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18 Organizational and Individual Decision Making

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18.1 INTRODUCTION

Organizations do not make decisions, people do. This observation is a statement of both structural and operational fact: organizations (as physical realities, not accounting or legal entities) are made by, and are composed of, people. There may be transportation, transformation, technological computation, and communication infrastructures to support human decision makers. These infrastructures generally have differential impact on the individuals in question. These infrastructures affect what information people have access to, and so what decisions they make. Nevertheless, organizations are all created, supported, maintained, and operated by these individuals. Thus, the issue of socially constrained, but nevertheless indvidual, decision making, lies at the heart of research on organizational decision making.

That humans make up organizations is neither a questionable nor a key issue from an organizational decision-making perspective. What is important is whether any (or all) of individual behavior can affect the constructs theorized or measured at the organizational level. Some researchers have argued that human behavior is largely irrelevant. For example, Schelling (1978) presents the game of musical chairs as an example of a class of organizational behavior patterns that are realized in the aggregate independent of how the individuals who form the aggregate behave (within the rules of the game). No matter how the individuals play the game, one will always be left without a chair. Thus, if one has a theory of the game, the players are simply agents carrying out the rules and roles of the game, and general outcome can be predicted without models of the individual agents (again, as long as they play by the rules). Thus the form of the game itself makes the specific model of the individual agent irrelevant. Second, it has been argued that because of scale, the specific model of the individual agent is irrelevant. This would suggest that for markets, national economies, and social structures, it is important to measure the aggregate or collective behavior of players, but not the individual microprocesses underlying these individual behaviors. In this sense, individuals may be (succinctly) represented in an aggregate manner (e.g., a production function or a cost curve) that reflects their collective behaviors. Third, it has been argued that there are general principles of organizing that are true for any collection of entities and not peculiar to humans. Thus, these principles should be applicable to any collection of intelligent, adaptive agents, such as individuals, Webbots or robots, engaged in distributed and collaborative work.

Establishing a model of the individual agent requires making a series of simplifying assumptions. For Schelling (1978) these assumptions include that the game does not

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change and that the agents follow the rules of the game. In neoclassical economics and political economy, on an aggregate level (for macroeconomics, the industry; for microeconomics, the firm), there are underlying assumptions of the participating agents' perfect knowledge and perfect choice. Making simplifying assumptions is an important step in science. For some types of questions these are acceptable simplifying assumptions. Nevertheless, it should be realized that these assumptions, as a representation of decision-making reality within organizations, are largely incorrect. Organizations, like games, are "artificial" in the sense that they are crafted by humans (Simon, 1981a). But, unlike many games, organizations are very volatile or fluid constructs. Within organizations it is the norm that the rules change, the players change, and the situations change (Cohen et al.,

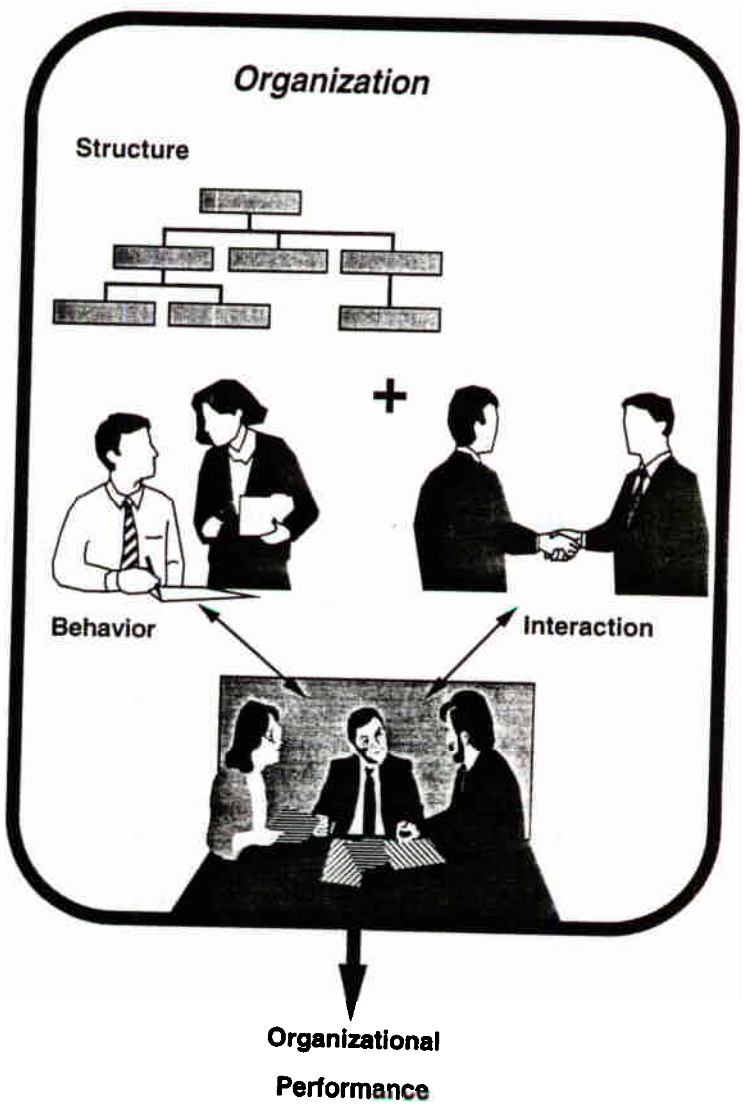

Figure 18.1 Factors afffecting organizational performance.

1972; March and Romelaer, 1976). This volatility is due in large part to the agents who compose them. Hence, within organizations, the form of the game depends on the agents and their personal history. From a managerial perspective, this strong interaction between cognition and task opens the avenue to strategies involving changing not just the task but the type of agents who engage in a task to achieve a particular level of performance.

Now consider the scale argument. The rational expectations model opposes much of what is known of human reasoning (Simon, 1979) and as a representation of decision making is largely incorrect (Simon, 1959, 1979). The principles of organizing argument is, from an organizational standpoint, the most intriguing. This argument cannot be easily wiped away by pointing to the interaction between agent cognition and task. Rather, the issue here forces the researcher to establish the general principles and then generate the conditions under which, and the ways in which, agent cognition matters.

For the most part, organizational theorists interested in individual and organizational decision making take this latter perspective and argue for the relevance of the agent model. In this case, organizational behavior is seen as an emergent property of the concurrent actions of the intelligent adaptive agents within the organization. This body of research has been informed by the work in distributed artificial intelligence, computational biology, information systems, social networks, behavioral decision theory, and human computer interaction and is influencing work in organizations, particularly that on organizational decision making and distributed work.

