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PERMEABLE BOUNDARIES IN ORGANIZATIONAL LEARNING: COMPUTATIONAL MODELING EXPLORATIONS.

Theme: The Social Processes of OL and KM

Hazy, James K.

The George Washington University

Tivnan, Brian F.

The George Washington University

Schwandt, David R.

The George Washington University

Contact author: Hazy, James K
The George Washington University
Center for the study of learning
20101 Academic Way, Suite 228
Ashburn, Virginia
USA
22011-2604

Telephone: 908-713-9820
E-mail: Jim.hazy@att.net

Abstract

In this paper we investigate the nature of the organizational boundary in the context of organizational learning. Using the Organizational Learning Systems Model (OLSM (Schwandt, 1997) and building upon computational organization theory (Carley & Prietula, 1994b) we precisely define boundary permeability and decompose it into constituent parts: information gathering efficiency, search intensity and knowledge diffusion effectiveness. Hypotheses are developed and tested using data from 5,500 artificial organizations. We find strong support for the usefulness of boundary permeability as a predictor of organizational learning and agent survival and suggest ways to operationalize this construct in future laboratory and field studies .

The recent collapse of the internet bubble highlights the importance of remaining in tune with the environment during times of rapid change. In the context of organizational learning research (Schwandt & Marquardt, 2000), we examine information flow through an organization's boundary and its impact on the organization's survivability. As a mechanism for studying emergent structures in complex social systems, we computationally model a nonlinear application of structuration theory (Giddens, 1984) as a mechanism for organizational learning.

Organizational learning literature highlights the importance of permeable boundaries in organizational learning (Argyris & Schon, 1978; Daft & Weick, 1984; Fiol & Lyles, 1985; Hedberg, 1981; Huber, 1991; Lundberg, 1989; Schwandt, 1997; Schwandt & Marquardt, 2000). In addition, organizational learning literature, offers a rich vein supporting organizational learning as a real, and measurable phenomenon at the collective level (Fiol & Lyles, 1985; Hedberg, 1981; Huber, 1991; Schwandt & Marquardt, 2000; Walsh, 1995).

In this paper we use computational modeling to explore explicitly the impact of various levels of boundary permeability on organizational learning with the understanding that information and knowledge are distributed both inside and outside the collective (Tsoukas, 1996).

We test this broad notion using agent-based modeling techniques to explore agent activities at the organization's boundary and how these micro-effects are aggregated at the organizational level and enable the collective to sense the nature of its environment through its perceptual filter (Daft & Weick, 1984; Hedberg, 1981) as is described in organizational learning. Our intent is to test the notion that "boundary permeability," as a measure of the collective's ability to sense its environment, that is, gather information external to the organization and diffuse it internally, is a robust and cohesive construct at the organizational level. We do this by defining boundary permeability in the context of an agent-based view of organizations (Carley & Prietula, 1994a), and by varying aspects of agent level interaction at the boundary. Through a series of virtual experiments, we measure boundary permeability and its impact on organizational learning variables and organizational outcomes. We address the research question: What is the relationship, if any, between boundary permeability and computational organizations' outcomes, and how does environmental turbulence affect this relationship?

Background in theory and prior results

The theoretical context of our organizational learning research is Schwandt's Organizational Learning Systems Model (OLSM) (Schwandt & Marquardt, 2000). The OLSM is viewed through the lens of computational organization theory (Carley & Prietula, 1994b). Prior results marrying these two approaches have demonstrated the usefulness of this approach.

The organizational learning systems model (OLSM)

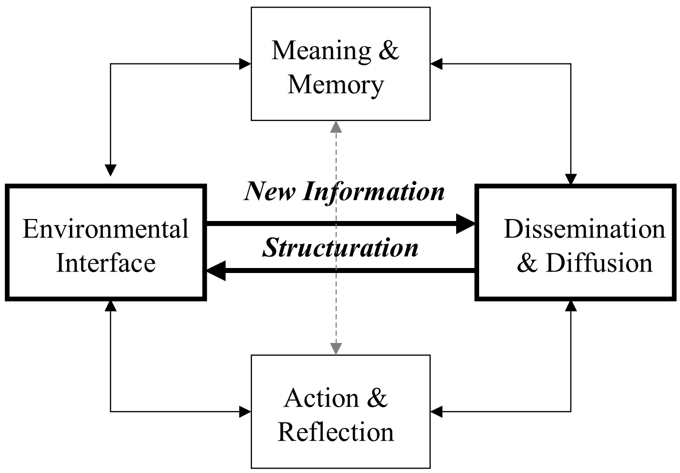
Consistent with the systems theory approach to organizational learning (Lundberg, 1989; March & Olsen, 1988/1975; Orton & Weick, 1990) Schwandt defines organizational learning as "a system of actions, actors, symbols and processes that enables an organization to transform information into valued knowledge which in turn increases its long-run adaptive capacity" (Schwandt, 1997: 8). For this study we focus on the environmental interface and the dissemination/diffusion subsystems and their respective interchange media, new information and structuration.

As is shown in Figure 1, the environmental interface subsystem acts as the information input mechanism for the organizational learning system (Schwandt, 1997: 9). This subsystem focuses externally to relate the organizational learning system to its environment and to develop the means by which the organizational learning system pursues different learning goals and meets changing environmental conditions. The environmental interface subsystem produces new information for use by other subsystems of the OLSM.

The dissemination/diffusion subsystem moves, transfers, retrieves, and captures information and knowledge for the learning system. The actions of this subsystem are characterized by their ability to meet the integrating requirements of the other learning subsystems and include communication, networking, management, coordination, and the implementation roles supporting the norms associated with the movement of information and knowledge (Schwandt & Marquardt, 2000). The interchange medium, structuration (Giddens, 1984), is more than a structure of the social system; it is an integration of organizational structures, roles, norms, objects, and processes that provide this dynamic quality Giddens called structuration (Schwandt & Marquardt, 2000).

Figure 1

The Organization Learning Systems Model



For this study, we model only the input or sensing subsystems described above. In addition to these subsystems, the OLSM also includes the meaning and memory and the action and reflection subsystems that describe how action occurs in the system. The meaning and memory subsystem takes its inputs form the other systems, that is, it takes in new information and structuration from the subsystems described above, as well as, goal-referenced knowledge which emanates from the action and reflection subsystem described below. The meaning and memory subsystem processes these inputs and makes sense of them for the collective. As such, its interchange medium is sensemaking.

The action and reflection subsystem takes its inputs from the other subsystems to enable collective action. The results of action – processed as new information and structuration feedback though the sensing subsystems -- are compared to goals, reflected upon and output as goal-referenced knowledge. Goal-referenced knowledge becomes an input to the other subsystems and thus impacts structuration and the new information imported into the collective from beyond the organizational boundary.

The computational approach to organization theory

The use of computer simulations to develop theoretical concepts and to generate research questions, proposals and hypotheses has been gaining momentum in recent years (Gilbert &

Troitzsch, 1999; Lomi & Larsen, 2001; Prietula, Carley, & Gasser, 1998). In particular, the use of agent-based models has been shown to produce useful insights across multiple social science domains such as anthropology, economics and ecology (Kohler, 2000; Leydesdorff & van den Besselaar, 1994). "Research using these models emphasizes dynamics rather than equilibria, distributed processes rather than systems-level phenomena, and patterns of relationships among agents rather than relationships among variables" (Kohler, 2000:2). In short, they can be used to identify emergent phenomena that could not otherwise be isolated for study.

Many of these techniques seem to have promise as an important research technique in organizational science. Burton (2001) has described this promise in the context of three unique characteristics of simulation: the discipline surrounding the needed specification of the detailed interactions that are being modeled, the versatility of the medium with respect to the variety of research issues that can be addressed, and the relative efficiency of virtual experiments in a simulated organization versus real-world experiments. March recently wrote, "it is easy to anticipate a bright future for simulation modeling in organization studies" (March, 2001: xvi). He continued, "Simulation represents an approach that appears both to match the phenomenon of interest and to provide some analytical power" (March, 2001: xvii). Simon (2001) saw the potential of computational modeling for organization level and population level analysis. An example of this approach from the organizational learning literature is work by Carley and Svoboda (1996) in which organizational learning and adaptation was simulated computationally as an annealing process.

Theoretical foundations in computational organization theory

As a starting point, we accept the axiomatic framework of Carley and Prietula (1994*a*) where "organizations are viewed as collections of intelligent agents who are cognitively restricted, task oriented, and socially situated" (Carley & Prietula, 1994a: 56). Upon this axiomatic base and later additions (Carley & Gasser, 1999; Carley & Wallace, 1996), we adopt a precise description of an organization as a connected network linking persons, resources, tasks, and knowledge to each other (Carley & Krackhardt, 1999; Carley, Ren, & Krackhardt, 2000; Krackhardt & Carley, 1998).

The above-described meta-matrix representation (Krackhardt & Carley, 1998) is static, however, and only describes connections in the network at a point in time. We therefore adopt an intelligence mechanism that enables the agent to change the network connections (its social, task, resource, and knowledge situation) in its local environment (Hazy & Tivnan, 2003).

