InFo
Vol. 8, Nos. 1 & 2
2005
pp. 59 – 78

FEATURE

No Right Way: How to Structure Tasks to Maximize Organizational Learning

Ronald Vyhmeister

Abstract *– Organizational learning is known to be a key to organizational performance. This paper builds on prior research and shows that no single task structure is ideal for all situations. Task elements such as the number of inputs, the decision function, feedback, missing information, and information sharing are among those elements which have a significant impact on the learning process. In addition, the timeframe is also important, with some task structures being better suited for rapid learning (but having a lower long-term potential for learning) while others are better for learning in the long run. The present study leaves some questions still unanswered, but it gives guidance as to possible future steps in developing a better understanding of the choices among the various task designs.*

Organizations operating in today's rapidly changing and competitive business environment are finding that doing business as usual is inadequate for long-term survival, and they are forced to restructure and reorganize in order to remain in business. Reorganization may be presented using various names, such as *downsizing*, *rightsizing*, *reengineering*, or *flattening*. The goal of all these reorganizations is the same: to improve the productivity and effectiveness of employees. Many times reorganizations are accompanied by large layoffs—AT&T is a prime example (Thyfault, 1996). At the same time, organizations expect that information technology will enable the remaining employees to fulfill the mission of the organization as well as before.

This paper builds on a paper presented at the CMOT Workshop, Cincinnati, OH, May, 1999 as well as Ouksel & Vyhmeister (1999) and Vyhmeister (2000).

Both organizations and individuals must learn to assimilate the added information flows created by an accelerated rate of change in the environment and the increase in communication which makes this information available to them. Some writers have expressed serious concerns about the limits of individual information-processing capabilities and information overload as individuals face the additional information-processing requirements of today's work environment (Davenport 1996). This situation creates the need for organizations to be designed in order to assimilate the information rapidly and to make the learning process more efficient and effective.

The impact of organizational structure on organizational learning and performance has been modeled by Carley (1990, 1992, 1996) and by Mihavics and Ouksel (1996). In these studies, the organization had either a flat structure or a small hierarchy. Each organizational structure was evaluated on its performance, which was defined as the percentage of correct decisions over a specific time period. Mihavics and Ouksel's study of the impact of organizational design on organizational learning and performance confirms that no organizational structure is ideal for all scenarios, but rather that the ideal structure is contingent on the organizational environment. They showed that (a) newly formed organizations (or established organizations facing a new problem) learn at different speeds, and (b) some structures are better over the short run, while others perform better in the long run. Ouksel, Mihavics, and Carley (1997) developed mathematical expressions which model the decision-making task of every individual in the organization. Further research by Ouksel and Vyhmeister (1999) shows that the complexity of choosing the appropriate decision-making structure is even more complicated than had previously been thought.

This paper is based on the work done by Ouksel, Mihavics, Carley, and Vyhmeister. It focuses on explaining the significance of the research findings to decision-makers, because it is important to understand that choosing an organizational design which improves learning is complex, and that there is no ideal organizational structure for all circumstances.

The Study of Organizational Structure and Learning

The question of what makes an organizational structure "good" or "bad" within a determined context remains, especially in the light of repeated failures of reengineering and reorganization. Researchers today realize that merely changing the structure of an organization does not guarantee success and that even a complete reengineering often fails (Schein, 1996). There is increasing interest in determining what factors, in addition to the organizational structure, contribute to the long-term success of an organization. An organization's ability to learn from its experiences shows significant promise in helping comprehend why certain institutions succeed or fail (Senge, 1990; Levitt & March, 1988), and this learning ability is posited by some (Moingeon & Edmondson, 1996) as providing a competitive advantage to the firm.

Organizational Learning

Every organization strives to meet one or more goals. To reach these goals, organizations must have the ability to learn, since by learning from their experience they are able to avoid repeating costly mistakes and failures. The ability to learn separates successful organizations from those that fail.

For the purposes of this study, we will define organizational learning as "the ability of an organization to measure its past experiences against some aspiration level and to adjust its future decision making behavior in order to move closer to that level" (Mihavics, 1995; p. 19). This concept of organizational learning is experience-based and is totally dependent on the individuals in the organization learning from their own experience, as well as from the feedback they receive from the environment. For organizational learning to take place there must be both knowledge of past experiences and a measuring stick to indicate whether the desired objectives (performance) have been achieved. There must also be a desire within an organization to achieve change and adapt to circumstances to achieve better performance.

The average lifetime of any organization is significantly less than 100 years. Some continue substantially longer, while others last much less. Recent research indicates that the ability of the organization to adapt and learn over time can be a key determinant of organizational longevity (Senge, 1990; Davenport, 1993). If organizations desire longevity, the question is not "what organizational structure is best?" but "what organizational structure learns best in the current context?"

