Formalizing Theoretical Insights from Ethnographic Evidence:

Revisiting Barley's Study of CT-Scanning Implementations

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Abstract

Few ideas offer more potential for improving our understanding of organizations and how they react to the introduction of new technology than the notion that human action and social structure recursively interact. Like all major advances, however, notions of structure and structuring pose numerous challenges for refining current conceptions of organizations and the processes of organizing. In this paper we offer an approach for theorizing about the recursive interactions between action and social structure occasioned by the introduction of new technology. Our method integrates three elements from social and organization theory: a focus on activities, attention to accumulations of knowledge by individuals in those activities, and the recursive relationship among activities and accumulations. We apply this lens to Barley's study of two hospitals implementing a CT scanning technology. Through the development and analysis of a simulation model we show how the relative distribution of expertise between doctors and technologists in using the technology recursively interacts with the conduct of the scanning activity to determine the patterns Barley observed.

Formalizing Theoretical Insights from Ethnographic Evidence: Revisiting Barley's Study of CT-Scanning Implementations

Few ideas offer more potential for improving our understanding of organizations than the notion that human action and social structure recursively interact (e.g. Giddens, 1984). Most prominently, a number of recent studies have used this idea to transcend a long-standing debate over the logical ordering of technology and organizational behavior. Technology, this view holds, is neither a totally objective force that produces regular changes in behavior independent of the context, nor a completely malleable product of action and interpretation. As argued by Orlikowski (1992: 406), technology, while being both physically and socially constructed, also tends to become "…reified and institutionalized", eventually appearing to be "… part of the objective structural features of an organization." Recursive conceptualizations of technology and its influence on organizations have provided a useful window on a variety of technology-related phenomena (e.g., Barley, 1986; Orlikowski, 1992).

Like all major advances, however, recursive notions of structure and structuring pose numerous challenges for refining current conceptions of organizations and the processes of organizing. We lack a common language and set of metaphors to help ground intuition concerning the nature and function of structuring processes. While theories based on mono-causal logic (e.g. the technological imperative) are amenable to traditional methods of theory development and representation, more recursive views of technology and organizations are hard to operationalize and represent using conventional frameworks (Barley, 1986, 1990). Not surprisingly, given these challenges, empirical work in this vein is largely qualitative, relying on "thick description" (Geertz, 1973) to capture the mutual influences of technology and social structure (e.g., Barley, 1986; Orlikowski, 1992; Carlile, 2002). Given the deterministic and static notions that authors are trying to avoid, contributors to this line of inquiry are often reluctant to take a strong stance on the question of which features in a given context are most important in generating the observed patterns of behavior. Yet, until we are able to identify and represent the specific interactions among technology, social structure and human action that generate such patterns, it will be difficult to extend the critical insights developed from this line of research beyond the contexts in which they were derived. The challenge in continuing to develop the structuration line of inquiry lies in linking the existing rich descriptions of specific episodes of technology implementation to operational and generalizable characterizations of the interactions between human actions and institutions, between structuring and structure, that generate the observed patterns of interactions

In this paper we take one step towards meeting this challenge by developing a formal model to capture the dynamics documented in a widely cited study of technology implementation, Barley's (1986) study, “Technology as an Occasion for Structuring: Evidence from Observations of CT Scanners and the Social Order of Radiology Departments”. Barley's detailed documentation of evolving interactions between doctors and technologists at two hospitals implementing a new imaging technology (computerized tomography, or CT) provides an ideal data set from which to theorize about the dynamics occasioned by new technology. To develop a more formal explanation for the different dynamics Barley observed, one that is both grounded in the operational details of the original data and potentially generalizable to other settings, we build on three themes in the organizational literature: a focus on the day-to-day *activities* and practices through which people enact organizations (Weick, 1979; Lave, 1988; Orlikowski, 2000); attention to the *accumulations* of knowledge and power that often determine which actors get to engage in what activity (e.g. Bourdieu, 1980; Pfeffer, 1981; Perrow, 1986); and a recognition of the *recursive* relations between activities and accumulations (Giddens, 1984; Bourdieu, 1980).

