

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

[Re-submitted to *Nonlinear Dynamics, Psychology, and Life Sciences*, December 4, 2002]

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November 6, 2002

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We wish to give special thanks to: Janet Fulk for steering us in the right direction with many helpful comments; Bennett Levitan for sharing the source code; and Yajun Wang for modifying the code. All remaining errors are, nevertheless, our responsibility.

Abstract

For many firms, producing information and 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 model, in particular a "humanized" version of Kauffman's NK model, to study the situated nature of learning. Based on the simulation results, we suggest seven 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 the situated learning. (198 words)

Keywords: situated learning theory, group learning, rate of learning, complexity catastrophe, agent-based models, Kauffman, NK model, rugged landscapes

1. Introduction

Information and knowledge have become the primary basis of a firm's competitive advantage in modern societies (Castells, 1996; Drucker, 1999; Argote, Ingram, Levine & Moreland, 2000). 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 (Hutchins, 1990, 1991; Carley, 1999a; Carley & Gasser, 1999), 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* 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.¹ Uzzi (1997) observes the negative effect of too much network complexity has also been observed in organizations. In this paper, we concentrate on the study of the within-group dynamics at the core of organizational learning.

We begin by elaborating the argument that situated theory of learning is to be preferred over the traditional

¹ For the record we note that, for Kauffman, "complexity catastrophe" thwarts the Darwinian natural selection process—a truly catastrophic outcome for biologists. This usage clearly differs from, and is almost opposite from, Thom's (1975) catastrophe theory wherein surpassing critical values on control parameters shifts a system into discontinuous change.

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). Based on the simulation results, we suggest 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.

2. Traditional vs. Situated Learning Theory

Tradition

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 (Greeno & Moore, 1993; Glynn, Lant & Millikan, 1994; 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).

Situated² 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; Lave & Wenger, 1991; Hutchins, 1993; Glynn, Lant & Milliken, 1994; Wenger, 1998; Taylor, 1999). 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.

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 (Lave & Wenger, 1991; Greeno & Moore, 1993; Weick & Roberts, 1993; Glynn, Lant & Millikan, 1994; Lant & Phelps, 1999; Taylor, 1999; Weick & Ashford, 2000). Learners are not isolated individuals but participants within communities of practice (Lave & Wenger, 1991). It follows that (1) individual learning is inseparable from collective learning; and (2) 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 re-conceptualization 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) (McKelvey, 1997b, 1999a, 2002a; Anderson, 1999; Anderson et al., 1999; Baum, 1999; Levinthal & Warglien, 1999; Baum & Silverman, 2001; Carley & Hill, 2001; 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). But 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,

² 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 all learning activities.

coevolution among parts, time-dependent nature of relationships, and nonlinearity and discontinuity in the growth trajectories (Contractor, 1994; Arthur, Durlauf & Lane, 1997; Deetz, 2000).

According to Markovsky (1998, p. 2), CASs have the following characteristics:

- Large numbers of components coupled with even larger numbers of interactions.
- Self-organization.
- Adaptation to their environment over time.
- Dynamism and a kind of patterned liveliness.
- Interactions and feedback loops among components that produce higher level emergent behaviors that could not be understood by reducing it to parts.
- 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 the 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, 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

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 overabundance of social network ties can inhibit the adaptive capacities of firms and can lead to inflexibility and inefficiency.” This makes Kauffman’s (1993) “complexity catastrophe” theory relevant to organizations. He holds that for any given species formed of N genes, selectionist progression toward properties that are rare in a coevolving system of entities is overwhelmed by high levels of interdependencies (complexity), K , among the agents. Kauffman theorizes about coevolving adaptive-learning agents searching for improved learning on search spaces called “*fitness landscapes*,” drawing on Wright (1931). Applied to our context, group performance improves through coevolutionary learning at the agent level as agents interact in search spaces that are dynamically shaped and reshaped over time by other agents’ actions as each pursues his or her own learning—what Kauffman labels the “tuning” effect of K .

Learning in the 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 the 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.

A unique feature of Kauffman’s model is its “*rugged landscape*.” As N and K increase:

1. The number of fitness optima available to an agent increases geometrically,
2. The level of fitness at any given optima diminishes so peaks are less valuable if attained,
3. The predictability of finding a better than average fitness peak diminishes rapidly, and
4. Agents more likely will be trapped on suboptimal fitness peaks.