Organizational learning is complex because organizations are made up of agents who have complex learning patterns. For example, the specialist within an organization will remember a large amount of information about few variables, while the generalist will retain limited information on many variables. This happens because individuals generally have a limited capacity to store and process information relating to any given task (Evaristo, Adams, & Curley, 1995). Even when there is a desire to learn, human agents have a limited capacity to retain and process information (Levitt & March, 1988). Even in the case of digital agents, there are storage limitations due to speed and cost constraints. While it may be possible for an agent to have perfect memory, the cost might eventually outweigh the benefits of perfect information.

These memory limitations of individuals have become even more noticeable as the rapid increase in technology in the last few years has both forced and enabled organizations to adapt and change more rapidly than ever before. The amount of information that bombards the individuals who are expected to process it has grown almost exponentially, to the point that many today suffer from information overload. Just as mechanized farm implements have changed agriculture, so computers, telephones, fax machines, and other information technologies are changing business today. Where in the past it was necessary to wait for mail or a courier to deliver a message, today e-mail communicates almost instantly. Instead of waiting several days or even weeks to have a meeting, today we can hold a teleconference or even a video-conference at once. All these changes have only served to place additional strains on individual memory.

A Model for Studying the Impact of Organizational Structure on Organizational Learning

Organizations have realized that it is important during the planning phase of a reengineering process to assess the impact of proposed organizational structures on organizational learning. In order to achieve this it is important to understand not only what an organization is and what organizational learning is, but also how decisions are made in organizations.

Two main approaches are used to study how organizations make decisions: descriptive and normative (or prescriptive) (Vroom & Jago, 1974). Descriptive studies simply describe how decision making takes place, while normative research develops models which provide a rational basis for making decisions (Vroom & Yetton, 1973; Vroom & Jago, 1974; Simon, 1965). Descriptive research focuses on obtaining a detailed understanding of the situation, portraying in detail what happens in an organization. The results are difficult to generalize across organizations. Normative research, on the other hand, tends to focus on quantitative methods which enable rational decision making. These models, while not perfect, are more generalizable than descriptive models. Wanting to be able to generalize the results, we will use a normative model in this study.

The only model of organizations which captures both the structure and the decision-making process of an organization in a clear mathematical form has been developed through research on the relationship between organizational structure and organizational learning (Carley 1990, 1991, 1992; Lin & Carley, 1993; Carley & Lin, 1995, 1997; Mihavics, 1995; Mihavics & Ouksel, 1996; Ouksel & Vyhmeister, 1999). Research has identified the four main components of this model as evidence, decision rules, memory, and information processing structure. Information processing structure is composed of communication channels, formal relationships between individuals, and evidence input patterns. These elements of the decision-making process are operationalized as follows:

1. Organizational decision-making behavior is historically based.
2. Organizational learning depends on the boundedly rational decision making behaviors of the individual agents which form the organization.

3. Subordinates condense their input data into output recommendations to their superiors, and this information compression is lossy; uncertainty absorption (March & Simon, 1958) occurs at each node in the structure.
4. Overall organizational decisions do not require that a consensus be reached (e.g., a legitimate policy might be to let the majority opinion rule).
5. The organizational decision is two-valued (e.g., go/no go).
6. The organization faces quasi-repetitive, integrated decision making tasks: quasi-repetitive in that the tasks are typically similar although not identical to the previous tasks, and integrated, meaning that the task is too complex for a single agent to handle alone, forcing the combination of sub-decisions of multiple agents to reach an overall organizational decision. The tasks of interest here are assumed to be non-decomposable, meaning that combining the correct solutions to each sub-task may not always yield the correct solution to the overall task.

Within the constraints of these general assumptions, each decision task is represented by a binary string of N bits. Each bit is denoted x_i (also called "evidence"). Each of these bits represents the presence (1) or absence (0) of an environmental feature which is relevant to the decision task at hand. These bits are first viewed by agents (the first-level sub-decision makers), who each have access to a portion of the task, $x_i, x_{i+1}, \ldots, x_j$ where $1 \leq i \leq j \leq N$ and $(j-i) < N$. Each agent examines its local memory of prior instances of the task (bit patterns) as well as the corresponding outcomes of these past decisions, and uses this information in combination with the appropriate decision function (or classification function) to make an informed decision. Each agent's decision is communicated to the respective superior agent, which in turn makes its decision based on its own decision function (independent of the decision function used by lower level agents). This process is repeated until the organizational "summit" (top-level agent) is reached, and the final decision is made.

