Organizational Culture from a Complex Dynamic Systems Perspective: Moving from Metaphor to Action in Healthcare

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Introduction

As noted by Boan and Funderburk (2003), people in healthcare organizations work, relate, and interact in ways that are guided by the norms of their organization, their professions, and the healthcare industry as a whole. Organizational culture is often called upon as a descriptive, organizing and/or explanatory construct to characterize the shared beliefs, perceptions, expectations, norms and acceptable behaviors of individuals as they interact within and between the various groups and organizations that they represent. The construct has been linked in the literature to various aspects of organizational performance including profitability, quality, customer and employee satisfaction, safety, and innovation (e.g., Clarke, 2002; Denison, 1984; Fisher & Alford, 2000; Hodges & Hernandez, 1999; Mechanic, 2002; Shortell et al., 2000). Management models that draw inspiration from the literature on complex adaptive systems suggest that the cultures that support successful transformational enterprises could be the result of a combination of individual and organizational learning coupled with evolutionary processes (e.g., Axelrod and Cohen, 2000; Bar-Yam, 1997; Baskin, 2000), but specific strategies to change organizational cultures in a positive manner are less well documented.

In the healthcare arena, many discussions of organizational culture and change have contrasted mechanistic management theories, stressing hierarchical command and control mechanisms, with the more holistic view of the organization as complex adaptive systems, stressing decentralized flexibility and continuous learning (e.g., Zimmerman et al., 1998). Such discussions help to illustrate the pervasive role of individuals' mental models, descriptive linguistic conventions, and belief systems as they jointly strive to develop successful and responsive business enterprises (e.g., Lissack, 1999; Weick, 1995) but the "complexity sciences" offer more than just a convenient conceptual framework (with a new set of metaphors) to the leaders of healthcare organizations as they work to bridge what has become known as the "Healthcare Quality Chasm," as described in the recent Institute of Medicine report (2001; see also: Berwick, 2002; Fernandopulle et al., 2003; McGlynn, 2003; Jencks, 2000; Jencks et al., 2003).

This paper presents a brief survey of several formal dynamic and/or network-based models that are relevant for healthcare policy development and evaluation, giving special attention to the class of social phenomena typically subsumed under the broad category of organizational culture. The technical characteristics of these approaches as well as their practical implications for improving the quality of healthcare, and the quality of life of people in our own communities will be considered.

An Overview of the Models Considered

The social behavioral responses of two individuals (or "agents") as they interact in a specified environmental context may be considered a rudimentary model of organizational culture. The patterns of responses that characterize this interaction over time can be interpreted as showing information exchange, trust, cooperation, and competition. As these interactions are repeated over time, one can trace the development of behavioral norms and evaluate how these relate to both individual and group benefits. Indeed, such models have been well characterized by Axelrod (e.g., 1984) in the Prisoner's Dilemma paradigm. An understanding of how characteristic strategies of performance emerge under this model has been found useful in addressing a wide range of social problems. The models considered here represent an extension of that work to a much broader set of problems involving interaction among multiple agents or entities with more realistic social and structural characteristics. These additional layers of complexity often prevent simple analytic solutions to the problems that are posed so a common method of study involves a descriptive analysis of patterns of collective behavior from multiple perspectives -- considering the structure of the system under study, the patterns of interactions among agents and entities, and various feedback processes that produce changes in these structures and interaction patterns in both the short- (e.g., individual and/or organizational learning) and the long-run (evolutionary organizational processes).

Often these issues are addressed through computer simulations. Under this approach the researcher creates an environment in which agents or entities with specific characteristics are allowed to interact and affect one another through the operation of simple specified rules. Data on changes in the state of the system and the interaction processes are collected during these simulations. Typically, agents (reflecting people in a healthcare organization) "self-organize" to produce aggregate patterns of characteristic behavior that in aggregate reflect the "culture" of some organizational components or even the organization as a whole. Such cultural characteristics, in turn, alter the environmental context experienced by the various agents, leading to further adaptive change at the broader system level[1]. Axelrod and Cohen (2000) suggest that three main features of this interplay must be understood in order to effectively harness this complexity and develop productive courses of action. These are: 1) variation among agents, 2) patterns of interactions, and 3) selection of agents or strategies to carry forward. These elements are found to some extent in all of the approaches considered in this presentation.

