails, the individual who was wrong alters his or her operative hypotheses about the other agent. This cognitive change and the behavioral modifications coupled with it are likely, in turn, to create a failure in the second agent's internal model. When this second agent then modifies his or her own

preferred hypotheses and behavior, the first agent will shortly thereafter discover a new failure in his or her own most recent internal model. And so the cycle continues.

Kauffman hypothesizes that this coevolutionary process produces dynamical changes in the complexity of each agent's internal model. Following a disconfirmation, an agent will generally adopt a simpler, more general model that is less likely to be wrong, but also is less useful for precise predictions. As the agent gradually accumulates reliable data from new interactions, he or she will find it advantageous to once again develop a more detailed internal model of the second agent's behavior. This process of adding complexity continues until the first agent is once again confronted with a disconfirmation. In short, Kauffman suggests that a coevolutionary agent's internal model is driven back toward a self-organized critical state, poised at the edge of chaos, whenever it strays too far away.

### Coevolutionary Relationships

Coevolution among CAS takes many different forms; among the most common is the predator–prey relationship. In nature, these pairings of species often display either a steady equilibrium or an oscillating Lotka–Volterra cycle such as that observed between the Canadian lynx and the snowshoe hare (Sigmund, 1993). In this latter case, an initial increase in the number of predators leads to a decline in the availability of prey; this constraint on food supply then reduces the number of predators that can survive, thereby enabling the prey population to grow once again. The increased availability of prey, however, will precipitate a rise in the predator population, and so on.

Nowak and Lewenstein (1994) have suggested that this same cyclical pattern may fit the system dynamics of pickpockets and naive victims (i.e., those who fail to adequately protect themselves from theft) in contemporary society. Such a model would work in the following way: With many pickpockets at work, the number of people willing to walk the streets unprotected would quickly diminish. This decline would then curb the profitability of picking pockets, forcing many to find alternative means of financial support. As the pickpockets vanish,

however, potential victims would become less vigilant, which would lead to a rekindling of opportunities for would-be thieves. In short, as each group alternately becomes too successful in relation to the other, the seeds are planted for its own at least temporary demise.

Baron, Amazeen, and Beek (1994) have proposed that a similar coupling may describe majority–minority relations. If the majority grows too large (and the minority too small), it may cease to adequately monitor the quality of its functioning (e.g., values and goals) and therefore suffer the loss of disenchanted supporters. If the resulting increase in the size of the minority is too dramatic, however, the overall group cohesiveness can be shattered—a troubling consequence for even the minority supporters themselves. Indeed, a further shift of allegiances or splintering of the group may occur before the minority is able to achieve majority status. Because healthy group functioning may therefore depend on a certain ratio of majority-to-minority sizes, the authors described the challenge as follows:

> At issue here is getting outgroup strength to be high enough to increase ingroup cohesiveness given that if outgroup pressure is too weak, internal cohesiveness may suffer. On the other hand, if outgroups grow too powerful, internal cohesion, instead of increasing, may jump in the opposite direction, with members leaving the group. (p. 136)

In contrast to the cycling described above, competition among species or complex adaptive systems can sometimes lead to a coevolutionary "arms race." This phenomenon is epitomized by van Valen's (1973) *Red Queen hypothesis*, which refers to any situation in which continuing adaptation is necessary just to maintain relative fitness. Heylighen and Campbell (1995) emphasize that such an arms race is most likely between similar systems that depend on the same resources; the outcome can be detrimental to all parties involved. They offer as an example the forest trees that grow ever taller—and increasingly vulnerable—as they compete with each other for sunlight.

Similar coevolutionary arms races can also be seen in human society. Saperstein (1990), for example, has described the commonplace escalation of weapons development and deployment between hostile nations. Each nation's security policy decisions are based on an evaluation of the armament stocks of their opponents. The

rapid response capabilities provided by strategic nuclear weapons only serve to tighten these interconnections. Saperstein concluded that "One cannot be confident of 'pushing' an opponent safely around the 'policy field' when there may be a precipice in that field over which each might drag the other" (p. 179). Mayer-Kress (1990), in analyzing his own simulation models, added that the arms race between nations can be precipitated by even a small change in one nation's response to a perceived threat from another.