In the initial research using this model, all bits of evidence were modeled as having equal weights, resulting in the *uniform* model. In order to better model reality, recent versions of the model allow each bit of evidence to be assigned an explicit weight which is a measure of the relative importance of that evidence bit in relationship to the decision (Ouksel, Mihavics, & Carley, 1996). For example, in a case where the evidence bit pattern is 0 1 0, and corresponding weights are 1 3 1, the weight of the second bit (3) shows that it is more important than the other two evidence bits combined, and would be the key factor in the decision, regardless of the evidence found in the other bits. On the other hand, if the weights were equal, the decision would be based on a simple majority of the evidence. While the weight of the evidence exists, the agents in the organization are only aware of its relative importance through learning. Initially the agents have no idea which bits are more important, but over time they learn which ones should be given greater weight. This approximates reality in that individuals learn by trial and error what is right and what is wrong.

The correct organizational decision for a problem with binary evidence can be mathematically computed for any set of inputs. Once each agent makes his or her decision and the correct organizational decision is known, each individual is informed what the correct overall decision should have been, providing the necessary feedback for learning. An entry is then made into each individual's memory, indicating that this last evidence pattern should be associated with a 0 or a 1, depending on what the correct organizational outcome should have been. Each time a decision must be made, individuals match the evidence pattern to their memory. Initially, the agent's memory is empty, so the agent will make a decision based on a simple majority rule. Once an agent has seen a given pattern it will select either a 0 or a 1, always choosing the decision that the specific pattern has matched most often. If the number of matches is equal for 0s and 1s, the decision is arbitrarily made on a random basis.

Two basic decision-making structures exist: an expert team and a democratic (or voting) team. It is possible to combine multiple layers of these to create a hierarchy. Organizational decisions are made in different ways, depending on the selected organizational structure.

Expert teams (Figure 1) are composed of multiple agents and a team leader. Each agent makes a decision based on the current evidence and its memory of prior events. This decision is communicated to the team leader, who makes the organizational decision based on the decisions communicated to it by subordinate agents, as well as its memory of prior events.

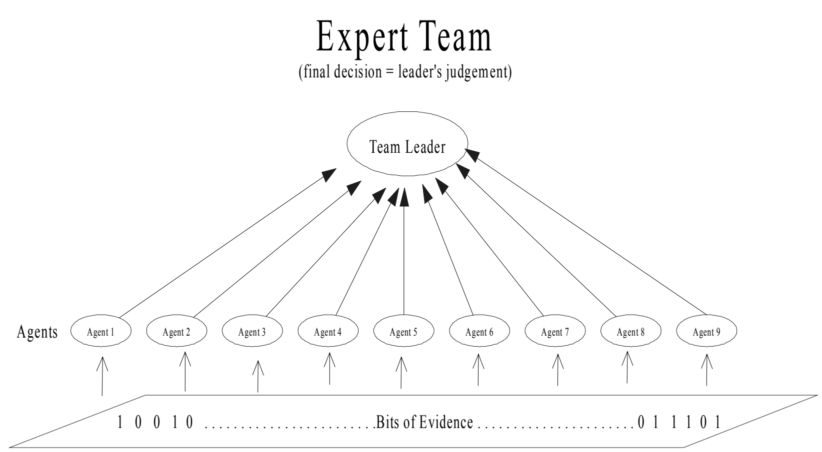

Figure 1

In a *democratic team* (Figure 2) the organizational decision is made by a simple majority vote of the member agents. Each agent makes its decision based on the evidence it receives and memory of past events. The role of the leader is merely to tabulate the votes of the agents and to report the results in the decision.

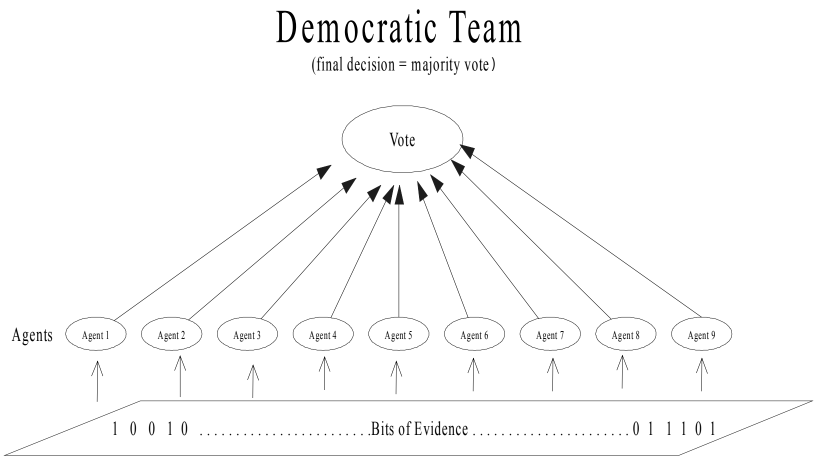

Figure 2

Hierarchies have at least three kinds of agents: those agents who see the initial evidence, middle managers that receive information from agents and/or other middle managers, and a leader (or top decision maker) who receives information from middle managers. Each agent (regardless of which level of the hierarchy it belongs to) makes a decision based on its evidence and memory. Every agent communicates its decision to the next higher level in the hierarchy, where it becomes evidence for the superior agent. This process is repeated until the decision of the highest possible layer of middle managers reaches the organizational leader (or top decision maker), who then makes the organizational decision. The hierarchical process inherently causes the decision to be made with more information loss than expert or democratic teams. In the simplest hierarchy where there are nine agents and three middle managers (see Figure 3), the decision-maker would only see three bits of information, which will never be as informative as receiving all nine, as would happen in an expert team. On the other hand, this reduced number of possibilities allows for easier pattern recognition and faster learning.