In this sense, an agent's social situation has duality analogous to Giddens' duality of structure in structuration theory (Giddens, 1976/1993). The agent's position in the network constrains its ability to act, just as in structuration theory, social structure is said to "produce" behavior. On the other hand, action by an agent can make persistent changes to the network that impact the ability of the agent and possibly other agents to act in the future. In structuration theory, an individual's actions are said to "reproduce" behavior by creating social structure that persists across time and space (Giddens, 1976/1993; Taylor & Van Every, 2000). In the same way, we define computational structuration as the effects of and changes to network connectedness of agents that persist through time and space.

As described by Hazy and Tivnan (2003) the intelligence mechanism is based on an agent's boundedly rational "mental model" of its local environment (Simon, 1957/1997). In other words, an agent can make changes only in the context of the intersection of its perceived and real possibilities. Thus, an agent's actions are "cognitively restricted" (Carley & Prietula, 1994a). The relationship among an agent, its local network, and the way it can change its local network is a micro example of social structure in organizations. We believe that agent interactions of this type are the "social structure primitives" from which organizations emerge. These primitives involve, at once, both the agent and its position as embedded in a network, a true duality directly analogous to Giddens' (1976) social structures.

Prior results

Prior studies have demonstrated the usefulness of the above theoretical framework (Hazy & Tivnan, 2003; Hazy, Tivnan, & Schwandt, 2002). Agent based modeling consistent with this approach was used to study the implications of boundary spanning activity on organizational learning (Hazy et al., 2002) in a study involving over 11,000 artificial organizations. Results indicated that the level of boundary spanning activity of agents has a non-linear relationship with collective outcomes such as production and number of surviving agents. More boundary spanning at first increases outcomes and then has little incremental and perhaps a negative effect. The specific characteristics of this relationship are dependent upon environmental turbulence, the initial positive effect of boundary spanning being more pronounced with greater turbulence. These computational experiments also found that when an agent was able to change its local network by learning and performing new tasks, outcomes increased at all levels of boundary spanning.

In a second study, the effect of differential rewards to agents on organizational outcomes was studied in the context of agent learning and collective performance (Hazy, Tivnan, & Schwandt, Under review). Results of this study showed that when rewards are distributed based upon contribution, either to actual production or to the diffusion of knowledge that informed production, outcomes improve. Because collective outcomes improve, *an individual agent's survival potential* improves if it participates in production or the diffusion of knowledge– essentially, an agent is rewarded for contributions of either exploitation or exploration (March, 1991). When rewards are provided to the agents that provided relevant knowledge to other agents, more agents tend to survive.

The purpose of the present study is to build upon these prior results to demonstrate in a computational model that small changes to quantity and quality of interactions at the level of agent interactions, can have measurable effects at the organization level, that is, in boundary permeability, and that these affects can be understood in the context of the environmental interface and dissemination/diffusion subsystems of the OLSM (Schwandt, 1997).

Boundary Permeability

To define Boundary Permeability in the context of the organizational learning systems model (Schwandt & Marquardt, 2000), we look at the collective's need to perceive the environment (Hedberg, 1981), interpret the information and pass the benefit of this interpreted information deep into the collective to enhance future collective activities (Daft & Weick, 1984).

As a collective level construct, the organizational boundary represents the distinction between "outside" and "inside" and, by default, the organ through which agents inside the collective (participating in collective activities) sense their collective's environment (that is, they import information from outside the boundary). But at the same time, we must recognize that in reality it is boundary spanning agents that cross the boundary of the organization to search for and bring back new information. Therefore, to be meaningful as an organization level construct, boundary permeability must capture more that simply the number of boundary crossings by agents. It also has to take into account the efficiency with which new information is gathered outside the boundary and the effectiveness with which the new information is integrated or diffused inside the system's boundary as knowledge relevant to collective activities and potential benefit.

The system dynamics at the organization's boundary

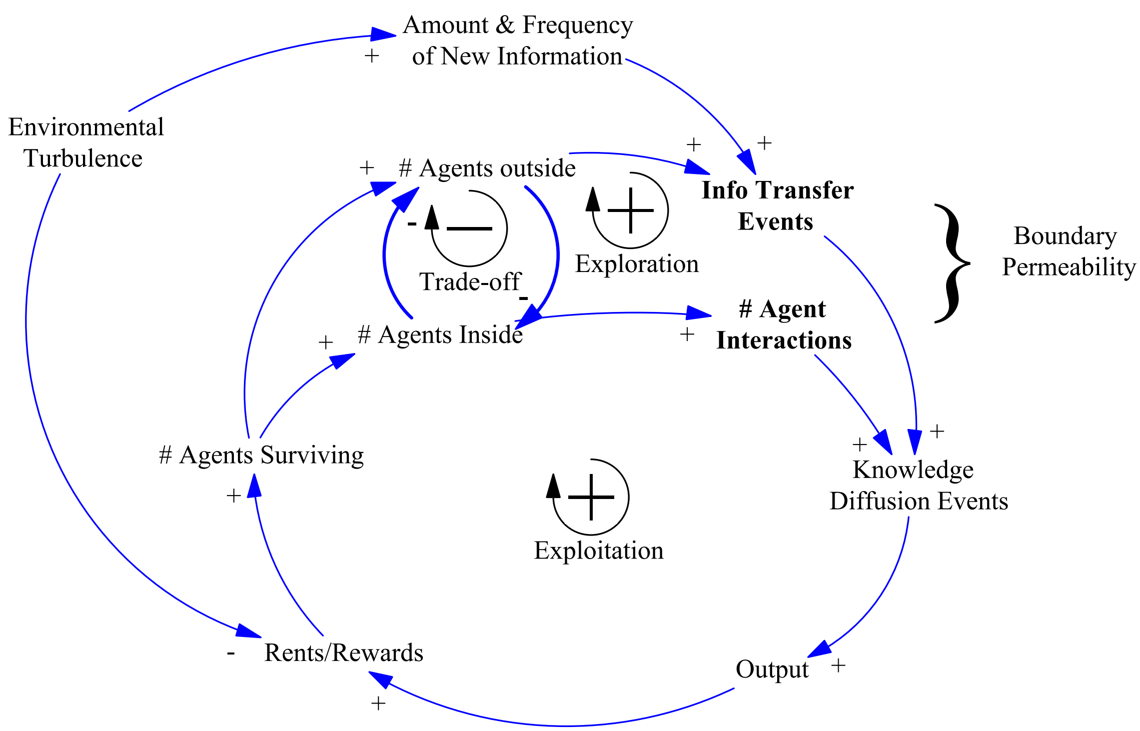
As shown in Figure 2, the dynamics that define an organization's boundary can be analyzed using system dynamics techniques (Sterman, 2000). The number of surviving agents in a collective is the relevant stock in a self-reinforcing exploitation feedback loop. Agents inside the organization interact with one another and in so doing diffuse the knowledge that enables greater rent to be extracted from the environment. More rent implies more reward for individual agents. Under an appropriate reward structure, it thus allows more agents to survive.

The environment changes, however, and thus produces new information at some rate. This new information must be imported for the agents within organization to remain current. Some agents are sent out across the boundary (where they can no longer produce output) to obtain new information. Importantly, more new information also leads to greater knowledge diffusion and thus these choices also create a self-reinforcing feedback loop, the exploration loop.

Two balancing loops regulate this activity. Increased exploration dampens the exploitation loop and greater exploitation dampens the exploration loop. This classic tension (March, 1991) is embodied in the construct we are calling boundary permeability.

Figure 2

Non-linear dynamics of boundary permeability and collective survival



Surviving agents as an outcome metric

For the purposes of this analysis, we use number of surviving agents as the measure of organizational outcomes. Because the level of agent interaction that creates product is random throughout, each agent, if it survives, would be expected to produce, on average, roughly the same amount of output. Thus there is a positive relationship between individual production and organizational outcomes in the aggregate, and it follows that the number of surviving agents will positively predict output.

Boundary Permeability defined

To capture these relationships, we define boundary permeability as relevant interaction activity outside the organization, that is, actual exploration learning activity (information transfer events among agents outside) divided by interaction activity inside the organization that could diffuse knowledge, that is, the appetite for learning in support of exploitation (total agent interactions inside the organization). When two agents interact, an information transfer event or a knowledge diffusion event may or may not occur. An event is counted only when one agent gets new information from another agent. If the agent already has access to the other agent's information, no information transfer event occurs. If both agents gain new information or knowledge, two events are counted in a single interaction.

An organization that has little appetite for learning is unlikely to benefit from new information. At the same time, if the amount of new information that crosses the boundary is limited, the amount of knowledge diffusion events inside is limited, regardless of the organization's appetite for new knowledge to diffuse. Therefore, we define boundary permeability as the ratio of new information gained as compared to the organization's appetite for knowledge. More specifically, we define it as the number of actual learning events outside the organization as compared to the number of potential learning events inside. In equation form we say:

$$\text{Boundary Permeability} = \frac{\text{\# of Information Transfer Events Outside}}{\text{\# of Total Agent Interactions Inside}}$$

In other words, we capture the number of information events that occur during search outside the organization and compare it to the interaction activity inside the organization, activity that could potentially support knowledge diffusion inside the organization. As shown in Figure 3, Boundary permeability is assumed to moderate the impact of environmental turbulence on rents and rewards collected by the system, and thus the number of surviving agents.