The effects of competitive selection are, consequently, suppressed.³

Kauffman also 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.

Rate of Learning⁴

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 on.

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), firms that

gain 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.

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. While the importance of rate of learning is well documented, it is also clear that few firms accomplish high learning rates.

3. 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, 2002b). Epstein & 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 the 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 (2002b) argues for the adoption of a model-centered epistemology. A theory can be summarized and/or formalized in the

³ Details about how the *NK* model translates to organizational phenomena appear in McKelvey (1999a and 1999b).

⁴ As operationalized in the Method section, we focus on factors inhibiting the speed at which a group reaches its maximum learning (when all agents reach their Nash equilibrium), rather than what it would take to stay ahead of the learning rates of competitors.

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. Through a series of virtual experiments and analyses of a model’s results, researchers can examine, extend, and integrate these theories, and generate improved hypotheses before taking on the arduous task of real-world empirical testing.

We adopt a similar approach. 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 the 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 its 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 that an agent has as 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:

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

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 No.5, for instance) is higher than $f_{5,t-1}$. But if at the same time, the performance improvement of group member No.5 brings about a decrease in performance from other members of the group that /she is connected to, and thereafter a decrease in overall group performance W_t ($W_t < W_{t-1}$), such a change in the system will be dropped.

Group Size: *N* can have a significant impact on within-group interactions because, as group size increases, the number of possible ties increases too, and, therefore, learning opportunities among group members grows geometrically. But, research also shows that an increase in a group’s size leads to increases in social loafing, interpersonal conflict, and dissatisfaction, and most relevant to this study, decreased participation opportunities.⁵ Even under $K = 0$ conditions, Kauffman argues (1993, pp. 52–54), and shows in his Fig. 2.4 (p. 54), that as *N* increases group learning decreases—because the *N* agent learning levels are drawn from a uniform distribution ranging from 0.0 to 1.0 and the averaging follows the Central Limit Theorem.

Network Density: Another important factor in Kauffman’s model is *K*, which is used to designate the average level of communication links (or coordination constraints) among group members. When they do not have many communication links with other people, group members 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. While there are many 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. Kauffman refers to the biological equivalent of these as “*epistatic*” links.

Complexity Catastrophe—Combined *N* & *K* Effects: So far we have presented Kauffman’s argument that, as both *N* and *K* increase, the learning levels of agents diminish toward the mean of 0.5. As a result, the learning level of the group does so as well. 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

⁵ For a more detailed review of these studies, see Arrow, McGrath & Berdahl (2000, pp. 74–76).

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 Figure 1 and Kauffman's Tables 2.1 and 2.2—the targets of our docking analyses.

>>> Insert Figure 1 about here <<<

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 Figure 2.1(a), 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.⁶ That is, in equation #3, given $N = 8$ and $K = 7$, for $w_j, j =$ agents 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 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 pattern is called "*adjacent walks*." Group members may also select their interaction partners randomly. As depicted in Figure 2.2(a), 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 equation #3, given $N = 8$ and $K = 7$, for $w_j, j =$ random selection among agents 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*."

>>> Insert Figures 2.1 and 2.2 about here <<<

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:

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

Inserting equation #1 results in:

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

⁶ Weinberger (1991) discusses this in his paper as an n -bit string energy optimization model—physics not biology. But the underlying logic fits Kauffman's NK model as well.

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.

Humanizing Kauffman's NK Code and the Effect of Group Structure on Learning

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.

Simulating the Distribution of K : Group structure is *differentiated* if the differences in the number of links across people are considerable. It is *undifferentiated* if the most connected members do not have very many more ties than the least connected ones. Translating this dimension into the NK model, 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 Figure 3, 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 Figure 2.1(b) for sequential and Figure 2.2(b) for pooled interdependency, the standard deviations of the K distribution grow accordingly.

>>> Insert Figure 3 about here <<<

Choosing the K Distribution: 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 $K + (2 \times \text{Standard Deviation}) > N$.

Deviation) $> N$ so that fewer data are winsorized, and the curve more likely remains normal.

In our virtual experiments, to counter the effect of randomness in assigning (1) the level of learning contribution from each agent, and (2) number of interactive links among agents in each adaptive walk across the learning improvement “landscape” (search space), we make the agents to conduct their walks for 100 times to deal with the first randomness factor in the model, and 50 times to balance the second factor. A walk stops when a group’s overall performance stops improving after the members have made up to 5,000 attempts. Overall, it means that the group needs to make $50 \times 100 = 5,000$ walks for each K by K -distribution configuration. The average level of performance from these walks is then calculated and reported in our results section.