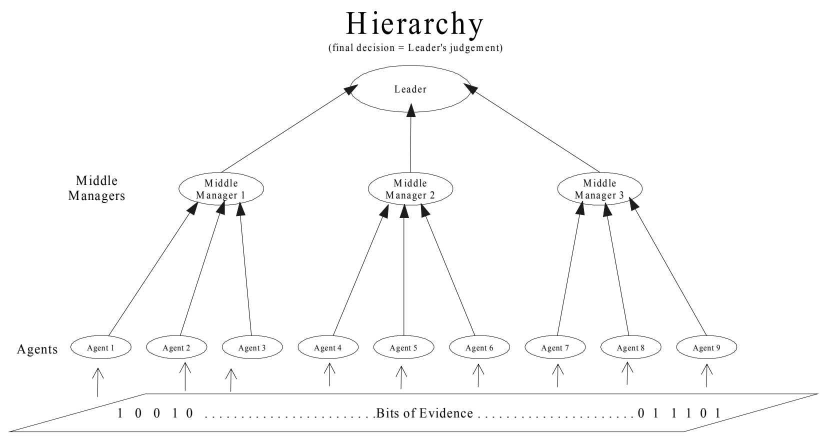

Figure 3

These three organizational models are foundational for all organizational structures. All decision-making structures employ one or more of these models. A hierarchy might use democratic teams at some point and a “middle manager” might not be a person, but a committee. Regardless of formal organizational structure, almost all portions of an organization’s structure can be mapped into one of these three decision-making forms. Organizations, unfortunately, do not generally fit these “clean” designs perfectly. Because of many factors, organizations tend to have non-symmetric designs, as well as non-hierarchical links. In today’s environment applications of information technology such as e-mail and workflow are often used to create other structures. Some organizational cultures emphasize the chain of command, while others encourage cross-functional (and therefore lateral) communication.

In order to attempt to capture some of these non-standard structures Carley and Lin (1993) studied what they called the *matrix* organization (Figure 4). This model operated much in the same way as a hierarchical organizational, with the difference that each agent reported to two different middle-managers.

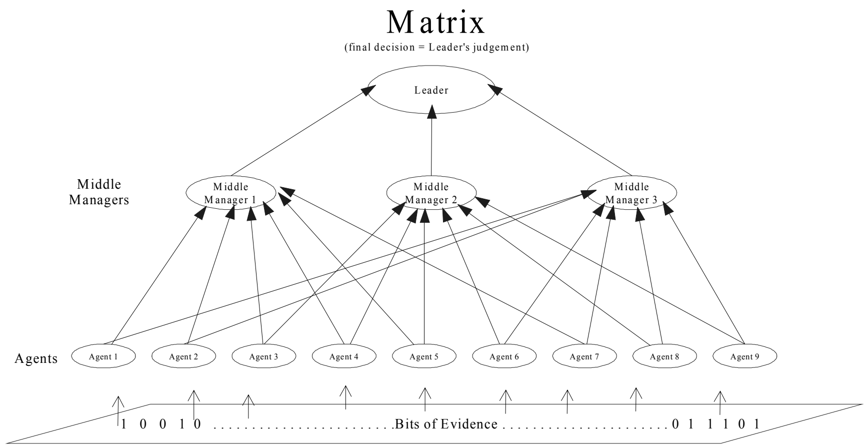

Figure 4

In order to study these different models of organizational structure and their impact on organizational performance and organizational learning, past studies have used five fundamental parameters. Each of these can take on several values, creating a large number of possible permutations. Following is a brief description of each.

1. Number of agents. The number of individuals at the bottom layer in the organizational structure.
2. Bits per agent. The number of elements of evidence that each agent processes for any given organizational decision.
3. Decision-making structure. The organizational structure used to evaluate learning ability. Expert teams, democratic teams, hierarchies, and matrix organizations have been evaluated in the past. When hierarchies have been used, there has been only one layer of middle management, as well as only three middle managers.
4. Evidence weighting. The distribution of evidence weights for inputs into the organizational decision. Weighting can be assigned randomly or intelligently. It can be evenly distributed or clustered. Weights are typically assigned in one of three different ways: *uniform*, *non-uniform dispersed*, or *non-uniform clustered*. All evidence bits have a weight. The default weighting mechanism is *uniform* weighting, where each evidence bit is assigned identical weight (typically a weight of one). With *non-uniform dispersed* weights, the first bit is assigned a weight of one, the second one a weight of five, and the third a weight of nine. This process is repeated until all bits have received weights. When *non-uniform clustered* weights are

used, the first third of all bits is assigned a weight of one, the next third is assigned a weight of five, and the last third has a weight of nine.