We combine these elements into an analytical approach for understanding Barley’s data using the methods of system dynamics (e.g., Forrester, 1961; Sterman, 2000). With its emphasis on operational representation of feedback processes and consequent analysis via computer simulation, system dynamics is a useful means for representing the interactions that generate organizational outcomes and provides an analytical approach for exploring the internal consistency of the resulting theory. From this analysis we define a set of recursive relations among actors (e.g., doctors and technologists), their accumulations of knowledge, and the activities they enable, that taken together explain the different patterns Barley observed.

The central contribution of our study is to offer a new characterization of the dynamics occasioned by the introduction of technology that requires collaboration between two occupational groups—in this case, technologists producing computerized scans and radiologists rendering diagnoses from the images. Revisiting Barley's data and building on his analysis, we identify three possible patterns of interaction between doctors and technologists: *collaboration*, in which both groups contribute from their respective functional or occupational expertise; *professional dominance*, in which doctors minimize the role of technologists; or *occupational separation*, in which the two groups seek to minimize their interaction. While the collaborative pattern is characterized by ongoing learning by both groups, learning is restricted in the other two.

Our analysis also identifies the conditions under which each pattern is most likely. Most strikingly, having more experienced technologists or doctors does not necessarily lead to increased collaboration and better long-term performance. We find that significant imbalances in knowledge related to using the new technology between the two groups can occasion a set of pathological dynamics that lead to either professional dominance or occupational separation, constricting learning and collaboration in the process. Building on this characterization of the dynamics of relative expertise, our analysis provides an internally consistent and accessible explanation for the different outcomes that Barley observed. More broadly, our study provides the beginnings of a new approach for theorizing about "technologies . . . as occasions that trigger social dynamics, which in turn modify or maintain an organization's contours" (Barley, 1986: 81).

In the next section we provide a brief summary of Barley's original study and discuss our approach to analyzing it. We then describe the structure of our model and the results of our analysis. Finally, we discuss how the analysis contributes to understanding the interactions of technologists and professionals, with broader implications for theorizing about organizing and organizations.

DATA AND METHODS

Barley's Story

Barley's 1986 *ASQ* article details the efforts of two Massachusetts hospitals to implement Computed Tomography (CT) scanning. By observing day-to-day operations and shadowing doctors and technologists both before CT scanning was introduced and for nearly nine months after it became operational, he documented how the new technology, implemented similarly at two hospitals (comparable in nearly every respect), led to significantly different patterns of social interaction. We briefly summarize the unfolding events at hospitals Barley called Suburban and Urban (see Table 1).

Suburban. Suburban launched its scanning area by hiring one experienced radiologist and two experienced technologists. Two inexperienced technologists were also transferred from other areas. Barley divided his observations into two phases based on the distinctive characters of the interactions before and after a change in staffing. Phase 1, Negotiation of Discretion, was characterized by role-clarifying interactions and scripts labeled Unsought Validation (in which technologists provided justification for actions that the physician confirmed as appropriate); Anticipatory Questioning (in which technologists asked operationally oriented questions); and Preference Stating (in which the radiologist stated his preference for scanning procedures, often volunteering a rationale). In this phase the interactions became increasingly collaborative as technologists grew more facile with the CT equipment and doctors became better at asking for what they wanted. Barley (1986: 91) writes:

> As the technologists demonstrated responsibility and competence, the radiologist began to grant them greater discretion. By the end of the third week a tentative climate of joint problem solving arose to create an atmosphere that more closely resembled the ideal of complementary professions working in concert.

Phase 2, Usurping Autonomy, began in the fourth week, when the five inexperienced radiologists began rotating through the CT area. As technologists tried to interact with the inexperienced physicians, the scripts evolved into Clandestine Teaching (of doctors by technologists), Role Reversals (in which radiologists asked technologists about pathology and technologists offered interpretations of scans), and Blaming the Technologist (for problems that really lay in the equipment). Of this phase, Barley (1986: 93-94) writes:

> As role reversals, clandestine teaching, and incidents of blaming the technologist gradually defined a new interaction order, the radiologists' moral authority tarnished and the technologists...formulated the view that the radiologists knew less than they rightfully should.... Unaccustomed to having their knowledge perceived as inadequate, anxious they might make a serious mistake, and baffled by the computer technology, they [radiologists] began to express hostility toward the technologists.

