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Situated Learning Theory: Adding Rate and Complexity Effects via Kauffman's *NK* Model

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Abstract: *For many firms, producing information, knowledge, and enhancing learning capability have become the primary basis of competitive advantage. A review of organizational learning theory identifies two approaches: (1) those that treat symbolic information processing as fundamental to learning, and (2) those that view the situated nature of cognition as fundamental. After noting that the former is inadequate because it focuses primarily on behavioral and cognitive aspects of individual learning, this paper argues the importance of studying learning as interactions among people in the context of their environment. It contributes to organizational learning in three ways. First, it argues that situated learning theory is to be preferred over traditional behavioral and cognitive learning theories, because it treats organizations as complex adaptive systems rather than mere information processors. Second, it adds rate and nonlinear learning effects. Third, following model-centered epistemology, it uses an agent-based computational model, in particular a"humanized" version of Kauffman's NK model, to study the situated nature of learning. Using simulation results, we test eight hypotheses extending situated learning theory in new directions. The paper ends with a discussion of possible extensions of the current study to better address key issues in situated learning.*

Key Words: situated learning theory, group learning, rate of learning, complexity catastrophe, agent-based models, Kauffman, *NK* model, rugged landscape

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INTRODUCTION

Information and knowledge have become the primary basis of a firm's competitive advantage in modern societies (Argote, Ingram, Levine & Moreland, 2000; Castells, 1996; Drucker, 1999). How organizations create, retain, share and transfer knowledge has become a heated topic attracting attention from diverse disciplines, including cognitive psychology (e.g. Thompson, Gentner & Lowenstein, 2000), artificial intelligence (Carley, 1999a; Carley & Gasser, 1999; Hutchins, 1990, 1991), group dynamics (Argote, 1999; Moreland & Myaskovsky, 2000; Paulus & Yang, 2000), strategic management (Brockmann & Anthony, 1998), and macro organization theory (Miner & Anderson, 1999). Increasing the *amount* of organizational learning has become the centerpiece of research on organizational strategy, structure and process (Cross & Israelit, 2000; Nonaka & Nishiguchi, 2001). Amount of learning is surely important, but increasing the *rate* of learning could be even more important for firms competing in hypercompetitive, high velocity contexts (D'Aveni, 1994; Prusak, 1996; Brown & Eisenhardt, 1997).

Existing research on organizational learning roughly classifies into two camps: symbolic information processing and situated learning (Greeno & Moore, 1993). The symbolic information processing perspective, dominating traditional learning theory, focuses primarily on individual minds, and downplays the importance of context. The situated learning perspective, by contrast, views learning as grounded less in individual cognitions than in *interactions* among people and between people and their environmental context. That agents interact and influence each other is fundamental to the coevolutionary basis of the nonlinear dynamics studied by complexity scientists (Arthur, 1990; Arthur, Durlauf & Lane, 1997).

Kauffman (1993) argues that increasing numbers of links among interacting agents have a *nonlinear* effect, resulting eventually in "*complexity catastrophe*." His use of "catastrophe" is to signify that while increasing social connections at first facilitates learning, at some point too much interactive complexity thwarts adaptive learning and stops the Darwinian natural selection process. The negative effect of too much network complexity has also been observed in organizations (Uzzi, 1997). In this paper, we concentrate on the within-group dynamics at the core of organizational learning.

For the record we note that, for Kauffman, "complexity catastrophe" thwarts the Darwinian natural selection process—a truly catastrophic outcome for biologists. This usage differs from Thom's (1975) catastrophe theory wherein surpassing critical values on control parameters shifts a system into discontinuous change.

We begin by elaborating the argument that situated theory of learning is to be preferred over the traditional behavioral and cognitive theories of learning. Our theoretical development rests on two recent shifts in organizational research: (a) from treating organizations as mere information processors to complex adaptive systems; and (b) from a reductionist to a holistic perspective focusing on emergent collective properties. Given these theory issues, we take an agent-based simulation approach. Heterogeneous agent models are particularly well suited to the study of interactive agent connections, nonlinear interaction, emergent structure and supervenience (downward causality). Using a computational simulation, we test several hypotheses extending situated theory in new directions. We conclude with a discussion of possible extensions of the current study to better address remaining issues in the situated learning theory.

TRADITIONAL VS. SITUATED LEARNING THEORY

Traditional

Traditional learning theories divide roughly into two perspectives: behavioral and cognitive (Greeno & Moore, 1993). The behavioral approach focuses on how people learn through stimulus-response conditioning, ignoring mental processes through which human beings develop internal perceptions of external objects. Cognitive theories of learning, regardless of the distinctions among the constructivist, psychoanalytic, and critical cultural perspective (Fenwick, 2000), rose as antitheses to the behavioral approach for explaining how cognitive agents learn through symbolic information processing (Glynn, Lant & Millikan, 1994; Greeno & Moore, 1993; Moore, 1998). Although most traditional theories of learning acknowledge the existence of interactive relations between the agents and the external contexts that may impact the development of agents' intellectual capabilities for knowledge acquisition, the dialectic interplay between agents and the contexts has never been fully explored (Greeno & Moore, 1993). In traditional learning theories, the primary unit of analysis is the individual mind (Lave & Wenger, 1991; Sfard, 1998), and as a result, the concept of learning is a "lonely one, analytically removed from the rich textures of everyday experience" (Hutchins, 1993, p. 743).

Situated Learning Theory

Situated learning theory scholars argue that learning activity takes place not only within the individual learner's mind, but also among learners within an interactive community. Group knowledge is not only the property of individuals who have the knowledge, but also of the speech community or the social network in which such knowledge is negotiated and justified (Giddens, 1984; Hutchins, 1993; Glynn, Lant & Milliken, 1994; Lave & Wenger, 1991; Taylor, 1999; Wenger, 1998). Argote (1999) defines a group as a collection of individuals who share task interdependencies, who see themselves and are seen by others as members of an intact social entity, and who are embedded in a larger social system. Group learning is a collective experience in which group members generate, retain, and transfer knowledge.

According to Greeno and Moore (1993), the more commonly used term "situated cognition" implies that some types of cognitions are situated while others are not. They suggest the term "situativity" instead of "situated" to describe a general characteristic of cognition, arguing that "situativity is fundamental in all cognitive activity" and "cognition that involves symbols" is only "a special case of cognitive activity" (p. 50). Although we use the more popular term here, we agree with Greeno and Moore that being situated in social contexts is fundamental for most learning activities.

Situated learning theory shifts attention from individual minds to connections among minds; and from the properties of individual persons or of their environments to the interactions between people, and between people and their environment (Greeno & Moore, 1993; Glynn, Lant & Millikan, 1994; Lant & Phelps, 1999; Lave & Wenger, 1991; Taylor, 1999; Weick & Ashford, 2000; Weick & Roberts, 1993). Learners are not isolated individuals but participants within communities of practice (Lave & Wenger, 1991). It follows that (a) individual learning is inseparable from collective learning; and (b) situated learning should be understood primarily as evolving within "an interactive context and is embedded in the context and the process of organizing" (Lant & Phelps 1999, p. 233), and is "best modeled in terms of the organizational connections that constitute a learning network" (Glynn, Lant & Millikan, 1994, p. 56).

Situated learning theory advocates a fundamental reconceptualization of the processes of human cognitive activities (Greeno & Moore, 1993; Hutchins, 1993; Glynn, Lant & Millikan, 1994; Lant, 1999). This view is also consistent with two changes in organizational studies in recent years. The first one is the shift from viewing organizations as linear information processors to treating them as complex adaptive systems. The second reflects the studying learning from a holistic, emergent, multi-level mutual-causality perspective. We elaborate these below.

Situated Learning in Complex Adaptive Systems

Situated learning theory's argument that learning stems from social interactions may be further elaborated given that social interactions usually occur within complex adaptive systems (CASs) (Anderson, 1999; Anderson et al., 1999; Baum, 1999; Baum & Silverman, 2001; Carley & Hill, 2001; Levinthal & Warglien, 1999; McKelvey, 1997b, 1999a, 2003; Rivkin, 2000). Complexity has been a central construct in organization science ever since the open-systems view of organizations began to diffuse in the 1960s (Anderson, 1999). The latter focuses on how interdependent parts of organizations interact with each other and with some larger environment to exchange resources (Monge & Eisenberg, 1987). However, the premises at the core of contemporary "complexity theory" did not emerge until after scholars realized that the general systems approach fell short in accounting for such issues as self-referencing capabilities of systems, coevolution among parts, time-dependent nature of relationships, and nonlinearity and discontinuity in the growth trajectories (Arthur, Durlauf & Lane, 1997; Contractor, 1994; Deetz, 2000).

According to Markovsky (1998, p. 2), CASs have the following characteristics: (a) large numbers of components coupled with even larger numbers of interactions; (b) self-organization; (c) adaptation to their environment over time; (d) dynamism and a kind of patterned liveliness; (e) interactions and feedback loops among components that produce higher level emergent behaviors that could not be understood by reducing it to parts; (f) Nonlinearity, in that the parts of complex systems do not sum.