In summary, organizational performance is a function of both individual actions and the context in which individuals act (see Fig. 18.1). This context includes the web of affiliations in which the individual is embedded, the task being done, and the organization's structure and extant culture. Any model that does not include both individual cognition and context and the way in which these mutually coadapt will not be able to explain or predict behaviors associated with collaborative and distributed work.

18.2 THE INDIVIDUAL IN THE ORGANIZATION

Perhaps the individual who could best be described as the founder of the work on individual decision making within organizations would be Chester Barnard. In 1938, Barnard published the book, *The Functions of the Executive*. His analysis of individuals in organizations, particularly of individuals in cooperative systems, was the precursor for many future studies, as was the work by Roethlisberger and Dickson (1939). Barnard's work suggests that others' evaluations, particularly the manager's, directly affect concrete rewards such as pay. Feelings of fairness and equity in how one is treated in an organization stem from discrepancies between self and others' evaluations. Such discrepancies, therefore, should affect job satisfaction, organizational commitment, performance, and turnover. However, extensive studies of the relationships among job satisfaction, organizational commitment, individual and organizational performance, and personnel turnover have led to a set of complex and inconsistent results (Mowday et al., 1982; Mobley, 1982). Moving beyond this subarea, however, major advances in individual and organizational behavior have followed from alternative perspectives. Among these alternative perspectives are a predominantly psychologically and economically based behavioral perspective, an information-processing perspective, a cognitive perspective, and a structural or social network perspective.

18.2.1 The Individual as Behavioral Agent

Outside the field of organizations per se, there is an enormous body of research on individual decision making. Somh of this work lies in the field known as Behavioral Decision Theory (BDT). Depending on the perspective chosen by organizational researchers, BDT concepts have been applied to many levels: the individual in organizations, the individual in groups, or groups in organizations. Interestingly, not unlike the delineation between researchers of culture and those who research climate (Dennison, 1996), BDT seems to have two antecedent streams of research that can be grossly categorized as the psychological/descriptive approach and the economic/normative approach. Whereas both streams of research are considered predictive, the economic approach focused on the rational decision maker, and the approach that is somewhat more psychologically based attempts to describe and explain consistent deviations from rationality. It is this attempt by both psychologists and behavioral economists to explain fluctuations from rationality that can best be described as the field of Behavioral Decision Theory.

Although many individuals consider Bernoulli (1738) to be the forefather of modern day BDT, the major innovation to the concept of a rational decision process must be attributed to von Neumann and Morgenstern, with their publication of the book *Theory of Games and Economic Behavior* in 1947. This book, laid the framework for what was later to be referred to as Game Theory (see also Luce and Raiffa, 1957). Von Neumann and Morgenstern (1947) made explicit the assumptions and constraints that would provide for a rational (i.e., consistent and predictable) decision. This economic approach resulted in what is referred to as Expected Utility (EU) Theory. After von Neumann and Morgenstern (1947), researchers suggested variations on the strict interpretation of EU, still from the perspective of economics. Savage (1954) suggested that the actual process of decision making was modeled through a subjective expected utility. Moreover, researchers were (and still are) trying to develop methods to measure the difficult concept of utility (Marschak, 1950; Becker et al., 1964; Edwards, 1992). As Dawes (1988) wrote, "People, groups, organizations, and governments make choices. Sometimes the consequences of their decisions are desirable, sometimes not" (p. 2). Or, in a related vein, as others have argued, the choices made by individuals and groups are not rational (where rational is defined as making that decision predicted by EU theory). It was not until the 1970s and early 1980s that further major revisions to EU theory were published. Kahneman and Tversky (1979) broke ground with their Prospect Theory, which suggested that individuals have a different perception when considering losses vs. gains. Machina (1982) attempted to describe EU when one of the assumptions, called the independence axiom, is relaxed. Both Bell (1982) and Loomes and Sugden (1982) suggested that decisions were made on the basis of regret (i.e., what could have been) instead of the expected benefit (i.e., utility) of an outcome.

Essentially, this work has led to a wide range of findings concerning departures from rationality and biases common to social judgment processes (Ross et al., 1977; Kahneman et al., 1982). This research includes that on the framing effect (Tverksy and Kahneman, 1981), false consensus effect (Dawes and Mulford, 1996; Dawes, 1989, 1990; Orbell and Dawes, 1993), group think (Janis, 1982), and altruism (Orbell et al., 1988; Orbell and Dawes, 1993). The false consensus bias is premised on an individual's belief that everyone responds in the same manner as they do. In fact, we overestimate the degree to which our past behavior, as well as our expected behavior, is truly diagnostic of other individuals' future behavior. BDT and social psychology have examined this bias and have assessed that it is prevalent among individuals (Dawes and Mulford, 1996). Groupthink, on the other hand, is the tendency in groups for a convergence of ideas and a sanctioning of aberrant ideas to occur. Related to groupthink are the concepts of group polarization, and risky shifts (Pruitt, 1971a,b). However, this overdetermination of either the group's or an individual's future behavior is not seen when we examine how individuals compare themselves to others. In general, over 50 percent of the population, when asked to rate themselves on some mundane task, such as driving ability, see themselves as better than average. Of course, this is statistically impossible.

Biases also exist in the way individuals make judgements about individuals, future events, or causes. These biases are due in part to the personal characteristics of the individuals making the judgments (Fischhoff et al., 1981; MacCrimmon and Wehrung, 1986), as well as certain cognitive heuristics (i.e., mental short cuts or limitations) to which all of us are prone (Kahneman et al., 1982; Plous, 1993).

Kenneth MacCrimmon and Donald Wehrung (1986) provide a framework, as well as an assessment tool, which describe the risk propensity of a given individual. In addition, MacCrimmon and Wehrung describe the risk-taking behavior of 509 top-level executives and allow the readers to compare themselves with these managers. Borrowing from Fischoff et al. (1981), making choices under uncertainty predicates the prior judgment of (1) the uncertainty about the problem definition; (2) the difficulty in assessing the facts; (3) the difficulties in assessing the values; (4) the uncertainties about the human element; and (5) the difficulties in assessing the decision quality. It is this judgment process, affected by the risk propensity of various managers which MacCrimmon and Wehrung discuss. Of course, outside of the personality or characteristics of each manager (i.e., their risk propensities) there are also cognitive and perceptual biases that would need to be understood in order to understand theories of human action in organizations or in society. Amos Tversky and Daniel Kahneman (1974) discuss a number of the different types of biases inherent in the decision-making process that affect, if not all, the vast majority of us, at least unconsciously. Some of the heuristics that lead to biases discussed and elaborated in the book edited by Kahneman et al. (1982) are representativeness, availability, and adjustment and anchoring.

