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ORGANIZATIONAL LEARNING AND PERSONNEL TURNOVER*

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The impact of personnel turnover on an organization's ability to learn, and hence on its ultimate performance, is explored for organizations with different structures and different tasks. A model of organizational decision making is presented where: (1) the organization is faced with a continuous sequence of similar but not identical problems; (2) each problem is so complex that no one person has access to all of the information nor the skill to comprehend all of the information necessary to make the decision; (3) individual decision makers base their decisions on their own previous experience; and (4) there is personnel turnover. Using simulation the impact of turnover on the rate and level of learning for hierarchies and teams is examined. This research suggests that while teams in general learn faster and better than hierarchies, hierarchies are less affected by high turnover rates particularly when the task is nondecomposable. Institutionalized memory, as embodied in the memories of distributed individuals and in the advisory relationships between individuals, determines the consequences of personnel turnover.
(SIMULATION; PERSONNEL TURNOVER; LEARNING; INSTITUTIONAL MEMORY)

For individuals, experience is expected to lead to improved performance and a higher percentage of "correct" decisions. Since organizational or group performance is dependent on the experience and capabilities of individual members (see Shaw 1981 and Hastie 1986 for reviews), organizations should learn as their personnel learn. Since experience is a function of the individual's position in the organization and the relationships among individuals (Cohen 1962; Cohen et al. 1969; Shaw 1954, 1981), organizations with different structures should exhibit different abilities to learn. Since turnover affects the balance and location of experience in the organization, turnover should also affect the organization's ability to learn and its performance.

However, the relationship among turnover, performance, and organizational structure is problematic. When people leave, without mechanisms for transferring personal experience among decision makers, the lessons of history are lost, knowledge disappears, the institution's memory is reduced (Grusky 1964; Carroll 1984; Neustadt and May 1986), and the organization's effectiveness and productivity decrease (Price 1977). Yet, when new skills are gained, turnover can benefit the organization (Price 1977; Dalton and Tudor 1979; Price and Mueller 1981). Although turnover and experience are related, experience alone does not suffice to explain the impact of turnover for certain tasks (Argote et al. 1987). Moreover, at certain organizational levels, such as executives (Tushman, Virany and Romanelli 1989), the impact of turnover seems independent of experience. Since individuals at each level in the organization (executive, staff, analysts...) have to face different information-processing demands and garner different types of experience, turnover at different levels may affect the organization differently. For example, although Price and

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Mueller (1981) suggest it may take a 50% turnover rate among nurses before the net effect is negative, few would suggest that hospitals could withstand the same rate of turnover among doctors.

In this paper, the impact of personnel turnover on across-problem[1] organizational learning in hierarchies and teams is examined using a model of organizational decision making in which individuals base their decisions on their experience. Thus, this paper is in a long tradition of interest in organizational decision making in which the organization's behavior is seen as affected by the intendedly, but boundedly, rational behavior of individual decision makers (Simon 1947; March and Simon 1958; Cyert and March 1963; Steinbruner 1974; March and Olsen 1975; Padgett 1980a; Carlet 1986a). What matters is not the quality or correctness of a specific decision but the organization's ability to learn to make a greater proportion of correct decisions over time. This paper emphasizes organizational across-problem learning as a function of individual across-problem learning in a distributed decision making task. In such a task it is not necessary (and often not possible) for individuals to reach consensus; information pooling occurs through institutional design rather than individual choice (Panning 1986). Thus, this study differs from research that emphasizes the historical development of routines, standard operating procedures, and accounting procedures (Cyert and March 1963; March and Olsen 1975; March 1981; Nelson and Winter 1982; Johnson and Kaplan 1987; Levitt and March 1988), cumulative production skills (Preston and Keachie 1964; Rosenberg 1982; Dutton and Thomas 1984; Argote et al. 1987), single-problem learning,[2] mutual influence, and the production of consensus (Bavelas 1950; Cohen 1962; Cohen et al. 1969; DeGroot 1974; Hastie 1986), decision making when information is redundant (Hastie 1986),[3] determination of the optimal decision rule (Marschak 1955; DeGroot 1970; McGuire and Radner 1986; Grofman and Owen 1986), and the learning of (or emergence of) effective communication structures (Leavitt 1951; Shaw 1954; Shaw and Rothschild 1956; Guetzkow and Dill 1957; Cohen 1962).[4]

Types of Structure

Hierarchies and teams as idealized structural types are of particular interest because they may be differentially affected by turnover. Hierarchies are characterized by a set of decision makers that are organized in a chain of command[5] (Cohen's 1986 hierarchical authority structure) such that decision makers at different levels have access not only to different information but also to different types of information (Weber 1922; Downs 1967; Chandler and Dames 1980) and such that the top manager makes the ultimate decision (Padgett 1980a; Carley 1986b). By contrast, teams are characterized by a set of decision makers that act autonomously (there is no chain of command), have access to different information, and have equal voice in the final decision.

[1]This is also referred to as across-trial learning.

[2]This also is referred to as within-trial learning.

[3]As noted by Hastie (1986, p. 157) "...research is needed to investigate the relationship between information pooling and accuracy. In the empirical literature the most glaring omission we found was the lack of research on group accuracy under conditions in which nonredundant sources of information are pooled. On the theoretical side there are no treatments of information-pooling processes and group accuracy." The symbol task used by Cohen (1962, 1969), however, does require individuals to pool information that is only partially redundant.

[4]Cohen (1962, 1969) considers across-problem learning; however, unlike this study he focuses on the emergence of structure rather than performance improvements.

[5]Although Mintzberg (1979, 1983) has demonstrated that there are communication structures other than the command and information access structures, in this study the only lines of communication are the authority relations.

Hierarchies have a variety of advantages and disadvantages. Hierarchies enable specialization (Duncan 1973), emerge in response to distributed or specialized information (Cohen 1962), potentially decrease competition and deception and admit better auditing (Williamson 1975), reduce coordination costs (Malone 1986, 1987), and are most effective when the task and technology are simple (Thompson 1967). Experimental evidence also suggests that when the task is simple such centralized structures tend to solve problems more quickly and with fewer errors than decentralized structures (Cohen 1962; Shaw 1981, pp. 150–161).[6] However, when the task is more complex the opposite is the case (Shaw 1981, pp. 150–161). In addition, hierarchies may exhibit lower performance than other organizational forms due to information distortion (Jablin et al. 1986, pp. 610–613) which may result from condensing information as it goes up the chain of command (Downs 1967, p. 269) or from uncertainty absorption (March and Simon 1958). Further, information channeling within the hierarchy may inhibit innovation and discovery (Burns and Stalker 1961).

Alternate structures have been proposed that, in contrast to hierarchies, provide more effective communication for single-problem learning (Wilensky 1967; Simon 1973; Galbraith 1973), permit more rapid problem solving (Carley et al. 1988), optimize the decision for a single problem (Marschak 1955; DeGroot 1970; McGuire and Radner 1986; Grofman and Owen 1986), admit flexibility (Davis and Lawrence 1977), or are more egalitarian (O'Neill 1984). While none of these structures is identical to the teams examined in this paper, they do bear certain resemblances.[7] They are decentralized and there is no chain of command (Cohen, March and Olsen 1972; Anderson and Fischer 1986; Masuch and LaPotin 1989). Masuch and LaPotin (1989), contrasting such structures with hierarchies, found that randomness decreased productivity, and hierarchical authority relations improved performance only when decision makers were committed. Markets, like teams are decentralized, and Williamson (1975) argued that they are highly efficient on a variety of dimensions as long as specialization is not required.[8] Further teams without managers must be explicitly coordinated to perform effectively. Though such coordination may be done through negotiation (Strand 1971; Bar-Shalom and Tse 1973; Tsitsiklis and Athans 1984), the equal allocation of resources and effort that can result may not be the optimal coordination strategy (Arrow and Radner 1979; Carley 1988).

In summary, hierarchies and teams (or extremely similar structures) have emerged as organizational structures of great interest. The relative ability of these structures to exhibit across-problem learning when decisions and not information are communicated and their resiliency in the face of turnover has not been systematically examined. However, the literature does make several predictions (at least by analogy with single-problem learning) which include but are not limited to the following. Teams will learn faster and better than hierarchies when the task is complex, but

[6]These communication studies follow in the tradition of Bavelas (1950) and Leavitt (1951), and use an experimental setup in which decision makers typically communicate while solving the problem, do not turnover, and are given different initial information but information of the same type. Even the most centralized of the communication networks analyzed (the wheels) are not organizational hierarchies as all decision makers get the same type of information and the group's final decision is not made by a single individual. Moreover, the most decentralized structures (the completely connected networks) are not teams as the group members do not act autonomously but communicate in order to solve the problem.

[7]Actually, the organizations of team theory (Marschak 1955; Radner 1987; McGuire and Radner 1986), when there is no communication while solving a single problem, are similar to the teams studied herein. However, team theory is concerned with locating the optimal decision rule and not with learning.

[8]Markets differ from teams in that members may not work cooperatively toward a single goal. Moreover, markets typically are modeled as completely connected or decentralized communication networks whose members may communicate while solving a problem.

hierarchies will fare better when the task is simple. Due to the speed with which they learn, teams should be less affected than hierarchies by increasing task complexity and turnover.