The CAS view parallels situative learning theory because it also locates learning not only in individual minds, but also in connections between minds. Furthermore, the CAS view suggests that interactions between agents are dynamic over time and nonlinearly generative of emergent, group-level learning properties from individual group members (hereinafter, *agents*). This results in shared meaning, facilitates sense making (Weick, 1976), and produces emergent collective knowledge (Monge & Fulk, 1999; Monge & Contractor, 2000). CAS and situated theory converge in identifying the core role of relational interactions and emergent properties in learning.

Multi-Level Coevolution

Given its emphasis on individual and emergent collective properties, complexity theory takes a holistic, multi-level, coevolutionary perspective. The situated theory of learning emphasizes the importance of participation, arguing that "learning should be viewed as a process of becoming a part of a greater whole" (Sfard, 1998, p. 6). While the *acquisition metaphor* (AM) of traditional learning theories stresses the individual mind and what goes "into it," the *participation metaphor* (PM) of the situated theory of learning shifts the focus to the evolving bonds between the individual and others. While AM emphasizes the inward movements of the object known as knowledge, PM gives prominence to the aspect of mutuality characteristic of part-whole relations. Indeed, PM makes salient the dialectic nature of the learning interaction: The whole and the parts affect and inform each other.

A holistic perspective does not mean that researchers should only concentrate on the collective properties of the system and ignore the micro dynamism of and between individual components. Compared to the aggregation model of the positivist-reductionist approach, macro-level studies can get us closer to the true nature of the global properties of a system. Even so, they fall short of capturing the processes by which the global properties of the system come into being—as do reductionist approaches. Following the CAS arguments, because the global properties of a system are not static, but emergent from lower-level interactions, the focus of research attention should be placed on agent-level interactions, either among agents or between agents and the environmental context (Holland, 1996; Monge & Contractor, 2000). In the case of learning theories, it means that the extreme version of situated learning theory, which proposes to explain learning only from the effects of context, is as inadequate as the proposal to concentrate on decontextualized actors (Moore, 1998; Sfard, 1998; Weick & Ashford, 2000).

KAUFFMAN'S *COMPLEXITY CATASTROPHE* THEORY APPLIED TO LEARNING

Learning in Kauffman's *NK* model encompasses both the interactions among individual agents and between agents and the group. Interactions among agents exist because, so long as group members are connected to each other, one group member's contribution to the overall performance of the group is influenced by his or her interactions with the others. Part-whole interactions progress in two ways. Bottom-up interaction happens when the performance of the group is influenced by how much each individual member contributes. Top-down influence occurs when a decision at the group level, as to whether to incorporate an individual person's learning as collective learning, is made based on its value to the whole group, not to that particular individual person. The "agents" (for us, group members) coevolve toward improved individual fitness (learning) over time by searching out and then adopting the fitness attributes of other agents. Agents systematically *select for* improved learning and the group *selects against* agents having lower learning—following Darwinian selectionist theory. Applied to our context, group performance improves through coevolutionary learning at the agent level as individuals interact in search spaces that are dynamically shaped and reshaped over time by other individuals' actions as each pursues his or her own learning.

Kauffman theorizes about coevolving adaptive-learning agents searching for improved learning on search spaces called "*fitness landscapes*," drawing on Wright (1931). The configurations of the landscape are shaped mainly by two factors, *N* and *K.* In his original theory, *N* measures the number of genes that form a genotype. In our case, *N* is designated to measure the number of people forming a group. The second component, *K* measures the average number of linkages that each gene has with the other genes forming the same genotype in the original theory. In our case, it is a measure of the number of communication linkages among people.

Amount of Group Learning

Impacts of Network Density *K* on Amount of Group Learning

In Kauffman's model, *K* is used to designate the average level of communication links (or coordination constraints) among group members. As discussed earlier, situated learning theories maintain that the dynamics of group interaction have a significant impact on group learning. When group members do not have many communication links with other people, they will not have adequate opportunities to learn from others; so, adding links improves the likelihood of increased group learning. But too many linkages can also cause problems as people are boundedly rational and it can be costly to maintain extensive network ties. Students of social network analyses have established the importance of network density in shaping learning within groups. Uzzi (1997), however, observes that firms dependent on dense ties have vulnerabilities. Thick networks can "gum up" the system and make firms slow to adapt. Podolny (1993) finds that strong long-run networks can thwart renewal and change. Galaskiewicz and Zaheer (1999, p. 258) conclude that "an over-abundance of social network ties can inhibit the adaptive capacities of firms and can lead to inflexibility and inefficiency." While there are innovative exceptions, in many organizations, the more people have to coordinate the higher the probability is that *bureaucratic constraints* such as rules and attitudes favoring the status quo will prevail. Based on these observations, we propose that *over time and across many interactions* (ceteris paribus)

> **H_1**: *The amount of group learning is a nonlinear nonmonotonic (inverted U) function of K.*

Impacts of Group Size *N* on Amount of Group Learning

How group size *N* influences the amount of group learning is open for debate. *N* can have a positive impact on within-group interactions because, as group size increases, the number of possible ties among group members may grow geometrically (Arrow, McGrath, & Berdahl, 2000). This creates more learning opportunities among group members. But, research also shows that an increase in group size leads to increases in social loafing, interpersonal conflict, and dissatisfaction, and most relevant to this study, decreased participation opportunities. Also, as size increases communication becomes more inefficient, and it may be harder to find out where useful information lies (Argote, 1999). In fact, most research on the effect of group size on participation consists of snapshot studies. We will explore whether a dynamic analysis produces similar results. Absent a clear prediction, we propose that:

> **H_2:** *Ceteris paribus, the amount of group learning is influenced by group size, N.*

Rate of Learning

In a fast changing world, it is not just the final amount of improved learning that counts, but how fast a group or firm can learn as compared to competitors. Prusak (1996, p. 6) says that, "The only thing that gives an organization a competitive edge—the only thing that is sustainable—is what it knows, how it uses what it knows, and how fast it can know something new!" Fisher's (1930) theorem holds that organisms having higher internal change rates are less susceptible to the Law of Competitive Exclusion. Anyone with a personal computer knows about the high rate at which fixed-disk capacity skyrocketed while at the same time disk size shrunk rapidly in size during the 1990s. To stay in the "Red Queen" race, firms had to start innovation two product life cycles ahead just to stay even. Modest learning early on may prove more important for survival than much learning later. As operationalized in the Method section, we focus on factors inhibiting the speed at which a group reaches its maximum learning, rather than what it would take to stay ahead of the learning rates of competitors.

The importance of *rate* of learning is well documented in observations of successful firms competing in high velocity environments. High profits (economic rents) go to firms such as British Airways, Gillette, Netscape, 3M, and Intel because their product development rates allow them to constantly get new products to market ahead of their competitors (Brown and Eisenhardt, 1997; 1998, p. 166). Competitive advantage goes to firms: staying ahead of the efficiency curve (Porter, 1985; 1996), gaining industry control before competitors (Hamel & Prahalad, 1994), winning in hypercompetitive environments (D'Aveni, 1994), and keeping pace with value migration (Slywotzky, 1996). In case after case Stacey (1995) finds that fast paced learning in dynamic ill-structured environments is the basis of competitive advantage by allowing firms to stay ahead of others in their industry. After in-depth studies of 7 exemplar firms, O'Reilly and Pfeffer (2000, p.

259) conclude: “Speed cuts costs, and the things companies do to build speed, commitment, and intelligence therefore provide them with substantial cost advantages.”

Impacts of Group Size *N* on Rate of Group Learning

In light of these findings we use Kauffman’s model to study the possibility that interconnectivity proliferation could diminish the *rate* as well as *amount* of learning. Small groups reach their optimal level fast because for a group of 3 people, only 2^3 types of combinations are possible. In contrast, for a group of 8 people, the number of possible combinations rises exponentially to 2^8. Therefore, when group size is small it takes less time for the system to find the optimal group composition. On the other hand, large groups converge quickly as well, but this is because they get trapped on lower, suboptimal peaks that are easier to reach quickly—because the peaks are lower.