The representativeness heuristic suggests that individuals base judgements on similarity of characteristics and attributes. As Tversky and Kahneman (1974) suggest, people often make judgments based on "the degree to which A is representative of B, that is, by the degree to which A resembles B" (p. 1124). The representative heuristics can lead to the belief in "the law of small numbers," that is, that random samples of a population will resemble each other and the population more closely than statistical sampling theory would predict (Plous, 1993). Moreover, utilizing the representative heuristic can also result in people ignoring base-rate information (a base rate is the relative frequency an occurence is seen in the general population). The representative heuristic might be seen as a not-too-distant cousin to the availability heuristic.

The availability heuristic is the mental shortcut that allows individuals to "assess frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind" (Tversky and Kahneman, 1974, p. 1127). This heuristic does not necessarily result in a biased judgment. However, it can when the majority of available information is inaccurate because of recency or primacy effects. For example, the likelihood that your car is going to be stolen might very well be affected by the saliency of the information that your next door neighbors had their car broken into twice in the last two years. However, we rarely ask our other neighbours how often their cars have been broken into. Thus, the neighbor's information may become more salient only in our making the decision to purchase an antitheft device.

The heuristic of adjustment and anchoring causes extreme variations among judgments of individuals. This heuristic suggests that we take a piece of information, even a randomly chosen (i.e., noninformative) one, and then attempt to adjust our judgments around that piece of information. In other words, if I were to ask you the estimated income from a new sales project and told you that project alpha last year earned $40,000 your estimate for the expected income would be higher than if I told you that it only earned $4,000. Judgment makers tend to unconsciously anchor on a number and insufficiently adjust (either up or down) around that anchor. In fact, if I just had a wheel with dollar amounts ranging from $400 to $4,000,000 and spun a pointer so that it randomly landed on one value, your estimate would still be anchored and your judgment would be biased accordingly.

Thus, individual judgments of future events, outcomes, or processes are strongly affected by the information we perceive, we can remember, and the degree to which we are willing to expend energy on the judgment process. These judgment heuristics and the respective biases can be seen as limitations on the degree to which we can process information in a thorough and consistent manner (i.e., act rationally). They often lead to human and organizational error, a subject discussed in Chapters 17 and 19.

18.2.2 The Individual as Information Processor

The Carnegie School of Organizational Theory proposed an information-processing perspective in which individual and organizational decisions could be explained in terms of what information was available to whom, cognitive limits to information processing abilities, organizational (social and cultural) limits to access to information, the quality of the information, and so forth. Simon (1945), March and Simon (1958), and Cyert and March (1963) examined the decision-making components of organizational and firm action. Whether the decision was to restructure the organization or to outsource a given product, the firm was believed to follow a number of decision-making procedures prior to determining a solution. These procedures can be usefully represented using either formal logic or expert systems (Leblebici and Salancik, 1989; Salancik and Leblebici, 1988; Masuch and LaPotin, 1989). These procedures are both social and cognitive, are embedded in organizational routines and in individuals' mental models, and do not guarantee that the individual or the organization will locate the optimal solution for any particular task. Rather, individuals and organizations satisfice (Simon, 1959), that is, they make do with a decision that is satisfactory rather than one that is definitely optimal. Studies suggest that individuals in making decisions examine only a few alternatives, and even then do not consider all of the ramifications of those alternatives. As a result, decisions are more opportunistic than optimal.

This stream of research, which came to be known as part of the information-processing perspective, was later to include a rather well-known metaphor—the garbage can. Cohen et al. (1972) proposed a model of organizational choice that they entitled "A Garbage Can Model." Padgett (1980), Carley (1986a,b), and others went on to expand on this theory. According to this theory, organizational decision is a function of the flow of individuals, problems, and solutions. Individuals do not evaluate all possible solutions to a specific problem. Rather, in making a decision, individuals are prone to simply attach their favorite solution. Futher, whether or not a decision is actually made is a function of the effort that individuals expended on the problem and the number of individuals currently available to work on the problem. Researchers following Cohen et al. (1972) argued that the early model was insufficient to capture actual organizational behavior, as it ignored the role of organizational design and the limits on individual behavior dictated by organizational procedures such as those for data handling and personnel hiring. Recently, Carley and Prietula (1994b) demonstrated that to get interesting and detailed organizational predictions, one had to move beyond these models by incorporating a model of agents, organizational structure and situation, and task. In particular, task places an extremely strong constraint on individual and organizational behavior.

Information-processing theorists (March and Simon, 1958; Cyert and March, 1963; Galbraith, 1973, 1977) and social-information-processing theorists (Salancik and Pfeffer, 1978; Rice and Aydin, 1991) have argued that individual, and hence organizational, decisions depend on what information they have that in turn is constrained by the individual's position in the social structure. Structure influences individual decision making because it constrains access to information and because the decisions, attitudes, and actions of those to whom one is structurally connected have a strong influence on behavior. Further, the structure of the organization and the task limits access to information, determines the order of processing, and enables certain efficiencies. Moreover, the organizational structure can be viewed as a coordination scheme whose cost and performance depends on the network of connections and procedures within the organization (Malone, 1987; Krackhardt, 1994; Lin, 1994). Organizational slack as well as performance is thus a function of these information-processing constraints. This work is consistent with the arguments forwarded by, and is often carried out by, social network theorists.

18.2.3 Individuals as Intelligent Adaptive Agents

Organizations can be usefully characterized as complex systems composed of intelligent adaptive agents, each of which may act by following a set of relatively simple procedures or routines. However, if the agents coadapt, then the organization as a whole may exhibit complex patterns of behavior. In such systems, linear models cannot capture the complexities of behavior. Consequently, the level of prediction possible from the linear model is low.

Recently, computational organizational theorists and researchers in distributed artificial intelligence (DAI) have begun to study organizational adaptation, evolution, and learning using complex intelligent adaptive agent models. An intelligent adaptive agent is an agent (or set of agents) that makes decisions on the basis of information, but that information changes over time in response to the environment. Thus the agent (or set of agents) learns responses and may improve performance. An example of an intelligent adaptive agent would be an automated Web browser that searches for information on a particular topic, but it learns as it does so the preferences of the user for whom it is browsing. Models in this arena include those using simulated annealing, genetic programming, genetic algorithms, and neural networks. Some of these analyses focus on the evolution of industries and the sets of organizations within a market, rather than adaptation within a single organization (Axelrod, 1987; Axelrod and Dion, 1988; Crowston, 1994, 1998; Holland, 1975; Holland and Miller, 1991; Padget, 1998). Others explore issues of organizational performance and experiential learning (Carley, 1992; Lin and Carley, 1998; Verhagan and Masuch, 1994; Mihavics and Ouksel, 1996) or expectation-based learning (Carley and Svoboda, 1998). Another stream of research has occurred within DAI, one in which researchers have focused on the effect of coordination and communication among intelligent agents on performance (Durfee and Montgomery, 1991; Tambe et al., 1997).