5. Task Decomposition. Evidence is defined as seen by only one agent (*non-overlapping*), or by more than one (*overlapping*). Overlapping task decomposition can be seen from two perspectives: (a) *partial,* where only some of the evidence is seen by more than one agent, or *total,* where all evidence is seen by others; and/or (b) *blocked,* where the overlapping is all done within a constrained portion of the organization or *distributed,* where the overlapping takes place across the whole organization.

Three of the key assumptions in most of the simulated decisions have been (a) that every individual in the organization receives timely feedback, (b) that this feedback is accurate regarding the correctness or incorrectness of his or her decision, and (c) that feedback is never missing.

Past Applications of this Model

Kathleen Carley (1990) was the first to use some of these constructs to determine the impact of organizational structure on organizational learning. Her initial model has been expanded on and refined several times (Mihavics, 1995; Mihavics & Ouksel, 1996, Lin & Carley, 1993; Carley & Lin, 1995; Lin & Carley, 1996; Carley & Lin, 1997; Ye & Carley, 1996; Ouksel & Vyhmeister, 1999). Much of the analysis done has been based on simulations, because of the computational complexity of the empirical analysis. Mihavics and Ouksel (1996) developed mathematical models to determine the maximum organizational performance of various organizational structures.

Mihavics and Ouksel (1996) simulated organizational decision-making using three different dimensions: organizational structure, weighting mechanism, and task decomposition. Three organizational structures were investigated: majority teams, expert teams, and hierarchies. Three different weighting schemes were used: uniform, non-uniform clustered, and non-uniform dispersed. Finally, they analyzed organizations that used segregated task decompositions and those that used overlapping task decomposition. This resulted in eighteen different analyses of organizational learning. Using simulation and mathematical modeling, they found that different organizational structures have distinctly different learning speeds and vary widely in the maximum performance level each can attain. They concluded that a new approach to organizational design was needed; in it the organizational structure would be dependent on the organizational expectations of learning speed and ability.

One of the many topics studied using this organizational model was the impact of personnel turnover on organizational performance (Carley, 1992). Carley found that because each time an agent was replaced, organizational performance decreased due to the lost memory. In a stable environment this result is in line with rational expectations that turnover would lead to performance degradation. The question as to whether this remains true when the environment changes rapidly has not been addressed.

Lin and Carley's research (1993, 1995) used a total of seven parameters to develop 7680 cases in which organizational performance was analyzed. Five parameters related to organizational type: task environment, organizational structure, task-decomposition scheme, training scenario, and agent style. Agent style was defined as *proactive* (attempted to prepare for the decision) or *reactive* (reacted to inputs). The two internal conditions studied were type and degree of internal stress. Lin and Carley used the same three organizational structure types as Mihavics (1995). In addition, they employed the matrix organizational structure. The focus of their study was to determine the impact of agent style on organizational performance. Lin and Carley concluded that "agent style is a relatively weak factor in organizational decision-making performance, compared with factors such as organizational structure, task-decomposition scheme and task environment" (p. 284). In other words, whether an agent is proactive or reactive makes significantly less difference to organizational learning and performance than do other factors, making the organizational design more important than the individual characteristics of the agents.

A recent study by Lin and Carley (1995) develops a complex model with more than 460,000 different possible resulting structures. The model includes parameters of organizational design, task environment, stress, training, and agent style. Each model is simulated over 1000 decisions, which, given other research (Mihavics 1995), would not necessarily approach the maximum, or even stable, performance potential of the structures. The results indicate that an increase in information sometimes results in poorer decisions than when less information is available. Two possible reasons exist for this: information overload (individuals are incapable of processing the larger amounts of information), or simply that more information causes organizations to learn more slowly (because of the larger number of possible evidence patterns), without a negative impact on their maximum potential.

Ye and Carley (1995) studied the feedback (information as to what the decision should have been) that each agent received after making a decision. They sought to understand the impact of different feedback mechanisms on organizational performance. This study found that voting teams outperformed expert teams in organizational performance (percentage of correct decisions). However, voting teams had a significantly higher percentage of severe errors than expert teams. These results are based on simulations of 30 decisions per structure. There is no indication of how the performance would be affected by simulating larger numbers of decisions. Ouksel and Vyhmeister (1999) added the concepts of incorrect and/or missing feedback and missing and/or incorrect information. Their results demonstrate that prior results were valid, yet show that varying organizational forms react differently to missing/incorrect feedback/information.