Learning Behavior

To examine this problem a model of organizational behavior is developed and analyzed. This model's main assumptions are based on the following four observations. First, organizational behavior is historically based. Organizations rely on experience, incrementally adapting their response to similar problems as they receive feedback on their previous decisions (Lindblom 1959; Steinbruner 1974; Levitt and March 1988). Second, organizational learning depends, at least in part, on the memories of individuals and their ability to learn (Hastie 1984; Johnson and Hasher 1987). Third, organizations are disorderly (March and Romelaer 1976; Cohen, March and Olsen 1972; Padgett 1980a). One source of disorderliness which may be particularly crippling is personnel turnover and the movement of decision makers between decision arenas (March and Romelaer 1976; March and Shapira 1982; Carley 1986b; Grusky 1963; Pfeffer and Salancik 1978; Tushman, Virany and Romanelli 1985, 1989). Fourth, while organizations often are faced with highly similar problems, they are rarely faced with exactly the same problem. The problems faced are so complex that different types of expertise may be required; no one decision maker in the organization may be able to cope with, let alone have access to, all of the information needed to make a decision. I refer to sets of problems with these characteristics as quasi-repetitive integrated decision making tasks.

A task is quasi-repetitive if the same type of problem is faced multiple times but some of the information, constraints, parameters, etc. are different each decision period, thus producing slightly different decisions. A task is integrated[9] if the final organizational decision is determined by combining into a single decision a plethora of previous smaller or component decisions made by various decision makers (DMs) within the organization. Such quasi-repetitive integrated decision making tasks are quite common in the organizational arena. At a very general level such tasks include determining whether the positive implications of a possible policy outweigh the negative implications (e.g., determining for a new line of research or a new product whether the chances for success outweigh the chances for failure). At a more specific level, tasks with these characteristics include air traffic control (Steeb et al. 1980; Thorndyke et al. 1981; La Porte and Consolini 1988), sensor data interpretation (Smith 1980), and budgeting (Padgett 1980b). Despite the prevalence of such tasks in organizations, the relative ability of organizations with different structures to learn, despite turnover, when faced with such a task has not been explored analytically.[10]

The proposed model is based on assumptions which reflect these observations. Individuals are treated as perfect historians whose decisions are based on their personal previous experience. Thus, individual decision makers are intendedly adaptive (March and Olsen 1975). Further, in keeping with work in behavioral decision theory, individuals are modeled as imperfect statisticians insensitive to sample size (Tversky and Kahneman 1971), but adjusting their expectations on the basis of additional information (Tversky and Kahneman 1974), and effectively overconfident of their ability to correctly predict outcomes (Lichtenstein and Fischhoff 1977). In

[9] Integrated tasks do not require individual decision makers to reach a consensus in order to make a group decision.

[10] Experimental studies have employed such tasks (Leavitt 1951; Cohen 1962; Cohen et al. 1969, for example) but have focused on the emergence of structure (do humans learn who to communicate with) rather than changes in task performance.

keeping with the work in distributed decision making, individual decision makers are modeled as engaged in cooperative behavior (for an overview see Bond and Gasser 1988). The organization is modeled as a set of decision makers who change over time and are engaged in a quasi-repetitive integrated decision making task for which there is unambiguous and rapid feedback. Illustrative organizations with many, if not all of these characteristics, are air traffic control and financial trading.

Simulation[11] of the proposed model is used to explore the impact of personnel turnover and organizational structure on the rate and level of learning achieved by the organization, while controlling for other factors that affect the experience of individuals (task complexity, task type, and personal experience). In theoretical analyses the researcher typically derives logically implied consequences from a minimal set of premises. As models increase in complexity our ability to locate analytic solutions decreases in which case simulation becomes an attractive alternate method for deriving theoretical consequences. Thus, the simulation results should be viewed as derived predictions which can be tested empirically. Further, the results should not be viewed as tests against nature but as tests of the ability of the model's assumptions to generate observable outcomes.

1. Model

The organization operates across a sequence of decision making periods. Each period the organization faces a new problem that is similar, but not identical, to previous problems. During each period, information on the new problem is evaluated by analysts acting autonomously, a final organizational decision is made, and then each member of the organization receives feedback. This feedback is the "true" decision for that problem. How the final organizational decision is made is different for the team and the hierarchy. Further, even though the organization and its members know what type of decision is supposed to be made, the individual decision makers do not necessarily know when to make a specific decision. Rather, they have to learn the rules that associate specific inputs with specific decisions. For example, radar operators may know they are to determine whether the radar configuration signals that a missile is approaching; however, they do not know initially, and thus must learn, which particular configurations correspond to missiles. A brief outline of the model is provided in Appendix 1.[12]

1.1. *Organizational Structure*

Two organizational structures are examined: the centralized hierarchy and the team which differ only in the presence of upper level management.

Centralized Hierarchy. The centralized hierarchy is modeled as a three-tier organization composed of a chief executive officer (CEO), a set of assistant executive officers (AEOs), and a set of analysts. In this paper, the specific centralized hierarchy examined has 13 DMs[13] with 3 under each "manager" or "executive". There are 9 analysts. Each analyst, each decision period, receives some information on the problem (a subproblem), integrates the information to make a decision (yes or no), and sends this decision to his or her AEO. The AEO uses the 3 analysts' decisions to make an integrated decision (yes or no), and sends this decision to the CEO. The

[11] The simulation program is written in C, will run on a UNIX workstation. and is available from the author upon request.

[12] Appendix available upon request from *Organization Science's* Editorial Office at The Institute of Management Sciences, 290 Westminster Street. Providence, RI 02903.

[13] A hierarchy of 13 DMs is the minimum nontrivial hierarchy that can be examined such that the hierarchy has 3 levels and an odd number of DMs under each "manager".

CEO integrates the AEOs' decisions and makes the final, organizational, decision (yes or no). Then all DMs are given, as feedback, the "true" decision. The true decision is the decision for the entire problem that a perfect DM given the entire problem and having perfect knowledge of what pattern corresponds to which solution would give as the answer. The DM's experience thus includes what patterns of information the DM has seen, and the number of times in that DM's experience that when that pattern was observed the true decision was a yes (or no).

Team. The team is modeled as a single-tier organization composed of a set of 9 analysts.[14] Each decision period, each analyst receives information (a subproblem), and makes a decision (yes or no) independent of the other analysts. The final, organizational, decision is the majority vote of the analysts.[15] Next, the analysts find out the true decision.

1.2. *Task*

The task is a very general one involving elements of both pattern matching, and determining statistical relationships. The organization must determine which configuration of 1's and 0's in a binary word of length N goes with a yes or no answer. The decision makers do not know initially whether the correct pattern-response configuration is majority classification, even/odd classification, parity, etc. By altering which pieces of information or "bits" in the word a particular analyst sees or by altering the probability that the true decision is a "1" or "0" tasks with different characteristics can be examined.

Task complexity is defined as the number of bits or positions in that word that can be 1 or 0 (N). For a given level of task complexity (N) there are potentially 2^N problems. Thus, as task complexity increases the likelihood of seeing an identical problem two periods in a row decreases. Task complexity has several real world analogues such as the amount of information that needs to be processed for a task or the number of different variables that need to be examined. For example, adapting off-the-shelf inventory control software for small personal businesses is a less complex task than designing and building specialized inventory systems for large hospitals in part because it involves fewer design variables. Task complexity does not change over time. In this paper, four levels of task complexity are examined; very low ($N = 9$), low ($N = 27$), medium ($N = 45$), and high ($N = 63$).[16]

Each decision period the organization is faced with a particular problem. Problem solution requires integrating the decisions made by the analysts. For each problem there is a decision provided by the organization (the final decision) and a true decision. Such a problem is divisible into a set of subproblems, each of which is a portion of the word. Each analyst has a distinct subproblem; that is, each position or

[14] The team has 9 DMs in order to match the number of analysts in the hierarchy. The number of analysts, rather than total DMs, is matched so that the complexity of the subproblem seen by each analyst is identical for teams and hierarchies for the same size problem while maintaining no overlap in the subproblems seen by the different analysts.

[15] The simple voting scheme is employed in order to focus the results on the impact of organizational structure (i.e., the fact that hierarchies have more levels of information integration and segregation than teams).

[16] Given the constraints that (1) there is no overlap in the subproblems seen by different analysts, (2) the number of bits in the full problem must be odd in order to guarantee an unambiguous true decision, and (3) the number of analysts is 9, then the possible choices of task complexity are odd multiples of 9 (9, 27, 45, 63, . . .). Nine, although a trivial case (each analyst has access to only one piece of information), is considered for the sake of completeness. In addition, task complexities of 27, 45, and 63 are examined. These values were chosen as they represent the simplest cases that can be examined and yet have a difference in task complexity.

"bit" in the word is evaluated by only one analyst. Given a subproblem each analyst must decide—yes ("I think the answer is 1", represented by a 1) or no ("I think the answer is 0", represented by a 0). In addition, in the hierarchy, the AEOs and CEO take as their subproblem the decisions of their subordinates and then, like the analysts, decide—yes ("I think the answer is 1" represented by a 1) or no ("I think the answer is 0" represented by a 0). Thus, each decision maker is making a recommendation for what he or she thinks the final decision should be. The individual decision maker by passing on a 1/0 decision rather than the number of 1's has compressed information; hence, there is information loss. And the degree of information loss is higher the more complex the task.