Organizational Culture and Structure May Co-Evolve

A model in which the agents can exhibit only very simple behavior, respond in fixed ways to very simple rules, and whose interactions and payoff matrices are determined randomly provides a useful anchor point for investigating organizational development. Westhoff et al. (1996) explored patterns of changes in organizational structure from the perspective of Kaufman's very basic NK fitness landscape system models (e.g., Kauffman, 1990, 1993). As a concrete example, changes in the management and structure of firms in Britain and the United States during the Second Industrial Revolution were considered. Within this context, N referred to the number of characteristics on which firms were considered to differ as represented by the elements in the system (family vs. professional management, small vs. large scale of operations, little vs. extensive vertical integration, unidivisional vs. multidivisional structure) and K referred to the degree of independence among the elements in the system. Kauffman has reported that specification of these system parameters is central to understanding many types of robust biological dynamic systems – such as metabolism and genetic regulatory networks. The results discussed by Westhoff et al. suggest that similar effects may also exist in social-organizational systems. Under such a model the culture of the organization might be conceptualized as particular sets of canalizing functions that dominate or guide local interactions toward a particular type of attractor, producing order in the system. Kauffman's approach also generalizes to situations where one set of sub-system functions can alter the fitness landscape of other sub-systems, resulting in co-evolution. If such findings were to be consistently replicated in this arena, the results could be used to identify potential leverage points for system change where relatively small changes to inputs are likely to produce maximum system impact. A related implication is that as the degree of

1 An overarching view of how models such as those considered here relate to the policy development and evaluative dilemmas that confront healthcare decision makers is provided by Bankes (1993, 2002) in what he terms "exploratory modeling." This general framework provides a protocol for coping with the uncertainty inherent in addressing complex policy problems. Although Bankes does not explicitly mention organizational culture in his work, his account of issues in policy decision making provide a useful context for the more specific applied questions that we will consider. Bankes argues that the emergence that characterizes complex systems makes precise forecasting of detailed system behavior impossible, and that policy models that rely on optimizing some "best estimate" model are likely to perform poorly in many instances. They are also likely to underestimate potential adverse effects of policy decisions. As an alternative Bankes proposes a structured approach for developing ensembles of alternative models, ensembles of alternative scenarios, and ensembles of candidate policies. Alternative combinations of models and candidate policies can then be simulated, subjected to sensitivity analysis, and tested for robustness – resulting in a set of satisfactory policies for coping with matched sets of contingencies. Lempert (2002) offers a further extension of these approaches that combines (through inductive reasoning) the quantitative and qualitative features of information gleaned from such computational experiments to produce practical computer-based decision aids for policy-making. The model development process for specific healthcare system issues is not yet at the "point and click" interface stage. However, insights from modeling efforts to date suggest that some aspects of organizational culture, when viewed from a complex dynamic systems perspective, might be leveraged to help promote systemic change and healthcare quality improvement.

independence among elements increases (and fitness landscapes become more "rugged"), the strategy of identification and promotion of universal "best practices" becomes progressively less tenable.

On a broader scale, this model also suggest that organizational forms observed in such systems may be due to structural constraints in addition to (or even in spite of) selection pressures based on the relative contribution that particular cultural traits or characteristics make to overall system fitness or performance. The consolidation of managed care organizations and pharmaceutical firms into increasingly larger entities may be examples of such constrained systems that have broad and substantial impacts in the healthcare arena. Such consolidation may enable beneficial efficiencies in certain tasks (e.g., billing and payment processing, efficient drug development and marketing), but may be counterproductive for other types of tasks (locally-tuned quality improvement efforts, disease prevention efforts or drug discovery activities).

Agent-Based Computational Models

While models such as those described by Westhoff and colleagues emphasize structural characteristics as determinants of system behavior, they do not consider how individual elements or agents within an organization might work together to alter organizational behavior. These issues, however, have been addressed in agent-based computational models of the sort proposed by Axelrod (1997) and Epstein and colleagues (e.g., 1999, 2003; Epstein & Axtel, 1996). These approaches have been described as "generative" models because they attempt to produce certain characteristic patterns of system behavior that might be reflective of a culture or society through specification of parameters that control the interaction patterns among agents within the system. Epstein thus regards culture as a "distributed computational device," with social dynamics as one type of computation. The organizational culture emerges from the operation of this device over time. Axelrod (1997) proposed a similar definition of organizational culture.

In contrast to the agents in the Westhoff et al. approach, the agents in these models are both heterogeneous and adaptive. They differ in initial sensitivity to particular aspects of the environment and are subject (often in different degrees) to change in response to dynamic interactions with other agents and with the environment in general. These agents interact within an explicitly-defined environment that sets the occasion for interactions among agents by specifying certain resource constraints, the extent to which resources are renewable and so on. The systems of heterogeneous autonomous agents/actors with bounded information and computing capacity who interact locally seem to possess a certain degree of "face validity" with respect to our own organizations. This feature may well facilitate the transfer of findings from this type of research into clinical and organizational practice (see, e.g., Batalden & Splaine, 2002; Berwick, 2003).