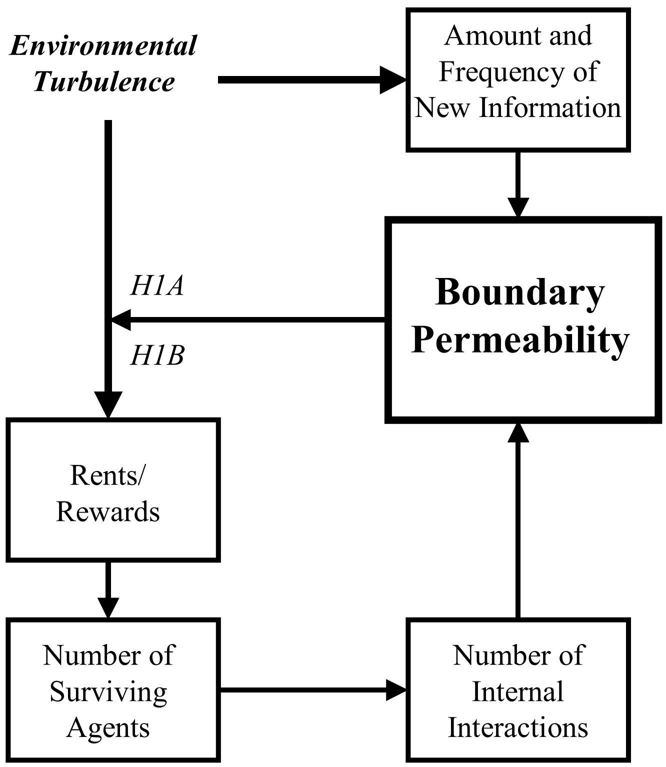
The boundary permeability ratio says something about the efficiency of agent search, its intensity and its effectiveness inside the organization. Given the principle of requisite variety (Morgan, 1997), it is not unreasonable to suspect that the appropriate level of boundary permeability, and therefore internal complexity, would depend upon the level of turbulence in the environment, greater turbulence implying greater boundary permeability. Also, results from Hazy, Tivnan and Schwandt (2002) imply turbulence increases the impact of boundary spanning to collective outcomes. As the boundary permeability ratio increases significantly beyond one, that is, much more information is being gathered that the organization can consume, this positive relationship would be reduced. As such, as shown in Figure 3, we tested the following hypotheses:

Hypothesis 1A: *High* environmental turbulence implies that the *Boundary Permeability* will be positively related to the number of surviving agents so long as the boundary permeability ratio is not significantly greater than one.

Hypothesis 1B: *Low* environmental turbulence implies the *Boundary Permeability* will be negatively related to the number of surviving agents.

Figure 3

Boundary Permeability Moderates the Affect of Environmental Turbulence on Agent Survival Level in Collective Activities



When number of surviving agents is considered as a 3-dimensional surface on the dimensions of boundary permeability and turbulence, the conditions of these hypotheses imply the surface has varying peaks depending on the underlying dimension. A schematic of the expected shape is summarized in Figure 4.

Figure 4

Summary of Hypotheses 1A and 1B

Boundary Permeability	Environmental Turbulence: High	Environmental Turbulence: Low
High	**Peak**	**Trough**
Low	**Trough**	**Peak**

Relative Number of Surviving Agents Shown In Box

To fully understand boundary permeability and the implications of efficiency of collection outside the boundary, the intensity of search across the boundary and the effectiveness of diffusion inside, we need to unpack the boundary permeability construct and understand the variables that comprise it and how they interact.

Information Gathering Efficiency defined

To understand how a collective senses its environment in the course of organizational learning, it is useful to unpack boundary permeability. To do this, we decompose it according the OLSM subsystems (Schwandt & Marquardt, 2000). In the context of the environmental interface subsystem, we define information gathering efficiency outside the organization as the number of information transfer events that occur divided by the number of agents exiting the organizations (Hazy et al., 2002). In other words, efficiency measures the amount of information gathered per boundary spanning agent that leaves the collective to engage in search. In equation form:

$$\text{Information Gathering Efficiency} = \frac{\text{\# of Information Transfer Events Outside}}{\text{\# of Agent Exits from the Organization}}$$

Because an information transfer event implies an agent has access to new or better information or knowledge, it is not unreasonable to assume a positive relationship between

Information Gathering Efficiency and organizational outcomes. Therefore we tested the following:

Hypothesis 2: *Under all* environmental turbulence conditions, *Information Gathering Efficiency* will *positively* predict the number of surviving agents.

Search Intensity defined

Next we measure the physical intensity, the cost to the collective, of agents crossing the boundary to the outside. We define the intensity with which boundary spanners leave the collective to search for new information. Since knowledge diffusion is an important aspect of learning, we realize that boundary spanners represent a cost to knowledge diffusion. Therefore, we measure intensity of boundary spanning in relation to the number of knowledge diffusion events that are occurring, that is, agent exits per knowledge diffusion event. In other words, at what level does the collective choose to forgo potential collective benefit of the internal agents collective activities by allocating certain agents to search (exploration) in contrast to continued knowledge diffusion (exploitation) (March, 1991). Therefore, we define intensity as the total number of agent exits across the boundary as compared to the total number of knowledge diffusion events. In equation form we have:

$$\text{Search Intensity} = \frac{\text{\# of Agent Exits from the Organization}}{\text{\# of Knowledge Diffusion Events}}$$

The tension between participation in internal activities and performing search activities is an important notion in organization theory (Levinthal & March, 1981; March, 1991). The notion of search intensity embodies this tension. As such, it is reasonable to assume that there is no one optimal value for this variable. Rather it is dependent upon the environmental challenges faced by the collective, that is, the relative importance of exploitation versus exploration (March, 1991). The principle of requisite variety (Morgan, 1997) provides guidance here and led us to test the following:

Hypothesis 3A: *High* environmental turbulence implies that the *Search Intensity* will be positively related to the number of surviving agents so long as the boundary permeability ratio is not significantly greater than one.

Hypothesis 3B: *Low* environmental turbulence implies that the *Search Intensity* will be negatively related to the number of surviving agents.

Knowledge Diffusion Effectiveness defined

Finally, we look to the dissemination and diffusion subsystem to understand how information is diffused throughout the organization as knowledge useful for collective benefit (Schwandt & Marquardt, 2000). As described earlier, this occurs through the process of structuration (Giddens, 1984; Schwandt & Marquardt, 2000) as operationalized in computational structuration (Hazy et al., Under review). How effectively new information is diffused into the system as knowledge is an important aspect of structuration (Hazy et al., Under review). Because each agent interaction represents a potential opportunity for knowledge diffusion, we represent effectiveness as actual diffusion events divided by opportunities for diffusion. Restated, Knowledge Diffusion Effectiveness measures the amount of knowledge actually exchanged per interaction opportunity. Therefore, we define effectiveness as the ratio:

$$\text{Knowledge Diffusion Effectiveness} = \frac{\text{\# of Knowledge Diffusion Events}}{\text{\# Total Agent Interactions Inside}}$$

Because the diffusion of knowledge leads to higher reward, one would expect a positive relationship between the effectiveness of knowledge diffusion and organizational outcomes. Therefore we tested the following:

Hypothesis 4: *Under all* environmental turbulence conditions, *Knowledge Diffusion Effectiveness* will *positively* predict the number of surviving agents.