Which of the potential problems the organization faces and how the problem is divided across analysts determines the "type of task." Two task types are considered in detail—nondecomposable and decomposable-consensual. A problem is decomposable given a particular organizational structure if the subproblems given to the analysts are independent and the set of solutions to these subproblems accurately reflects all incoming information. In general we can think of a problem as decomposable if a division of a problem into "x" subproblems does not yield a different answer than a division into "less than x" subproblems. When problems are not decomposable, pertinent information may be lost when decisions are made on subproblems thus resulting in potentially incorrect final decisions. An example of a nondecomposable task is design, e.g., aircraft or car design. A problem is consensual given a particular organizational structure if the correct solutions to the subproblems given to the analysts are identical. A problem where each analyst sees an identical subproblem is consensual. In theory, tasks such as proposal evaluation where each analyst evaluates the same set of proposals have this consensual property. These task types are examined as they represent idealized types that are interesting due to their prevalence in real organizations and on which hierarchies and teams may perform differently.

Nondecomposable Task. A problem is a word drawn from this set of 2^N words with replacement such that all problems are equally likely to be drawn. This guarantees that 1's and 0's are equally likely in every bit and that the bits are independent. Each analyst has a distinct subproblem that is a contiguous set of positions and each position in the word is evaluated by only one analyst. For example, we can imagine an organization with 3 analysts that is faced with the problem—101010001; in this case, the first analyst sees the first 3 positions (101), the second analyst sees the next three positions (010), and the third analyst sees the last three positions (001). In the nondecomposable task no one analyst, or set of analysts, has enough information to always make the true decision. Each analyst, however, as he or she gains experience by seeing a sequence of subproblems learns what patterns typically are associated with what response. For example, an analyst might learn that when the subproblem 110 is observed the true decision is typically 1.

Decomposable-Consensual Task. A problem is a word drawn from the set of 2^N words with replacement such that all subproblems are identical. As in the nondecomposable task, each analyst has a distinct subproblem that is a contiguous set of positions; each position in the word is evaluated by only one analyst. For example, we can imagine an organization with 3 analysts that is faced with the problem—101101101; in this case, the first analyst sees the first 3 positions (101), the second analyst sees the second three positions (101), and the third analyst sees the last three positions (101). In the decomposable-consensual task each analyst has enough information to always make the true decision. Each analyst always makes the correct decision after gaining enough experience to know what pattern is associated with what response. This happens after seeing the pattern once.

These two tasks can be thought of as extreme points in a continuum of tasks. For the nondecomposable task each analyst sees a somewhat different subproblem whose pattern is indicative of, but not completely diagnostic of, the final result. In contrast, for the decomposable-consensual task each analyst sees the identical subproblem whose pattern is diagnostic of the overall pattern. The decomposable-consensual task is an "easier" task; i.e., when consensuality is enforced, for the same level of task complexity, the number of possible problems is lower for the decomposable-consensual task than for the nondecomposable task. Consequently both teams and hierarchies should learn faster when they work on a decomposable-consensual task than when they work on a nondecomposable task.

1.3. *Decision Procedure and Learning*

All DMs, regardless of position (analyst, AEO, or CEO), learn from experience and employ the same learning algorithm. Each DM keeps a cumulative record of the subproblems it receives and the true decision. For each DM each subproblem falls into a particular class. A class is a particular pattern of 1's and 0's, such as 010. For the two types of tasks examined the classes of subproblems seen by the analysts are identical and all classes of subproblems are equally likely. As task complexity increases (9, 27, 45, 63), the number of bits of information seen by each analyst increases (1, 3, 5, 7) and the number of classes of subproblems or patterns that the analyst must choose between increases (2, 8, 32, 128).[17] Regardless of task complexity managers always see the same number of bits—3. As the DM encounters subproblems it builds up, for each class of subproblems, an expectation as to whether its decision when it sees a problem in that class is a 0 or a 1. Each DM basically keeps two counters for each class of subproblems—the number of times the true decision was a 0, and the number of times the true decision was a 1. Each decision cycle, each DM simply ups the appropriate counter. Since each DM sees the true decision, organizational structure does not affect what is learned. The DM's expectation that its answer is a 0 (1) is defined as the proportion of times in this DM's experience that, given this class of subproblems, the true decision was a 0 (1). When the DM is faced with a subproblem, the DM uses this experiential information to make a decision using the following procedure:

1. Determine what class the subproblem is in.
2. If the expectation of a 0 is greater than the expectation of a 1, return 0 as the decision.
3. If the expectation of a 0 is less than the expectation of a 1, return 1 as the decision.
4. If the expectation of a 0 is equal to the expectation of a 1, return either a 0 or a 1 as the decision with equal likelihood. In other words, in the absence of sufficient information—guess.

This learning procedure guarantees that each DM learns the conditional probabilities that the true decision is a 1 (or 0) given a particular pattern. The decision procedure guarantees that the DM will pass on as his or her decision the value whose conditional probability is higher. By using this decision/learning procedure the DMs learn to match incoming information to possible decisions in much the same way that parallel distributed processing systems learn to match particular patterns to particular

[17] Since each analyst sees the same number of bits, each will be faced with $2^{N/9}$ classes of subproblems, where N is the level of task complexity.

outputs (Rumelhart et al. 1986; McClelland et al. 1986). The proposed procedure in effect is weighting each input separately and equally. As such, this learning procedure guarantees that the decision maker will come to attend more to that incoming information that "will match" the correct response. Given the right sequence of problems this learning procedure will produce what might be interpreted as superstitious learning, i.e., doing what one did last time because it worked. Further, this same learning procedure in the short run, and in the face of turnover, creates the appearance that upper-level managers attend more to those analysts who have a history of producing correct decisions.[18]

1.4. *Turnover*

Organizational turnover occurs when members of the organization leave and are replaced by new personnel. Turnover is implemented by having a DM leave the organization, and another immediately enter the organization periodically over time as a Poisson process. Which DM leaves the organization is determined randomly; all DMs at the same organizational level are equally likely to be chosen to leave. I define the rate of turnover as 1 over the mean number of decision periods between these exits/entrances (mean interarrival time). Four turnover rates are examined: (1) no turnover; (2) low—0.01 arrivals per decision periods (ADPs) for analysts, 0.0033 ADPs for AEO's, and 0.0011 ADPs for CEO's; (3) medium—0.02 ADPs for analysts, 0.0067 ADPs for AEO's, and 0.0022 ADPs for CEO's; and (4) high—0.1 ADPs for analysts, 0.033 ADPs for AEO's, and 0.011 ADPs for CEO's. These are chosen so that, if the same turnover rate is used at all levels in the organization, the probability of a particular individual leaving during a particular time period is the same for all individuals regardless of level.

When turnover occurs the organization loses the expertise and experience of the DM who leaves and gains the experience of the DM who joins the organization. The level of DM experience is the number of subproblems it has observed. The type of DM experience is defined by the task it has faced. Incoming analysts can differ in level and type of experience. For analysts, three different forms of experience are examined: (1) novice—no experience; (2) good fit—moderate experience (500 subproblems) with exactly the same task, and (3) poor fit—moderate experience (500 subproblems) in an organization with a slightly different task (one in which likelihood of a 0 in each bit is 54% rather than 50%). In contrast all new managers are treated as novices. This reflects the assumption that new managers do not enter new jobs with preconceptions about which of their subordinates are most likely to produce correct decisions, but rather, adapt to their new job by "listening first."

2. Organizational Performance

The organization's performance at a particular time is a function of whether the final, organizational, decision is a correct decision. A correct decision occurs if the final decision matches the true decision. The organization's performance can be determined analytically when (1) the true decision is known, (2) the frequency of each pattern of subproblem is known, and (3) the conditional probability of a 1 (or 0) given a particular subproblem is known. For example, in this paper, unbeknownst to the individual decision makers, 1's and 0's are equally likely and the true decision is a "1" if there really are more 1's than 0's in the problem and "0" if there really are more

[18] Actually, this procedure results in upper-level managers attending more to those analysts who are either consistently correct or consistently wrong. However, since the learning procedure results in analysts trying to be right, in effect the upper-level managers end up attending just to those analysts who are consistently correct.

0's than 1's.[19] Initially, for all organizations examined, all DMs are novices and so randomly guess. In this case, the model can be solved analytically, with the result that initially the organization makes the correct decision only 50% of the time.

2.1. *Ultimate Performance*

Organizational performance is not dependent on the vagaries of individual experience once individuals are fully trained and know which pattern corresponds to which solution. Under such conditions structural and task factors should dominate. For complex tasks teams should outperform hierarchies (Shaw 1981) as hierarchies have greater information distortion (Downs 1967; Jablin et al. 1986), greater uncertainty absorption (March and Simon 1958), and less flexibility (Davis and Lawrence 1977); whereas, for simple tasks, hierarchies should be more efficient and exhibit better performance (Thompson 1967; Shaw 1981). Further, performance should decrease as tasks increase in complexity due to the increased likelihood of error (Perrow 1984) and the increased information-processing and decision-making demands (Galbraith 1973).

For the proposed model, ultimately all DMs, regardless of level,[20] will act as majority classifiers and so can be thought of as employing as a standard operating procedure "propose as their guess about the global majority whatever is in their local majority". The performance of an organization with such a standard operating procedure can be analytically determined[21] and the result is the theoretical optimum performance level (see Table 1).