> **H_3:** *Ceteris paribus, the rate of group learning is a nonmonotonic function (U shape) of N, with the medium size groups taking longest to fully explore the groups’ learning capability.*

Impacts of Network Density *K* on Rate of Group Learning

Similar to our analysis about the amount of group learning, we predict that network density *K* also has a curvilinear effect on the rate of group learning. The reason is that when interactivity is low, it takes longer for a group to acquire and learn new knowledge. But high interactivity slows down the rate just as it does the amount of collective learning because people are boundedly rational. Based on these arguments, we propose:

> **H_4:** *Ceteris paribus, the rate of group learning is a nonlinear nonmonotonic (inverted U) function of K.*

Complexity Catastrophe

One significant contribution of Kauffman’s *NK* model is the complexity catastrophe effects that may work against selection. Kauffman finds that (1) in precipitous rugged landscapes, adaptive progression is trapped on the many suboptimal “local” peaks; or (2) as peaks proliferate beyond the rugged few, they become less differentiated from the general landscape. In either case, even in the face of strong selection forces, the fittest members of the population exhibit characteristics little different from the entire population. He labels these "*complexity catastrophes*" because either one or the other is inevitable if the "complexity of the entities under selection increases." Thus, complexity imposes an upper bound on adaptive progression via selection "when the number of parts exceeds a critical value" (1993, p. 36). In this way complexity catastrophe thwarts the selection process. His "*catastrophe*" sets in because, even though Darwinian selection processes continue, the learning options from nearest neighbors are increasingly reduced toward the mean of 0.5 and further reduced by the web of constraints imposed by the *K* linkage constraints—resulting in the flatter search landscape. His Tables 2.1 and 2.2 (1993, pp. 55–56) demonstrate this. When *K* is very small, the increased number of links allows improved group learning (even if *N* is large)—thus temporarily thwarting the size effect. But as *K* increases toward $K = N–1$, group learning is reduced toward the mean. This is shown in our Fig. 1 and Kauffman's Tables 2.1 and 2.2—the targets of our docking analyses. Based on these findings, we propose:

H_5: *Ceteris paribus, the rate of group learning is a nonmonotonic function (U shape) of N, with the medium size groups taking longest to fully explore the groups' learning capability*;

H_6: *For low K, the rate of group learning is a positive function of K.*

Thompson's Task Interdependencies

Communication interdependencies leading to coevolutionary agent learning, and ultimately improved group-level learning, could be constrained by task interdependencies. Thompson (1967) distinguishes among three types of task interdependencies: pooled, sequential, and reciprocal. Consequently, in Thompson's terms, we posit that sequential task interdependencies steer communication interactions toward nearby neighbors in the task sequence and consequently inhibit the freedom of agents to find more fit agents and thereby more quickly coevolve toward improved levels of group learning. Thus:

H_7: *Pooled task interdependencies improve the rate and amount of group learning more than do sequential task interdependencies.*

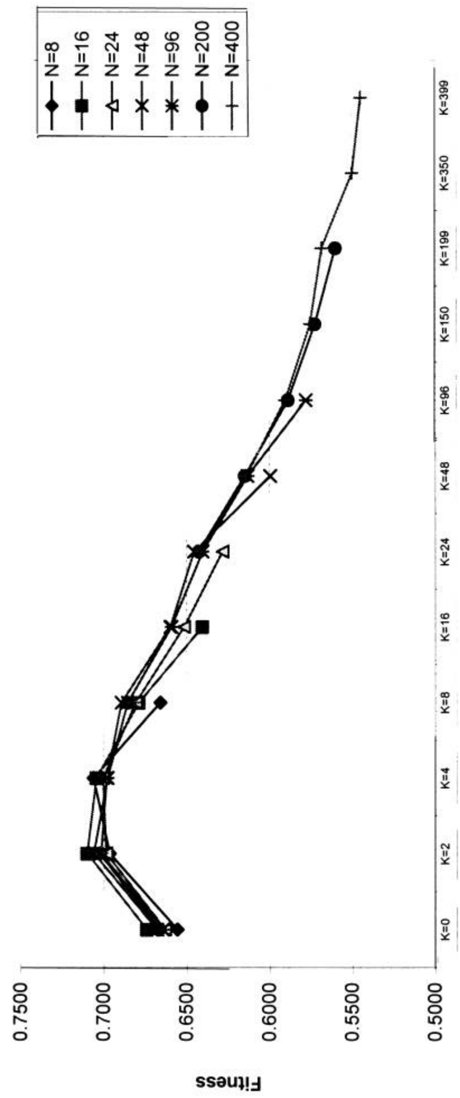


Fig. 1. Results from our simulation tests for Docking Table 2.1 from Kauffman's (1993) book.

**Effect of Group Structure on Learning:
Humanizing Kauffman's *NK* Code**

Recent applications (Levinthal, 1997; Levinthal & Warglien, 1999; Rivkin, 2000) of the *NK* model to social settings use it unmodified, as best we can tell. McKelvey (1997a) offers some ideas for "humanizing" Kauffman's *NK* model. One of them deals with the number of links an agent may have with others—what we term the "*K*-distribution" effect. In Kauffman's verbal formulation of his theory, *K* is designated to represent the *average* number of links among agents. However, in the formulations codified into his computer program, *K* is exactly the same for all members. In this formulation, although *K* still represents the average number of links that a group member may have, the generalizability of the model is jeopardized because its completely uniform set of connections is only one very narrow special case. In real organizations, hierarchical control and social preference structures always exist, and differences in tasks are reflected in varying levels and types of task interdependencies. Group structure is *differentiated* if the differences in the number of links across people are considerable—resulting in *Stars* (many links) and *Isolates* (few links). It is *undifferentiated* if the most connected members don't have many more ties than the least connected ones.

> **H_8:** *Ceteris paribus, the greater the trend of communication ties toward the extremes of stars and isolates, the lower the amount of group learning.*

METHOD

Studying Situated Learning With Agent-Based Models

To study situated cognition, ethnographic thick descriptions have proved a useful tool (Brown & Duguid, 1996). As noted previously, situated learning theory calls for studying learning in an interactive context. Agent-based models offer an alternative approach that has at least three advantages. First, agent-based models allow us to manipulate conditions affecting both the complex interactions among individual agents and between agents and their environment (Carley & Svoboda, 1996; Holland, 1996; McKelvey, 1997b, 1999a, 2002). Epstein and Axtell (1996) observe that agent-based models simulate two types of emergence: the emergence of global properties of an organization or group at the collective level from micro-level agent interactions, and the emergence of micro-level properties of agents because the model has feedback loops from the organization or group to the agents. These characteristics of agent-based models match perfectly with key elements of situated learning theory.

Second, agent-based modeling is particularly useful for modeling interactions when they are nonlinear and multiplicative, when the dynamics of the interactions are time-dependent, and when the different mechanisms that drive interactions among agents may contradict each other (Axelrod & Cohen, 1999; Contractor et al., 2000). This approach frees researchers from the limitations of the additive, linear models that have dominated traditional learning theory and formal modeling in general (Henrickson & McKelvey, 2002).

Third, because the interactions in complex adaptive systems are complicated and hard to predict, agent-based models help researchers run computational experiments for the purpose of improving theories and generating hypotheses (Carley, 1999b, 2000). McKelvey (2002) argues for the adoption of a model-centered epistemology. A theory can be summarized or formalized in the model and the model then can be used to elaborate nuances of the theory. A coevolving theory–model development results. Researchers start with a model combining several existing theories of interest, each of which may be taken as a generative mechanism prescribing rules governing communication interdependencies. Computational models may also be used to create virtual experiments with which researchers can examine, extend, integrate these theories, and test hypotheses under conditions not easily created in the real world. This facilitates the creation of sounder theories and hypotheses before taking on the arduous task of actual real-world empirical testing.

In this beginning study, we take the simulation approach to testing our hypotheses. In particular, we use Kauffman's *NK* model to investigate what factors may influence situated learning within groups. There are two reasons why we use this model in preference to other learning models. First, Kauffman's *NK* model has become a classic in theoretical biology and has recently been used to study self-organization in organizations, including design of robust organizational forms (Levinthal, 1997; Levinthal & Warglien, 1999), implementation of effective collective control (Baum, 1999), development of core competencies (McKelvey, 1999a,b), and optimization of organizational strategies (Rivkin, 2000). Second, we think that the central ideas of the *NK* model, though originally developed to study biological phenomena, are consistent with the major arguments of situated learning theory. The model studies interactions both between agents, and between the agents and the environment. This point will be further elaborated in the following section of the paper.

One difference you will see in our results is that we mostly avoid the "hi-tech, multi-color" graphics characteristic of many simulation outputs. Instead of showing cute graphics for results and referring vaguely to statistics in a footnote, we use the various simulation runs to produce samples of numbers and then report out our results in the form of *t*-tests and regressions.

Operational Measures

Amount of Group Learning

In Kauffman's *NK* model, an agent, first, searches for a better position on a fitness improvement landscape—called an adaptive walk (1993, pp. 36–40). In each of some number of generations or time periods, *g*, the agent compares it's fitness, *w*, with a nearest neighbor's and adopts the latter's fitness level if it is higher. The agent keeps searching in successive time periods until it gets trapped on a suboptimal peak (usually the case when $K > 0$)— because all neighboring positions have lower fitness levels. *N* measures the number of components of a collective entity—group in our case. At any given point in time, *t*, as the model iterates over the ($t = 1 \rightarrow g$) generations:

$$W_t = \frac{1}{N}\sum_{i=1}^{N} f_{i,t} \mid \text{IFF} \quad W_{i,t} > W_{i,t-1} \qquad (1)$$

where W_t represents group learning at time *t*, and $f_{i,,t}$, represents the performance contribution from each individual person in the context of his/her interaction with other members of the group at time *t*. W_t increases only if it is larger than the previous time iteration. The equation implies collective learning at the group level dominates individual learning. It may happen that at certain iteration, $f_{5,t}$ (representing performance contribution from group member #5, for instance) is higher than $f_{5,t\text{-}1.}$ But if at the same time, the performance improvement of group member #5 brings about a decrease in performance from other members of the group that /she is connected to, and therefore a decrease in overall group performance ($W_t < W_{t-1}$), such a change in the system will be dropped.