Fish (1994) speculated that the arms race phenomenon is also central to the coevolutionary battle between government forces and the purveyors of illegal drugs:

> When the police get more firepower, the drug lords escalate their armaments. Greater ingenuity in tracking illegal funds is met by improved methods of hiding them. Stiffer sentences for adult drug dealers lead to the recruitment of children who are not subject to those penalties. (p. 15)

Fish has also maintained that the symmetrical escalation has led to both greater violence and greater drug abuse. It is interesting to note Fish's expectation that any change in drug policy will likely be discontinuous—the kind of sudden alteration that typifies a bifurcation point.

The computer simulations of investigators outside the social science arena also provide pertinent insights into the coevolutionary dynamics of interacting CAS. Ray (1992, 1994), for example, created an entire virtual computer world called *Tierra* and initially populated it with self-replicating machine-code creatures that competed for limited CPU time and memory space. Tierra also included a reaper function to cull flawed algorithms from the "soup" as well as a mutation function to mimic biological evolution. Over time, metabolic parasites capable of using the procedure codes from other creatures appeared and multiplied. This led to a decline in the original host population, and then a significant drop in the number of these parasites. After a subsequent rebound in the size of the host population, parasites proliferated once again.

At the same time this cycle was unfolding in Ray's study, an evolutionary arms race escalated in which host creatures developed immunity to the parasitic invaders, then the parasites found ways to circumvent the immunity, and so on. After the succession of many generations, Ray

discovered even more complex creatures such as *social hyper-parasites* that could self-replicate only when together in groups, and *cheaters* that would infiltrate these social groups and steal the exchanges between them. It is of interest here that Hillis (1992), in his own work with sorting networks, discovered that optimization procedures were actually more effective and more efficient when coevolving parasitic codes were included in the programming environment. By uncovering and exploiting any weaknesses, the parasites pushed the system away from local maxima and toward the optimal global solution instead.

Similarly, Holland (1994, 1995) has developed his ECHO computer model to simulate the flow of resources among reproducing artificial agents. The world in which these agents move is a connected array of sites, each of which provides variable amounts of renewable resources. An agent must obtain a sufficient reservoir of such resources in order for it to successfully self-replicate. In addition, the agents also directly interact and exchange resources with each other. They vary, however, in their abilities to force the outcome of an interaction, resist another agent's own efforts, and organize themselves into larger, more complex meta-agents. The ECHO system specifications can be designed to study phenomena such as interactions in natural ecosystems, the evolution of organizations, economic activity in modern societies, and immune system responses.

Finally, Hubler and Pines (1994) have conducted numerical experiments investigating the interaction patterns of CAS dyads. In their simulations, each agent's primary goal is to discover regularities in their shared environment; meanwhile, even without direct communication, the paired agents can both enhance and diminish each other's predictive abilities. Depending primarily on the combinations of active versus passive adaptation employed by the agents, the researchers uncovered a variety of coevolutionary dynamics. For example, a leader–follower configuration at the edge of chaos tended to be the most stable paired arrangement. Hubler and Pines also found that active adaptation was preferable to passive adaptation under most circumstances, and that the agent with the more complicated strategy was generally victorious in any direct competition.

## Game Theory

Analyses of coevolutionary behavior in complex adaptive systems often rely directly or indirectly on *game theory* principles, which can generally be applied to any potential conflict situation where the outcome is determined by the participants' choices. Formulated initially by von Neumann and Morgenstern (1944) as a model for economic behavior, game theory has proven useful in many other contexts, including the study of cooperation (e.g., Axelrod, 1984), escalation (e.g., Shubik, 1971), and evolution (e.g., Maynard-Smith, 1982). The most well known of these games is the Prisoner's Dilemma, although others such as Chicken, Stag Hunt, and Deadlock can also be viewed as building blocks of complicated coevolutionary interactions (Kelly, 1994; Poundstone, 1992).

An important distinction made by game theorists is whether the situation under consideration is a *zero-sum* or *non-zero-sum* game. The former describes a strictly competitive situation in which the combined total payoffs for the players are fixed. That is, one agent can benefit only at the expense of another agent. In contrast, a non-zero-sum game can provide positive or negative outcomes to all players depending on their collective actions (e.g., Luce & Raiffa, 1957). In the classic Prisoner's Dilemma, for example, each agent's best individual outcome is obtained by defecting, but their best combined outcome requires mutual cooperation. Interestingly, it is not unusual for agents to misperceive their payoff matrix; they often behave competitively when cooperation would be more profitable for all (Axelrod, 1984).