These three streams of research collectively demonstrate the power of computational models and the intelligent adaptive agent approach for theorizing about organizational dynamics. These models employ the use of "artificial" agents, acting as humans. The agents in these complex intelligent adaptive multiagent models are nondeterministic and undergo a coevolutionary process. During their lifetimes, they may move through and interact with the environment, reproduct, consume resources, age, learn, and die. Although the agents are typically adaptive, they may vary in their intelligence and complexity. Using these models the researchers generate a series of predictions about the behavior of the system. Because the agents are artificial, the predictions may be equally applicable to organizations of humans and to organizations of "nonhumans" (Webbots, robots, etc.) Depenting on the assumptions built into the agent models, the results may be interpreted as predictions about organizing in general or about organizing in a particular context. Research is needed in this area to determine when artificial and human organizations are similar (Carley, 1996).

Most researchers in this area contend that organizational dynamics are due to, and may even emerge from, the adaptiveness of the agents within the organization. This process has been referred to by a variety of names, including colearning (Shoham and Tennenholtz, 1994), synchronization, and concurrent interaction (Carley, 1991b). For Carley (1991a) concurrent interaction and the coevolution of self and society is necessary for the emergence of social stability and consensus. For Shoham and Tennenholtz (1994) colearning is "a process in which several agents simultaneously try to adapt to one another's behavior so as to produce desirable global system properties." Collectively, the findings from these models indicate that emergent social phenomena (such as the emergence of hierarchy) and the evolutionary dynamics (patterns of change) depend on the rate at which the agents age, learn, and the constraints on their adaptation of interaction.

18.2.4 The Individuals' Mental Models

An alternative perspective on individual and organizational decision making has arisen out of the cognitive sciences. Here the focus is not on what decisions are made, or on rationality per se, but on how the individual and the team thinks about problems (Reger and Huff, 1993; Johnson-Laird, 1983; Klimoski and Mohammed, 1994; Eden et al., 1979; Carley, 1986c; Fauconnier, 1985; Weick and Roberts, 1993). As such, researchers draw from and make use of work on the coding and analysis of individual and team mental models. This research derives from work in cognitive psychology, philosophy, and artificial intelligence. Recent advances in textual analysis point to a future in which intelligent systems will exist for parsing and coding texts (Bechtel, 1998; Golumbic, 1990; Gazdar and Mellish, 1986; Winghart, 1988; Zock and Sabah, 1988). Since these techniques enable more automated coding of texts, they should make possible the analysis of larger quantities of texts, and thus make possible the empirical analysis of complex processes such as team mental model formation, negotiation, and the use of organizational rhetoric in establishing organizational effectiveness.

The expectation is that these systems will enable the researcher interested in individual and organizational decision making to move beyond content analysis to more relational modes of text analysis (Schank and Abelson, 1977; Sowa, 1984; Roberts, 1989, 1998) The expectastion is that by examining not just words, but the relations among concepts within the text, the researcher will be better able to analyze differences in meaning across individuals, groups, and organizations (Roberts, 1998; Carley and Palmquist, 1992; Carley, 1994; Carley and Kaufer, 1993; Kaufer and Carley, 1993). By focusing not just on words but on the relationships among the words present in the texts, researchers can examine texts for patterns of cognitive behavior, decision-making protocols, and can trace the logic of arguments. Texts as networks of concepts can then be analyzed using standard social network techniques (Carley, 1998a). Additionally, narratives or stories can be analyzed as event sequences (Heise, 1979, 1991; Ericsson and Simon, 1984), thus enabling organizational researchers to address the relationship between individual action and organizational behavior. An advantage of these techniques is that they allow the researcher to take rich verbal data and analyze them empirically. Empirical analysis makes it possible to statistically test hypotheses about the formation, maintenance, and change in team mental models over time and across teams.

Individuals' mental models can be characterized as the information known by the individual and the pattern of relationships among these pieces of information (Carley and Palmist, 1992). A mental model is not just all the information that in an individual's head. Rather, a mental model is a structure of information that gets created, and can be called up or used, in specific contexts. Individuals have many mental models about themselves, others, objects, the world, tasks, and so forth. These mental models include social, historical, cultural, environmental, personal, and task knowledge, and are specialized based on varying contexts and needs. From an organizational perspective it is useful to note that an individual's mental model includes the individual's perception of the sociocognitive structure—the sets of relations that an individual perceives as existing between other pairs of individuals (Krackhardt, 1987, 1990) and their understanding of others' knowledge and beliefs (Carley, 1986c). Problem solving involves searching through the set of salient mental models. As such, mental models influence not only what decisions individuals make, but their perceptions of others' decisions. According to this perspective, cognition mediates between structure and outcome, that is, it is the individual's perception of social structure (as encoded in the individual's mental model) that influences behavior, attitudes, evaluations, and decisions, and not the structure itself (Carley and Newell, 1994).

Individuals' mental models are thought to develop as they interact with other individuals. As a result, concurrent actions, interactions, and adaptations emerge more or less simultaneously at the individual, organizational, and social levels (Carley, 1990a, 1991a; Kaufer and Carley, 1993). In particular, individuals construct definitions of self that depend on their sociocultural–historical background and their interactions with others (Greenwald and Pratkanis, 1984; Higgins and Bargh, 1987; Markus, 1983). Individuals' mental models not only contain different information (as a result of their private history of interaction with others), but individuals may use the same information in different ways in making decisions. Attributions are a type of decision that has been widely studied from the mental mode perspective. Despite this research, how individuals make attributions about self and others remains unclear. For example, Heider suggested that a "person tends to attribute his own reactions to the object world, and those of another, when they differ from his own, to personal characteristics" (Heider, 1958, p. 157). This idea was extended by Jones and Nisbett (1972), who claimed that all attributions reflect the following bias: individuals tend to think that they themselves are responding to the situation or environmental demands, but they generally see others as behaving in particular ways because of their personality traits. In contrast, Bem (1965) argued that there is no difference in the factors individuals use to make attributions about their own and others' behavior. In their review of the literature Monson and Snyder (1977) concluded that there are systematic differences between attributions of self and others. However, the differences are not consistently in the direction predicted by either Heider or Jones and Nisbett. In fact, the differences appear to be a function of both cognitive and structural factors.