The range of agent characteristics that have been considered in agent based models further supports their potential utility in providing practical guidance to healthcare leaders. Some authors have explicitly included social-psychological knowledge into the modeling process. Frank & Fahrbach (1999), for example, developed a model of organizational culture that incorporated the effects of information needs and affective balance/attitude into the interactions among individual agents. Organizational cultures, Frank & Fahrbach maintain, are produced by the interaction of agents over time. Two basic processes – influence and selection – determine the type of organizational culture that will result. The interactions among agents can produce changes in attitudes (influence) and changes in subsequent patterns of interaction (selection). Their simulations, which examined the effects of these variables on the development of organizational culture under a variety of prevailing internal structures and in response to external shocks (e.g., severing of links between various agents), demonstrated that a range of organizational cultures (characterized as types of system equlibria) could be produced using this framework. Among their more intriguing findings was that attempts to increase consensus by increasing the level of influence that agents had on their neighbors could actually produce polarization of subgroups under conditions where the effect of influence became completely dominant over informational needs. This finding (along with those of Axtell et al., 1996 and of Macy et al., 2002) replicates a provocative finding of Axelrod (1997), who reported consistent patterns of polarization in a variety of social influence models. Indeed, polarization was found even when convergence toward a neighboring agent was the only allowable mechanism of change. As Axelrod noted, polarization in such situations need not be due to any divergent process. Dal Forno & Merlone (2002) discuss other ways in which a culture, defined as a common level of effort among agents, can evolve to either boost or minimize work effort (and presumably productivity). These findings provide examples of how a computational modeling approach can be used to better understand unanticipated sources of "policy resistance" that often undermine rational efforts to introduce organizational change in healthcare systems through Total Quality Management (TQM) or similar efforts.

Organizational Culture as Shared Knowledge

Lemon & Shaota (2003) have defined organizational culture as a knowledge repository that is related to the innovative capacity of the organization. In this context, organizational culture is seen as a facilitator or constraint on knowledge development processes. Another approach that stresses knowledge management systems as a key component of organizational culture is the system dynamic model proposed by Yim et al. (2004). This model considers not just the generation, storage and dissemination of knowledge within an organization, but also explicitly considers how such codified information is used in organizational decision-making. A key issue under this approach is how individual "mental models" are translated into strategies to define system performance and develop diagnostic strategies to identify root causes of system problems. This approach builds on the work of Senge (e.g., 1990), Sterman (e.g., 2000), Burchill & Kim (1993), and Wolstenholme (2002) for understanding and communicating the possible nonlinear processes that can result in unanticipated and/or unwanted system outcomes, but adds a tripartite typology of organizational knowledge -- know how, know who, and know why -- to help guide change efforts. These models can provide an effective means of communicating key systems thinking concepts to healthcare providers and seem well suited to translating empirical findings from agent-based simulations into a framework for action in the healthcare workplace. Such approaches are also consistent with concerns about knowledge management issues in healthcare (e.g., Batalden et al., 2002; Fernandopulle et al., 2003).

Social Networks

Social network models offer one way of exploring the diffusion of information and knowledge in organizations (e.g., Breiger, 2003; Wasserman & Faust, 1994). The general strategy in the application of these techniques is to identify each individual ("agent") as a node in the network and to examine the flow of information ("knowledge resources") within the network. Measures of network location ("centrality") help to characterize the importance of a particular node in the network[2].

Even though social network models are primarily descriptive, they have produced results that have relevance for healthcare problems. Collins et al. (2000) used this type of approach in an effort to identify "genuine opinion leaders" in the adoption of practice guidelines in a hospital setting, illustrating how these approaches can provide a useful strategy for segmenting individuals or organizations for targeted communications. Another example is the effect that various patterns of social networks can have on the well-being of individuals in a healthcare system. Kef et al. (2000) noted that social structure could have a profound effect on the self-reported well being of visually impaired adolescents. Satisfaction with extant social support and breadth of an individual's network was positively related to reported well-being. Achat et al. (1998) noted that women with broader social networks were more resilient to environmental stress, and reported better health-related quality of life. Funderburk et al. (2004) reported similar effects among children with cerebral palsy, noting that harnessing the power of existing social networks and facilitating the development of new social support networks through collaborative interagency agreements may offer a cost-effective strategy for improving the quality of healthcare, and the quality of life, in vulnerable populations