Of particular relevance to coevolving CAS are situations that involve repeated interactions over time—that is, *iterated games.* When agents recognize that they may have multiple encounters (perhaps even indefinitely) with each other, their strategies often become more complicated as memory of past outcomes and anticipation of future contact affect current decisions (e.g., Axelrod, 1984; Poundstone, 1992; Sigmund, 1993). For example, Lindgren (1992) designed an elaborate computer simulation of an iterated Prisoner's Dilemma game in order to study coevolution in an artificial population. He observed a variety of evolutionary phenomena, including "periods of stasis, punctuated equilibria, large extinctions, coevolutions of mutual-

ism, and evolutionary stable strategies" (p. 295). Lindgren also discovered that agents were able to limit how successfully competitors could tune their strategies by including occasional mistakes or random choices as components of their own strategies.

Similarly, Marks (1992) has analyzed political change in authoritarian systems from a game theory perspective; his particular focus is on the strategic interactions that characterize mass protest by the political opposition against the ruling elite. Each of these coevolving groups can adopt either of two policies: the ruling elite can choose to tolerate or suppress its opponents and the political opposition can choose to operate within the system or challenge it. However, the situation is further complicated by factions within the ruling elite and, because mass protest requires coordination among a large number of individuals, by the decisions of each opposition member. As a punitive measure against a suppressing ruling elite, a public protest will have the desired impact only if it is of sufficient size; otherwise, those who protest may be worse off than the nonprotesters.

The system dynamics, then, share some features with other collective action problems. Here, the eventual number of protesters depends on the potential participants' own expectations about whether or not a critical mass will be achieved. Furthermore, the elite regime's actions (e.g., mobilizing additional troops) contribute to determining how many of the political opposition are necessary to constitute a critical mass. For all involved, information about intentions is crucial. For example, if the ruling elite should decide to adopt an attitude of toleration rather than suppression, the implications can be profound. As Marks (1992) explains: "The critical task for the political opposition in this scenario is to limit protest despite the penchant of individual oppositionists to protest previously bottled-up anger, grievances, and demands" (p. 411). That is, the leadership must now reverse course and encourage a policy of working within the system for continued change. Indeed, mass protest at this juncture could be self-destructive if it induces the ruling elite to reinstitute a policy of suppression.

As a final illustration, Messick and Liebrand (1995) have employed the Prisoner's Dilemma to examine changes in the frequency of coop-

eration over time. Using computer simulations, they created artificial populations in which all of the agents relied on the same strategy in deciding whether to cooperate or defect. Three different decision heuristics were explored: *tit-for-tat*, in which the agent adopts the choice made by the neighbor with which it most recently interacted; *win-stay/lose-change*, in which the agent compares its most recent outcome with those of its neighbors and then maintains its choice if the comparison is favorable or switches if the comparison is unfavorable; and *win-cooperate/lose-defect*, in which the agent cooperates if its previous outcome was favorable in comparison to its neighbors and defects if social comparison revealed the previous payoff to be unfavorable. Under all these conditions, the agent's decision heuristic was applied successively to whichever of its neighbors (from among the eight surrounding cells of a larger grid) was randomly selected for its next interaction.

In summarizing their many findings, Messick and Liebrand (1995) emphasized that significant levels of cooperation persisted over time— regardless of which choice strategy was homogeneously applied—as long as the overall population size exceeded a threshold value. In addition to the importance of group size, they found that the particular methods used in evaluating outcomes also made qualitative differences in the dynamics of cooperation. In describing the cooperation as an emergent social phenomenon that cannot be adequately explained on the basis of individual actions, Messick and Liebrand concluded that "simple behavioral rules, rules instantiating the most rudimentary forms of adaptive social interaction, can lead to unexpected global patterns in large groups" (p. 144).

## Implications for Behavioral and Social Science Research

This overview of complex adaptive systems has covered considerable ground. Many concepts have been presented, and numerous examples have been provided in an effort to give the reader a broad-based view of CAS applications in the behavioral and social sciences. In the process of answering some questions, other concerns have undoubtedly been raised. As noted in the introduction, given current knowledge, a conclusive evaluation of the merits and shortcomings of the CAS perspective will ultimately require an interdisciplinary dialogue. In this final section, several of the central issues are highlighted.

By way of a brief review, the key tenets of the CAS perspective are summarized well by each word in the term *complex adaptive system*. *Complex* conveys many attributes, the clearest of which may be the nonlinear nature of the world around us. According to complexity theory, small events (such as someone's slightly different idea) can have dramatic effects, and seemingly large events (such as a long-awaited conference of world leaders) can have no discernible impact at all. Simple processes (like a disagreement among family members) can mushroom out of control; intricate or massive structures (for example, the former Soviet empire) can collapse virtually overnight. Abrupt change (such as a calm neighborhood transformed into a riot-torn community) is often the norm rather than the exception.