In contrast to traditional expectations, the proposed model suggests that hierarchies do not outperform teams even when the task is simple and that task type in addition to task complexity and organizational structure determines organizational performance. We see in Table 1 that, ultimately, when there is no turnover: (1) when the task is decomposable-consensual all organizations learn to make all decisions correctly, (2) when the task is nondecomposable organizational performance decreases as complexity increases, and (3) when the task is nondecomposable teams learn more than hierarchies and so come to outperform them. In addition, the proposed model suggests that even in a stable environment in which the task does not change, experiential learning improves performance but does not guarantee perfect performance. Specifically, errors will still occur if the task is complex and nondecomposable. This is analogous to Perrow's observation (1984) that in tightly-coupled complex systems accidents are inevitable.

Two factors determine the organization's theoretical performance limit. First, information reduction occurs as analysts compress information into a decision. The greater the task complexity the greater the information reduction and consequently the lower the ultimate performance. Only when the task complexity is 9, and so each analyst sees only one bit of information, is no information lost when the analyst passes on his or her decision. The more diagnostic the task the lower the information reduction and consequently the higher the ultimate performance. Since the decomposable-consensual task is completely diagnostic no pertinent information is lost as the analysts make their decisions and so the theoretical optimum level always is 100%. Second, information reduction occurs as DMs combine their decisions. Ana-

[19]For the problems examined, the word size is odd (9, 27, 45, and 63) and there is a true decision.

[20]The manager will attend to the analyst who has a history of being correct. In the limit, since the bits are independent and weighted equally, this is equivalent to being a majority classifier.

[21]Computing these theoretical performance limits requires calculating the conditional probabilities for each individual decision maker. Consequently for the nondecomposable task generally it is not practical to compute these optimums as to do so involves solving 2^N problems. Thus, the numbers in Table 1 for nondecomposable tasks are estimates based on solving 1,000,000 problems.

TABLE 1
Theoretical Optimum Performance Levels

Each cell contains the limiting probability times 100 for one type of organization faced with a particular type of task with a particular level of task complexity.

TASK COMPLEXITY	very low	low	medium	high
HIERARCHIES				
nondecomposable task	89.415	80.450	79.071	78.443
decomposable task	100.000	100.000	100.000	100.000
TEAMS				
nondecomposable task	100.000	85.173	83.240	82.419
decomposable task	100.000	100.000	100.000	100.000

lysts, whether in teams or hierarchies, learn exactly the same thing when faced with the same problem. Thus performance differences across organizational structures have to do with the way the analysts' decisions are combined. In the hierarchy, information reduction occurs three times (when the analysts, AEOs, and CEO integrate information to make a decision) and information channeling occurs twice (when different information is distributed across analysts, and then AEOs). In teams, information reduction occurs twice (once by the analysts and once when the vote is taken) and information channeling occurs only once (when information is distributed across analysts). The more levels at which decisions are combined the greater the information reduction and the lower the ultimate performance. Thus, hierarchies are more severely affected than teams. Further, one would expect that the "flatter" the hierarchy (fewer levels) the less its performance would be affected. The more consensual a task the less information is lost as decisions are combined and the higher the ultimate performance. Since the decomposable-consensual task is completely consensual all analysts produce identical decisions and so no information is lost as their decisions are combined.

2.2. *Simulation and Measuring Learning*

Organizations, however, rarely operate in this optimal mode. Rather, personnel may be poorly trained or may leave the organization. Consequently it is important to consider whether the foregoing conclusions hold even when the organization is still learning or when there is turnover. The proposed model cannot be solved analytically under these conditions as the DMs' decision rules continually change and the proportion of DMs using each rule is not known. Thus, to examine organizational performance under less than optimal conditions it is necessary to turn to simulation.

In the foregoing discussion the following parameters were identified: organizational structure, task complexity, turnover rate, experience, and task type. To determine the impact of varying these parameters on organizational learning Monte Carlo analysis is used. Each organization is simulated 400 times (400 runs). Within each of these 400 runs each organization is simulated for 2500 decision periods (hence it is faced with a sequence of 2500 problems).[22] The random sequences for both turnover and problem

[22] The exception here is organizations with no turnover. These organizations were simulated for a sufficient period of time that they reached their ultimate performance level. For all other organizations, i.e., those with turnover, 2500 was chosen as this provided sufficient time that, in trial runs, the learning curve was no longer rising during the last 200 to 500 time periods.

are not repeated across runs nor across organizational types in order to prevent bias from a particular random sequence choice.[23]

Two measures of learning are used—final level of learning (or final performance level) and rate of learning. The final level of learning is defined as the percentage of correct decisions made between decision period 2300 and 2500 by the 400 organizations of that type. This final level is a measure of how much the organization can learn, and hence how well it can ultimately perform. Most organizations examined have stabilized their behavior by this point. Each value for final level of learning is based on 80,000 decisions. This averaging approach is taken to reduce the variance of the estimator. Since the percentage of correct decisions, denoted by p, is based on the sum of 80,000 binary decisions the standard deviation of this percentage can be determined as: $((p(1-p))/80{,}000)^{0.5}$. If p is 0.5 then the standard deviation is 0.0018, if p is 0.8 then the standard deviation is 0.0014, and if p is 0.9 then the standard deviation is 0.0010. In general, for the organizations examined, the percentage of correct decisions ranges between 50% and 90% and the standard deviation thus ranges between 0.18% and 0.10%.

The rate of learning is defined as the average number of decision periods it takes until the organization has increased its performance by 10% (learned to make 60% rather than 50% of its decisions correctly) as measured in ten decision period time windows. By definition, if a 10% performance increase does not occur during the 2500 decision periods it will be defined as occurring at time 2495 (the middle of the last time window).[24] The standard deviations provided are the standard deviations of these means. In order to measure the resiliency of organizations in the face of turnover I use as a baseline their performance when there is no turnover.[25]

By varying these parameters many types of organizations can be identified. In this paper, 256 types of organizations are examined. Both hierarchies and teams, for both types of tasks, for the 3 turnover rates among analysts greater than none, for all 4 levels of task complexity, for the 3 types of experience are simulated (144 types), as are hierarchies and teams for both types of tasks for all complexity levels when there is no turnover (16 types). Thus, there are 80 matched pairs of organization types such that one member is a team and the other is a hierarchy. In addition, in order to examine the impact of executive turnover, hierarchies for both types of tasks for the 3 turnover rates among managers greater than none, for all 4 levels of analyst turnover, for all 4 levels of complexity are simulated (96 types).

3. Simulation Results

As previously discussed, performance degrades with complexity and teams outperform hierarchies unless the task is decomposable-consensual (in which case all organizations perform perfectly). Such ultimate performance occurs once the organization, and all its members, have learned all that can be learned. Now, simulation will

[23] Although the hierarchy and team each sees a different set of 400 sequences of 2500 problems, this does not affect the results as these sets are drawn from the same underlying distribution. Similarly, although which DM leaves is different for hierarchies and teams this does not affect the results as the DMs selected are drawn from the same underlying distribution. And, although when a DM leaves is different for hierarchies and teams, this does not affect the results as the exit times are drawn from the same underlying distribution.

[24] This definition has little impact on the reported results. First, only 24 of the 256 organizations exhibit such slow learning and of these cases, 17 occur when there is executive turnover. In only one case do comparable teams and hierarchies both exhibit such slow learning. Further, since the learning rate degrades monotonically with respect to turnover rate and task complexity the interpretation of the results is not affected by any numeric bias that limiting the learning rate to 2495 might impute.

[25] This is equivalent to using the "majority rule SOP" as a baseline.

be used to examine (1) whether structure and task have the same impact on rate of learning that they do on ultimate performance and (2) whether the relation among structure, task, rate and level of learning holds in the face of turnover. Complete data from these simulations are provided in Appendix 2. (Appendix 2 available from TIMS, see footnote 12.)

3.1. *Structure, Task and Rate of Learning*

In the organizations examined, typically, teams learn more quickly than hierarchies, organizations facing low-complexity tasks learn more quickly than those facing high-complexity tasks,[26] and organizations facing decomposable-consensual tasks learn more quickly than those facing nondecomposable tasks.[27] For teams the average learning rate is 177.5 ($\sigma = 61.0$) whereas, for hierarchies (both with and without executive turnover), the average learning rate is 453.2 ($\sigma = 60.3$).[28] This difference is significant (one-tailed $t = 33.639$, $p < 0.0005$, df = 79). For organizations faced with a very low complexity task the average learning rate is 20.9 ($\sigma = 2.8$); whereas, for organizations faced with a high complexity task, the average learning rate is 799.4 ($\sigma = 125.5$). This difference is significant (one-tailed $t = 6.2$, $p < 0.0005$, df = 63). For organizations faced with a nondecomposable task the average learning rate is 710.5 ($\sigma = 82.1$); whereas for organizations faced with the decomposable-consensual task the average learning rate is 23.5 ($\sigma = 1.9$). This difference is significant (one-tailed $t = 8.4$, $p < 0.0005$, df = 127).