Often in individuals' mental models, people do not seem to discriminate between causality and correlation. People appear to construct correlations to confirm their prior expectations about what causes what (Chapman and Chapman, 1967, 1969). People appear to look for salient cues in suggesting causal links, rather than simply computing them from the statistical occurrences, as Heider had suggested. As such, individuals seek out obvious indicators of what they think should be causing some outcome and use such cues to make predictions about another's behavior or attitude. A possible explanation for this is that ambiguity in the organization may make evaluation of others difficult (Festinger, 1954). This forces individuals to use cues, as they are not privy to direct or statistical knowledge (Salancik and Pfeffer, 1978). Further, for some types of decisions, it may not be possible to determine the requisite information. For example, consider decisions that require evaluating an individual's contribution to a collaborative project. For this type of decision, it may not even be possible to evaluate the separate contribution of each organizational member (Larkey and Caulkins, 1991); thus, the decision maker must rely on organizational cues.

The relation of individual mental models to team mental models, and the value of team mental models to team and organizational performance are currently the subject of much debate. The construction of and change in team models is seen as integral to collaborative work. Differences in individual mental models are seen as potentially valuable in collaborative projects, as they enable the organization to learn from different individual's experiences (Knorr-Cetina, 1981; Latour and Woolgar, 1979). Team mental models are seen as critical for team learning and team performance, as they provide a shared understanding that enables action in the face of ambiguity and without making all information explicit (Hutchins, 1990, 1991a,b). Polanyi (1958, esp., pp. 216–219, 264–266) implicitly defined social knowledge and so team mental models as the articulation of "common experience." Thus, through articulation, a "tacit consensus" and understanding are developed. For Polanyi, social knowledge requires a transitivity of appraisal across a continuous network of individuals. What this means is that each piece of social knowledge in the team mental model is commonly, but not necessarily uniformly, shared. As such, the team mental model represents the tacit consensus to a set of information. It is not necessary for all members of a team to know that a piece of information is part of a team's mental model for it to be included. In contrast, Klimoski and Mohammed (1994, p. 422) suggest that a team mental model is an emergent group phenomenon. Since these team mental models facilitate group coordination and the allocation of resources "some level of awareness is necessary." In this case, there is a need for actual and not simply tacit agreement in order for a piece of information to be part of the team mental model. Among the issues being currently investigated in the area of distributed work is the extent to which individuals should share their mental models if they are to operate effectively as a team, and whether certain types of information more commonly appear in team mental models than others.

18.2.5 The Individual and the Social Network

From both an information-processing and a structural perspective has come a view that the organization, particularly its design or architecture, can be characterized as networks of people, tasks, and resources. In particular, attention has been paid to social network models of organizations and sets of organizations that are described in terms of the relationships or ties among individuals or organizations (for reviews, see Krackhardt and Brass, 1994). Researchers distinguish between the formal organizational structure (the organizational chart dictating who must report to whom) and the informal organizational structure (the emergent set of advisorial and friendship relations among the individuals in the organization). Social network models have successfully been used to examine issues such as organizational adaptation (Carley and Svoboda, 1998), power (Burt, 1976, 1992; Krackhardt, 1990), diffusion (Burt, 1973; Carley and Wendt, 1991; Carley, 1995a; Granovetter, 1973), changing jobs (Granovetter, 1974), structuration (DiMaggio, 1986), innovation (Burt, 1980), and turnover (Krackhardt, 1991; Krackhardt and Porter, 1985, 1986). These studies demonstrate that the structure of relations, both within and between organizations, in and of itself can affect individual and organizational behavior. Moreover, the informal structure often has as much or more influence on behavior than does the formal structure. This is probably particularly true for distributed teams. In teams and collaborative work groups, individuals are linked informally by many types of ties, including monetary, advisorial, and friendship (Boorman and White, 1976; White et al., 1976; Burt, 1976, 1977). The greater the overlap of different types of ties, the more effective the relationship and the more constraining on individual and group decision making.

Organizational learning is also intimately tied to the sharing or diffusion of information. As noted by Granovetter (1973, 1974), connections or ties among individuals determine what information is diffused and to whom. However, the strength of the ties among individuals may actually inhibit information diffusion. One reason for this is that in groups where the level of shared information is high, communication may tend to become ritualized and centered on repeating known information (Kaufer and Carley, 1993). In this case, the likelihood of new information diffusing along existing ties can actually decrease as individuals within the organization work together and become more similar in what they know. We can think of this as collaborative teams becoming stale over time as no new members are added. Both the level and pattern of ties among individuals in the group influences the speed with which information spreads and whom it spreads to (Becker, 1970; Burt, 1973, 1980; Coleman et al., 1966; Granovetter, 1973, 1974; Lin and Burt, 1975) and when it jumps organizational boundaries (Carley, 1990b). Individuals who are more tightly tied are less likely to be innovators (Burt, 1980), but may be more important in mobilizing others for change, which may be important for the development of coalitions such as unions or strikes (Krackhardt, 1990; Carley, 1990a). Further, Burt (1992) suggests that individuals can learn to control their corporate environment, their own career within the organization, and the organization's ability to respond to events by controlling the pattern of ties among individuals within the organization. Information technologies, however, may influence the pattern of these ties (Freeman, 1984) and their relative effectiveness for communicating different information (Carley and Wendt, 1991). Advances in the area of diffusion that are particularly relevant to organizations have been made by researchers using social network techniques. This work demonstrates that how integrated the individual is into the organization influences the likelihood that this person will diffuse new information and adopt innovations (Burt, 1973, 1980; Kaufer and Carley, 1993).