Rate of Group Learning

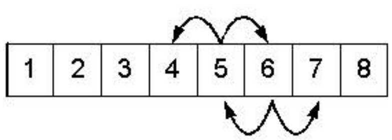
We define rate of group learning as the number of time periods (iterations) it takes for an agent to reach its (usually) suboptimal point (which defines maximum group learning). Thus:

$$\frac{\Delta W}{\Delta t} = \frac{W(x_2) - W(x_1)}{t_2 - t_1} \tag{2}$$

Inserting Eq. 1 results in:

$$\frac{\Delta W}{\Delta t} = \frac{W\left(\frac{1}{N}\sum_{i=1}^{N} f_{i,t_e}\right) - W\left(\frac{1}{N}\sum_{i=1}^{N} f_{i,t_b}\right)}{t_e - t_b}, \tag{3}$$

where: t_b is the beginning of the search process, and t_e marks the end of the search process—when the agent reaches the local optima. We suppress the "IFF" part for presentation purposes.



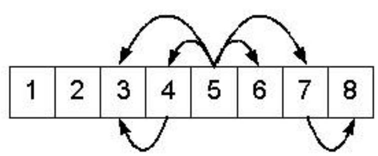


Fig. 2. Adjacent walk -- sequential interdependency: (left) same number of links for Person 5 and 6; (right) differences in the number of links for stars (Person 5) in contrast to isolates (Person 6).

Task Interdependency—Adjacent and Random Walks

In the *NK* model, in any given iteration, agents may choose to interact (at random) with only one of their most adjacent (nearest) neighbors. As depicted in Fig. 2 (left), group members may be assigned to a sequence of tasks. For the person that occupies the 5th position, for example, if N = 8 and K = 2, s/he can only interact with the people occupying the 4th and the 6th positions. That is, in Eq. 3, given N = 8 and K = 7, for w_j, j = persons 4, 6, 3, 7, 2, 8. And for the person in the 6th position, s/he can only interact with the person in the 5th and the 7th positions. Although in a simulation (or any other situation) it is not guaranteed that coevolutionary learning follows a pre-determined sequence, the interaction pattern is sequential because, in such a setting, who can communicate with whom is determined predominantly by their position in the production sequence. This is our operationalization of Thompson's (1967) depiction of *sequential* workflow interdependence. In *NK* models, agents' movements are called "walks," and when they are sequential the movements are called "*adjacent walks*." Group members may also select their interaction partners randomly. As depicted in Fig. 3 (left), for $N = 8$ and $K = 2$, the person in the 5th position can go outside his/her immediate neighborhood and interact with, say, a person in the 1st or 8th positions. In Eq. 3, given $N = 8$ and $K = 7$, for w_j, j = random selection among persons 2 to 8. This is similar to the idea of Thompson's *pooled* interdependency, in which each member makes a contribution to the overall performance of the group, with no restriction on whether the interactions follow a workflow sequence or not. In *NK* modeling, such interactive movements are called "*random walks*."

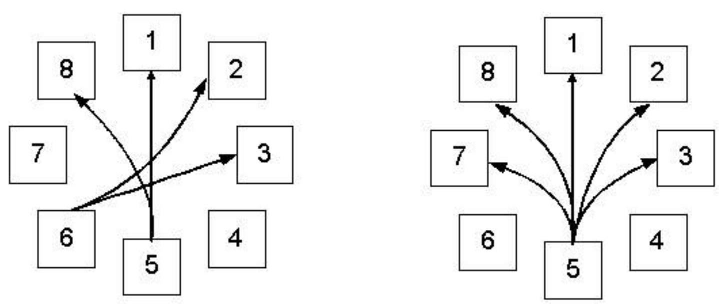


Fig. 3. Random walk -- pooled interdependency: (left) same number of links for Person 5 and 6; (right) differences in the number of links for stars (Person 5) in contrast to isolates (Person 6).

Stars and Isolates: Operationally Changing the Distribution of *K*

We implement the differences between differentiated and undifferentiated group structures by the manipulating the distribution of *K*, that is, the standard deviation of *K* in a normal distribution. As depicted in Fig. 4, for a group of $N = 48$, $K = 24$, the line representing the average, with a close-to-zero standard deviation depicts what occurs in Kauffman's original model—a completely undifferentiated group—all members have the same number of links. As the difference in the numbers ties across group members increases, the standard deviation increases and the curve flattens. For an illustration, see Fig. 2 (right) for sequential and Fig. 3 (right) for pooled interdependency, the standard deviations of the *K* distribution grow accordingly.

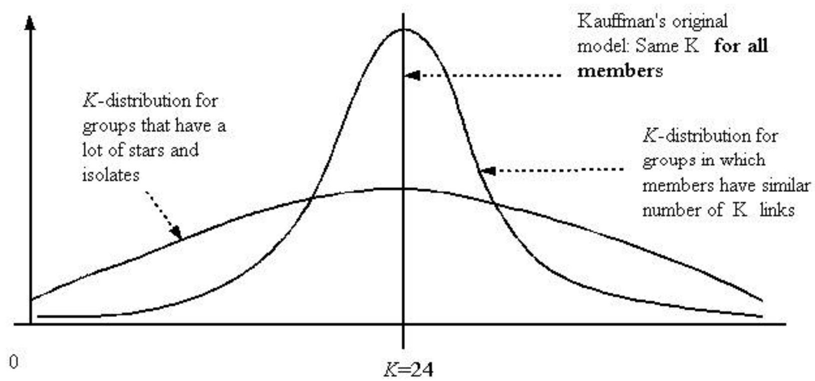


Fig. 4. The *K* distribution effect.

We examine the humanized model of situated learning using a group of $N = 48$, a relatively large group in organizations. Smaller *N*s could be chosen, but given the relationship between *N* and *K*, that is, $0 < K \pm (2 \times \text{Standard Deviation}) < N$, a larger, yet realistic number allows more data points to be gathered. The reason that we select 2 standard deviations away from the mean as the standard is that under a normal curve, around 95% of the total area is covered in this region. We stopped generating new data when $K - (2 \times \text{Standard Deviation}) < 0$, or when $K + (2 \times \text{Standard Deviation}) > N$ so that fewer data are winsorized, and the curve more likely remains normal.

In our virtual experiments, to counter the effect of our use of random draws to assign (a) the level of learning contribution from each agent, and (b) number of interactive links among individuals in each adaptive walk across the learning improvement “landscape” (search space), we make the agents conduct their walks 100 independent times (100 computational runs) to deal with the first randomness factor in the model, and across 50 runs to balance the second factor. A walk stops when a group’s overall performance stops improving. Overall, it means that the group-learning search process requires $50 \times 100 = 5{,}000$

independent computer runs for each K by K-distribution configuration. The average level of performance across all these runs (walks) is then calculated and reported in our results section.

SIMULATION RESULTS

In our docking analysis, shown in Fig. 1, we reproduce Kauffman's (1993) Tables 2.1 and 2.2 at correlations of 0.979 and 0.976, respectively.

Table 1. Descriptive Statistics for the Non-humanized model (100 Simulation Runs)

Variable Name	*Mean*	*Std. Dev.*	*2*	*3*	*4*	*5*
Amount of learning (Fitness)	.66	.05	-.81*	-.66*	-.39*	–.17
Communication ties (K)	44.32	83.96		.56*	.51*	.05
Complexity catastrophe ($K/(N$-1))	.33	.33			-.09	.40*
Group Size (N)	151.20	147.15				–.77*
Rate of learning (Mean rate)	626.20	869.95				

*$p < 0.01$ level (2-tailed).

Kauffman's Original Model: Effects of Size and Ties

For each simulation test, given different K and N combinations, we save the resulting fitness level for each walk in an SPSS data file, and then use these numbers for data analysis. We show the descriptive statistics to ensure that there are no serious violations of the normality assumptions of linear regression—see Table 1. Of the five research variables included in the study, communication ties (*K*) and rate of learning are both very positively skewed. Following Tabachnick and Fidell's (1996) suggestion, we take logarithmic transformations of the two variables; the distributions of both variables approach normal after transformation. We then use scatter plots to examine bivariate relationships between independent and dependent variables in our study—see Fig. 5. If the relationships look curvilinear, we include a quadratic term.

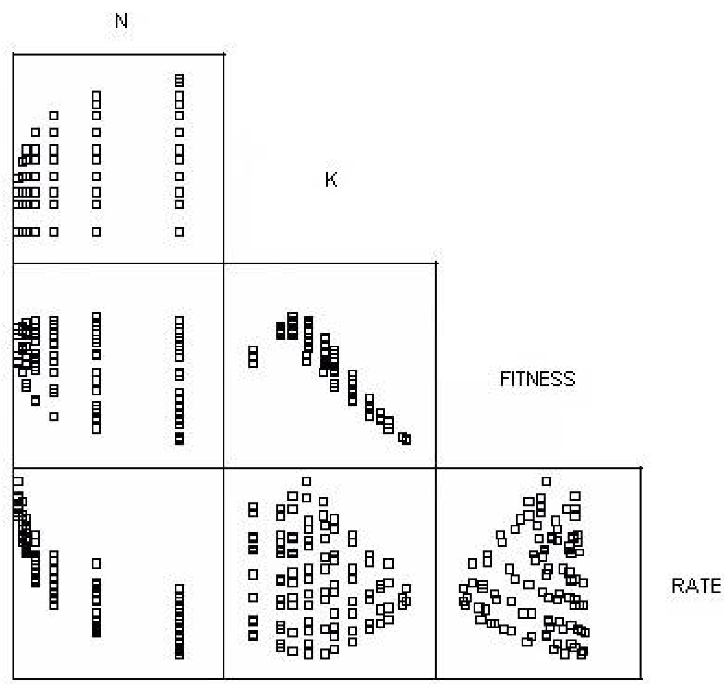


Fig. 5. Scatterplot of the relationship between variables N, K, and the amount and rate of learning.