In the proposed model, analysts, whether in a team or hierarchy, learn at the same rate and ultimately achieve the same performance level for the same task. Since the tasks examined are quasi-repetitive and individuals have "perfect" memories, the rate at which individuals learn is a function of how frequently the same problem repeats. The simpler the task the more frequently problems repeat. Thus, learning is faster in low-complexity and decomposable-consensual tasks. But for teams and hierarchies organizational performance differences are attributable to structural factors. Teams learn faster than hierarchies as the organizational learning rate is controlled by the analysts' learning rate; whereas, in the hierarchy, it is also dependent on the managerial learning rate. Consequently, in hierarchies, managerial learning slows the rate of organizational learning. To demonstrate this point, I will contrast the 16 hierarchies in which there is no managerial turnover and all new personnel are novices (4 rates of turnover for each of the 4 levels of complexity) under conditions where managers do not learn but instead perform optimally by simply employing a

[26] In this analysis the size of the organization is fixed. Since organization size and task complexity together determine the size of the analyst's subproblems and hence the rate at which analysts learn, the ratio of the two also determines the rate and level of organizational learning. For the same complexity of task, larger organization will fair better, as analyst's subproblem will be smaller and there will be less to learn. The results in this paper suggest that the effect is nonlinear, although this is a point for future research. A more important effect of size, however, may be that for a task of a given complexity the larger the organization the greater the level of information redundancy it can achieve while keeping the size of all analysts' subproblems the same. Whether such redundancy improves performance is a point for future research.

[27] Identical "on average" results occur for the final level of learning.

[28] In addition, as task complexity increases the drop in the learning rate is greater for hierarchies than for teams (hierarchies take 643 decision periods more, on average, to make 60% of their decisions correctly when task complexity is high than when it is low, whereas teams take only 486 more decision periods). Ultimately, however, hierarchies are more resilient than teams to task complexity (when task complexity is high hierarchies make 15.4% fewer correct decisions than when it is low, whereas teams make 21.6% fewer correct decisions). Increased task complexity increases information loss for the nondecomposable task and so increases the likelihood of making an incorrect decision. In the hierarchy, the additional information loss due to information reduction and channeling at the managerial level already was causing the hierarchy to make some of these same mistakes. Consequently the hierarchy is more resilient to complexity.

majority classification rule and so always attend equally to each DM under them[29] with these same 16 hierarchies where managers learn (as previously specified). When managers learn the average final performance level is 71.99 and the average learning rate is 788.8; whereas, when managers always act optimally the average final performance level is 72.46 and the average learning rate is 365. Thus, managerial learning does not significantly alter how much the hierarchy learns (one-tailed $t = 0.111$, $p > 0.25$, $\mathrm{df} = 15$) but it does significantly reduce how fast the hierarchy learns (one-tailed $t = 1.493$, $p = 0.077$, $\mathrm{df} = 15$).

These results confirm traditional expectations with the exception that hierarchies do not learn faster than teams even when the task is simple. These results, however, are "on average" results. A closer examination of the data reveals that hierarchies learn faster than teams when the task is nondecomposable, complex, and the new personnel are a poor fit with the organization. Of the 80 pairs of organizational types, such that the only difference is organizational structure, in 62 of the pairs teams learn as much or more than the hierarchies and in 77 of the pairs teams learn as fast or faster than the hierarchies. Teams are slower and learn less when personnel who are a poor fit are hired. For the remaining 176 organizational types, which are hierarchies with executive turnover, the corresponding team always learns as fast or faster and more than the hierarchies.

3.2. *Turnover and the Organization's Ability to Learn*

In the organizations examined, typically, organizations learn slower (Figure 1) and less (Figure 2) the higher the runover rate.[30] As expected, organizations facing simple tasks (decomposable-consensual or low complexity) are more resilient in the face of turnover and still outperform their counterparts facing complex tasks.[31] However, in contrast to the prediction, teams are more affected than hierarchies by turnover. For the same increase in turnover teams experience a greater decrease in how much is learned than hierarchies (hierarchies make 8.1% fewer correct decisions when analyst turnover is high and there is no executive turnover than when there is no turnover, whereas teams make 13.9% fewer correct decisions). Consequently when turnover is severe, hierarchies are more resilient and actually may come to outperform teams, but will do so exceedingly slowly.

Turnover reduces organizational performance because portions of the institution's memory leave as personnel leave. The higher the turnover the more likely it is that personnel leave before they are fully trained and consequently the lower the organization's final level of learning. Simpler tasks require less training; consequently, it takes a much higher turnover rate before organizations facing such tasks are even affected by turnover. Hierarchies are more resilient than teams as they are less vulnerable to the single random analyst. In the worst case, turnover converts analysts into random guessers. In a fully-trained organization one analyst randomly guessing will decrease organizational performance in just those cases where one analyst's decision makes a difference. This problem can be solved analytically. As can be seen

[29] The 16 specified organizational types were simulated, using the same Monte Carlo procedure specified earlier. The only difference between the model simulated, and the model described in this paper, is that the managers do not learn. The results for the 16 simulated organizations where managers do not learn are given in Table A3 in Appendix 2.

[30] Since organization size and turnover rate jointly determine the amount of information lost when personnel leave they combine to determine the rate and level of organizational learning. For the same turnover rate, larger organizations will fair better as less information will be lost when personnel leave. Whether larger organizations are more able to withstand the same proportional loss in information due to turnover is a point for future research.

[31] Similarly, in hierarchies, as the managerial turnover rate increases these organizations learn more slowly and less and still perform the best and are the most resilient when the task is simple.

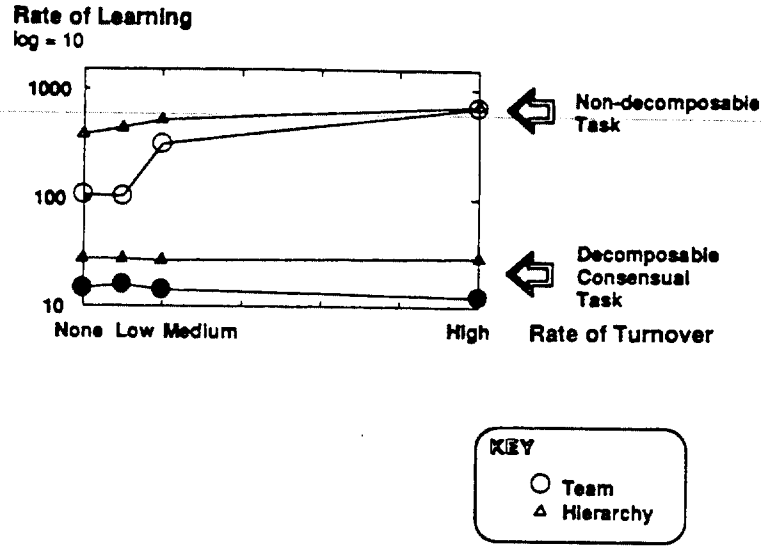

FIGURE 1. Organizations Learn Slower the Higher the Turnover.

The average rate of learning, plotted on a log 10 scale, for hierarchies (triangles) and teams (circles) for both decomposable-consensual (bottom) and nondecomposable (top) tasks as the turnover rate among analysts increases is shown. In the hierarchies there is no executive turnover. Each mark indicates the average number of time periods until all organizations with that structure, faced with that type of task, and level of turnover (regardless of personnel experience or task complexity) learn to make 60% of their decisions correctly. Thus, the higher the mark the lower the rate of learning. When there is no turnover each mark represents the average of 400 organizations of 4 types, thus $N = 1{,}600$. When there is turnover, the new personnel can be either novices, or have a good fit or poor fit with the organization and so each mark represents the average of 400 organizations of 12 types ($N = 4{,}800$).

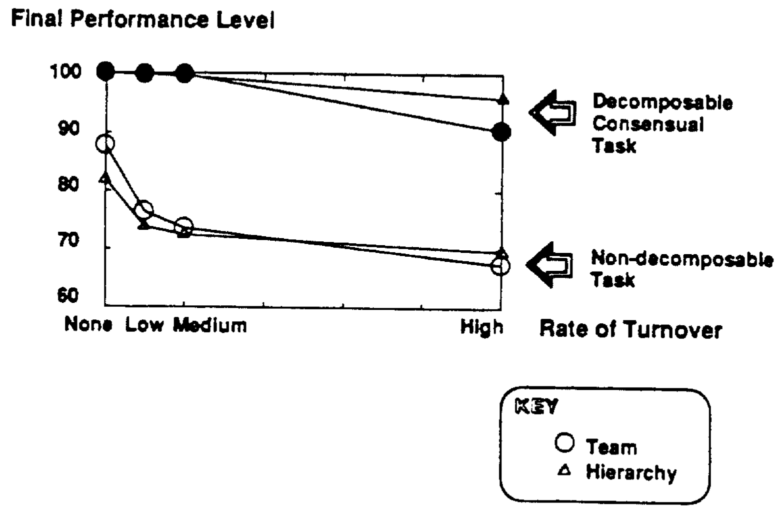

FIGURE 2. Organizations Learn Less the Higher the Turnover.

The average final performance level for hierarchies (triangles) and teams (circles) for both decomposable-consensual (top) and nondecomposable (bottom) tasks as the turnover rate among analysts increases is shown. In the hierarchies there is no executive turnover. When there is no turnover each mark represents the percentage of decisions made by 400 organizations of 4 types over 200 decision periods that are correct, thus $N = 320{,}000$. When there is turnover, the new personnel can be either novices, or have a good fit or poor fit with the organization and so each mark represents the percentage of decisions made by 400 organizations of 12 types over 200 decision periods that are correct ($N = 960{,}000$).