Finally, this research has demonstrated that there is no single adequate measure of structure (Krackhardt, 1994; Lin, 1994). This is true even if the focus is exclusively on the formal structure. The situation is compounded when one considers that the organization is really a composite of multiple structures such as the command structure, communication structure, task structure, and so forth. Thus, to understand the impact of structure on

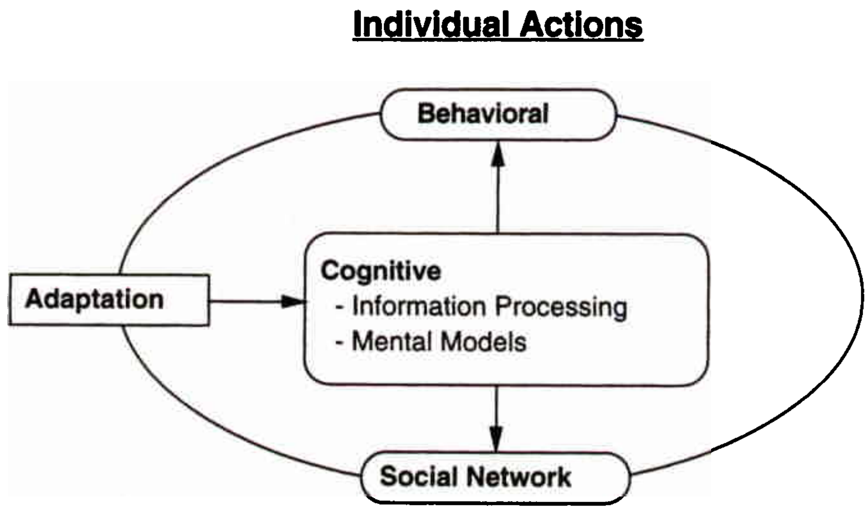

Figure 18.2 Factors affecting individual actions.

collaborative work and distributed teams, it is necessary to simultaneously consider many measures.

18.2.6 The Situate Individual

Collectively these perspectives on the individual are leading to a broader understanding of the individual as a situated agent in the organization. Individual cognition mediates the individual's actions in, responses to, and interpretations of the context in which the individual is working (see Fig. 18.2). This cognition comprises both an architecture for processing information and a suite of mental models. The individual, however, is an intelligent adaptive agent. Through adaptation the individual changes the content, number, and type of mental models that are drawn on. Unlike some work on individual adaptation, however, within organizations the individuals' adaptation is constrained by their previous behaviors and their positions in the social network and organizational structure. Thus it is important to link a more macroperspective on the organization as a whole with the more microperspective on the individual.

18.3 THE ORGANIZATION

The vast majority of organizational decisions require attention from multiple individuals. That is, they are not the result of a single individual acting in isolation. Much of the research in organizational theory has been focused on examining how the organization's form, design, the task the individual is engaged in, or the environment in which it operates influences the decisions made by the organization. Decision makers may have access to different information, may have access to different technology for evaluating and gathering information, may have different criteria or goals for evaluating that information, may have different training or skills, and so forth. Thus, factors such as information flow, lack of resources, attention, timing, commitment, the degree to which consensus needs to be reached, and organizational design have as much influence on the organizational decision as the cognitive process by which individuals make decisions. Clearly both the social network and the information-processing approaches previously discussed point in this direction. Building on these traditions and other research on organizational design, researchers have begun to use computational models to address issues of organizational decision-making performance, learning, and adaptation.

18.3.1 Computational Organization Theory

Organizational decision-making theory has been strongly influenced by computational approaches (Ennals, 1991; Carley, 1995b). Early work was influenced by research in the areas of cybernetics and general systems (Ashby, 1956), system dynamics (Forester, 1961), economics and cognitive psychology (Cyert and March, 1963), information technology (Bonini, 1963), and social behavior and process (Dutton and Starbuck, 1971). Cyert and March's *A Behavioral Theory of the Firm* (1963) is a landmark text for organizational theorists interested in formal models. Cyert and March demonstrated the impact of bounded rationality on organizational decision making and the value of process models for understanding organizational decision making. With this work, a tradition began in which the organization is modeled as a collection of agents (who are at least boundedly rational), organizational behavior emerges from the concurrent interactions among these agents, and decisions are constrained by both agent capabilities and the social structure in which the agents are placed. In the past three decades there has been a tremendous growth in the use of mathematical and computational models for examining organizational decision making, particularly in complex or distributed settings. This area has come to be known as *computational organization theory*.

Computational organization theory focuses on understanding the general factors and nonlinear dynamics that affect individual and organizational behavior (Masuch and Warglien, 1992; Carley and Prietula, 1994a; Carley, 1995b) with special attention on decision making, learning, and adaptation. In these models, information, personnel, decision responsibility, tasks, resources, and opportunity are distributed geographically, temporally, or structurally within, and sometimes between, organizations. These models extend work in team theory by focusing on the nonlinear dynamics (Marschak, 1955; McGuire and Radner, 1986; Radner, 1993). Organizational decisions are seen to result from processes as diverse as problem resolution (rationally solving the problem), ignoring the problem, accident (as in a fortuitous result of solving a related problem), coordination of multiple decision-making units, and political negotiation among multiple decision makers. These models have been used to explore the way in which information technologies and tasks, individual, informational, cultural, environmental, demographic, and organizational characteristics impact the frequency, timeliness, accuracy, cost, complexity, effectiveness, and efficiency of organizational decisions, organizational learning, and organizational adaptation. Most of the current models come from either a neo-information-processing/social network perspective, or a DAI perspective (Bond and Gasser, 1988; Gasser and Huhns, 1989).

Models in this area range from simple intellective models of organizational decision-making behavior (Cohen et al., 1972; Carley, 1992) to detailed models of the decision processes and information flow that can emulate specific organizations (Levitt et al., 1994; Zweben and Fox, 1994) or follow specific management practices (Gasser and Majchrzak, 1992, 1994; Majchrzak and Gasser, 1991, 1992). These models vary in whether they characterize generic decision-making behavior (Cohen et al., 1972), make actual decisions in organizations (Zweben and Fox, 1994), make actual decisions given a stylized task (Durfee, 1988; Durfee and Montgomery, 1991; Carley and Prietula, 1994b; Lin and Carley, 1998; Carley and Lin, 1998), enable the researcher to examine the potential impact of general reengineering strategies (Gasser and Majchrzak, 1994; Carley and Svoboda, 1998), or enable the manager to examine the organizational implications of specific reengineering decisions (Levitt et al., 1994). These models typically characterize organizational decisions as the result of individual decisions, but they vary in the way in which they characterize the individual agent. Typical agent models include the agent as bundles of demographic and psychological parameters (Masuch and LaPotin, 1989), as simple information processors constrained by in–out boxes and message-passing rules (Levitt et al., 1994), or using some form of adaptive agent model (see following discussion). Further, most of these models characterize the organization as an aggregate of discrete and concurrently interacting complex adaptive agents (Prietula and Carley, 1994) or as a set of search procedures (Cohen, 1986) or productions (Fararo and Skvoretz, 1984).