4. Simulation Results

In our docking analysis, shown in Figure 3 and further described in the appendix, we reproduce Kauffman’s (1993) Tables 2.1 and 2.2 at correlations of 0.979 and 0.976, respectively.

>>> Insert Figure 3 about here <<<

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 Figure 4. If the relationships look curvilinear, we include a quadratic term.

>>> Insert Table 1 about here <<<

As reported in Table 1, because the average 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. Given the high correlation between N and K , what is most striking about Figure 4 is that K correlates strongly with amount of learning and N correlates with rate of learning—with modest nonlinearity showing. Right away our use of an agent model pays off. There is no reason in the prevailing theory to expect this.

Amount of learning: We use stepwise regression to more clearly analyze the relative importance of communication ties and group size in influencing collective learning. A scatter plot shows that the relationship between group learning and communication ties is curvilinear—see Figure 4. 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 ($\beta = -.803, p < .05$).

>>> Insert Figure 4 and Table 2 about here <<<

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. As K increases “complexity catastrophe” sets in, which in Kauffman’s model means that even though agent intercommunication increases there are diminishing improvements to group learning. Based on the statistical analyses of our simulation results, we reaffirm Kauffman’s basic theory. We propose the following—baseline—hypothesis for future empirical tests:

Hypothesis 1: *Over time and across many interactions, the amount of group learning is a nonlinear nonmonotonic (inverted U) function of K .*

Step 3 of Table 2 tests the effect of N , group size, on learning, controlling for the number of communication ties. This test reports the unique contribution of group size on learning, with the influence from network density partialled out. The result 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 ($\Delta R^2 = .014, p < .05$). Based on this, we propose:

Hypothesis 2: *Over time and across many interactions, the amount of group learning is a positive function of group size, N .*

Rate of learning: The scatter plot in Figure 4 shows that group size has a non-linear relationship with rate of learning. Therefore, in the stepwise regression reported in Table 3, we include both the first and second order terms for N . Step 1 shows 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 ($\beta = -.2404, p < .05$) 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. 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. Based on these results, we suggest:

Hypothesis 3: *Over multiple time periods and across many interactions, the rate of group learning is a nonmonotonic function (U shape) of N , with the medium size groups taking the longest time to fully explore the groups' learning capability.*

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 ($\Delta R^2 = .014$, $p < .01$). Based on this result, we propose that:

Hypothesis 4: *Over multiple time periods and across many interactions, and for low K , the rate of group learning is a positive function of K .*

>>> Insert Table 3 about here <<<

Complexity Catastrophe: As noted earlier, Kauffman argues that for a given group size, when K increases, complexity catastrophe sets in and hinders group learning. To offer a more rigorous test of this effect, 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 Figure 5. 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 consistent with Kauffman's observation 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. Translated, we suggest that:

Hypothesis 5: *Over multiple time periods and across many interactions, the higher the network density, the faster the group learns, but the easier it gets trapped at lower levels of collective learning.*

Hypothesis 6: *Over multiple time periods and across many interactions, as K approaches $N-1$ (and especially when N is large), adaptive learning ceases altogether (the catastrophe effect).*

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 $K/(N-1)$ standardization.

>>> Insert Figure 5 and Table 4 about here <<<

Thompson's Task Interdependencies: To compare whether level of group learning and rate of learning change under different task interdependency conditions, an independent-sample t -test is used. 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 ($t(86.6907) = -1.817$, $p = 0.073$). However, neither of the two differences is statistically significant. Based on these results, only a null-hypothesis can be proposed about the impact of task interdependence on the rate and amount of group learning.

Hypothesis 7: *Over multiple time periods and across many interactions, there is no difference in the rate and amount of group learning under different task interdependency conditions.*

Results from the Humanized NK model: The “K-distribution” Effect

Stars and Isolates: 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 Figure 3.

In Figure 6, 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

⁷ Adjusted degrees of freedom for the t -test given that equal variance between the two sets of data cannot be assumed.

with amount of learning, we include both first and second order terms in our analysis.