TABLE 2

Theoretical Final Performance When One Analyst Is Random

Each cell contains the limiting probability times 100 for one type of organization faced with a nondecomposable task with a particular level of task complexity. In the fully-trained organization all analysts act like majority classifiers. In the one-random organization 8 analysts act like majority classifiers and one analysts acts randomly.

TASK COMPLEXITY	very low	low	medium	high
HIERARCHIES				
nondecomposable task	89.415	80.450	79.071	78.443
one-random	81.660	75.821	74.817	74.466
TEAMS				
nondecomposable task	100.000	85.173	83.240	82.419
one-random	86.325	79.136	77.824	77.417

in Table 2, when a single analyst acts randomly the team's ultimate performance is more affected than is the hierarchy's; for example, when task complexity is low teams make 14% more errors when a single analyst guesses whereas hierarchies make only 8% more errors. Teams are more vulnerable than hierarchies to a single random analyst as there are more cases when one analyst's decision makes a difference in the team (70 cases) than in the hierarchy (64 cases).[32] Further, since hierarchies composed of a single random analyst and otherwise fully-trained analysts exhibit high resiliency, it can be concluded that resiliency is due to structure not learning. These results suggest that, in hierarchies, upper management serves as a form of institutional memory buffering the organization from the "big mistakes" that employees might make while they come up to speed (learning and re-learning). Managers, by reducing the number of cases in which an analyst can affect the organization, act as a buffer zone in which institutional memory takes precedence over lower level decisions. Whereas, in the team, institutional memory is housed within each analyst and so becomes integrated into the lower level decisions. Thus, the team, whose performance is dependent on the unbuffered performance of its members, is more prone than the hierarchy to making the same "mistake" over and over again.

Vulnerability is modulated by a variety of factors. The fewer analysts who are fully-trained, the greater the number of cases where a single analyst's decision matters. For the decomposable-consensual task the only time a single analyst's decision matters is when other analysts are also guessing. Indeed, in the nondecomposable task increased executive turnover increases the hierarchy's resiliency in the face of analyst turnover (see Table 3).

3.2.1. *Modulation of the Impact of Turnover Due to New Employee's Experience.* Contrary to previous literature and predictions, turnover always degrades the organization's final performance level even when experienced personnel are hired. How-

[32] In the team, a single analyst can change the final decision only when without that analyst there is a tie. Since there are 9 analysts in the organizations examined, ties can occur among 8 analysts in $\binom{8}{4}$ or 70 ways. In the hierarchy, a single analyst can change the final decision only when its AEO without knowing the random analyst's decision is faced with a tie and the two other AEOs disagree. There are two ways in which the random analyst's AEO can be faced with a tie. And the two other AEOs will disagree just in case there are 3 ones, or only one of the two AEOs has exactly two ones, or only one of the two AEOs has exactly two zeroes. Thus, there are $\binom{6}{3} + 2 \times \binom{3}{2} + 2 \times \binom{3}{2}$ ways in which the two other AEOs can disagree. Consequently in the hierarchy there are only $2 \times \left(\binom{6}{3} + 2 \times \binom{3}{2} + 2 \times \binom{3}{2}\right)$ or 64 ways in which a single analyst can make a difference.

TABLE 3
Regardless of Rate of Executive Turnover Hierarchies Are More Resilient than Teams in How Much They Learn if the Task Is Nondecomposable

Each cell contains data on the resiliency of the one type of organization defined by the cell's position. Resiliency is defined as final performance with no turnover minus final performance when there is a high rate of analyst turnover. All new analysts are novices. The cell value is based on comparing the final performance level for 400 pairs of organizations. Since final performance level is based on averaging 200 time periods, $N = 80{,}000$.

	For a Task Complexity of:			
	VLow	Low	Med	High
Nondecomposable Task				
HIERARCHIES				
Rate of Executive Turnover				
None	7.8	17.4	22.7	26.9
Low	8.0	17.4	18.2	14.7
Medium	7.1	16.4	16.6	12.6
High	4.2	9.6	9.1	5.8
TEAMS	12.3	20.5	24.5	28.5
Decomposable-Consensual Task				
HIERARCHIES				
Rate of Executive Turnover				
None	0.0	0.1	2.7	19.1
Low	0.0	0.3	3.2	19.0
Medium	0.0	0.4	3.4	18.9
High	0.2	1.3	4.1	19.1
TEAMS	0.0	0.0	2.3	17.7

ever, hiring experienced personnel can increase the learning rate. In keeping with the predictions, organizations faced with simple tasks are less affected by hiring experienced personnel than are organizations faced with complex tasks. And, in contrast to the prediction, training alone is not sufficient as even a very small amount of inappropriate experience can actually be worse than no experience. Further, the relationship between structure and experience is complex. While hierarchies typically learn faster (Figure 3) and better (Figure 4) when they hire experienced personnel as opposed to novices, teams do worse by hiring novices than appropriately trained personnel and still worse by hiring personnel with inappropriate experience particularly if they work on a nondecomposable task.[33]

Organizations learn more quickly when they hire appropriately trained personnel as the new analysts do not just guess but instead return the majority decision more often than chance. The more appropriate the previous experience the more likely it is that personnel will become majority classifiers prior to turnover and consequently the higher the organization's final level of learning. When inappropriately trained personnel are hired, organizational performance is affected by two competing mechanisms. First, some of the experience may be transferable. In this study, only 4% of the problems seen by the inappropriately trained personnel were "different." Thus, 96% of what they had previously learned should be transferable. Second, the inappropriate experience may make the analyst less likely than chance to make the correct decision. Teams, because they are more vulnerable to the erroneous analyst, will be more

[33]The foregoing results are fairly impervious to executive turnover in the hierarchy as long as the rate of turnover among executives is lower than it is among analysts.

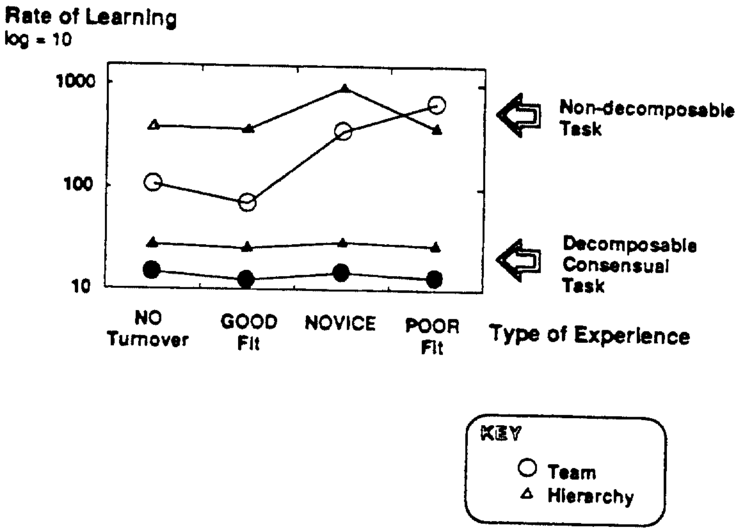

FIGURE 3. Hierarchies Learn Faster by Hiring Experienced Personnel.

The average rate of learning, plotted on a log 10 scale, for hierarchies (triangles) and teams (circles) for both decomposable-consensual (bottom) and nondecomposable (top) tasks for the different types of experience that the analysts might have is shown. In the hierarchies there is no executive turnover. Each mark indicates the average number of time periods until all organizations with that structure, faced with that type of task, and that type of new personnel (regardless of level of turnover or task complexity) learn to make 60% of their decisions correctly. Thus, the higher the mark the lower the rate of learning. When there is no turnover each mark represents the average of 400 organizations of 4 types, thus $N = 1{,}600$. When there is turnover, for each type of new personnel 3 rates of turnover and 4 levels of complexity are simulated and so each mark represents the average of 400 organizations of 12 types ($N = 4{,}800$).

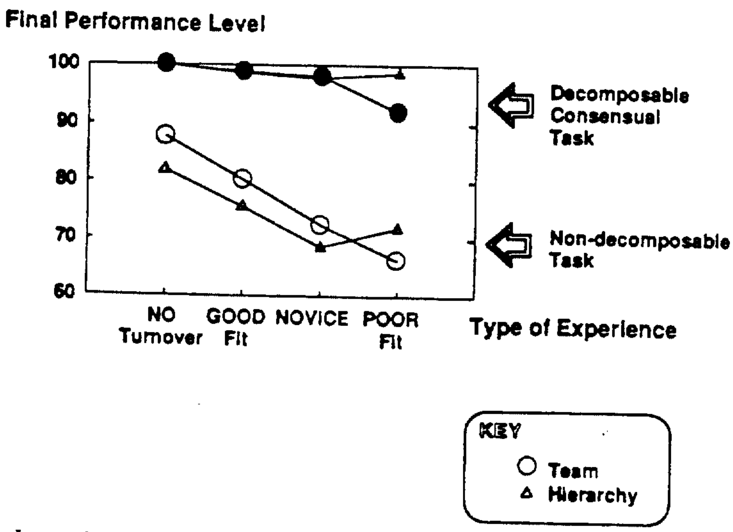

FIGURE 4. Teams Learn the Most When Hiring Personnel Who Are a Good Fit but for Hierarchies Any Type of Experience Will Do.