Collectively, this work demonstrates that individual, task, environment, and design factors interact in complex and nonobvious ways to determine overall organizational performance. Task and environment are often the major determinants of organizational behavior. However, they interact with individual learning to the point that, depending on the complexity of the task and the quality of the feedback, the same people and the same organizations will in one circumstance overlearn, mislearn, and engage in otherwise maladaptive behavior and in another learn appropriate behavior. Moreover, as the level of detail with which task and organizational structure is modeled increases, the specificity and managerial value of the model's predictions increase. Finally, this work suggests that realistic organizational behavior, including errors, often emerge from processes of individual learning only when what the individual can learn is constrained by the organizational design, time, or the amount of information available.

18.3.2 Adaptive Organizations

Computational models of organizational decision making are particularly useful for examining issues of organizational learning and adaptation. Much of this work, particularly on the formal side, borrows from and is informed by work on adaptive architectures, more generally, and the work in computational biology and physics. Simon (1981a,b) has repeatedly argued that any physical symbol system has the necessary and sufficient means for intelligent action. The work by computational organizational theorists moves beyond this argument by arguing that a set of physical symbol systems that can communicate and interact with each other have the necessary and sufficient means for intelligent group means. Moreover, if the physical symbol systems can adapt in response to their own and other's actions, then the collection of such systems will exhibit emergent collective behavior.

While most of the organizational models share the perspective that organizational behavior emerges from the actions of intelligent adaptive agents, they differ in the way in which individual agents are characterized. A variety of agent models have been used, including traditional learning models (Carley, 1992; Lant and Mezias, 1990; Glance and Huberman, 1993), genetic algorithms (Holland, 1975, 1992; Holland and Miller, 1991;

Crowston, 1994), cognitive agent models like Soar[1] (Carley et al., 1992; Ye and Carley, 1995; Verhagen and Masuch, 1994; Carley and Prietula, 1994b), nodes in a neural network (Kontopoulos, 1993), and agents as strategic satisficers using simulated annealers (Carley and Svoboda, 1998). Regardless, individual learning is generally seen as one of the central keys to organizational learning (Lant, 1994), survival (Crowston, 1994, 1998), problem solving (Gasser and Toru, 1991), cultural transmission (Harrison and Carrol, 1991), emergent organizational behavior (Prietula and Carley, 1994), cooperation (Glance and Huberman, 1993, 1994; Macy, 1991a,b; Axelrod and Dion, 1988), and effective response to environmental uncertainty (Duncan, 1973). Most of the work in this area aggregate individual actions to generate organizational behavior. However, there is a smaller second tradition, a search procedure, in which the organization as a whole engages, and organizational behavior, and in particular learning, results (Lant and Mezias, 1992; Levinthal and March, 1981).

Organizational learning focuses on performance improvement and adaptation to the organization's external and internal environment. Thus, organizational researchers have found that modeling organizations as collections of intelligent adaptive agents acting more or less concurrently is critical for understanding issues of organizational learning and design. Currently, the four dominant methods used by organizational and social theorists to examine organizational adaptation are rule-based processors with detailed individualized models, neural networks (Rumelhart and McClelland, 1986; McClelland and Rumelhart, 1986; Wasserman, 1989, 1993), genetic algorithms and classifier systems (Holland, 1975, 1992; Holland et al., 1986), and simulated annealing (Kirkpatrick et al., 1983; Rutenbar, 1989).

The detailed rule-based models capture, using knowledge engineering and protocol analysis techniques, the detailed rules of behavior used by experts in performing some task. These rules or procedures are then placed in an artificial agent, who is given that and similar tasks to perform. In part, the goal here is emulation of an expert. Elofson and Konsynski (1993) apply AI and machine learning techniques to the analysis of organizational learning for the purpose of monitoring and analyzing decisions relative to organizational structure, and for monitoring organizational changes as part of the organizational learning and adaptation cycle. Their analysis demonstrates that increased flexibility is possible by knowledge caching, which provides a means of realizing an explicit organizational memory where information and processing capabilities are distributed among the organizational members. Such distributed agents cannot act in a completely concurrent fashion, as one agent may not be able to begin a particular task until another agent has finished a different task. The key issue then is how to schedule and coordinate these intelligent agents. Coordination of these intelligent agents can be characterized as a search process through a hierarchical behavior space, in which case coordination emerges through a set of cultural- or task-based norms of behavior and response to other agents (Durfee, 1988; Durfee and Montgomery, 1991).

Neural networks are a computational analog of the biological nervous systems and represent the learning entity as a set of predefined nodes and relations in which the relations can change over time in response to inputs. Kontopoulos (1993) suggests that neural

[1]Soar can be characterized as a model of cognition in which all problem solving is search, and learning occurs through chunking.

networks are an appropriate metaphor for understanding social structure. In a neural network, information is stored in the relations between nodes that are typically arranged in sequential layers (often three layers) such that the relations are between nodes in contiguous layers but not within a layer. These systems learn slowly on the basis of feedback and tend to be good at classification tasks. For example, Carley (1991b, 1992) used a model, similar to a neural network, to examine how organizational structure constrains the ability of organizations to take advantage of the experiential lessons learned by the agents in the organization and demonstrated the resiliency of the hierarchical structure and not the team structure in the face of turnover. Carley demonstrated that when organizational learning was embedded in the relationships between agents and not just in the agents, the organization was more robust in the face of "crises" such as turnover and erroneous information.

Genetic algorithms are a computational analog of the evolutionary process. A genetic algorithm simulates evolution by allowing a population of entities to adapt over time through mutation and/or reproduction (crossover) in an environment in which only the most fit members of the population survive. These models require that the there is a fitness function against which each organization, or strategy, can be evaluated. The smoother the surface given the performance function, the more likely it is that this approach will locate the optimal solution. For example, Macy (1991a) utilizes evolutionary techniques to examine cooperation in social groups. One of the most promising uses of genetic algorithms is in the area of organizational evolution, in which the genetic algorithm is used to simulate the behavior of populations of organizations evolving their forms over time. Here, the concurrency across multiple organizations is key to determining the dynamics of organizational survival. Crowston (1994, 1998) has used this approach to examine Thompson's theory of organizational forms and the evolution of novel forms.

Simulated annealers are a computational analog of the process of metal or chemical annealing. Eccles and Crane (1988) suggest that annealing is an appropriate metaphor for organizational change. Simulated annealers search for the best solution by first proposing an alternative from a set of feasible and predefined options, seeing if this alternative's fit is better than the current system's, adopting the alternative if it is better, and otherwise adopting even the bad or risky move with some probability. The probability of accepting the bad move decreases over time as the temperature of the system cools. In organizational terms we might liken temperature to the organization's willingness to take risks. Like genetic algorithms a fitness function is needed in order to generate emergent behavior. Carley and Svoboda (1998) have used simulated annealing techniques to look at strategic change in organizations and suggest that such change may effect only a minimal change in performance over that made possible by simple individual learning.