>>> **Insert Figure 6 and Table 5 about here <<<**

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, $p < .05$ and $\beta = .556$ for its quadratic term $p < .05$). Though small ($\beta = -.063$, $p < .05$), the K -distribution effect is statistically significant, bringing an increase in the overall fit of the model (ΔR^2) up by .003 ($p < .05$).⁸ Based on this result, we propose that:

Hypothesis 8: *Over time and across many interactions, the greater the trend of communication ties toward the extremes of stars and isolates, the lower the amount of group learning.*

>>> **Insert Table 6 about here <<<**

5. 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 the 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

⁸ We realize this appears to be a small effect, but actually it is remarkable that it emerged at all, given how the program works. As Figure 6 shows, the effect attenuates as K increase, which is to be expected. Consistent with most learning appearing when $K = 8$ in Figure 3, we note that the effect in Figure 6 is largest in the $K = 8$ situation. Further, since the program allows group learning to increase only when agents improve their individual learning contribution (governed by IFF condition in equation #2), the negative group learning impact of isolates is negated. In short, the “star/isolate” effect prevails even under very unfavorable simulation circumstances. The main message from Kauffman’s work, our work, and Guastello & Guastello’s (1998) implicit learning simulations is that increasing K works to shut down group learning.

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. Then we follow Carley’s (1999b) conceptual framework, and use agent-based computational models as hypotheses-generators. 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. 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. On the basis of these statistical test results, we generated eight hypotheses that can be used to guide future empirical studies of situated learning in 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 & 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 (Krackhardt and Carley, 1998; Argote and Ingram 2000; McGrath and Argote, in press). 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: (1) coupling it with the more realistic dynamical (nonlinear) coevolutionary theories of complex adaptive systems; and (2) 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 the propositions generated from the model-experiments is also an integral part for furthering our understanding of situated learning. By advancing in the direction we outline here, we can better understand situative 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 nonverbal and/or unconscious learning (Seger, 1994; Guastello and Guastello (G&G) 1998), whereas situated learning attends to contextual effects:

1. G&G 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. G&G 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 (2000, Ch. 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 subgrouping 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) (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).

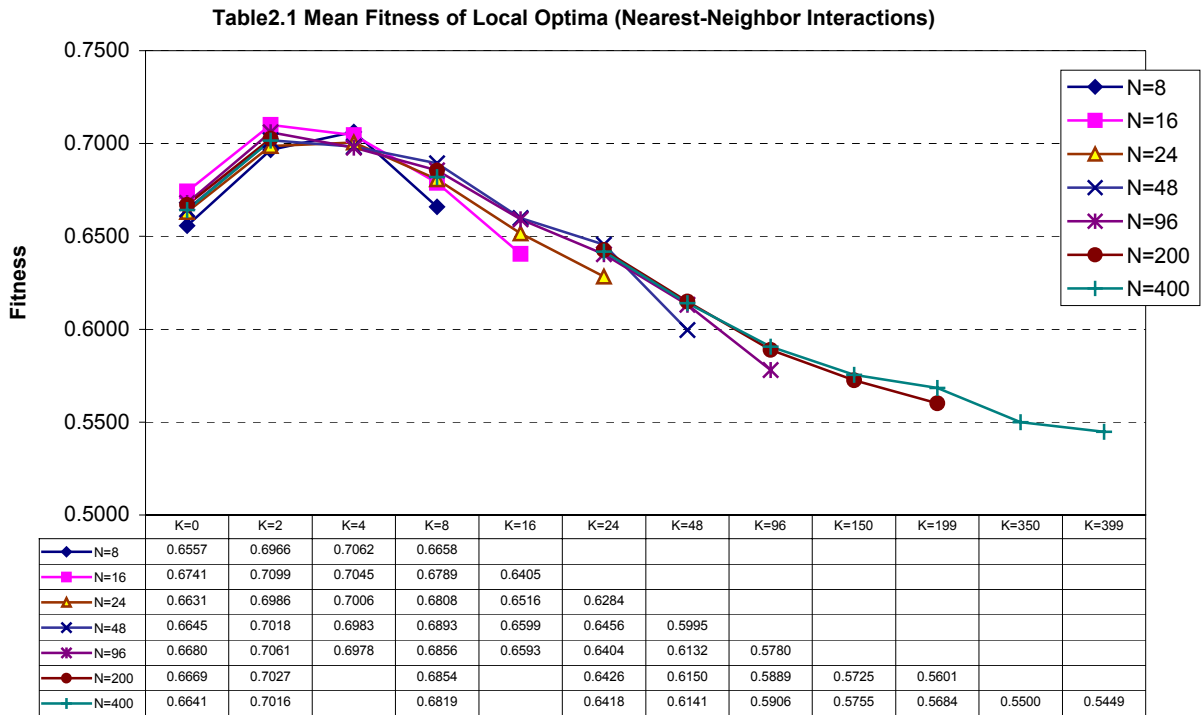
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FIGURE 1 Docking Table 2.1 in Kauffman’s 1993 book



Along main diagonal of table, K=N, actual K value is K-1.