The Boundary Permeability Equation

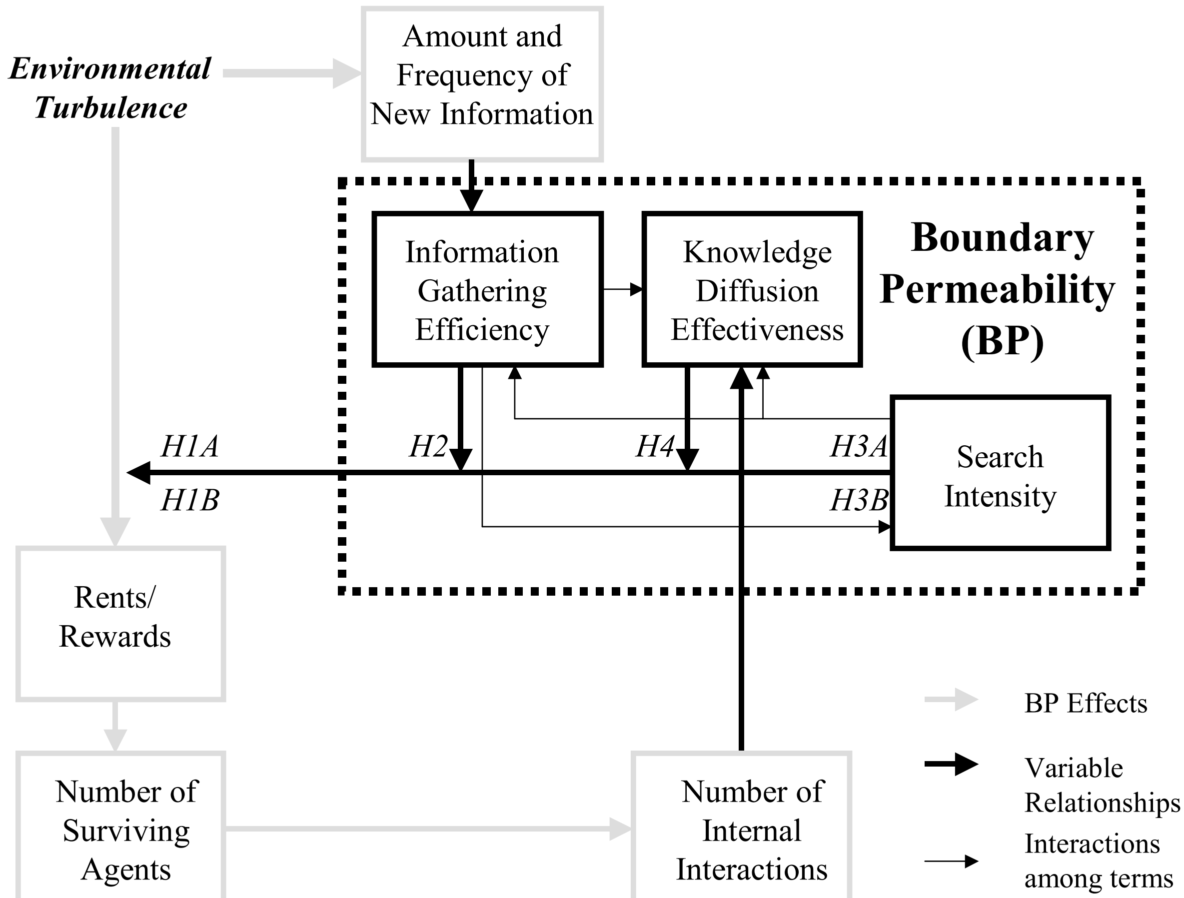
When these variables are combined, we see that Boundary Permeability is in fact comprised of these three variables and their interactions. The non-linear dynamics at work among these variables that describe the organization's boundary, as well as the hypotheses considered in this analysis, are shown in Figure 5. Note that, within boundary the permeability construct, the sub-variables interact with non-linear dynamics. The number of information transfer events influences the number of knowledge diffusion events if new information is carried back inside the system. Likewise, search intensity influences the number of knowledge diffusion events since more agents are searching for an bringing back knowledge. Although much of the richness of the non-linearity is lost, these complicating interactions can be eliminated for simplicity. This is done by introducing the mathematical relationship among these variables -- the boundary permeability equation. It is as follows:

$$\text{Boundary Permeability} = \text{Information Gathering Efficiency} \times \text{Search Intensity} \times \text{Knowledge Diffusion Effectiveness}$$

By eliminating interacting terms and looking only at the independent entities: information transfer events in the numerator and total internal interactions in the denominator, a simplified metric be used as a first approximation. To really understand what is happening at the boundary, however, all of the terms of the boundary permeability equation must be understood.

Figure 5

Conceptual Framework with Hypotheses (H#) Indicated



Research design and methods

Answering the call for agent-based modeling in organizational science research (McKelvey 1999b), we built an agent-based model to explicitly represent boundary spanning activities by agents. We then ran computational experiments to test the above hypotheses derived from organizational learning literature.

To do this, we created an artificial organization that included: agents (or persons) that were members of an organization and some that were outsiders, a habitat defined as a spatial grid with resources scattered randomly across it, and a time-stepping process that allowed agents to move, interact and either prosper or die over a defined period of time (Epstein & Axtell, 1996). It is important to note that for the purposes of this research, the organizational boundary, considered to be both socially constructed (Lissack, 1999; Weick, 1995) and emergent and temporal (Richardson & Lissack, 2001) is represented as a static entity within a particular model run merely for the purposes of computational simplification. By manipulating characteristics of this artificial organization and its inhabitants and then watching it develop over time, we ran computational experiments that would have been difficult or impractical to duplicate in the real world.

The Value Chain Model

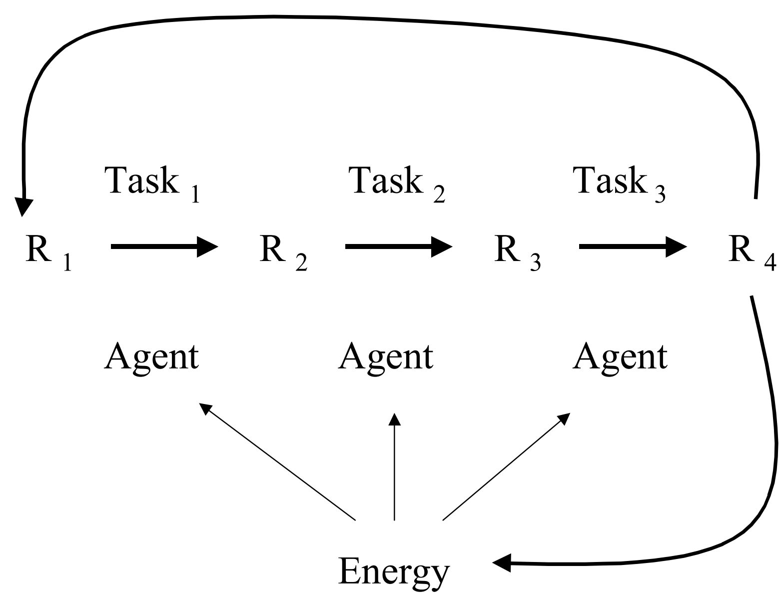
To make the artificial world organizationally realistic, we structured the task and resource environment around the value chain (Porter, 1980, 1985). Resources were transformed at various stages of value creation by the action of agents with appropriate task assignment and knowledge. Agents consumed energy with each step and energy was replenished for agents only when the collective goal was achieved. Failure to continually achieve this collective goal led to the death of individual agents and eventually, to the end of the collective.

The artificial organization was designed to simulate conditions that characterize collective action, that is, task interdependence, reward interdependence and collective potency (Lestor, Meglino, & Korsgaard, 2002; Shea & Guzzo, 1985). As such, in the base case no agent could perform all of the tasks itself and all of the tasks had to be completed for any reward to be distributed. Also, the fact that resources, tasks and relevant knowledge were available to agents simulated the collective attribute called potency, that is, collective ability, i.e., "potency" to execute successfully (Shea & Guzzo, 1985). In addition, rewards were distributed to surviving agents at final production according to their contribution to production of output and the diffusion of knowledge that supported the production. Because no one agent could produce the final good independently, collective action and collective success were both necessary for individual survival.

As Figure 6 indicates, there were N independent tasks, each transforming one resource, R_j, in the value chain into the next resource, R_{j+1}. When any agent that was connected to task T_j became connected to resource R_j by random movement, resource R_j was transformed into R_{j+1}. Production efficiency depended on the currency of the agent's task knowledge.
The above "production process" continued until the completion of final task, T_N wherein a final product, R_F, was created, and a payoff function exercised. This payoff function added energy to the appropriate agents and provided new raw resource, R_1, to re-initiate the production process. In this way, the collective could sustain itself and individual agents could survive by benefiting from collective success.

Figure 6

The Value Chain Model (Porter, 1980;1985)



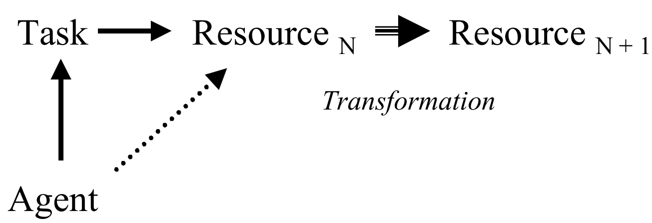
Representing an organization as a network

To link the model to computational organizational theory, all activities within the model were decomposed into primitives such that at each time step the organization's state could be represented as a network consistent with the meta-matrix representation of persons, tasks, resources and knowledge (Krackhardt & Carley, 1998; Carley & Ren, 2001) and an intelligence mechanism that enables agents to change the network locally (Hazy & Tivnan, 2003).

To begin, each agent was randomly assigned to one and only one task, and each task to one and only one type of resource as input. Effectively, there were N types of agents, one for each task type, T_j. Likewise, each task, T_j, was attached to a resource, R_j, as an input and to R_{j+1} as an output. As is shown in Figure 6, the following actions occurred: agent A_i moved to a space adjacent to resource R_j enabling agent A_i to perform task T_j thereby converting resource R_j to resource R_{j+1}. Thus, these actions represented a change to the network of connections among agents, tasks and resources by the action of an agent.

Figure 7

A representation of change to the network of resources



The impact of knowledge transfer and diffusion

For our study, we introduced into this artificial organization the concepts of information transfer knowledge and knowledge diffusion. To produce an output from a resource input and thereby complete a task, an agent had to be connected to knowledge that was relevant for the agent-task pairing. In addition, depending on the turbulence in the environment (in this case, defined as frequency of change in knowledge generation), the payout value of an agent's knowledge decreased over time. The consequence of knowledge value decrease was a decline in production efficiency. Agents accumulated knowledge by interacting with other knowledge-bearing agents. Knowledge was refreshed with new generations of knowledge by interaction with other member and outsider agents bearing information that was more current. Information was assumed to become knowledge once it was useful for the execution of tasks and the production of output, that is, once it was inside the organization and became embedded in the organizations network. In these artificial organizations, new information that was potentially useful in creating new knowledge was always introduced outside the organization's boundary.