These different studies have enhanced our understanding of the relationship of organizational structure and decision-making to organizational learning. The model presented is clear and simple, and gives us a substantially better understanding of how different organizational forms impact learning.

Past parameters used can be divided into two categories: those which relate directly to the organizational structure and the information it processes (form, task decomposition, amount of information, information per agent, missing information, etc.) and those which do not (training, style, turnover, etc.).

Results

The most complete results (from Vyhmeister, 2000) shown in Tables 1 through 5, summarize the key findings. The problem size is the raw number of bits of information for the problem, and the number of bits per agent is independent of the number of agents in the organization. Tables 1, 2, and 3 do not show the full range of possibilities because the pattern already evident as presented is merely continued to the maximum organizational size studied (891 bits, or 81 agents with 11 bits each).

The results confirm Mihavics' results that majority teams and expert teams perform better than hierarchies when weights are uniform or dispersed for organizations facing a 27-bit problem. As the problem size increases, however, the expert team loses its advantage and actually performs worse than hierarchies (see Table 1). We also find that when both problem and overlap size increase, hierarchies actually outperform both majority teams and expert teams (see Table 2).

The assertion that hierarchies outperform majority teams under clustered weights is still true for the cases Mihavics explored. As the problem size increases, the difference in performance remains similar with no overlapping. We notice, however, that as overlap increases, the performance difference disappears, and the majority teams perform slightly better (see Table 3). At the same time we find that adding overlap or increasing the problem size does not negatively impact the advantage the expert teams held when weights were clustered.

Another finding was that majority teams facing clustered weights perform better with overlapping tasks (Table 4). This is especially true in cases where the agents initially only had 3 bits of evidence. If agents already have 9 bits of evidence, the additional overlap only serves to slow the learning process, which makes the organizational performance after 100,000 decisions lower than the performance without overlap. It is clear from the graph of organizational performance (Figure 5) that organizational forms with large numbers of bits per agent and/or large amounts of overlap have not achieved their maximum potential after 100,000 decisions.

Table 1
Organizational Performance Using Dispersed and Uniform Weights

Problem Size	Weighting Scheme	Expert Team	Hierarchy	Majority Team
27	Dispersed	80.93	79.17	79.97
	Uniform	82.01	81.09	82.68
33	Dispersed	79.64	76.95	79.66
	Uniform	80.13	78.49	82.54
45	Dispersed	76.53	76.22	75.21
	Uniform	76.26	77.99	78.77
55	Dispersed	72.98	72.49	75.17
	Uniform	72.22	72.94	76.38
63	Dispersed	72.76	74.43	71.91
	Uniform	71.34	75.25	73.38
77	Dispersed	67.42	69.40	70.54
	Uniform	66.10	69.75	71.58
81	Dispersed	69.08	73.12	68.38
	Uniform	66.27	73.8	70.51
99	Dispersed	62.98	70.04	66.48
	Uniform	61.08	70.76	67.45
121	Dispersed	58.78	64.02	64.74
	Uniform	56.21	61.11	64.37

Table 2
Impact of Evidence Overlap on Organizational Performance Under Dispersed or Uniform Weights

Problem Size	Weighting Scheme	Overlap Bits	Expert Team	Hierarchy	Majority Team
27	Dispersed	0	77.85	74.98	77.97
		1	80.09	78.80	76.36
		2	84.04	80.96	84.82
		3	85.69	81.95	86.35
	Uniform	0	82.63	80.70	82.23
		1	79.15	80.26	80.25
		2	84.76	82.31	85.33

table continues

Table 2 (*continued*)
Impact of Evidence Overlap on Organizational Performance Under Dispersed or Uniform Weights

Problem Size	Weighting Scheme	Overlap Bits	Expert Team	Hierarchy	Majority Team
33	Dispersed	0	76.05	71.66	74.10
		1	80.58	76.89	81.89
		2	82.33	78.60	83.41
		3	83.18	80.64	84.80
	Uniform	0	77.41	76.17	79.30
		1	81.38	79.07	84.78
		2	82.58	79.57	85.01
		3	81.88	79.14	84.31
45	Dispersed	0	78.29	74.30	76.38
		1	75.22	76.43	72.30
		2	77.46	76.97	76.84
		3	74.71	77.20	75.88
	Uniform	0	79.00	78.36	80.98
		1	74.51	78.22	76.46
		2	78.19	78.18	79.61
		3	72.35	77.21	75.94

Table 3
Organizational Performance under Clustered Weights

Problem Size	Overlap Bits	Expert Team	Hierarchy	Majority Team
27	0	84.51	80.00	75.23
	1	82.39	79.41	76.97
	2	85.37	81.40	82.20
	3	85.46	81.40	82.43
33	0	80.81	75.73	73.54
	1	79.72	76.27	77.85
	2	82.28	80.29	80.84
	3	83.34	79.66	81.59

Table 4
Impact of Overlap on Clustered Majority Teams

Overlap	Performance
0	69.04
1	70.43
2	72.51
3	75.08

The results confirm that the performance of majority teams is negatively impacted when weights are clustered rather than dispersed. For larger decision tasks the negative impact of clustered weights is smaller. Adding overlap bits also reduces the negative impact of clustered weights. This is to be expected, since as overlap increases the effective clustering decreases.