FIGURE 2.1 Adjacent walk-Sequential interdependency

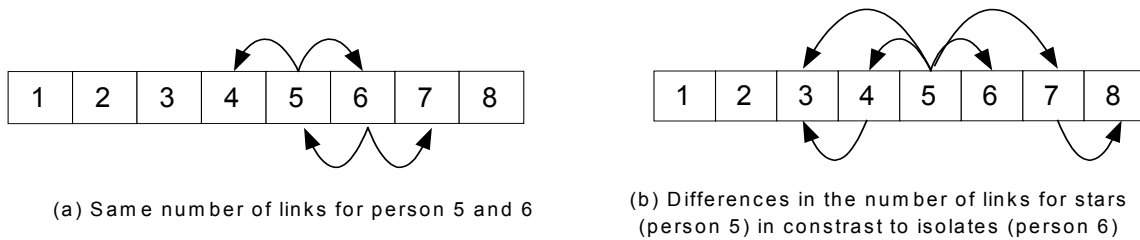


FIGURE 2.2 Random walk-Pooled interdependency

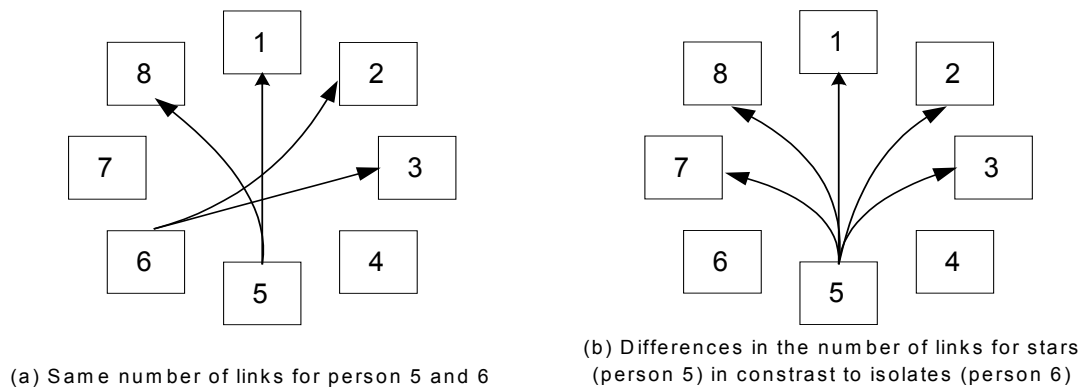


FIGURE 3. The K distribution Effect

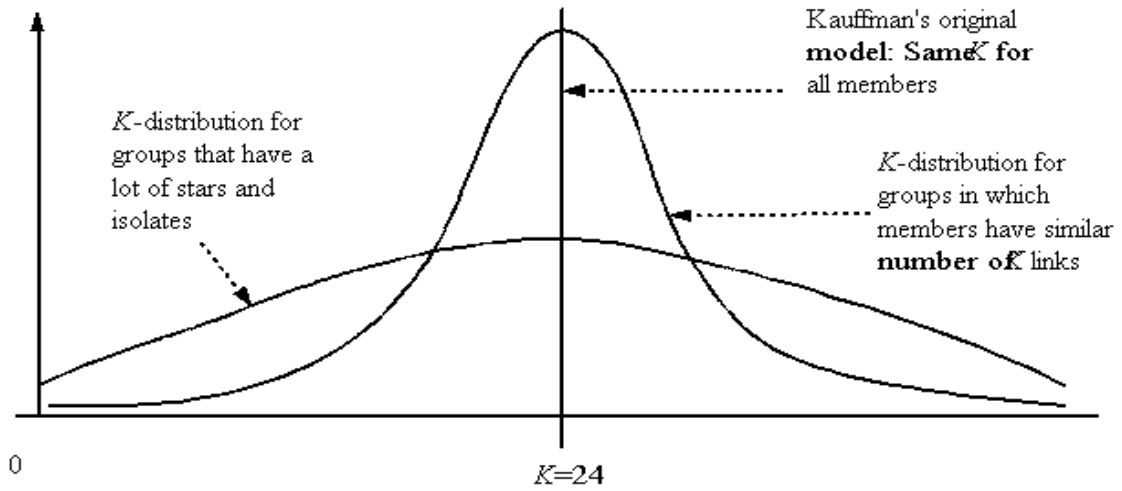
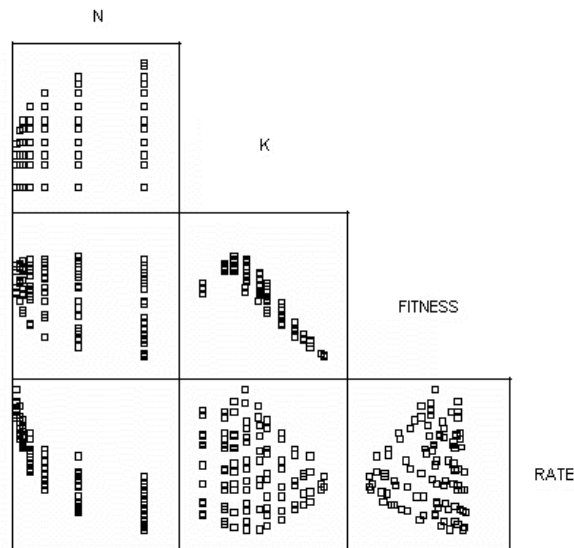


FIGURE 4 Scatter plot on the relationship between variables, N , K , and the Amount and Rate of learning⁹



⁹ Logarithmic transformations have been done on K and the Rate of learning to counter the skewness