The average final performance level for hierarchies (triangles) and teams (circles) for both decomposable-consensual (top) and nondecomposable (bottom) tasks for the different types of experience that the analysts might have is shown. In the hierarchies there is no executive turnover. When there is no turnover each mark represents the percentage of decisions made by 400 organizations of 4 types over 200 decision periods that are correct, thus $N = 320{,}000$. When there is turnover, for each type of new personnel 3 rates of turnover and 4 levels of complexity are simulated and so each mark represents the percentage of decisions made by 400 organizations of 12 types over 200 decision periods that are correct ($N = 960{,}000$).

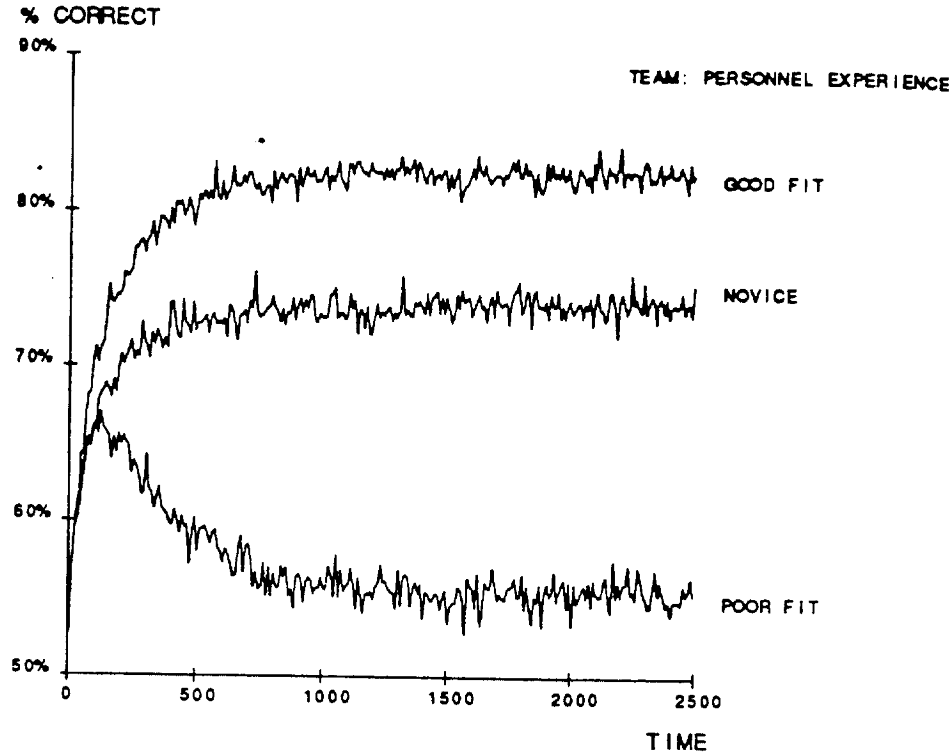

FIGURE 5. Teams Are Devastated by Inappropriate Employee Experience.

The percentage of correct decisions made by teams who hire personnel with different types of experience are plotted over time. The three types of experience, going from top to bottom, are: good fit—new personnel were trained on 500 problems drawn from an identical task, novices—new personnel have no experience, and poor fit—new personnel were trained on 500 problems drawn from a slightly different task (4% 0 bias). Each line represents the averaged behavior of 400 teams with a medium turnover rate.

affected by inappropriately trained analysts than will hierarchies. Thus, when incoming personnel have inappropriate experience, the team starts out learning, but as more people with inappropriate experience are hired the team's performance deteriorates and it "unlearns" (see Figure 5 for an example). Consequently by hiring the right personnel the team can outperform the hierarchy, but if the wrong personnel are hired the team is devastated. Since management buffers the hierarchy from the mistakes of lower-level personnel the hierarchy, unlike the team, can take advantage of any experience. Teams, however, are more vulnerable to analyst error, cannot take advantage of experienced transfers, and so are less resilient to turnover when they hire inappropriately trained personnel.

3.2.2. *The Relative Effect of Executive and Analyst Turnover.* Since managers "see the big picture," require more extensive training, make less structured decisions, and so on, managerial turnover generally is presumed to be more debilitating than turnover at lower levels. The proposed model, however, suggests that although executive turnover is more debilitating than analyst turnover when task complexity is low (i.e., the same turnover rate leads to lower final levels of learning), when task complexity is high the opposite is true (Figure 6). As task complexity increases a shift occurs in where the greatest information loss occurs in the hierarchy. At the managerial level, regardless of task complexity, information loss due to reduction and channeling is constant. However, as task complexity increases the information loss at

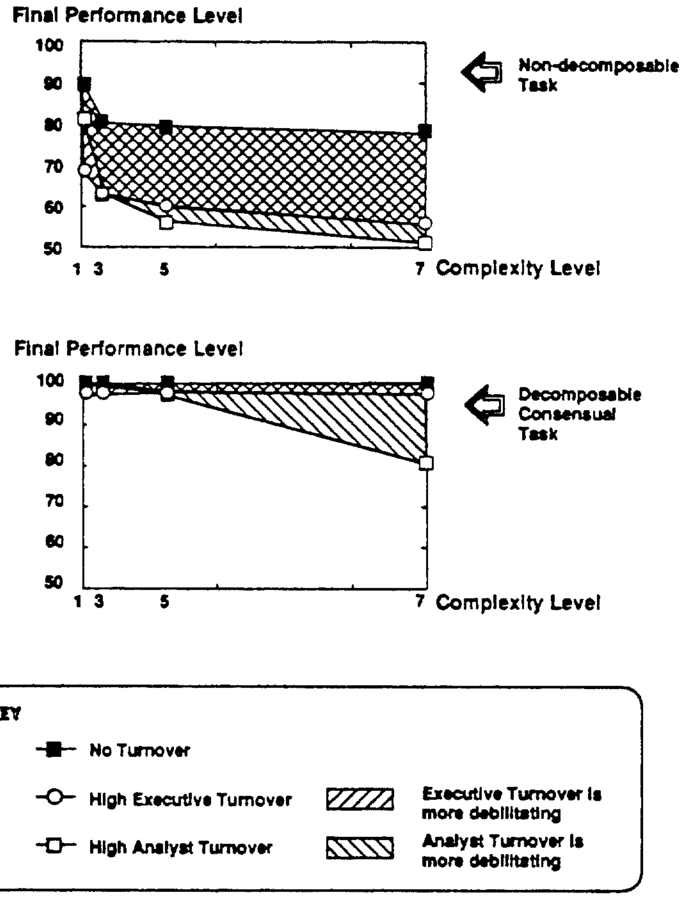

FIGURE 6. Executive Turnover Is More Debilitating When Task Complexity Is Low; but Analyst Turnover Is More Debilitating When Task Complexity Is High.

The average final performance level for hierarchies for both nondecomposable (top) tasks and decomposable-consensual tasks (bottom) as the level of task complexity increases is shown. The top line (marked with black squares) is the case where there is no turnover among analysts or executives. The line marked with circles is the case where there is high executive turnover and no analyst turnover. The line marked with white squares is the case where there is high analyst turnover and no executive turnover. The difference between the top line (no turnover) and the other shows the degradation in performance attributable to that type of turnover. Both new executives and new analysts are novices. Each mark represents the percentage of decisions made by 400 organizations of that type over 200 decision periods that are correct ($N = 80{,}000$).

the analyst level increases. Consequently as task complexity increases the proportion of information lost at the analyst level increases and so the value of the analyst relative to executive increases.

4. Discussion of Model Limitations and Possible Extensions

The model proposed is an oversimplification of individual and organizational behavior. Let us consider the effect of some of these simplifications on the observed results. Future work should consider eliminating these simplifications.

Individual Behavior. In the proposed model, individuals do not exhibit all of the cognitive limitations known to affect humans. For example, there are no framing effects (all subproblems are correctly categorized) and there are no saliency effects (all previous experience is remembered and used) which have been demonstrated to affect individual (Tversky and Kahneman 1981, 1973; Nisbett and Ross 1980) and organizational (Argote et al. 1987; Levitt and March 1988) decision making. As a result the predicted rate and level of learning and length of recovery from turnover may be higher than would be observed in human organizations.

Cooperation. In the proposed model decision makers are engaged in effectively cooperative behavior relative to the organizational goal, despite often having different personal goals. Although the model captures many of the nuances of goal related intendedly rational behavior, by focusing on cooperative behavior, the effect of such forces as differential goal setting, negotiation, bargaining, persuasion, and gaming are missing from this formulation. And, it is assuredly the case that within organizations such behaviors do occur (March and Shapira 1982). Typically it is assumed that such noncooperative behavior decreases the organization's ability to learn as it increases the ambiguity inherent in the organization. If so, then modeling decision makers as essentially cooperative leads to organizations that learn faster and better than would uncooperative organizations.

Turnover. Turnover in the proposed model is treated as a Poisson process where all DMs at the same level are equally likely to leave. Yet, in real organizations, there often are systemic controls on who leaves such as tenure or performance. Typically, performance improves with tenure (Price and Mueller 1981). Were leaving positively correlated with tenure, the organizations would have exhibited lower final levels of learning as the people who were making the most correct decisions would be leaving. Were leaving based on poor performance, on average the newest people would be leaving, and the organization's final level of learning would have been higher. A mixed firing strategy would probably have produced results similar to those observed.