*Adaptive* reflects the perspective's focus on the change and evolution that characterize individuals, groups, and societies. Equilibrium states (for example, group consensus on an issue) are viewed as transient because they are repeatedly disrupted by both internal phenomena (such as one member's increasing animosity toward another) and external influences (such as new information about a competing group's latest strategy). Periods of disorder and instability (for example, the turmoil of adolescence) are recognized as natural and necessary stages on the path toward greater self-organization. The search for optimal fitness, however, often includes frequent detours and shifting terrain as other individuals or groups struggle to adapt on the same landscape.

The final word *system* emphasizes interconnections. A CAS can be readily apparent (as in the case of a close-knit family), or shrouded and concealed (as with the relationships among distant nations). As a result of the dynamical interactions among the component parts of the system, collective behavior emerges (such as political revolt) and often catches people by surprise—no matter how well we understand the individual elements separately. Therefore, policy measures (for example, economic tariffs, mandatory drug testing, or parental limits on sibling disputes) frequently have unintended consequences as they work their way through a

network of intermediaries, each of which contributes its own fingerprint to the message it transmits. Simple cause-and-effect relationships evaporate, leaving instead patterns and regularities to decipher.

The behavioral or social scientist faces many challenges in translating complexity theory principles, originally formulated in the natural sciences, to areas such as psychology, sociology, economics, or political science. Most clearly, people have characteristics that make them different from purely chemical or physical systems. For example, although the evolution of human social systems may at times be misguided, it is rarely blind. Our self-organizing enterprises are distinctive because they typically involve attempts to intelligently plan structures (e.g., Weidlich & Haag, 1983). This aspect alone contrasts sharply with the unknowing movements of fluids or gases. Furthermore, even if individuals are generally limited in their rationality and not always intentional in their actions, it remains problematic to adequately control or eliminate the influence of their awareness and perceptions. Hinterberger (1994) summarizes the situation in the following way: "All physical and biological laws and processes apply to social processes but special aspects of human abilities, human culture and social life require a broader theory that also allows us to explain the specialties based on the specifically human ability of active, conscious and intelligent decision-making" (p. 38).

More generally, the individual components making up systems in the behavioral and social sciences (e.g., people, groups, societies) tend to be far more complicated than the corresponding components that create systems in the natural sciences (e.g., molecules). Indeed, a single living organism is a collection of many simpler CAS. Additionally, in contrast to physical or chemical systems, the interactions among the same group of individuals often take a multitude of different forms (Weidlich & Haag, 1983). As a result of this greater complexity, it can appear as if deterministic causal laws do not govern social phenomena. Accurate measurement in itself can be a significant obstacle for the social scientist attempting to develop an explanatory model of a complex adaptive system (Nowak, Vallacher, & Lewenstein, 1994).

In a related vein, whereas natural scientists direct their efforts toward heightening our objective understanding of the world in which we live, behavioral and social scientists are burdened with the additional expectations of both explaining and improving the world(s) we create. Loye and Eisler (1987) refer to this as the "normative aspect of social theory, or the requirement of attention to the systems guidance question of ideal developmental forms that must be the prime concern of all policy makers" (p. 56). In the context of complex adaptive systems, this mission includes such goals as enhancing communication patterns, redressing the inequitable distribution of benefits within a society, uncovering peaceful solutions to group or international conflicts, and discovering mechanisms to make organizations and governments more responsive and effective.

In short, the added complexity of CAS in the behavioral and social sciences can create serious and sometimes intractable modelling problems. Indeed, many adherents to the complexity paradigm acknowledge that, once outside the natural scientist's laboratory, researchers may be limited to qualitative analysis. Weidlich and Haag (1983), for example, suggest that mathematically accurate and detailed descriptions of microlevel processes may be unattainable, though they believe significant insights can be garnered nonetheless. In this regard, Nowak and Lewenstein (1994) see considerable value in simply uncovering similarities between specific aspects of dynamical systems and human social behavior. But at the same time, it is necessary to distinguish thorough qualitative analyses—such as many of the investigations reported here— from those in which complex systems terminology is used in a merely metaphorical manner.