With respect to agent learning capacity, any agent could carry (be linked to) and transfer any and all knowledge types, but each knowledge type was linked to one and only one task type. Therefore, initially, only one knowledge type was useful to a particular agent (i.e., the knowledge relevant to its task type). As new knowledge about different tasks was acquired, those tasks were automatically assigned and could be executed, that is, the new knowledge became relevant to task execution and the agents were cross-trained. Outsider agents acted as carriers of the latest knowledge and refreshed the knowledge of the member agents with whom they interacted. Outsider agents performed no organizational tasks and consumed no organizational resources.

To initialize the artificial organization, we defined agents that represented the organization's members and randomly assigned each a task type (which determined which type of resource it consumed and the output it generated as well as the knowledge type needed). We next defined the rules or methods that governed their interaction with other network elements. Certain agents were designated as boundary spanners. Each member agent began with the necessary knowledge to perform its task, but that knowledge became less valuable over time. Outsider agents were also initialized and given all the knowledge needed by the member agents to perform their tasks.

In this study, the organization and its agents exist and interact on a grid representing positions in an abstract space representing inclusion, i.e. being inside, and exclusion, i.e. being outside, of a collective. Each agent represents a person who, when inside, executes assigned tasks and consumes resources to produce outputs. The productivity of resource transformation is determined by the agent's knowledge. Knowledge is gathered by exchanges among agents as they interact. The utility of knowledge decays with time. Knowledge is refreshed by importation of new information from beyond the organization's boundary. This occurs when agents who have been outside the boundary return with refreshed knowledge to exchange with other agents inside the boundary.

Boundary defined for the study

We define the inside, outside and boundary of an organization as follows: a position on the spatial grid is "outside" the collective when no tasks can be performed for the benefit of the collective at that location; a position is "inside" when tasks can be performed for the benefit of the collective at that location; and, the organization boundary consists of all "outside" positions that are adjacent to "inside" positions.

Virtual experiments

Because the variables that make up boundary permeability and are the subject of the hypotheses interact with one another, we chose to create many artificial organizations in which the initial conditions were controlled, certain parameters were varied in known ways and the organizations were allowed to develop stochastically over many time steps. In particular, for these virtual experiments, we varied only the turbulence in the environment and the number of boundary spanners in the organization. All other aspects of the organization were identical as the models were initiated. Of course, it is the nature of stochastic agent-based modeling that each run of the model, each artificial organization, is unique and cannot be replicated. The model thus shows sensitivity to initial conditions since, under very similar initial conditions, some organizations survived and prospered while others withered and died.

In the end the data set described 5,500 artificial organizations that developed under varied environmental states and with varying levels of boundary permeability. Likewise, when boundary permeability was decomposed into its constituent variables, information gathering efficiency, search intensity and knowledge diffusion effectiveness, varying combinations of constituent values characterized the data set.

Description of analysis performed

As is noted above, the boundary spanners were set and remained constant for a given run. Thus, although boundary permeability, because it is a function of several interacting variables, changes its value through time, the value was always constrained by the number of boundary spanners that initialized the system. That is, although individual agents died during a model run and thus the proportion of boundary spanners varied over time, the organization did not proactively adapt to the environment by increasing or decreasing the number of boundary spanners in response to environmental conditions. As such, the analysis performed conforms in one sense to that of population ecology (Hannan & Freeman, 1989). We looked at the variables describing the 5,500 artificial organizations at the end of the model runs and looked for patterns that either supported or refuted the various hypotheses. These results were plotted and statistical analysis performed.

Results and analysis

As a first step, 5,500 artificial organizations were created. Each began with similar initial conditions except with respect to environmental turbulence and number of boundary spanning agents at initialization. As such, a large sample of comparable artificial organizations, each having survived 3650 time steps (approximating ten years of organizational history), was available for analysis. To test for hypothesized relationships, the number of surviving agents in each scenario was compared with the various boundary permeability variables that characterized the scenario.

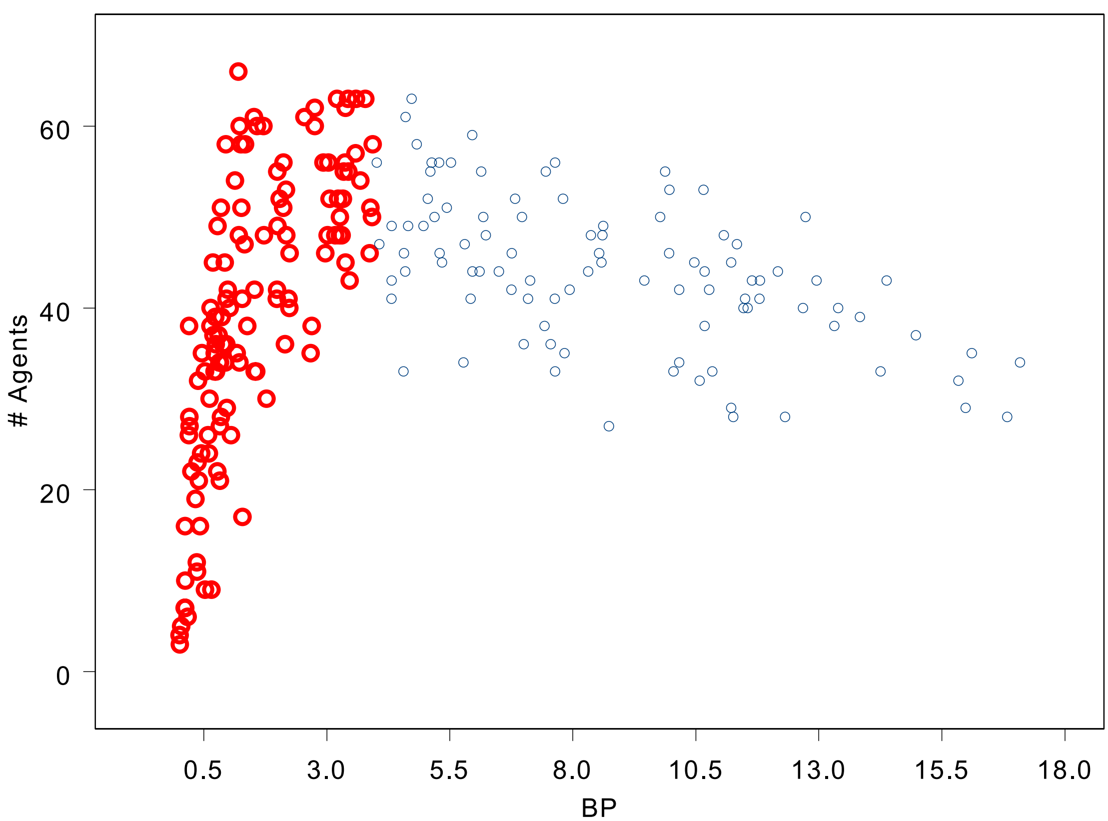
The impact of boundary permeability

As is shown in Figure 8, when number of surviving agents (#Agents) was compared with boundary permeability (BP) in a high turbulence environment (high turbulence environments are cases where new information was introduced from zero to fifty time steps) we found that, as expected, for BP less than one, the #Agents was positively correlated ($r = 0.73$, $r^2 = 0.53$) with BP, that is, as BP increased, so did #Agents. As BP increased beyond one, however, this relationship turned negative ($r = - 0.41$, $r^2 = 0.16$). These results imply that the benefit of increasing BP seems to reach an upper limit. These results, summarized in Table 1, strongly support Hypothesis 1A.

When the number of surviving agents (#Agents) was compared with boundary permeability (BP) in a low turbulence or stable environment (low turbulence environments are cases where new information was introduced every 1050 to 1095 time steps) we found that, as expected, for BP less than one, the #Agents was negatively correlated ($r = -0.74$, $r^2 = 0.55$) with BP, as BP increased, the #Agents decreased. As BP increased beyond one, this relationship continued ($r = -0.76$, $r^2 = 0.58$). For all values of BP, the negative relationship was strongly supported ($r = -0.87$, $r^2 = 0.76$). These results, summarized in Table 1, strongly support Hypothesis 1B.