Task. Performance limits cannot be overcome by changing the turnover rate or the experience of the personnel. Rather, overcoming performance limits requires organizations to change tasks (move to a different complexity), break the task up differently (change the organizational structure), or add redundancy to the system by giving different decision makers access to the same information. Such abilities represent other forms of organizational learning in which the organizations could engage.

Consider two hybrid tasks. In the first hybrid task, input is unequally weighted. For example, the information received by one analyst is much more important than that received by other analysts. In the second hybrid task one analyst, or subset of analysts, always receives information that is diagnostic of the result and information received by other analysts is indicative of the right answer. In the hybrid tasks, unlike those examined in this paper, different analysts (and hence different upper-level managers) have different probabilities for receiving the same information. Since the decision/learning procedure guarantees that DMs will learn to attend more to the incoming information that "will match" the correct response the analysts receiving the more important (heavily weighted) input or more diagnostic input will learn faster and better than his or her fellow analysts. An analyst can become a star simply by being in the right place, that is, by having access to better information.

The team cannot take advantage of such differentiation in information and learning as the final decision is made by equally weighting all analysts' decisions. The hierarchy, however, can take advantage of differentiation as the manager who manages the "stars" will learn to attend to them and weight their inputs more heavily. This process will make the manager who manages "stars" a star, and cause his or her manager to attend more to him or her. For these hybrid tasks hierarchies actually may learn faster than teams. This may be more true for the diagnostic than the weighted hybrid task as the diagnostic task is at least partially decomposable and the weighted task (depending on the weights) still may be nondecomposable.

Stable Environment. In the proposed model the organization is faced with a quasi-stable environment; i.e., the specific problems change over time but the task does not. This quasi-stability guarantees that experience is useful and that personnel and organizations can learn. In contrast, were the environment unstable, perhaps because the task changed, different results might emerge. In particular, in a highly turbulent environment turnover even may be beneficial to the organization.

This point is particularly relevant to the issue of executive succession where researchers have found that turnover among executives improves (Pettigrew 1985; Tushman, Virany and Romanelli 1989), has no effect on (Grusky 1963), and degrades (Grusky 1964; Tushman, Virany and Romanelli 1989) organizational performance depending on the conditions under which turnover occurs (see Tushman, Virany and Romanelli 1989 for an overview). For example, Tushman, Virany and Romanelli found that in stable environments where organizations performed well executive turnover degraded performance (turnover destroys competency); whereas, in a turbulent environment, executive turnover seemed necessary if the organization was to adapt to the changing environment (turnover enhances competency). The proposed model assumes a stable environment, in terms of task complexity and type of task, and predicts that executive turnover will reduce performance. Thus, as far as the model goes, it is in accord with the findings previously cited. Further, the proposed model is consistent with an argument that a changing environment (changing tasks) may necessitate executive turnover in order to maintain high performance levels as the old executives have no training on the new task and hence may slow the rate of adaptation over hiring new executives trained in that task. Moreover, the proposed model suggests that executive succession will have little effect on future performance when the organization is faced with extremely high turnover at other levels and is working on a highly complex task.

Organizational Learning. In this study, improved performance over time is attributable to improvements in the distributed memory, i.e., to improvements in the memories of the separate decision makers and, in the case of the hierarchy, to changes in the relationships between managers and their subordinates. Thus, turnover leads to information loss and a reduction in institutional memory as there is no repository for knowledge in the organization other than personnel. In contrast, other studies have shown or argued for improvements in performance due to increases in routinization (Cyert and March 1963; March and Olsen 1975; Levitt and March 1988) or in socially shared cognitions or memories (Argyris and Schoen 1978; Hedberg 1981; Daft and Weick 1984). These alternate learning modes require external knowledge repositories, such as standard operating procedures, forms in file cabinets, and computerized data bases. Adding such repositories to the model would probably make the organization's performance less susceptible to turnover.

Model as General Framework. Despite limitations, the proposed model captures many of the features of organizational behavior that relate to organizational learning. Thus, this model can serve as a framework to look at many of the issues just discussed. This model can be thought of as a series of interlinking modules—(1) problem generation, (2) decision making, (3) decision feedback, and (4) turnover—which are embedded within a loop such that each step is repeated each time period. In this paper, several different problem generation and turnover modules have been employed. For example, problem generation modules with different levels of task complexity and types of tasks were examined. Alternatively, other modules could have been explored such as turnover modules with different ratios of executive to staff turnover or even different types of turnover such as performance based or tenure based. As another example, this model could be adapted to explore whether the amount of information shared by personnel alters the impact of turnover on organizational performance. As a final example, this framework could be used to look at the impact of the timeliness and accuracy of feedback on organizational learning and hence performance.

5. Conclusion

This study suggests that while teams learn faster and often come to outperform hierarchies, hierarchies can buffer the organization from the effects of turnover. More specifically, teams learn faster and better than hierarchies when new personnel are novices or fit well with the organization, whereas hierarchies act as information warehouses and are less affected than teams by turnover. And in hierarchies the upper management acts as a buffer zone protecting the organization from turnover and personnel who make mistakes. Three basic mechanisms are at work: information loss through information reduction, managerial learning, and structural buffering. The less information is reduced, the faster and more the organization learns. Teams reduce information less and so learn faster and better than hierarchies. Managerial learning, by definition, only occurs in hierarchies and reduces the rate at which hierarchies learn relative to teams. Structural buffering occurs in hierarchies where the channeling of information to managers actually limits the "damage" a single analyst can do, thereby making hierarchies more resilient than teams. Since institutional memory is embodied in the memory of distributed individuals and the relationships between them, these three mechanisms combine to make hierarchies more resilient than teams. The team, without such relationships, is more vulnerable to the whims of individuals.

These findings resulted from a theoretical exploration of the impact of personnel turnover and organizational structure on organizational learning when the organization is faced with a quasi-repetitive integrated decision making task while controlling for various environmental conditions (task complexity, type of task, and personnel experience) conducted via simulation. These findings should not be treated as "facts" about organizations, but as model based predictions. Despite the simplicity of the proposed model, it enables an analytic treatment of complex issues and makes interesting predictions which, in turn, have interesting policy implications. Let us consider a few of these.

This study suggests that which organizational structure is "the best" is contingent on a variety of factors, but such contingencies are highly systematic. Thus two organizations in the same industry (and hence facing similar tasks with comparable complexity) can have different structures yet similar performance if they use different turnover rates or employ different types of personnel. Similarly, organizations in different industries may evolve the same structure but exhibit vastly different performance due to task differences or personnel turnover differences. But, because of the systematic way in which such contingencies affect organizational performance, the behavior of the organization can be characterized and possibly predicted.

There is a tradeoff between single-problem performance and across-problem performance. In the team, unlike the hierarchy, institutional memory is decentralized. Consequently, in the team, there is less information loss per problem and higher single-problem performance than in the hierarchy, but at the cost of greater organizational subjugation to personal memory and hence greater information loss across problems when personnel leave. There is also a tradeoff between performance and vulnerability. Hierarchies, by channeling different information to different managers, reduce organizational vulnerability by buffering the organization from the mistakes of personnel, but at the cost of greater information loss per problem and hence generally lower final performance and a slower learning rate. Thus the hierarchy plods along slowly and relentlessly, continues to learn and to make use of the lessons of history, despite high turnover levels, high complexity tasks, and hiring inappropriate personnel. In contrast, teams can exhibit high performance but at the cost of increased vulnerability. Thus, teams can skyrocket to a high performance position, only to suffer institutional senility as personnel start leaving. These results imply that in new areas where there are no existing practitioners it would be more efficacious to set up teams than hierarchies. For ease of learning, startup companies might be formed of a loose group of more or less equivalent individuals but will (or should) move to a hierarchical structure as they are faced with personnel turnover. Since teams have less latitude in their hiring decisions than do hierarchies, teams might take longer to hire and more intensely screen new personnel than might hierarchies.

Organizations are subject to performance limits such that although individuals continue to learn the organization does not. In a stable environment experience-based learning leads to a certain coherence and consistency in individual behavior as new experiences serve to reinforce the lessons of history. Such performance limits might be overcome if now and then personnel played a hunch or took a risk. March (March and Olsen 1975; March 1981) has argued that, within organizations, consistency limits learning and ambiguity in preferences is advantageous as learning often results from fortuitious accidents. In contrast, this paper suggests that even though consistency limits performance and occasional inconsistency improves performance on a single problem, learning may not accrue from such fortuitous accidents. The sheer rarity in which the hunch works, coupled with information loss due to nondecomposability, leads to such a dearth of information that learning is not possible. There are mechanisms which go beyond the personal memories of the decision participants and integrate information across individual decision makers that can be used to record the fortuitous accident and so reduce information loss in solving a particular problem. These include standard operating procedures, information sharing, institution-wide data bases, and lower levels of specialization. This research suggests that without such institution-wide mechanisms the lesson of the fortuitous accident will be lost. Thus, while institutional memory, as embodied in the memory of distributed individuals and the relationships between them, may be sufficient to buffer the hierarchy from the deleterious effects of turnover, institution-wide recording mechanisms may be necessary if the lessons of the fortuitous accident are not to be lost.

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