As reported in Table 1, because the average number of communication ties between people, *K*, cannot exceed the total group size, *N*, the two variables are highly correlated with each other ($r = .511$, $p < .05$). Therefore in analyzing how they may influence the amount and the rate of group learning, we put them in the same regression equation so as to analyze the unique contribution of each factor, controlling for the confounding effect of one on the other.

Table 2. Summary of Stepwise Regression for Variables Influencing the Amount of Group Learning (Fitness)

Variables	*B*	*SE of B*	*β*
Step 1			
Communication Ties (log*K*)	–5.482	.412	–.803*
Step 2			
Communication Ties (log*K*)	4.232	.831	.620*
Quadratic term of Comm Ties ($\log^2 K$)	–4.096	.333	–1.496*
Step 3			
Communication Ties (log*K*)	4.649	.804	.681*
Quadratic term of Comm Ties ($\log^2 K$)	–4.450	.336	–1.626*
Group size (*N*)	0.005	.001	.139*

Note: R^2 = .644 for Step1; ΔR^2 = .217 for Step 2; ΔR^2 = .014 for Step 3; *p < 0.01 for all cases.

Table 3. Summary of Stepwise Regression for Variables Influencing the Rate of Group Learning.

Variables	*B*	*SE of B*	*β*
Step 1			
Group size (*N*)	–.004	.000	–.815*
Step 2			
Group size (*N*)	–.012	.001	–2.404*
Quadratic term of group size (*N*)	1.882E-05	.000	1.633*
Step 3			
Group size (*N*)	–.014	.001	–2.724*
Quadratic term of group size (*N*)	2.097E-05	.000	1.819*
Communication ties (log*K*)	.311	.040	.309*

Note: R^2 = .644 for Step1; ΔR^2 = .217 for Step 2; ΔR^2 = .014 for Step 3; *p < 0.01 for all cases.

Amount of Learning

We use stepwise regression to more clearly analyze the relative importance of communication ties and group size in influencing collective learning. The scatter plot in Fig. 5 shows that the relationship between group learning and communication ties is curvilinear. Therefore, in the regression equation we include both the first and the second order terms for communication ties to capture the nonlinear nature of the relationship. As shown in Step 1 of Table 2, the first-order (linear) term of communication ties has a strong negative relationship with group learning ($\beta = -.803$, $p < .05$).

In Step 2, both the first and the second order terms are included, which causes a significant improvement in the overall fit of the model—variance explained increases by .217, from .644 to .861 ($p < .05$). The regression coefficients are also significant for both first ($\beta = .681$, $p < .05$) and quadratic ($\beta = -1.626$, $p < .05$) terms of the variable. The negative sign of the second order term indicates that the overall relationship between the two variables takes an inverted U-shape, with a medium level of communication ties producing the highest improvement in learning. Therefore $\mathbf{H_1}$ is supported: Amount of learning is nonmonotonically related to *K* (inverted U shape).

Step 3 of Table 2 tests Hypothesis 2, controlling for the number of communication ties. This result demonstrates the unique contribution of group size on learning, with the influence from network density partialled out. It shows that group size has a weak, but significant, linear positive effect on learning that is reflected in both the regression coefficient ($\beta = .139$, $p < .05$), and the change in R^2 ($\Delta R^2 = .014$, $p < .05$). $\mathbf{H_2}$ is also supported: Learning increases as *N* increases.

Rate of Learning

The scatter plot in Fig. 5 demonstrates the curvilinear nature of Hypothesis 3. In the stepwise regression reported in Table 3, we include both the first and second order terms for *N*. Step 1 tests the linear relationship between the variables. After the quadratic term is added in Step 2, the overall fit of the model increases from .661 to .801 ($\Delta R^2 = .140$, $p < .05$). Both the first order ($\beta = -.2.404$, $p < .05$) and second order ($\beta = 1.633$, $p < .05$) terms are significant. The positive sign of the second order term means that for groups of medium size, it takes longer for them to fully exploit their full learning capacity. $\mathbf{H_3}$ is supported: Rate of learning is a nonmonotonic function of *N* (U shape).

In addition, as depicted in Step 3 of Table 3, density of communication ties also has a significant impact on the rate of learning ($\beta = .309$, $p < .05$) above and beyond the influence of group size ($\Delta R^2 = .014$, $p < .01$). However, against our prediction, we did not find a significant curvilinear effect of *K* on rate of group learning. *Therefore*, $\mathbf{H_4}$ is partially supported: Rate of learning is a positive function of *K*.

Complexity Catastrophe

$\mathbf{H_5}$, as stated, is not confirmed. Following Wasserman and Faust (1994, p. 179), we create a standardized network density measure by dividing the number of communication ties, *K*, by *N*–1, and then use this ratio to predict the likelihood of change in the rate and amount of collective learning. The scatter plot of the relationships between variables is shown in Fig. 6. As shown in Table 4, the ratio of *K*/(*N*–1) has a significant *negative* linear effect on *amount* of group learning ($\beta = -.669$, $p < .05$), and a significant *positive* linear effect on *rate* of group learning ($\beta = .463$, $p < .05$). Note that nonlinearity has disappeared. Combining the two results together, we show that the higher the value of *K* relative to *N*, the faster a group learns, but, the amount of learning is attenuated. This is still consistent with Kauffman's observation, however, that when complexity catastrophe sets in—with a high *K* relative to *N*—the walk on the landscape toward fitness peaks is likely to be shorter—and thus quicker—because the peaks are lower, but because they are lower, fitness is also lower. The sense of $\mathbf{H_5}$ is confirmed, but the underlying causal process is different. $\mathbf{H_6}$ is also confirmed, but for the full range of *K*—rate of learning increases with *K* (but note that amount of learning decreases because the peaks are lower).

It is worth noting that a constant concern with simulations is that they are "cooked" or "unwrapped" to use Holland's (1996) term—meaning that the results are simply a function of how the simulation is coded up. Here we see that what appeared in the baseline hypothesis as the typical nonlinearity of the catastrophe effect of high *K* on amount of learning reappears as two nonlinear effects after we use the $K/(N\text{-}1)$ standardization.

Table 4. Summary of Regression Analysis of the Effect of $K/(N\text{-}1)$ Ratio on Group Learning

Variables	*B*	*SE of B*	β
Amount of learning			
Ratio ($K/(N\text{-}1)$)	–0.095	.011	–.699*
Rate of learning			
Ratio ($K/(N\text{-}1)$)	.968	.187	.463*

Note: R^2 = .448 for the effect of ratio on amount of learning; R^2 = .214 for its effect on rate of learning; *(p < 0.01 for all cases).

Table 5. Descriptive Statistics for the Humanized Model (N=54)

Variable Name	*Mean*	*Std. Dev.*	*2*	*3*
Amount of learning (Fitness)	.65	.03	–.98*	–.42*
Communication ties (K)	24	11.94		.33*
Standardized K-distribution (SD of K/K)	.19	.18		

* p < 0.01 level (2-tailed).

Table 6. Summary of Hierarchical Regression for Variables Influencing the Amount of Group Learning (Fitness)

Variables	*B*	*SE of B*	β
Step 1			
Communication Ties (K)	–.365	.023	–1.566*
Quadratic term of Comm Ties (K^2)	.003	.000	.610*
Step 2			
Communication Ties (K)	–.359	.022	–1.540*
Quadratic term of Comm Ties (K^2)	.003	.000	.556*
Standardized K-	–.990	.395	–.063*

distribution (*SD* of *K*/*K*)	

Note: R^2 = .972 for Step1; ΔR^2 = .003 for Step 2; $*p < 0.01$ for all cases.

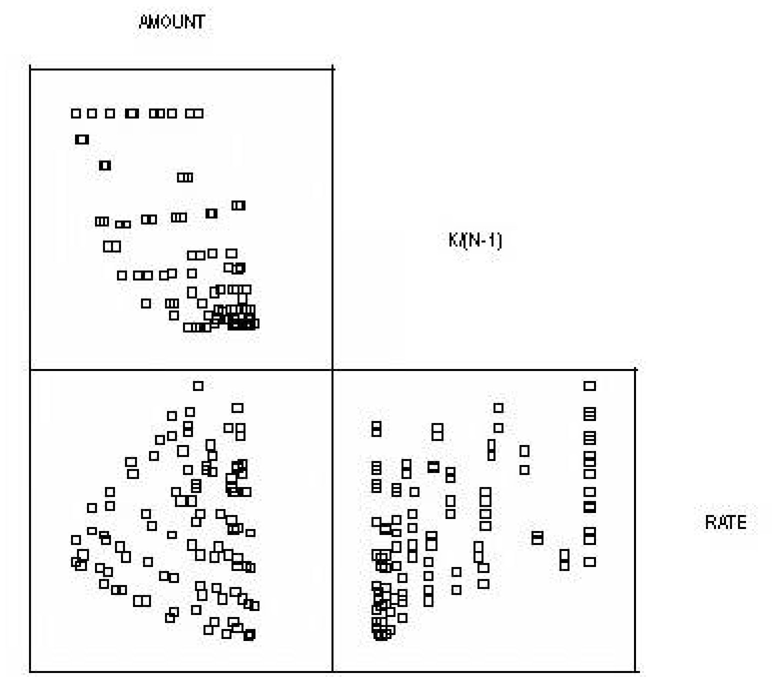


Fig. 6. Scatterplot on the impact of K/(N-1) on the amount and rate of learning.