Added information only has a small negative impact on the maximum amount of learning (performance beyond the 50% rate which is expected without learning) (Table 5). However, the amount of information that an agent must process significantly impacts the amount of time necessary until learning begins (the moment in time when performance is consistently better than 51%) (Table 5). Finally, the amount of time until learning stabilizes (the point in time when performance over 1000 decisions increases less than 0.1%) does not vary greatly with changes in information processing loads (Table 5).

Table 5
Impact of Information Load on Agents

Structure	Bits per Agent	Maximum Amount of Learning	Time Learning Begins	Time Stability Reached
Expert Teams	3	24.88	4.92	487.18
	5	24.97	15.42	654.96
	7	25.18	27.94	704.23
	9	27.55	44.10	738.06
	11	24.22	133.56	513.16
Hierarchies	3	13.67	257.16	605.79
	5	15.96	187.16	587.99
	7	14.54	323.66	477.56
	9	14.43	495.09	277.62
	11	13.72	1059.17	221.28

table continues

Table 6 (*continued*)
Impact of information load on Agents

Structure	Bits per Agent	Maximum Amount of Learning	Time Learning Begins	Time Stability Reached
Majority Teams	3	21.02	2.28	611.17
	5	20.61	6.92	656.66
	7	19.94	30.59	471.57
	9	20.23	136.69	388.34
	11	18.91	123.33	393.41

Finally, the assertion by Ye and Carley (1995) that democratic teams outperform expert teams, especially under information distortion, can be confirmed, although the negative impact of feedback distortion becomes smaller over time.

Asymptotic Behavior

From the analysis of the data, it becomes apparent that there is a pattern to organizational learning and performance. An inspection of the data from the new simulations shows that the results for the cumulative averages give a much smoother curve over time, while the raw results for a window give a somewhat ragged curve (Figure 5). A further analysis of the curves shows that the average curve for any given organization is best modeled by a cubic function of time, where the first inflection point comes after a random sequence (learning), and the second inflection point comes as the organizational performance for a given window stabilizes. There are therefore three phases: startup (before the first inflection point), learning (between the two inflection points), and stability (after the second inflection point). In addition to the two inflection points, we can also determine the maximum learning which the organization is capable of. From manual testing using the curve-fitting functions of SPSS, we are able to reasonably predict each of the three points, especially the maximum performance of each organization.

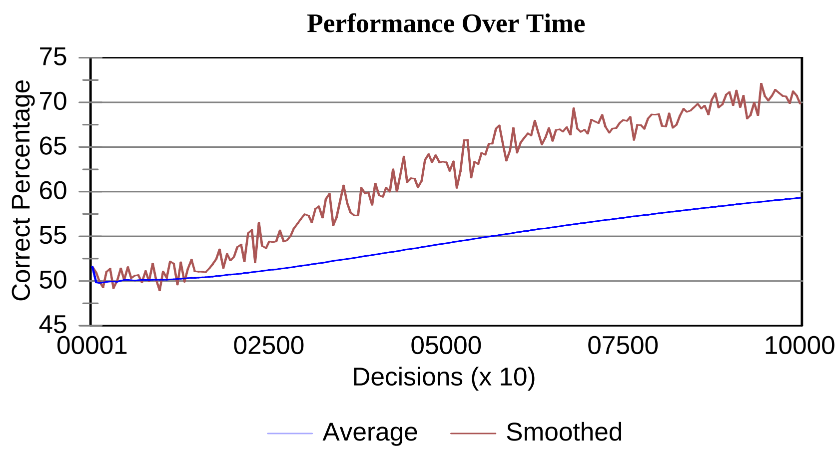

Figure 5. *Performance over time*

Conclusions

This study reviews the evidence that there are distinct task characteristics which impact organizational learning. Second, organizational performance when facing a new problem is demonstrated to have three distinct phases: startup, learning, and stability. Further study could be given to determine what variables allow us to determine both the point at which learning begins and the point when learning stabilizes. Furthermore, in order to better model reality, we should attempt to relax some of the model's assumptions in areas such as accuracy and timeliness of both feedback and information. By continuing this research it should be possible to develop a better understanding of the impact that organizational redesign will have on organizational performance. The possibility of understanding the impact of various organizational design parameters on both the maximum organizational performance as well as the curve leading to that performance would enable an *a priori* evaluation of some of the results of changing from one organizational design to another. At the same time, because the model used is boundedly rational, it is important to realize that design is only one of many factors to be considered in designing an organization.