It is important not to overlook the intellectual hazards associated with developing elegant metaphors while forsaking the construction of accurate models. A blurring of the two enterprises can inadvertently occur when the CAS models of behavioral and social scientists suffer from oversimplification. For example, Barton (1994) has pointed out that if consequential features of a system are ignored in order to make the investigator's inquiry and analysis more manageable, the resulting model may hold little promise for improving understanding. This "discontinuity between model and reality" (Barton, 1994, p. 10) can be further exacerbated by the difficulties or impossibility of testing precise hypotheses, which requires that the

system under investigation be sufficiently iso-
lated from the external factors impinging on it
(Barton, 1994). Echoing this last point, Kelso
(1995) expresses concern about the paucity of
actual experimental studies of complex adaptive
systems: "Little contact with experiment is
made, and interplay between theory and experi-
ment, so crucial to the development of science,
is lacking. Behavior as a source of insight into
principles of self-organization ... is virtually
ignored" (p. 28).

But despite obstacles to behavioral and social
science applications, significant insights rel-
evant to research design are provided by the
complexity paradigm. For example, a dynamical
systems orientation reveals that qualitatively
different behaviors do not require different
explanatory mechanisms (Kelso, 1995). In this
way, periods of linear change and episodes of
nonlinear discontinuity in a system's evolution
can both result from the same set of parameters.
Similarly, the CAS perspective encourages
investigators to consider the possibility that
change in a system may be a reflection of its
internal dynamics alone. Although a sudden
qualitative transformation in an object of study
often leads the researcher to suspect that a new
variable has entered the picture, complex
systems can exhibit such changes in the absence
of new or external influences (e.g., Newtson,
1994; Nowak, Vallacher, & Lewenstein, 1994).
Paradoxically, then, the CAS approach may
actually provide simpler explanations for a
variety of phenomena.

The complexity perspective also illuminates
the interplay between the fragility and stability
that characterizes many of the phenomena
explored by behavioral and social scientists. On
the one hand, under certain conditions even a
small change in a system's parameters can
produce dramatic effects. According to Holland
(1995), locating these lever points is essential
for producing major predictable and directed
change in the system. On the other hand, within
different parameter ranges, the same system
stubbornly refuses to change, and displays a
constancy that confounds all efforts directed
toward its alteration (whether measured in time,
money, or creative energy). In regard to this
discrepancy, Nowak, Vallacher, and Lewenstein
(1994) explained that a system's resting state
equilibrium can range from unstable to super-
stable. In the former condition, a slight external

influence can profoundly impact the system; in
the latter circumstance, the system eventually
returns to its equilibrium state regardless of the
outside force's magnitude.

For the behavioral or social scientist, the
identification and investigation of CAS can be
facilitated in several ways. Nowak, Vallacher,
and Lewenstein (1994) have recommended
looking for regularities or patterns rather than
focusing solely on uncovering one-way causal
links between variables; *bidirectional causality*,
in which each variable is simultaneously both a
cause and an effect, is commonplace in complex
systems. Within these observed patterns of
behavior, it may be possible to detect signs of
nonlinearity, including bifurcations and hyster-
esis. Such identifications obviously require
multiple observations over time (e.g., time-
series analyses). More generally, the mecha-
nisms underlying a system's organization can be
clarified both by observing as the system's
intrinsic dynamics unfold naturally and also by
deliberately perturbing the system and evaluat-
ing its response (Nowak, Vallacher, & Lewen-
stein, 1994).

In a related manner, Kelso (1995) has stressed
the importance of focusing on a system's
instabilities. It is at these critical points that
changes in patterns of behavior are most readily
distinguished. Furthermore, such points can offer
the best opportunity to identify the control
parameters that are in all likelihood relevant to
the system's linear behavior as well. More
generally, Kelso advises that knowledge is
necessary in three areas in order to understand a
particular complex adaptive system: (a) the
parameters that act on the system, (b) the
individual components that compose the system
itself, and (c) the behavioral patterns that
emerge from the interactions among these
components.

The effective study of complex adaptive
systems also requires the use of appropriate
techniques for data analysis. Important nonlin-
ear relationships among variables—a hallmark
of CAS—can go undetected if only traditional
statistical methods are used (e.g., Barton, 1994).
As Holland (1995) explained, "Nonlinearities
mean that our most useful tools for generalizing
observations into theory—trend analysis, deter-
mination of equilibria, sample means, and so
on—are badly blunted" (p. 5). For example,
critical information can be lost when parameter

values are averaged; such an approach often disguises or conceals temporal phenomena (e.g., cycles) characteristic of complex adaptive systems (Nowak, Vallacher, & Lewenstein, 1994).