Figure 8

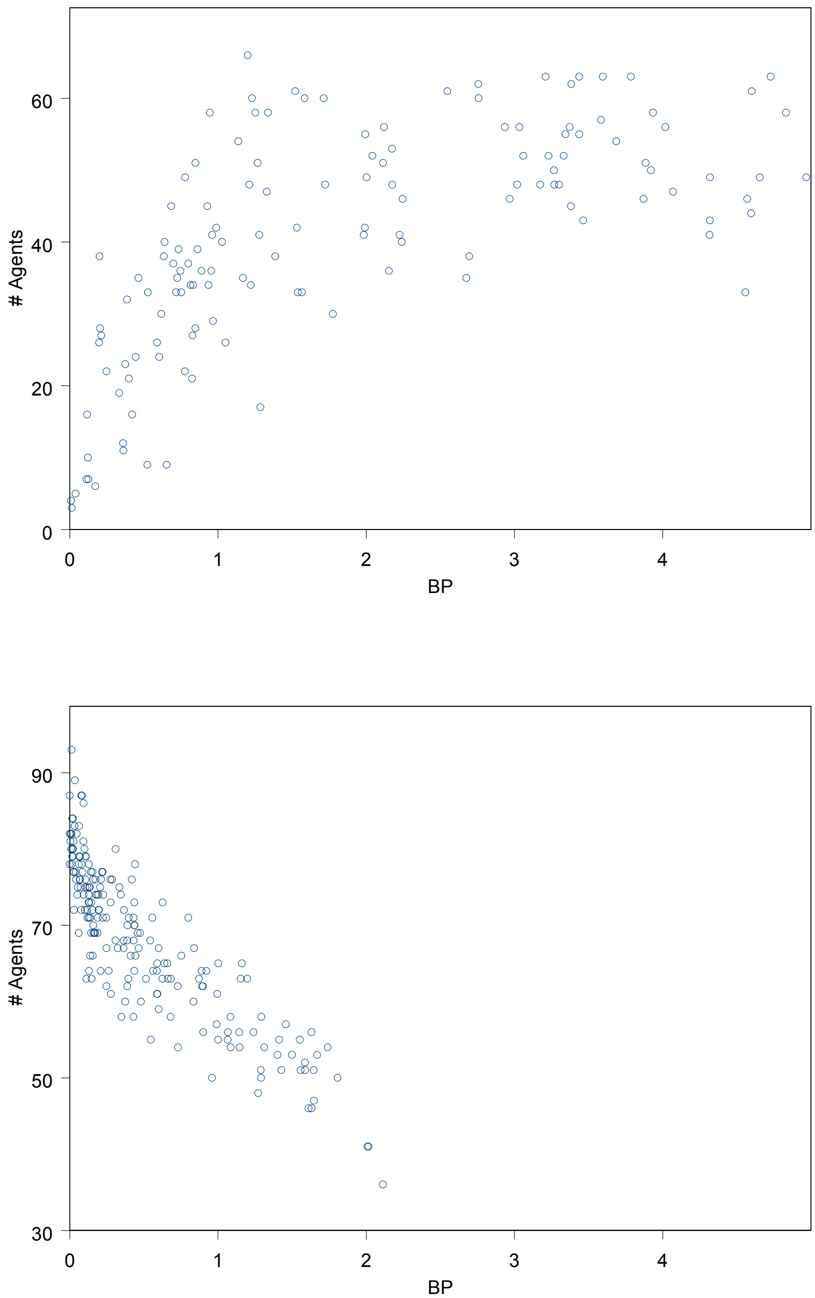
Number of surviving agents (# Agents) versus boundary permeability (BP) in high turbulence environments – Large points indicate positive gradient for low BP, and small points indicate negative gradient for high BP



In sum, as is shown in Figure 9, increasing BP (up to a point) has a positive effect in turbulent environments, but always has a negative effect in stable ones.

Figure 9

Number of surviving agents (# Agents) versus boundary permeability (BP) for environments with high turbulence (top) and low turbulence (bottom)



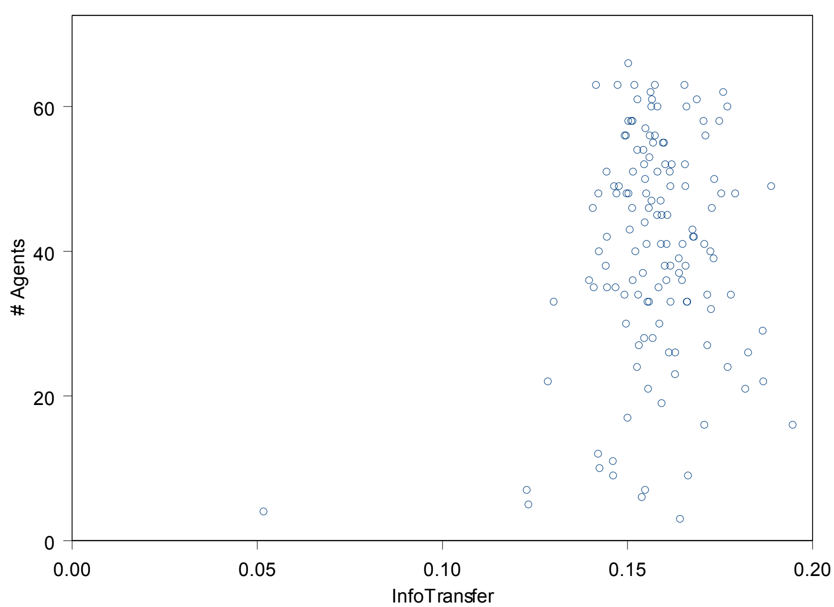
The impact of information gathering efficiency

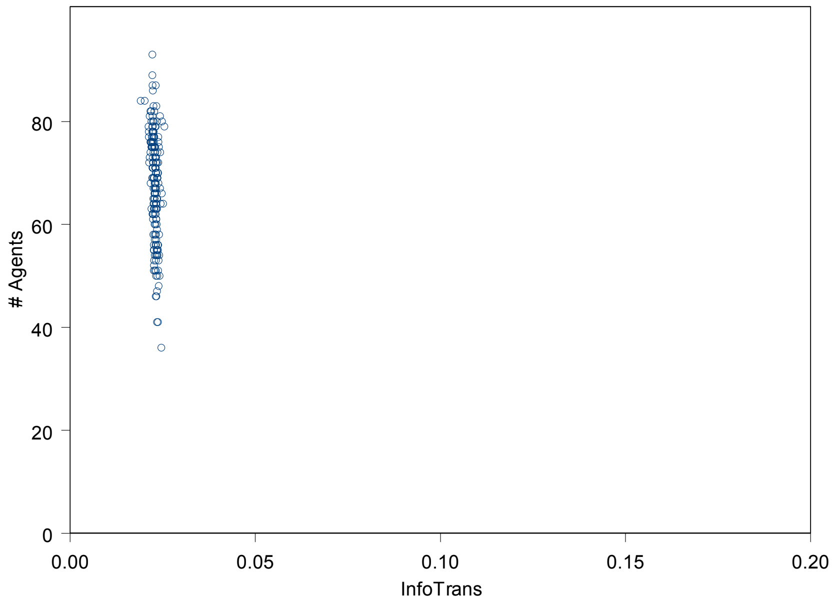
When number of surviving agents (#Agents) was compared with information gathering efficiency (InfoTransfer) in a high turbulence we found only a weak correlation ($r = 0.17$, $r^2 = 0.030$) and in low turbulence we found a negative and stronger correlation ($r = - 0.42$, $r^2 = 0.18$).

As is shown in Figure 10, values for InfoTransfer across the entire data set exist in a very tight range for each interval of environmental turbulence. This represents a limitation in the model such that in the model, each agent interaction results in an information transfer event when new information is available. The tight distribution of InfoTransfer thus represents a random distribution around the probability that an interaction will occur outside the organization's boundary. These results, summarized in Table 1, do not support Hypothesis 2.

Figure 10

Number of surviving agents (# Agents) versus information transfer efficiency (Info Transfer) for environments with high turbulence (top) and low turbulence (bottom)





The impact of Search intensity

When number of surviving agents (#Agents) was compared with search intensity (SI) in a high turbulence environment, we found that, as expected, for BP less than one, the #Agents was positively correlated ($r = 0.78$, $r^2 = 0.61$) with SI. As BP increased beyond one, however, this relationship, like BP, turned negative ($r = -0.4541$, $r^2 = 0.29$) implying that the benefit of increasing SI seems to reach an upper limit. It is worth noting that although directionally the same, these correlations are slightly higher than those relating #Agents with BP. These results, summarized in Table1, strongly support Hypothesis 3A.

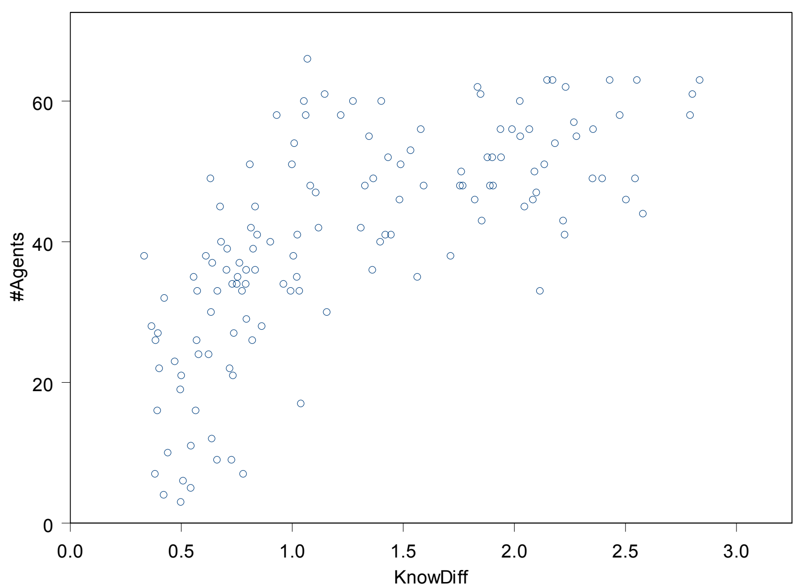
When number of surviving agents (#Agents) was compared with search intensity (SI) in a low turbulence or stable environment we found that, as expected, for BP less than one, the #Agents was negatively correlated ($r = -0.77$, $r^2 = 0.60$) with SI, as SI increased, the #Agents decreased. As BP increased beyond one, this relationship continued ($r = -0.54$, $r^2 = 0.30$). For all values of BP, the negative relationship was strongly supported ($r = -0.78$, $r^2 = 0.62$). These results, summarized in Table 1, strongly support Hypothesis 3B.