Thompson's Task Interdependencies

To test $\mathbf{H_7}$, we use an independent-sample *t*-test to compare whether level of group learning and rate of learning change under different task interdependency. Overall, the results show that, compared to the pooled-interdependency condition (random walks), the level of learning in the sequential-interdependency condition (adjacent walks) is lower (t (98) = –1.188, p = .238); and the rate of learning is also lower (t

(86.690[1]) = – 1.817, $\underline{p}$ = 0.073). However, neither of the two differences is statistically significant. **H_7** is rejected: No difference between pooled and task interdependencies in our simulation tests.

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[1] Adjusted degrees of freedom for the t-test given equal variance between the two sets of data cannot be assumed.

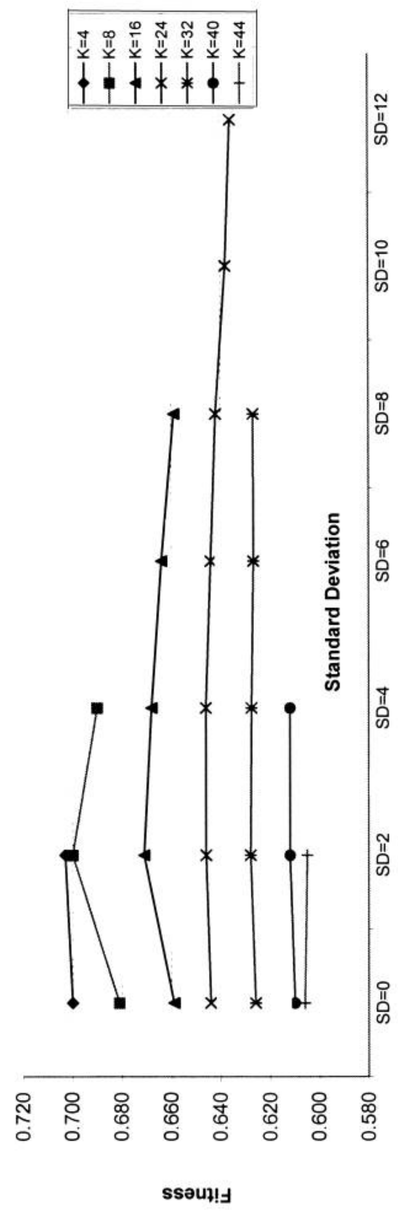

Fig. 7. Testing the *K*-distribution effect with N = 48 (random walk).

Stars and Isolates: The “*K*-distribution” Effect

Here is where we “humanized” the *NK* model by changing Kauffman’s programmed parameter requiring that all agents have the same K communication ties. In our model, though the average is, say, $K = 4$, agents can vary from $K = 0$ to $K = 7$ (given that $N = 8$). Since “all isolates” is the same as Kauffman’s $K = 0$ setting and “all stars” is the same as Kauffman’s $K = N–1$ setting, we posit that the “*K*-distribution” effect generally would lower the rate and amount of group learning and flatten out the nonlinear effect shown in Fig. 4.

In Fig. 7, we show plots for the random walk parameter setting with a group of $N = 48$. The plots are clearly flatter for all settings of the *K*-distribution—from $SD = 0$ to $SD = 12$. Note that the catastrophe effect still holds, since with a given group size $N = 48$, each plot line, from $K = 4$ to $K = 44$ is lower in amount of group learning than the line above. Therefore, to study the unique impact of group structure on learning, the impact of the number of communication ties between people needs to be controlled—that is, standardized across *K*s. We show descriptive statistics before actually doing the regression analysis—see Table 5. Although there are minor deviations, most variables of interest follow a normal distribution. Since a scatter plot (for $N = 48$; not shown here) indicates that K has a curvilinear relationship with amount of learning, we include both first and second order terms in our analysis.

To get a standardized measure of network differentiation across different K values, we divide the standard deviation of K by K, and use the newly created variable, *Standardized K-distribution*, to predict amount of learning with the effect of communication ties, K, controlled. As shown in Table 6, the number of communication ties between group members remains a dominant factor influencing group learning ($\beta = –1.540$ for the first order effect, $\underline{p} < .05$ and $\beta = .556$ for its quadratic term $\underline{p} < .05$). Though small ($\beta = – .063$, $\underline{p} < .05$), the *K*-distribution effect is statistically significant, bringing an increase in the overall fit of the model (ΔR^2) up by .003 ($\underline{p} < .05$). $\mathbf{H_8}$ is supported: If a group is characterized by mostly stars and isolates, amount of learning is impaired.

CONCLUSION AND DISCUSSION

Organizational learning has become a key concern in organization theory, research and practice. Recently, scholars have offered an alternative to linear, reductionist, intra-individual models of learning that have dominated in the past. So-called *situated learning* perspectives anchor learning not in individuals but in interactions among individuals and between each individual and his/her context. This has permitted new ways of examining the relationship of individual learning to the learning of the collective. It has also shifted analysis from the study of individual cognition to the study of emergent patterns of interaction.

To understand the complex, messy world of emergent learning and behavior, however, scholars must draw upon a wider set of concepts, models, and tools. To this end we combine situated learning theory with ideas from complexity science. The reason is that since organizations and groups are complex adaptive systems, direct studies of how group learning is shaped over-time by the complex, non-linear interactions among group members is difficult. Aided by agent-based modeling, in particular, a “humanized” version of Kauffman’s (1993) *NK* model, we study how amount and rate of group learning change over-time as influenced by group size, network density, different forms of task interdependencies and finally complexity catastrophe.

We first dock our model against results from Kauffman’s prior work. In our docking analysis, we replicate Kauffman’s original results to correlations of 0.976 or higher. We us his *NK* computational simulation model to test our hypotheses. The statistical tests of the simulation results show that communication interactivity is nonlinearly related to both amount and rate of group learning over time. Kauffman’s “complexity catastrophe” effect applies here as well—as communication interactivity becomes denser, and rate of learning speeds up, there are diminishing returns to improving group learning. However, density in communication interactivity is not independent of group size. Once we adjust for this effect via standardization of K by N–1, we find that the curvilinear effect disappears, but the catastrophe effect continues as a function of two linear variables. *Rate* of group learning remains a positive linear function of communication interactivity, but *amount* of learning becomes a negative linear function of interactivity density. Against our prediction, task interdependency, as operationalized here, has no effect on group learning. We find that altering the distribution of communication isolates and stars in groups has a statistically significant, but not very pronounced effect on the coevolutionary development of group-level learning over time. These results of our simulation studies can be used to guide future empirical studies of situated learning in real work groups.

Our study has several limitations, given the nature of the *NK* model. These also create opportunities for future research. Kauffman's *NK* model is parsimonious and has high heuristic value. Agents have very simple capabilities to learn and adapt; they do not have the complex psychological, cognitive capabilities to think and to make complex decisions. Many modelers argue that the best models are simple, focus on highlighting a very few real-world dynamics at any given time, and have few assumptions (Holland, 1996; Axlerod, 1997). For example, Epstein and Axtell (1996) are able to create a fairly realistic-looking society (Sugarscape) with just one agent rule, "Eat as much sugar as you can." Still, at the expense of being simple and general, the *NK* model may not be able to achieve a high level of accuracy (Weick, 1976). With appropriate caution, we mention some paths toward additional model-complexity that seem promising:

1. Agents could be given rules that allow them to approach Nash equilibria on variables other than fitness, learning or expertise: such as, social centrality (number of links), power, trust, decisiveness, listening, and so on.

2. The model could allow K to vary in density as the model iterates across time periods so that the possibility of an optimal K might emerge. In the *NK* model, once the configuration of the group has been set up at the initial stage of the simulation, it remains unchanged throughout the simulation tests. This can be constraining if research interest is on the process through which communication links emerge. This would allow much better explorations of the interaction of N and K with amount and rate of group learning.

3. The group learning rate and amount effects could be made a function of what Kauffman labels the "*C*" factor—ties between agents in different groups or organizations. The *NK* model, in common with many other approaches to learning, models context primarily in terms of interactions among agents within groups. Most group learning takes place within the context of other groups or environmental entities whose choices may similarly affect the fitness of each.

4. In Kauffman's model, only one network dominates—people-to-people. Task and resource networks are also important, resulting in six types of networks (Argote & Ingram 2000; Krackhardt & Carley, 1998; McGrath & Argote, 2002). It would be interesting to study how the fitness landscape (the solution space over which individual agents walk)

would form and deform given the within- and between-ties of these six kinds of networks.