Dynamic Social Network Models

In a broader context, Carley (2002) has described the emergence of computational organizational science as a distinct field of inquiry in which organizations themselves are viewed as complex computational and adaptive processing agents. Her approach extends traditional social network models to include higher-

[2] Centrality is a multidimensional construct that considers the number of direct connections with other nodes that characterize a particular node ("degrees"), the extent to which a particular node is a link between two (or more) sets of highly linked nodes ("betweenness"), and degree of connectedness with other nodes ("closeness").

order dimensions such as knowledge, technical resources, and tasks in a dynamic network environment. Carley (2002, pp 260) refers to these systems as socio-technical, specifically noting the link between organizational culture and organizational learning. She also suggests that operational definitions of culture that emphasize communication and codification of specific behavioral norms (e.g., Schein, 1992) are not inconsistent with this computational approach to organizational culture

As a way of systematizing the types of variables that might be used to understand the complex interactions that characterize the evolution of such networks Carley has advanced the concept of the meta-matrix (Carley, 2002). This device defines a core set of connected networks of people, knowledge/resources, events/tasks, and organizations that describes (in a probabilistic manner) the types of changes that might be expected to emerge in more distant networks as a result of changes in any of the 10 key cells defined in the meta-matrix. This linkage of change in one cell of the matrix to broader systemic changes (which in turn alter other networked components) provides a context for understanding the co-evolution of such systems.

Formal computational experiments provide a mechanism for developing, refining, and validating candidate models to explore and understand the co-evolutionary processes. A number of distinct models have been described in the literature (e.g., ORGAHEAD, DyNet, CONSTRUCT-O). Each was developed to focus on particular levels of analysis within the meta-matrix, but all are multiagent simulation approaches in which realistic cognitive, social, and political processes, including those considered under the rubric of organizational culture, can be evaluated through parametric changes in specific agent (and other entities such as knowledge, task or organization) characteristics and/or structural network distinctiveness. Agents and entities in these models learn or change as a result of their interactions over time. As would be expected from the accumulated literature on complex adaptive systems, small differences in initial values of some of the parameters can often result in substantial differences in terms of organizational effects.

Although a detailed review of these various models is beyond the scope of this presentation, a number of very intriguing results have been reported that could have important implications for healthcare organizations. In one study Carley (2003) explored cultural factors related to organizational success. Carley examined a set of 100 organizations with randomly determined initial architectures over time in response to both stable and changing environments, holding the metric of organizational performance constant during the experiment. The simulation produced patterns of interaction among the agents that could be characterized in terms of conflicts between structural and experiential learning. As might be expected, such conflict resulted in more diversity in structural form and performance. Over time, maladaptive organizations tended to become locked into counterproductive "local optima," manifesting, for example, alternating periods of hiring and down-sizing, while adaptive organizations tended to lock into strategies that involved retasking and task redesign that were more effective over the long run. Even when dealing with a relatively stable environment, adaptive organizations tended to be those that emphasized a balance of structural and individual learning and relied more on flexible task assignments to support diversity and growth. These results are consistent with Denison's model of organizational culture and with empirical findings indicating that a combination of maintaining flexibility to environmental perturbations without changing the core organizational goals (and mission) was a cultural trait characteristic of high-performing firms (e.g., Fisher & Alford, 2000). For healthcare organizations, the message may be to maintain flexibility in terms of how and by whom key tasks are performed, but to maintain strict attention to how the care system as a whole affects the quality of life of the people it is intended to serve.
Another study examined how organizational adaptability might be maintained. Patterns of agent interactions and links with specific knowledge resources contribute to the ultimate adaptability of the organization. Simulation experiments have found that situations in which agents that have learned to learn in a variety of situations interact with multiple other agents generally support long-range adaptive organizational behavior. Coordinated team efforts, in contrast, can increase short-term performance through task-specific tuning, low cognitive load for team members, and minimizing redundancy in effort. The apparent conflict between performance and adaptability may be resolved somewhat by noting that the type of tasks that are best suited to team approaches tend to be those that are complicated or large-scale, while those that are best suited to adaptive, interactive approaches tend to be complex, requiring awareness of multiple possible interactions and generalization of prior learning to specific instances in the absence of complete information (e.g., difficult medical diagnosis, person-centered planning). Bar-Yam (1997, pp 804-822) describes such situations in terms of a complexity transition – a comparison of the collective

complexity of the task with the maximum complexity of the individual agent or entity. Bar-Yam argues that performance will be enhanced in the hierarchically directed team model only if the collective behavior can be meaningfully simplified so that the task complexity does not exceed the complexity of the individuals performing the tasks. If the tasks to be performed exceed the complexity of the individual agent, then a network that allows for emergent collective behavior greater than that of the individual will be the more appropriate structure. Many of the problems that are faced in healthcare today can be understood within this framework. The key question to ask is: Are the structures that are designed to manage the tasks required to deliver quality healthcare congruent with the design of the organizational components that are in place?