The impact of Knowledge diffusion Effectiveness

When number of surviving agents (#Agents) was compared with knowledge diffusion effectiveness (KnowDiff) in a high turbulence environment we found only a weak correlation ($r = 0.35$, $r^2 = 0.12$) overall. However, when only scenarios with boundary permeability of less than one are considered, the correlation increased ($r = 0.504$, $r^2 = 0.254$). In low turbulence we found a negative and stronger correlation ($r = -0.62$, $r^2 = 0.39$). The scatter plots for these scenarios are shown in Figure 11. These results, summarized in Table 1, partially support Hypothesis 4, but only in high turbulence environments with and boundary permeability less than one.

Figure 11

Number of surviving agents (# Agents) versus knowledge diffusion effectiveness (KnowDiff) in environments of high turbulence (top) and low turbulence (bottom)



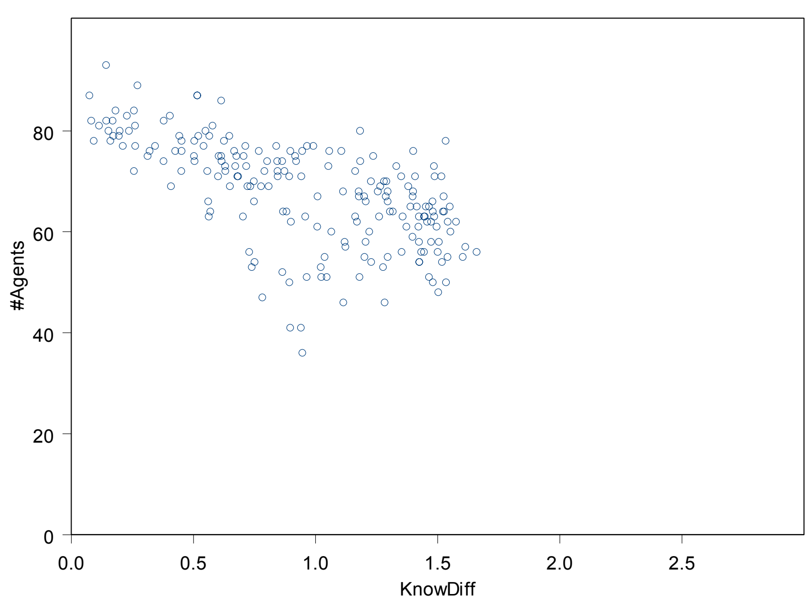


Table 1

Statistical correlations for hypothesized relationships with # of surviving agents

Relationship to # Agents	**Turbulence**	**Hypotheses**	**r See Note**	**r^2**	**Comments**
Boundary Permeability (BP)	High	H1A	0.728 -0.406	0.531 0.165	BP < 1 BP>=1
Boundary Permeability (BP)	Low	H1B	-0.744 -0.762	0.554 0.580	BP < 1 BP>=1
Information Efficiency	High	H2	0.277 Not Sign.	.0769	BP < 1 BP>=1
Information Efficiency	Low	H2	-0.346 0.508	-0.120 0.258	BP < 1 BP>=1
Search Intensity	High	H3A	0.780 -0.537	0.609 0.289	BP < 1 BP>=1
Search Intensity	Low	H3B	-0.772 -0.545	0.596 0.297	BP < 1 BP>=1
Knowledge Effectiveness	High	H4	0.504 -0.202	0.254 0.041	BP <1 BP>=1
Knowledge Effectiveness	Low	H4	-0.731 -0.394	0.535 0.155	BP <1 BP>=1

Note: all values listed are significant at the $\alpha = 0.05$ level.

Discussion

In this paper we investigated the permeable nature of the organizational boundary with respect to organizational learning. Using the Organizational Learning Systems Model (OLSM) (Schwandt, 1997) and building upon computational organizational theory (Carley & Prietula, 1994b) we precisely defined boundary permeability with respect to the amount of new information obtained in the environment and the number of agent interactions inside the organization's boundary. We then decomposed boundary permeability into constituent parts: information gathering efficiency, search intensity and knowledge diffusion effectiveness. Hypotheses were developed and tested based upon 5,500 artificial organizations which randomly evolved under controlled conditions.

Until now, nonlinear models of the collective have for the most part contributed only metaphorically to theory building (Eden & Ackermann, 1998). With this analysis we showed directly the dynamic nature of a collective's activities in the context of agent level interaction, especially in relation to organizational learning and planning (Eden & Ackermann, 1998; Mintzberg, 1994; Schwandt, 1997; Schwandt & Gorman, 2002).

The implications of results to theory

Our results showed that the number of agents surviving in an artificial organization is related to the characteristics of the organization's boundary. Further, we showed that the nature of this relationship depends upon the level of turbulence in the external environment. As expected, in stable environments, although some permeability is necessary for survival, in general, increasing permeability is always bad for survival. As turbulence increases however, increased permeability helps survival of agents, up to a point, after which survival potential declines. In effect, increasing permeability beyond a critical point allows too many agents to "leak out" and escape productive activity while providing little incremental benefit from learning.

When boundary permeability is decomposed into its constituent variables the picture is less clear. Indeed, our results for the metric search intensity -- which describes agent boundary crossing activity -- mirrors the boundary permeability results. This is particularly interesting in that search intensity, defined as the ratio of agent exits to knowledge diffusion events inside the organization, does not share any arithmetic factors with boundary permeability. Setting aside agent boundary crossings, however, the implications of learning activity outside the boundary as well as inside the boundary are far less clear from this research. The non-linear dynamics at work within the system complicate the analysis and limit the applicability of traditionally linear statistical techniques. Future research is needed to understand the nonlinear dynamic relationships among information gathering efficiency, search intensity and knowledge diffusion effectiveness and how they contribute to boundary permeability and thus to organizational learning.

Limitations

This analysis modeled an organization as a complex system of adaptive agents. It did not model the organization as a complex adaptive system. Agents learn and improve their ability to produce collective output. Thus the system improves its ability to exploit its existing capabilities. It does not, adapt, however, in the sense that the system cannot adjust its boundary permeability, or any other structural element for that matter, in response to the environment. By measuring the number of surviving agents, we use agent survival as a fitness measure and selected organizational forms (in the context of boundary permeability) that were most fit under various environmental states. In this sense we used a population ecology (Hannan & Freeman, 1989) epistemology to study the structure of organizational boundaries.

Until the action subsystems of the OLSM, that is, the meaning and memory (sensemaking) and action/reflection (goal referenced knowledge) subsystems (Schwandt, 1997), are modeled, the organization only "senses" its environment. Its agents learn from this information, but the organization as a complex system cannot change its structure to adapt to the environment. If an organization's boundary permeability is too great for the environment, the system simply perishes. Thus, "sensing in concert" is distinguished from "acting in concert." The latter begins with sensemaking (Weick, 1995) from the meaning and memory subsystem and ends with the action and reflection subsystem (Schwandt & Marquardt, 2000). Beyond the sensing studied here, for learning to occur, the collective must also act to change its internal configuration, to adapt to what is sensed, an aspect of organizational learning not studied here as left to future research.

Future directions

The results described support the possibility that boundary permeability could be a useful construct for organizational learning research. The complementary nature of boundary permeability (BP) and search intensity (SI) offer alternative ways researchers could operationalize these constructs in laboratory and field research. Although the constituent components of BP described showed mixed results, the decomposition also did no harm as SI results mirrored and in fact slightly improved those of BP.

In addition, the assumption that agent interaction leads to information and knowledge transfer in every case -- while helpful in simplifying the analysis -- may have contributed to the apparent redundancy in the boundary permeability and search intensity metrics. Future research that makes information and knowledge exchange less efficient may highlight the importance of the information transfer efficiency and knowledge diffusion effectiveness metrics to organizational learning. We believe further exploration of these factors is therefore warranted.

Concluding remarks

The artificial society created in this study constitutes a significant step towards our ultimate goal: the computational representation of organizations that is on the one hand, realistic, and on the other simplified and idealized so as to become tractable.

An organizationally realistic computational model is one that the informed observer would intuitively feel "looks like" what is happening in organizations, but at the same time, is rigorous in its depiction of the constraints and limitations of real organizational life.

In sum, we believe the framework developed here could be a first step toward a canonical, organizationally realistic modeling approach.

Bibliography

Argyris, C., & Schon, D. A. (1978). ***Organizational Learning.*** Addison-Wesley: Reading MA.