Similarly, the traditional cross-sectional study is of limited usefulness in analyzing behavioral or social systems that evolve over time (e.g., Gregersen & Sailer, 1993). Although inherently more difficult and expensive, longitudinal studies with multiple observation points enable the researcher to more realistically capture such a system's dynamics. Even with this approach, abrupt phase transitions may nevertheless be difficult to detect reliably because they typically occur within only a narrow band of the system's full range of operation (Kruse & Stadler, 1993). In a related manner, Gregersen and Sailer (1993) have pointed out that the examination of chaotic systems can be perplexing because they can display ordered behavior over a large part of their domain.

As suggested by the many examples presented in this paper, the computer simulation or numerical experiment is an especially important tool for behavioral and social scientists conducting complexity research. Indeed, simulations of actual phenomena are far more common than traditional experiments in this arena. A large and diverse group of investigators have endorsed and used the methodology (e.g., Allen, 1982; Axelrod, 1986; Glance & Huberman, 1994; Holland & Miller, 1991; Kauffman, 1993; Mayer-Kress, 1990; Messick & Liebrand, 1995; Nowak, Vallacher, & Lewenstein, 1994), although the simulation approach has its drawbacks too. For example, it inevitably puts some distance between the researcher and his or her subject of inquiry (e.g., Kelso, 1995). Furthermore, the models on which the simulations are based may themselves be faulty or oversimplified (e.g., Barton, 1994). Important variables may inadvertently be excluded; the relationships among parameters may be misspecified. Because of these and other potential distortions, comparing simulation results to real-world behaviors and social patterns is a mandatory step in the model-building and testing process.

It is important to recognize that the inherent complexities of the phenomena of interest place limits on the methods by which researchers can effectively study them. Writing about this issue, Holland (1995) stated, "The traditional direct bridge between theory and controlled experi-

ment is all but impossible in this situation. We cannot follow the traditional experimental path, varying selected variables under repeated runs while holding most variables fixed, because controlled restarts are not possible with most *cas*, and because some *cas* operate over long time spans" (p. 160). In a similar manner, many other investigators have emphasized that the theoretical models applicable to complex adaptive systems are often so complicated that computer simulations become necessary because even advanced analytical mathematics prove insufficient (e.g., Axelrod, 1986; Kollman, Miller, & Page, 1995; Messick & Liebrand, 1995; Miller, 1995; Nowak, Vallacher, & Lewenstein, 1994).

Another important virtue of computer simulations is that this methodology forces the investigator to carefully and precisely specify a model as a preliminary step in the research process. The exercise of writing the program itself can provide a test of the theory's completeness while highlighting any internal contradictions (Nowak, Szamrej, & Latane, 1990). When the simulation is then run, the consequences of the specific rules and relationships among variables can readily be observed. Mayer-Kress (1990), for example, pointed out that the use of simple computer models can uncover "possible counterintuitive consequences of decisions that appear to be good solutions at the time they are made" (p. 181).

Several other benefits to the simulation approach are detailed by Holland and Miller (1991). First, the use of *artificial adaptive agents* compels researchers to clearly specify their assumptions and also enables them to observe the behavior of their "subjects" step-by-step as it unfolds. Second, important parameters such as the amount of information available to the agents, their expectations, and how quickly they learn can be precisely determined and systematically modified. Third, the features of the environment can also be varied to explore alternative scenarios. Finally, and of no small significance, the artificial agents' "infinite patience and low motivational needs . . . implies that large-scale experiments can be conducted at a relatively low cost" (p. 366).

The complex adaptive systems perspective, with its dynamical models and computer-intensive research strategies, should not be viewed as a panacea for the puzzling and

intricate issues with which behavioral and social scientists must grapple. Nevertheless, this paper documents that complexity theory has already generated some important theoretical insights and research findings in psychology, sociology, economics, and political science. At this point, the cumulative evidence appears to confirm the legitimacy and potential for the approach; additional strides must now be taken both to refine the paradigm and to integrate it into the mainstream "toolbox" of researchers in diverse disciplines.

To achieve these next steps, however, broader implementation and evaluation—by both advocates and skeptics—are required. In particular, metaphors must be distinguished from working models and intriguing ideas must be honed into testable hypotheses. Furthermore, the statistical and computer-based skills necessary for studying complex adaptive systems must become more readily and widely available to interested parties. In all likelihood, progress will be most effectively accomplished through increased collaboration among researchers with differing perspectives and areas of expertise.

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