Despite these limitations, this paper advances situated learning theory by: (a) coupling it with the more realistic dynamical (nonlinear) coevolutionary theories of complex adaptive systems; and (b) recasting it in terms of a holistic perspective emphasizing the dynamical interaction between a group of interacting agents and group-level learning. These advances to situated learning theory are achieved with agent-based modeling. Needless to say, additional research efforts are warranted to further develop not only the theory, but also agent-based modeling of situated learning, some of which we mention. Collecting real-world data to validate our hypothesis testing via simulated experiments is also required to further our understanding of situated learning. By advancing in the direction outlined here, we offer some information with which to guide real-world tests, and thus better understand situated learning's role in how firms achieve competitive advantage.

Our results bear on implicit learning (Seger, 1994), even though definitional differences are obvious. Implicit learning focuses on non-verbal or unconscious learning (Guastello & Guastello 1998; Seger, 1994;), whereas situated learning attends to contextual effects:

1. Guastello and Guastello (1998) find that increasing coordination difficulty (similar to increasing K in our model) brings nonlinear outcomes in the form of attenuated group-level learning—the same basic effect that results from our studies.

2. Guastello and Guastello (1998) extend their human experiment results by using a computer simulation. Their "bridging forward" from experiment to simulation, lends some credence to the idea that one could also "bridge backward" from our simulation to real-world human behavior.

3. Guastello (2002, Chapter 8) extends these results from possible nonverbal to verbally based implicit learning. Since computer models appear to gloss over distinctions between verbal vs. nonverbal and conscious vs. unconscious learning (whether implicit or explicit), the fact that K-creation of nonlinear learning outcomes withstands broadening extensions, again, suggests our findings apply fairly generally to various kinds of learning.

Broader application of our results is also supported by Trofimova's EVS model (Trofimova, 2001; Trofimova & Mitin, 2002). Her measure of sociability, her most telling parameter, is essentially the same as our *K*. It governs the self-organization process in complex adaptive systems. As is also seen in Kauffman's prior work (1993), *K* affects the self-organization consequences of individual agent learning and the coevolving learning of interacting agents. The percolation and sub-grouping effects on the EVS model also reflect the earlier contributions of various studies from statistical physics by Derrida and Stauffer (1986), Stauffer (1987), Weisbuch (1991, as reviewed by McKelvey, 1999b).

The study of information, knowledge, and learning in organizations has taken an important step in moving away from the traditional symbolic information processing approach to situated learning theory. But situated theory's view that learning is a simple function of communication interactivity does not connect it well with how firms develop and use knowledge in the high velocity environments of the New Economy. To be useful to managers in the New Economy, situated theory has to be recast in a dynamical form. Managers need to know about communication interactivity effects over time, whether they are linear or nonlinear, what kinds of interactions and emergent dynamics there are between individual learning and group learning, and how different kinds of environmental contexts affect emergent individual and group learning. Most importantly, they need more information about the interaction between levels of individual learning, or human capital (Becker, 1975) and social capital—learning stemming from interactivity and network development (Burt, 1992).

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REFERENCES

Anderson, P. (1999). Complexity theory and organization science. *Organization Science*, *10*, 216–232.

Anderson, P., Meyer, A., Eisenhardt, K., Carley, K. A. & Pettigrew, A. (1999). Introduction to the special issue: Applications of complexity theory to organization science. *Organization Science*, *10*, 233–236.

Argote, L. (1999). *Organizational learning: Creating, retaining and transferring knowledge.* Boston, MA: Kluwer.

Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes*, *82*, 150–169.

Argote, L., Ingram, P., Levine, J. M., & Moreland, R. L. (2000). Knowledge transfer in organizations: Learning from the experiences of others. *Organizational Behavior and Human Decision Processes*, *82*, 1–8.

Arrow, H., McGrath, J. E., & Berdahl, J. L. (2000). *Small groups as complex systems: Formation, coordination, development, and adaptation.* Thousand Oaks, CA: Sage.

Arthur, W. B. (1990). Positive feedbacks in economics. *Scientific American*, *262* (February), 92–99.

Arthur, W. B., Durlauf, S. N., & Lane, D. A. (Eds.) (1997). *The economy as an evolving complex system*. Proceedings of the Santa Fe Institute, Vol. XXVII. Reading, MA: Addison-Wesley.

Axelrod, R., & Cohen, M. D. (1999). *Harnessing complexity*. New York: The Free Press.

Axelrod, R. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration.* Princeton, NJ: Princeton University Press.

Baum, J. A. C. (1999). Whole-part coevolutionary competition in organizations. In J. A. C. Baum & B. McKelvey (Eds.), *Variations in Organization Science* (pp. 113–135). Thousand Oaks, CA: Sage.

Baum, J. A. C., & Silverman, B. S. (2001). Complexity, (strange) attractors, and path dependence in innovation technologies. In R. Garud & P. Karnoe (Eds.), *Path as process* (pp. 169-209). Mahwah: NJ: Lawrence Erlbaum.

Becker, G. S. (1975). *Human capital* (2nd ed.). Chicago, IL: University of Chicago Press.

Brockmann, E. N., & Anthony, W. P. (1998). The influence of tacit knowledge and collective mind on strategic planning. *Journal of Management Issues*, *10*, 204–222.

Brown, J. S., & Duguid, P. (1996). Organizational learning and communities-of-practice: Toward a unified view of working, learning and innovation. In M. D. Cohen & L. S. Sproull (Eds.), *Organizational learning* (pp. 58–82). Thousand Oaks, CA: Sage.

Brown, S. L., & Eisenhardt, K. M. (1997). The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly*, *42*, 1–34.

Brown, S. L., & Eisenhardt, K. M. (1998). *Competing on the edge: Strategy as structured chaos.* Boston, MA: Harvard Business School Press.

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Carley, K. M. (1999a). Learning within and among organizations. *Advances in Strategic Management*, *16*, 33–53.

Carley, K. M. (1999b). *On generating hypotheses using computer simulations.* Working paper, Carnegie Mellon University, Pittsburgh, PA.

Carley, K. M., & Gasser, L. (1999). Computational organization theory. In G. Weiss, ed. *Multiagent systems: A modern approach to distributed artificial intelligence* (pp. 299–330). Cambridge, MA: MIT Press.

Carley, K. M., & Hill, V. (2001). Structural change and learning within organizations. In A. Lomi & E. R. Larsen (Eds.), *Dynamics of organizational societies: Computational modeling and organization theories* (pp 63-92). Cambridge, MA: MIT Press.

Carley, K. M., & Svoboda, D. M. (1996). Modeling organizational adaptation as a simulated annealing process. *Sociological Methods and Research*, *25*, 138–168.

Castells, M. (1996). *The rise of network society*. Oxford, UK: Blackwell.

Contractor, N. S. (1994). Self-organizing systems perspective in the study of organizational communication. In B. Kovacic (Ed.), *New approaches to organizational communication* (pp. 39–66). Albany, NY: State University of New York Press.

Contractor, N. S., Whitbred, R., Fonti, F., Hyatt, A., O'Keefe, B., & Jones, P. (2000). *Structuration theory and self-organizing networks.* Paper presented at Organization Science Winter Conference 2000, Keystone, CO.

Cross, R., & Israelit, S. (Eds.) (2000). *Strategic learning in a knowledge economy: Individual, collective, and organizational learning process*. Boston, MA: Butterworth/Heinemann.

D'Aveni, R. A. (1994). *Hypercompetition: Managing the dynamics of strategic maneuvering.* New York: Free Press.

Deetz, S. (2000). Conceptual foundation. In F. Jablin & L. Putnam (Eds.), *The new handbook of organizational communication* (pp. 3–46). Thousand Oaks, CA: Sage.

Derrida, B., & D. Stauffer (1986). Phase transitions in two-dimensional Kauffman cellular automata. *Europhysics Letters, 2*, 739.

Drucker, P. F. (1999). Knowledge-worker productivity: The biggest challenge. *California Management Review*, *41*, 79–94.

Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies.* Cambridge, MA: MIT Press.

Fenwick, T. J. (2000). Expanding conceptions of experiential learning: A review of the five contemporary perspectives of cognition. *Adult Education Quarterly, 50*, 243–272.

Fisher, R. A. (1930). *The genetical theory of natural selection*. Oxford, UK: Clarendon.

Galaskiewicz, J., & Zaheer, A. (1999). Networks of competitive advantage. In S. B. Bacharach, S. B. Andrews & D. Knoke (Eds.), *Research in the Sociology of Organizations* (Vol. 16), *Networks in and around organizations* (pp. 237–261). Stamford, CT: JAI Press.

Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration.* Cambridge, UK: Polity.

Glynn, M. A., Lant, T. K., & Milliken, F. J. (1994). Mapping learning processes in organizations: A multi-level framework linking learning and organizing. In C. Stubbart, J. Meindl & J. Porac (Eds.), *Advances in managerial cognition and organizational information processing* (pp. 43–83). Greenwich, CT: JAI Press.

Greeno, J. G., & Moore, J. L. (1993). Situativity and symbols: Response to Vera and Simon. *Cognitive Science*, *17*, 49–59.