Burton, R. (2001). Afterward. In A. Lomi & E. R. Larsen (Eds.), ***Dynamics of Organizations: Computational Modeling and Organizational Theories*** (pp. 439-444). : AAAI Press/MIT press: Menlo Park CA.

Carley, K. M., & Gasser, L. (1999). Chapter 7: Computational Organization Theory. In G. Weiss (Ed.), ***Distributed Aritificial Intelligence*** (pp. 299-330). MIT Press: Cambridge MA.

Carley, K. M., & Krackhardt, D. (1999, June, 1999). A Typology for C2 Measures. Paper presented at the 1999 International Symposium on Command and Control Research and Technology, Newport, RI.

Carley, K. M., & Prietula, M. J. (1994a). ACTS Theory: Extending the Model of Bounded Rationality. In K. M. Carley & M. J. Prietula (Eds.), ***Computational Organizational Theory*** (pp. 55-88). Lawrence Erlbaum Associates: Hillsdale NJ.

Carley, K. M., & Prietula, M. J. (Eds.). (1994b). ***Computational Organization Theory***. Lawrence Erlbaum Associates: Hillsdale NJ.

Carley, K. M., & Ren, Y. (2001, June). Tradeoffs Between Performance and Adaptability for C3I Architectures. Paper presented at the Command and Control Research and Technology Symposium, Annapolis, MD.

Carley, K. M., Ren, Y., & Krackhardt, D. (2000, June 26-28, 2000). Measuring and Modeling Change in C3I Architecture. Paper presented at the 2000 Command and Control Research and Technology Symposium, Annapolis, MD.

Carley, K. M., & Svoboda, D. M. (1996). Modeling Organizational Adaptation as a Simulated Annealing Process. ***Sociological Methods & Research,*** 25(1): 138-168.

Carley, K. M., & Wallace, W. A. (1996). Computational Organizational Theory: A new perspective. In S. Gass & C. Harris, M. (Eds.), ***Encyclopedia of Operations Research and Management Science*** (pp. 20 page manuscript). Kluwer Academic Publishers: Boston.

Daft, R. L., & Weick, K. E. (1984). Toward a Model of Organizations as Interpretive Systems. ***Academy of Management Review***, 9(2): 284-295.

Eden, C., & Ackermann, F. (1998). ***Making Strategy: The Journey of Strategic Management***. Sage: London.

Epstein, J. M., & Axtell, R. (1996). ***Growing artificial societies: Social science form the bottom up.*** Brookings Institution and MIT Press: Washington DC and Cambridge MA.

Fiol, C. M., & Lyles, M. A. (1985). Organizational Learning. ***Academy of Management Review,*** 10(4): 803-813.

Giddens, A. (1976/1993). ***New Rules of Sociological Method*** (Second ed.). Stanford University Press: Stanford CA.

Giddens, A. (1984). ***The Constitution of Society.*** University of California Press: Berkeley CA.

Gilbert, N., & Troitzsch, K. G. (1999). ***Simulation For the Social Scientist***. Open University Press: Buckingham.

Hannan, M. T., & Freeman, J. (1989). ***Organizational Ecology.*** Harvard University Press: Cambridge MA.

Hazy, J. K., & Tivnan, B. F. (2003, June 22 - 25). Representing agent intelligence as local network dynamics. Paper presented at the NAACSOS, Pittsburgh, PA.

Hazy, J. K., Tivnan, B. F., & Schwandt, D. R. (2002, December 7 to10). Boundary Spanning in Organizational Learning: Preliminary computational explorations. Paper presented at the Institute for the Study of Convergence and Emergence Managing the Complex IV conference, Fort Myers, Florida.

Hazy, J. K., Tivnan, B. F., & Schwandt, D. R. (Under review). Modeling Social Structure as Network Effects: Computational Evidence That Rewarding Learning Improves Performance., The George Washington University, Ashburn, Virginia.

Hedberg, B. L. T. (1981). How Organizations Learn and Unlearn. In P. C. Nystrom & W. H. Starbuck (Eds.), ***Handbook of Organizational Design*** (Vol. 1, pp. 3-27). Oxford University Press: New York.

Huber, G. P. (1991). Organizational Learning: The contributing processes and the literatures. ***Organizational Science***, 2(1): 88-115.

Kohler, T. A. (2000). Putting Social Sciences Together Again: And Introduction to the volume. In T. A. Kohler & G. J. Gumerman (Eds.), ***Dynamics in Human and Primate Societies: Agent-Based Modeling of Social and Spatial Processes*** (pp. 1-18). Oxford University Press: New York.

Krackhardt, D., & Carley, K. M. (1998, June). A PCANS Model Structure in Organization. Paper presented at the 1998 International Symposium on Command and Control Research and Technology, Monterrey, CA.

Lestor, S. W., Meglino, B. M., & Korsgaard, M. A. (2002). The Antecedents and Consequences of Group Potency: A Longitundinal Investigation of Newly Formed Work Groups. ***Academy of Management Journal***, 45(2): 352-368.

Levinthal, D. A., & March, J. G. (1981). A Model of Adaptive Search. ***Journal of Economic Behavior and Organization,*** 2: 307-333.

Leydesdorff, L., & van den Besselaar, P. (Eds.). (1994). ***Evolutionary economics and chaos theory***. St Martin's Press: New York.

Lissack, M. R. (1999). Complexity: the Science, Its Vocabulary and Its Relation to Organizations. ***Emergence,*** 1(1): 110-126.

Lomi, A., & Larsen, E. R. (Eds.). (2001). ***Dynamics of Organizations: Computational Modeling and Organization Theories.*** AAAI/Press/MIT Press: Menlo Park CA.

Lundberg, C. C. (1989). On Organizational Learning: Implications and opportunities for expanding organizational development. ***Research in Organizational Change and Development,*** 3: 61-82.

March, J. G. (1991). Exploration and exploitation in organizational learning***. Organization Science***, 2(1): 71-87.

March, J. G. (2001). Forward. In A. Lomi & E. R. Larsen (Eds.), ***Dynamics of Organizations: Computational Modeling and Organizational Theories*** (pp. ix-xviii). AAAI Press/MIT press: Menlo Park CA..

March, J. G., & Olsen, J. P. (1988/1975). The uncertainty of the past: organizational learning under ambiguity. In J. G. March (Ed.), ***Decisions and Organizations*** (pp. 335-358). Basil Blackwell: New York.

Mintzberg, H. (1994). ***The Rise and Fall of Strategic Planning.*** The Free Press: New York.

Morgan, G. (1997). ***Images of Organization.*** Sage: Thousand Oaks, CA.

Orton, J. D., & Weick, K. E. (1990). Loosely Coupled Systems: A Reconceptualization. ***Academy of Management Review***, 15(2): 202-223.

Porter, M. (1980). ***Competitive Strategy: Techniques for analyzing industries and competitors***. The Free Press: New York.

Porter, M. (1985). ***Competitive Advantage: Creating and sustaining superior performance.*** The Free Press: New York.

Prietula, M. J., Carley, K. M., & Gasser, L. (1998). A Computational Approach to Organizations and Organizing. In M. J. Prietula & K. M. Carley & L. Gasser (Eds.), ***Simulating Organizations: Computational Models of Institution and Change*** (pp. xiii-xix). AAAI Press/The MIT Press: Menlo Park CA..

Richardson, K. A., & Lissack, M. R. (2001). On the Status of Boundaries, both Natural and Organizational: A Complex Systems Perspective. ***Emergence***, 3(4): 32-49.

Schwandt, D. R. (1997). Integrating Strategy and Organizational Learning: A Theory of Action Perspective. In J. P. Walsh & A. S. Huff (Eds.), ***Advances In Strategic Management*** (Vol. 14). JAI Press, Inc.: Greenwich CT.

Schwandt, D. R., & Gorman, M. D. (2002, 11-13 July 2002). Foresight and Foreseeing: A Social Action Explanation of Complex Collective Knowing in an Executive Team. Paper presented at the An International Conference at the University of Strathclyde Graduate School of Business, Glasgow, UK.

Schwandt, D. R., & Marquardt, M. J. (2000). ***Organizational Learning: From World-class Theories to Global Best Practices.*** St. Lucie Press: Boca Raton.

Shea, G. P., & Guzzo, R. A. (1985). Leads on the determinants of group effectiveness (WP-533). Philadelphia: The Wharton School, University of Pennsylvania.

Simon, H. A. (1957/1997). ***Administrative Behavior:A Study of Decision-Making Processes in Administrative Organizations*** (Fourth ed.). The Free Press: New York.

Sterman, J. D. (2000). ***Business Dynamics: Systems thinking and modeling for a complex world.*** McGraw-Hill: Boston.

Taylor, J. R., & Van Every, E. J. (2000). ***The Emergent Organization.*** Lawrence Erlbaum Associates: Mahwah, NJ..

Tsoukas, H. (1996). The firm as a distributed knowledge system. ***Strategic Management Journal,*** 17(Special Issue:winter): 11-26.

Walsh, J. P. (1995). Managerial and Organizational Cognition: Notes form a trip down memory lane. ***Organizational Science,*** 6(3): 280-321.

Weick, K. E. (1995). ***Sensemaking in Organizations***. Sage: Thousand Oaks CA.