Simulation studies that have examined the effect of implementing technological solutions to common organizational problems have produced some surprising results. Carley (2003) describes a situation in which the effect of a database designed to retain organizational expertise actually slowed the rate at which expertise was diffused. Rather than compensating for the loss of information (e.g., through forgetting, attrition of key experts, etc.) the time spent contributing to the database reduced the time that individuals could spend on learning new information. The net result was a slower rate of organizational learning as well as a lower level of organizational knowledge (in terms of the percentage of individuals within the organization that had learned the new idea). Even more striking was the finding that the database did not facilitate the development of a unified organizational perspective. In fact, the effect was the opposite. Time spent contributing to the database reduced interpersonal interaction that supported the development of shared mental models. The rate at which knowledge was shared was lower with the database than without. Further, the percentage of knowledge that was shared with the database in place did not rise above the 60% range even in the long-run (1,000 experimental epochs). In the absence of the database a comparable level (60% knowledge sharing) was achieved in about 100 epochs; nearly 100% knowledge sharing was achieved by epoch 300. These results may be dependent on specific characteristics of the simulation reported, but Carley reported that the findings were robust across a range of conditions related to information seeking by the individual agents. At a minimum, the findings illustrate the value of simulations to highlight potentially counter-intentional effects of interventions in socio-technological systems. In the healthcare arena, Bodenheimer & Grumbach (2003) have noted that technological advances in electronic technology can sometimes interfere with the patient-physician relationship. They suggest that redesign of office processes might be required in order to benefit from advances in computer technology. It would be of interest to determine if more adaptive databases (e.g., those described by Rocha, 2001) might alleviate some of these potential barriers.

Conclusions

The results of the models discussed show striking parallels to some of the difficulties that have plagued the adoption of quality improvement innovations (e.g., Berwick, 2003; Jencks, 2000; Jencks et al., 2003) and general healthcare system improvement efforts (e.g., Batalden & Splaine, 2002 ; Berwick, 2002; McGlynn, 2003). Taken together the studies reviewed suggest that rigorous models of organizational culture can be developed and refined within a complex dynamic systems framework. Indeed, many of the models reviewed in this presentation have direct applicability to practical healthcare issues. Such findings support the recommendation of Fernandopulle et al. (2003) calling for an increased emphasis on complexity science research and theory as we search for new perspectives to guide healthcare policy.

A summary of key points in this presentation include an appreciation of the limits of linear cause and effect models, the consistent observation of counterintuitive effects that can be understood in terms of the basic principles of complex adaptive systems (e.g., efforts to create consensus that create polarization, databases that reduce knowledge sharing, the seemingly spontaneous emergence of phase transitions [from order to disorder and vice versa], the persistence of policy resistance), the need to consider carefully the congruence between scale and structure in the diagnosis of system failures and design of interventions and improvements (e.g., Bar-Yam, 1997; Carley, 2002; Wolsterholme, 2003), and the necessity of variation for sustainable improvement and system evolution (e.g., Kauffman, 1990, 1993).

Each of the various types of models considered seems to be tuned to address a specific set of healthcare issues. Kauffman's NK fitness landscape models suggest why transfer of "best practices" may be difficult to achieve in co-evolving systems, and remind us that structural constraints can cause even simple systems can get locked into policies that are sub optimal. Agent based modeling approaches seem most applicable to situations in which our degree of understanding does not yet allow for formal specification of relationships among variables. Such models can help us to better identify the level of detail required for valid modeling efforts. System dynamic approaches are most useful in dealing with "what if" scenarios when the relationships among variables are well understood. In these cases equation-based models can be used to develop training tools that aid better decision-making. Social network models provide a static characterization of the relationships among people at a fixed point in time and are therefore useful for baseline system diagnosis. Dynamic social network models provide an ontological extension of these relationships that can be helpful in linking multiple sub-systems (people, resources, tasks, organizations) thereby extending the range of systems that can be studied.

There is still much to be learned, but a variety of tools, metrics, and heuristics have been illustrated that provide fertile ground for translating the metaphors of complexity science to action. Action research from this perspective, in the contexts and operation of particular healthcare sub-systems, offers a way to create, evaluate, and rapidly apply the new insights gained to enhance the quality of life for the people served by the evolving system of healthcare.

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