Guastello, S. J., (2002). *Managing emergent phenomena: Nonlinear dynamics in work organizations*. Mahwah, NJ: Erlbaum.

Guastello, S. J. & Guastello, D. D. (1998). Origins of coordination and team effectiveness: A perspective from game theory and nonlinear dynamics, *Journal of Applied Psychology*, *83,* 423–437.

Hamel, G., & Prahalad, C. K. (1994). *Competing for the future.* Boston, MA: Harvard Business School Press.

Henrickson, L., & McKelvey, B. (2002). Foundations of new social science: Institutional legitimacy from philosophy, complexity science, postmodernism, and agent-based modeling. *Proceedings of the National Academy of Science, 99,* 7288-7297.

Holland, J. H. (1996). *Hidden Order.* Cambridge, MA: Perseus Books.

Hutchins, E. (1990). The technology of team navigation. In J. Galegher, R. E. Kraut & C. Egido (Eds.), *Intellectual Teamwork* (pp. 191–220). Hillsdale, NJ: Erlbaum.

Hutchins, E. (1991). The social organization of distributed cognition. In L. B. Resnick, J. M. Levine & S. D. Teasley (Eds.), *Perspectives on socially shared cognition* (pp. 283–307). Washington, DC: American Psychological Association.

Hutchins, E. (1993). Book review of "Situated learning-legitimate peripheral participation by Lave, J., and Wenger, E. *American Anthropologist*, *95,* 743–744.

Kauffman, S. (1993). *The origins of order: Self-organization and selection in evolution*. New York: Oxford University Press.

Krackhardt, D., & Carley, K. M. (1998). A PECANS model of structure in organizations. *Proceedings of the 1997 International Symposium on Command and Control Research and Technology.* June. Monterey, CA.

Lant, T. K. (1999). A situated learning perspective on the emergence of knowledge and identity in cognitive communities. *Advances in Management Cognition and Organizational Information Processing*, 6, 171–194.

Lant, T. K., & Phelps, C. (1999). Strategic groups: A situated learning perspective. *Advances in Strategic Management,* 16, 221–247.

Lave, J., & Wenger, E. (1991). *Situated learning: Peripheral participation.* New York: Cambridge University Press.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science*, *43*, 934–950.

Levinthal, D. A., & Warglien, M. (1999). Landscape design: Designing for local action in complex world. *Organization Science*, *10*, 342–357.

Markovsky, B. (1998). *Social networks and complexity theory*. Paper presented at International Conference on Social Networks and Social Capital (11/1/98), Duke University, Durham, NC.

McGrath, J. E., & Argote, L. (2002). Group processes in organizational contexts. In M. Hogg & R. S. Tindale (Eds.), *Blackwell handbook of social psychology, Vol. 3: Group Processes* (pp 603-627). London: Blackwell**.**

McKelvey, B. (1997a). *Complexity vs. selection: Retuning Kauffman's "tunable" landscape*. Working paper, Anderson School at UCLA, Los Angeles.

McKelvey, B. (1997b). Quasi-natural organization science. *Organization Science*, 8, 352–380.

McKelvey, B. (1999a). Avoiding complexity catastrophe in coevolutionary pockets: Strategies for rugged landscapes. *Organization Science*, 10, 294–321.

McKelvey, B. (1999b). Self-organization, complexity catastrophes, and microstate models at the edge of chaos." In J. A.C. Baum and B. McKelvey (Eds.), *Variations in Organization Science: In Honor of Donald T. Campbell* (pp. 279–307). Thousand Oaks, CA: SAGE.

McKelvey, B. (2002). Model-centered organizational epistemology. In J. A. E. Baum (Ed.), *Companion to organizations* (pp. 752–780). Oxford, UK: Thousand Oaks, CA: SAGE.

McKelvey, B. (2003). Emergent order in firms: Complexity science vs. the entanglement trap. In E. Mitleton-Kelly (Ed.), *Complex systems and evolutionary perspectives on organization* (pp. 99-125). Amsterdam: Elsevier.

Miner, A. S., & Anderson, P. (1999). Industry and population-level learning: Organizational, interorganizational, and collaborative learning processes. In A. S. Miner & P. Anderson (Eds.), *Population-level learning and organizational change. Advances in Strategic Management*, 16, 1–30. Stamford, CT: JAI Press.

Monge, P. M., & Contractor, N. (2000). Emergence of communication networks. In F. Jablin & L. L. Putnam (Eds.), *The new handbook of organizational communication* (pp. 440–502). Thousand Oaks, CA: Sage.

Monge, P. M., & Eisenberg, E. M. (1987). Emergent communication networks. In F. M. Jablin, L. L. Putnam, K. H. Roberts & L. W. Porter (Eds.), *Handbook of organizational communication: An interdisciplinary perspective* (pp. 304–342). Newbury Park, CA: Sage.

Monge, P. M., & Fulk, J. (1999). Communication technology for global network organizations. In G. DeSanctis & J. Fulk (Eds.), *Shaping organization form: Communication, connection and community* (pp. 71–100). Thousand Oaks, CA: Sage.

Moore, B. J. (1998). Situated cognition versus traditional cognitive theories of learning. *Education, 119*, 161–171.

Moreland, R. L., & Myaskovsky, L. (2000). Exploring the performance benefits of group training: Transactive memory or improved communication? *Organizational Behavior and Human Decision Processes*, *82*, 117–133.

Nonaka, I., & Nishiguchi, T. (Eds.) (2001). *Knowledge emergence: Social, technical, and evolutionary dimensions of knowledge creation.* Oxford, UK: Oxford University Press.

O'Reilly, C. A. III, & Pfeffer, J. (2000). *Hidden value.* Cambridge, MA: Harvard Business School Press.

Paulus, P. B., & Yang, H-C. (2000). Idea generation in groups: A basis for creativity in organizations. *Organizational Behavior and Human Decision Processes, 82*, 76–87.

Podolny, J. M. (1993). A status-based model of market competition. *American Journal of Sociology*, *98*, 829–872.

Porter, M. E. (1985). *Competitive advantage: creating and sustaining superior Performance*. New York: Free Press.

Porter, M. E. (1996). What is strategy? *Harvard Business Review, 74,* Nov.-Dec., 61–78.

Prusak, L. (1996). The knowledge advantage. *Strategy & Leadership*, *24*, 6–8.

Rivkin, J. W. (2000). Imitation of complex strategies. *Management Science*, 46, 824–844.

Seger, C. A. (1994). Implicit learning. *Psychological Bulletin, 115*, 163–196.

Sfard, A. (1998). On two metaphors for learning and the dangers of choosing just one. *Educational Researcher, 27*, 4–13.

Slywotzky, A. (1996). *Value migration.* Boston, MA: Harvard Business School Press.

Stacey, R. D. (1995). The science of complexity: An alternative perspective for strategic change processes. *Strategic Management Journal*, *16*, 477–495.

Stauffer, D. (1987b), "Random Boolean Networks: Analogy With Percolation," *Philosophical Magazine B, 56,* 901–916.

Tabachnick, B. G., & Fidell, L. S. (1996). *Using multivariate statistics* (3rd ed.). New York: HarperCollins.

Taylor, J. R. (1999). The other side of rationality: Socially distributed cognition. *Management Communication Quarterly*, *13*, 317–326.

Thompson, J. D. (1967). *Organizations in action.* New York: McGraw-Hill.

Thompson, L., Gentner, D., & Lowenstein, J. (2000). Avoiding missed opportunities in managerial life: Analogical training more powerful than individual case training. *Organizational Behavior and Human Decision Processes*, *82*, 60–75.

Trofimova, I. (2001). Principles, concepts and phenomena of ensembles with variable structure (EVS). In: Sulis, W., & Trofimova, I. (Eds.) *Nonlinear*

Dynamics, Psychology, and Life Sciences (pp. 217–231). IOS Press, Amsterdam.

Trofimova, I., and Mitin, N. (2002). Self-organization and resource exchange in EVS modeling. *Nonlinear Dynamics, Psychology, and Life Sciences*, *6*, 351–362.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly*, *42*, 35–67.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and application*. Cambridge, UK: Cambridge University Press.

Weick, K. E. (1976). *The social psychology of organizing* (2nd ed.). New York: McGraw-Hill.

Weick, K. E., & Ashford, S. J. (2000). Learning in organization. In F. M. Jablin & L. L. Putnam (Eds.), *The New Handbook of Organizational Communication* (pp. 704–731). Thousand Oaks, CA: Sage.

Weick, K. E., & Roberts, K. H. (1993). Collective mind in organizations: Heedful interrelating on flight decks. *Administrative Science Quarterly*, *38*, 357–381.

Weinberger, E. D. (1991). Local properties of Kauffman's *N-K* model: A tunably rugged energy landscape. *Physical Review A*, *44,* 6399–6413.

Weisbuch, G. (1991). *Complex systems dynamics: An introduction to automata Networks*, (trans. S. Ryckebusch). Lecture Notes Vol. II, Santa Fe Institute, Reading MA: Addison-Wesley.

Wenger, E. (1998). *Communities of practice: Learning, meaning and identity*. Cambridge, UK: Cambridge University Press.

Wright, S. (1931). Evolution in Mendelian populations. *Genetics*, *16*, 97–159.