in their original distribution. The scatter plot shown here provides a visual presentation of the relationships between different variables. For instance, the first square in the bottom row represents a negative relationship between N and rate of learning.

FIGURE 5 Scatter plot on the impact of $K/(N-1)$ on the amount and rate of learning

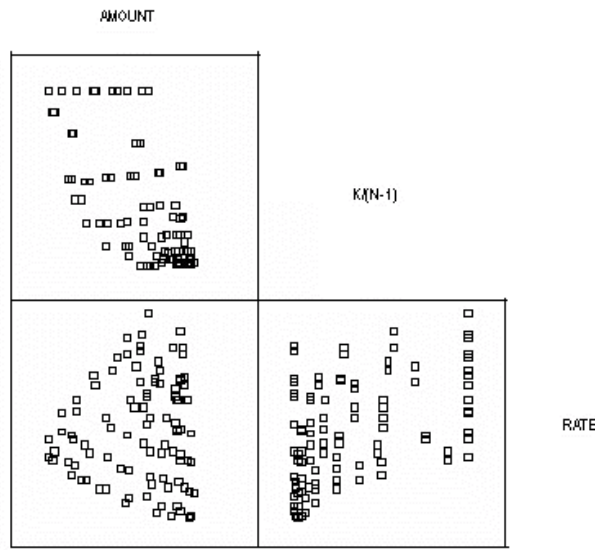


FIGURE 6 Testing the K -distribution effect with $N = 48$ (Random Walk)

N=48, K Distribution Effect (random interactions)