The strategic management literature suggests that executives can and do actively restructure their organizations (Baird and Thomas, 1985; Miller et al., 1982; Staw, 1982; Staw and Ross, 1989). For these researchers, the outcome of the individual decision-making process is an organizational goal. The research on managerial decision making and its effects on structure and efficiency have been examined empirically by MacCrimmon and Wehrung (1986), as well as researched by March and Shapira (1987), and March (1981). Researchers using computational models are taking these empirical findings and using them as the basis for the computational models. In particular, when the organization is modeled as a simulated annealer, different strategies can be fruitfully modeled as the move set for changing states in the annealer.

Most of the computational work using adaptive agent techniques of neural networks and genetic algorithms have examined networks of individuals that are largely undifferentiated in terms of their structural position and their organizational roles, and are somewhat simple from a cognitive standpoint. Consequently, this work provides little insight into how to design, redesign, or reengineer organizations. An intriguing possibility is the combination of these models with models of organizational or social structure. Such combined models may provide insight into the relative impacts of, and interactions between, structural- and individual-based learning. For example, Collins (1992) demonstrates that spatial constraints on evolution can aid social learning. Early results suggest that the existence of spatial or social structure may actually increase the effectiveness of individual agent learning, and may increase the robustness and stability of the collectivities' ability to problem solve in the face of change among the constituent members.

18.4 IMPLICATIONS FOR SYSTEMS ENGINEERING AND MANAGEMENT

Implications in two areas are considered: support for collaborative work, and understanding organizational learning. As to the first area, much of the research to date has focused on providing communication tools and databases in support of collaborative or distributed work. However, the work discussed on mental models and social networks can be read as suggesting the need for a different type of support. In particular, teamwork requires transactive memory, that is, knowledge of who knows what and knowledge about how to find things out. Teamwork also requires having some level of shared understanding. Thus tools that support the development of a shared mental model or the construction and maintenance of the informal social network should facilitate collaborative work.

As to organizational learning, the implication is that computational models are providing important insights and future progress will require more detailed computational models. Modeling organizations as collections of intelligent adaptive agents acting more or less concurrently is key to understanding issues of organizational learning and design. Organizational learning focuses on performance improvement and environmentally triggered adaptation. As an example, Elofson and Konsynski (1993) apply AI and machine learning techniques to the analysis of organizational learning for the purpose of monitoring and analyzing decisions relative to the organization's structure and for monitoring change as part of the learning cycle. They demonstrate that knowledge caching can increase flexibility and so provide a means of realizing an explicit organizational memory where information and processing capabilities are distributed among personel. Carley (1991b, 1992) used an approach akin to neural networks to represent hierarchies, and demonstrated that when organizational learning was embedded in the relationships between agents and not just in the agents, the organization was more robust in the face of various problems, such as turnover and information error. Results from work on the coevolution of intelligent adaptive agents suggests that the concurrent interaction among agents when combined with access to different forms of communication media can effect radical changes in the ability of subgroups to acquire novel information and to be socialized (Carley, 1995a). Moreover, work in this area suggests that simple access to different collaborative or communication technologies will not in and of itself be sufficient for guaranteeing access to new ideas, and thus may not lead to quality or performance improvements. Collectively, these and other results from ongoing research in the organizational, social, and psychological sciences suggests that organizations of agents often exhibit complex and high nonlinear behavior. As such, traditional methods for modeling these systems as systems may not suffice. In many engineering disciplines, engineers employ simulations to capture the complexity of higher-order systems. The same is true in systems engineering, where we will need to utilize simulations much more frequently if we are to assess the impact of the nonlinearities present in distributed and colaborative work.

18.5 CONCLUSION

In a way, these diverse approaches are growing together. Carley and Newell (1994) in their discussion of what it takes to create a model social agent point out that socialness and the ability to act like an organizational agent derives both from limitations to an agent's cognitive capabilities and acquisition of multiple types of knowledge as the agents tries to operate within a certain type of environment. Agents that are too capable cognitively, have no need for social interaction or learning. Agents that are not in a complex enough situation and do not have certain knowledge cannot engage in certain actions. Complex social and organizational phenomena emerge from concurrent interactions among even simple agents (Shoham and Tennenholtz, 1994), but the nature of the social dynamics and the speed with which they emerge are determined, at least in part, by the agents' cognitive abilities (deOliveira, 1992; Collins, 1992; Carley 1998b) and their sociocultural–historical position (White, 1992, Carley, 1991a; Kaufer and Carley, 1993). This development is seen both in the new work in social networks, in which there is a growing recognition of the cognitive abilities of the nodes and in multiagent models, in which there is a growing recognition of the need to incorporate more structural constraints on agent communication.

On the network front, researchers are increasingly examining both the individual's social network position and demographic and psychological characteristics. This research suggests that bringing the individual back into the social network affords a better understanding of actual organizational behavior (Krackhardt and Kilduff, 1994). Krackhardt and Kilduff argued that an observer's perception of an individual's performance was influenced by whether or not the observer perceived the individual as having an influential friend. Network theorists often argue that structure influences actions, decisions, attitudes, and so forth (Burt, 1982). By combining these perspectives, researchers in organizational decision making can examine how the structural position of the organizational agents influences what information they attend to and how they use that information, their perception of the social structure in making attributions about others and themselves, and how these attributions then affect their decisions and actions. Such a combination of perspectives leads to the argument that it is not structure per se, but individuals' perception of structure and differences in their perception of structure that influences their decisions, attitudes, and evaluations of self and others.

On the computational organization theory front, multiagent models of organizations, in which the agents have more restricted cognitive capabilities, exhibit a greater variety of social behaviors. By increasing the realism of the agent, either by restricting its cognitive capability, or by increasing the amount or type of knowledge available to the agent or the situation in which it must act, the researcher is able to produce models that are more capable of producing social behavior and a wider range of organizational behavior. For example, the agents in Plural-Soar (Carley et al., 1992) are more restricted than the boundedly rational agent used in AAIS (Masuch and LaPotin, 1989). The agents in the AAIS model, however, effectively had access to more types of social information than did the Plural-Soar agents. Combining the two models led to an agent that was capable of exhibiting a greater range of social behaviors (Verhagen and Masuch, 1994) than either of the parent models.

We began by noting that organizations do not make decisions, people do. The research on organizational decision making indicates that although this point is incontestable, the decisions that individuals made are highly constrained by the task they are doing, their position in the organization, and their sociohistorical–cultural position. The goal now is to present the specific way in which these factors influence the decisions made in teams.

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