While this current study presents an understanding of how organizational design impacts organizational learning and performance, there are at least three areas in which further research is necessary, but which were beyond the scope of this project. First, the impact of various decision functions needs to be evaluated. Concepts such as information interdependence (Mihavics & Ouksel, 1996) and data mining must be explored, especially as databases become larger and more pervasive. Second, the impact of primacy and recency effects needs to be studied, focusing on the possibility agents have to adapt their decision functions. Finally, fieldwork would be necessary to test the validity of the simulation results, both with intelligent agents and human agents.

It is impossible to define a "recipe" for organizations to follow in every circumstance. The complex reality of each circumstance must be evaluated in order for the organization to make the appropriate choice in designing the correct organizational structure for the task. Managers who ignore this complexity do so at the risk of failure for their new ventures, their organizations, and themselves.

References

Carley, K. (1996). CCOR Workshop. Pittsburgh, PA: Carnegie-Mellon University.

Carley, K., & Lin, Z. (1997). A theoretical study of organizational performance under information distortion. *Management Science, 43*(7), 976-997.

Carley, K. (1990). Proceedings of the 23rd Annual Hawaii International Conference on System Sciences.

Carley, K. (1992). Organizational learning and personnel turnover. *Organization Science, 3*(1), 20-46.

Carley, K. M., & Lin, Z. (1995). Organizational designs suited to high performance under stress. *IEEE Transactions on Systems, Man, and Cybernetics*, *25*(2), 221-230.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*, *2nd ed*., Hillsdale, NJ: Lawrence Erlbaum Associates.

Davenport, T. H. (1993). *Process innovation: Reengineering work through information technology*. Boston, MA: Harvard Business School Press.

Davenport, T. H., (1996). The fad that forgot people. *Fast Company, 1*(1), 70-74.

Evaristo, R., Adams, C., & Curley, S. (1995). "Information Load Revisited: A Theoretical Model". DeGross, J. and et. al. eds. Proceedings of the Sixteenth International Conference on Information Systems. Amsterdam, Netherlands, 197-206.

Lin, Z., & Carley, K. M. (1995). DYCORP: A computational framework for examining organizational performance under dynamic conditions. *Journal of Mathematical Sociology*, *20*, 193-217.

Lin, Z., & Carley, K. M. (1993). Proactive or reactive: An analysis of the Effect of Agent Style on Organizational Decision-making Performance," *International Journal of Intelligent Systems in Accounting, Finance and Management*, 2(4) 271-287.

Levitt, B. & March, J. G. (1998 August). "Organizational Learning." *AmericanReview of Sociology,* 14, 319-338.

March, J. G. & Simon, H. A. (1958). *Organizations.* New York: John Wiley & Sons, Inc.

Mihavics, K. (1995). *A model for the study of the effects of organization structure on organizational learning.* Unpublished PhD dissertation, University of Illinois at Chicago.

Mihavics, K. & Ouksel, A. M. (1996). Learning to align organizational design and data," *Computational and Mathematical Organizational Theory*, *1*(2), 143-155.

Moingeon, B. & Edmondson, A. (996). *Organizational learning and competitive advantage*. Thousand Oaks, CA: Sage Publishers.

Ouksel, A. M., Mihavics, K. W., & Carley, K. M. (1996). A mathematical model of organizational performance. Technical report, Information and Decision Sciences Department, University of Illinois at Chicago.

Ouksel, A., & Vyhmeister, R. (2000). Performance of organizational design models and their impact on organizational learning. *Computational and Mathematical Organization Theory, 6*(4), 395-410.

Senge, P. M. (1990). *The fifth discipline: The art and practice of the learning organization*, New York: Doubleday Currency.

Simon, H. A. (1965, March). Administrative decision making. *Public Administration Review*, 65, 31-37.

Thyfault, M. E. (1996, January 8). AT&T to cut 40,000 workers—industry changes prompt massive layoffs. *Information Week,* 561, 22.

Vroom, V., & Yetton, P. (1973). *Leadership and decision making*, Pittsburgh, PA: University of Pittsburgh Press.

Vroom, V. H., & Jago, A. G. (1974). *The new leadership: Managing participation in organizations*. Englewood Cliffs, NJ: Prentice Hall.

Vyhmeister, R. (2000). *A study of the impact of organizational design on organizational learning and performance*. Unpublished PhD Dissertation, University of Illinois at Chicago.

Ye, M., & Carley, K. M. (1995). Radar-SOAR: Towards an artificial organization composed of intelligent agents. *Journal of Mathematical Sociology*, 20, 219-246.

Ronald Vyhmeister, PhD
Associate Professor, Business Department, School of Graduate Studies
Adventist International Institute of Advanced Studies