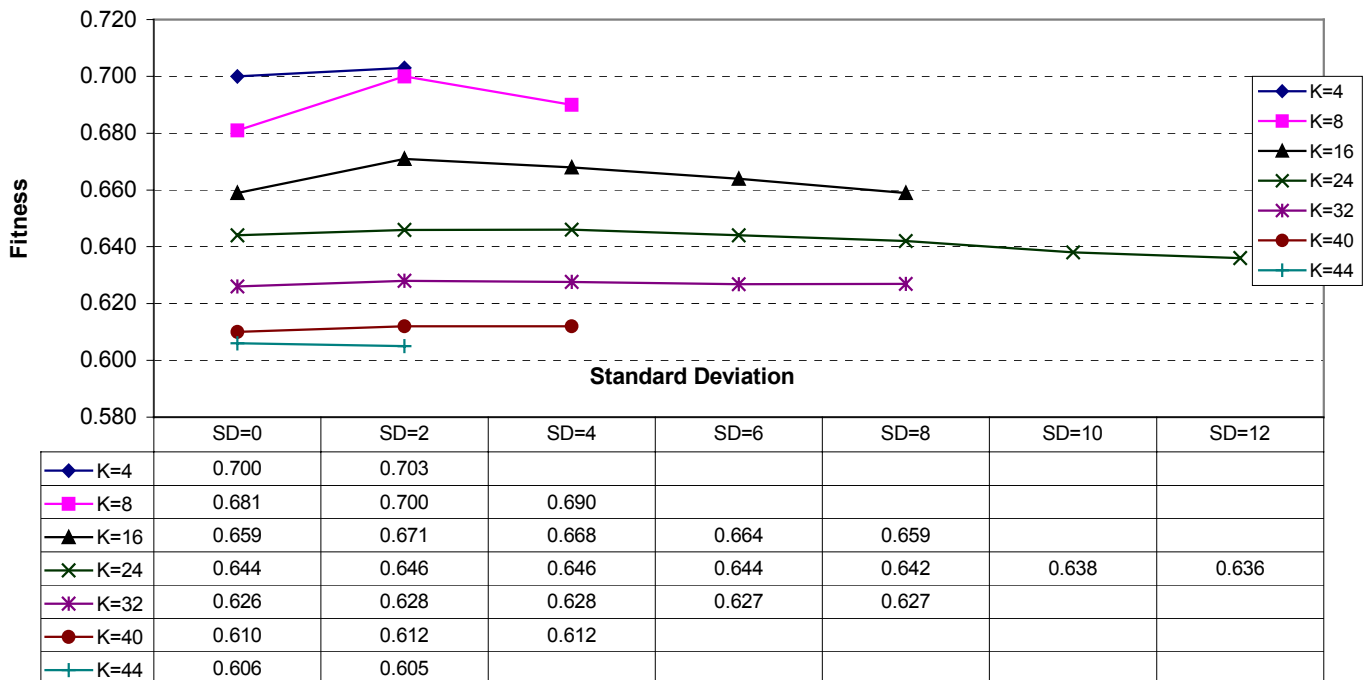


TABLE 1 Descriptive statistics for the non-humanized model (# of simulation runs = 100)

<i>Variable Name</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>
Amount of learning (Fitness)	.657	.050		-.808*	-.669*	-.393*	-.165
Communication ties (<i>K</i>)	44.320	83.956			.558*	.511*	.053
Complexity catastrophe ($K/(N-1)$)	.325	.329				-.088	.404*
Group Size (<i>N</i>)	151.2	147.146					-.768*
Rate of learning (Mean rate)	626.196	869.962					

* Significant at the 0.01 level (2-tailed).

TABLE 2 Summary of stepwise regression for variables influencing the amount of group learning (Fitness¹⁰)

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

Note: $R^2 = .644$ for Step1; $\Delta R^2 = .217$ for Step 2; $\Delta R^2 = .014$ for Step 3; *($p_s < 0.01$ for all cases).

TABLE 3 Summary of stepwise regression for variables influencing the rate of group learning

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

Note: $R^2 = .644$ for Step1; $\Delta R^2 = .217$ for Step 2; $\Delta R^2 = .014$ for Step 3; *($p_s < 0.01$ for all cases).

¹⁰ In the regression analysis we did a linear transformation on fitness by multiplying the fitness value obtained from the simulation test by 100, which according to Cohen and Cohen (1983, p. 33) will not affect the relationship between variables.

TABLE 4 Summary of regression analysis of the effect of $K/(N-1)$ ratio on group learning

<i>Variables</i>	<i>B</i>	<i>SE of B</i>	β
The effect on amount of learning Ratio ($K/(N-1)$)	-0.095	.011	-.699*
The effect on rate of learning Ratio ($K/(N-1)$)	.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)

<i>Variable Name</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>1</i>	<i>2</i>	<i>3</i>
Amount of learning (Fitness)	.645	.029		-.975*	-.420*
Communication ties (K)	24	11.937			.329*
Standardized K -distribution (SD of K/K)	.188	.178			

* Significant at the 0.01 level (2-tailed).

TABLE 6 Summary of hierarchical regression for variables influencing the amount of group learning (Fitness¹¹)

<i>Variables</i>	<i>B</i>	<i>SE of B</i>	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 -distribution (SD of K/K)	-.990	.395	-.063*

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

¹¹ In the regression analysis we did a linear transformation on fitness by multiplying the fitness value obtained from the simulation test by 100, which according to Cohen and Cohen (1983, p. 33) does not affect the relationship between variables.