As both technologists and doctors sought to reduce occasions for anxiety and hostility, technologists began making routine decisions independently while doctors withdrew to their office to avoid interaction with technologists and the technology. While Suburban started on a desirable path, with growing degrees of specialization and collaboration, the introduction of the inexperienced doctors sharply changed that direction. Specialization continued to increase—technologists ran the machines, doctors produced diagnoses—as doctors retreated to their offices, but collaboration and learning declined.

Urban. In contrast to Suburban, Urban launched its scanning unit by relying on experienced doctors. Barley identified four phases based on formal and informal changes in staffing policies and the character of interactions between doctors and technologists (See Table 1). Urban's Phase 1, Negotiating Dependence, was characterized by Direction Giving (by doctors to technologists, usually without providing a rationale), Countermands (when doctors contradicted their previous statements), Usurping the Controls (of the CT machine by doctors), and Direction Seeking (in which technologists cued doctors to tell them about the next task). These scripts, Barley suggests:

> ...affirmed the radiologist's dominance and created a work environment that the technologists perceived as arbitrary.... The technologists therefore continued to seek directions from radiologists not only because they did not know what to do, but because

> they were convinced that radiologists could potentially say what they wished.... Perversely, however, by continually seeking directions the technologists fostered a perception among the radiologists that the technologists were not attempting to learn, a perception that encouraged the radiologists to exert even greater control (1986: 97).

Barley called Phases 2 and 3 Constructing and Ensuring Ineptitude. Phase 2 began four weeks after the CT machine came on-line when doctors, in an effort to foster technologists' independence, agreed to stay out of the scanning area. Since technologists had discerned no method or reason in the doctors' directions, rather than proceed by trial and error, they often interrupted the radiologists in their office to seek direction. "Since the radiologists were now more than ever conscious of the technologists' dependency in routine matters," Barley writes, "…they became increasingly irritated and began to respond to the technologists' questions in a derisive manner" (1986: 97-98). Scripts called Unexpected Criticisms and Accusatory Questions characterized this phase. Phase 3 began when, at the end of the sixth week, radiologists returned to day-to-day CT operations, effectively reaffirming interactions that characterized the first phase, Direction Giving, Countermands, Usurping the Controls, and Direction Seeking.

Phase 4, titled Toward Independence, began when the four technologists regarded as least competent were transferred out of the CT group and inexperienced radiologists began rotating through the CT area as the experienced doctors resumed duties in other groups. In stark contrast to the experience of Suburban, the staffing change led to a significant improvement in the patterns of interaction. Redistributing practical experience between the two groups "resulted in more discretion for technologists, allowing them to develop additional skill, while the inexperienced radiologists were far more likely to ask for assistance" (Barley, 1986: 99). Technical Consultation (in which doctors asked technologists for direction) and Mutual Execution (in which doctors and technologists both asked for and received direction from one another) characterized the interactions of this phase.

Barley concludes his analysis with graphs showing the percentage of operational decisions made by doctors at each hospital through time, pictorially demonstrating the different patterns of decision-making at the two hospitals (Figure 1 reproduces the original graphs). At Suburban, after the introduction of CT technology, doctors initially made the majority of operational decisions, but technologists soon assumed significant responsibility in making operational decisions. At Urban, during much of the time that Barley observed CT operations, doctors made a high percentage of the operational decisions. Only after the introduction of the inexperienced doctors did technologists begin to make an appreciable portion of the operational decisions.

Figure 1 about here

Barley's analysis leaves us with two central questions. First, why, despite their seeming similarity, did the two hospitals react so differently to the introduction of the CT technology? Second, why did the identical intervention, rotating inexperienced radiologists into the CT area, produce such different outcomes? More generally, given Barley’s careful analysis of the evolution of these organizations, can we produce an operational and generalizable explanation for the behavior observed, one that both informs future research and provides insight to practitioners?

Inductively Building a Formal Model

To answer these questions, we formalize Barley’s analysis by developing a mathematical model. Unlike many formal models in the social science literature, ours is not deduced from arbitrary axioms that idealize human motivation and behavior, but, using the methods of grounded theory, our model is induced from Barley’s data and analysis. While commonly used to build theory from raw data using qualitative analysis, a grounded theory approach is not limited to this activity. Strauss and Corbin (1990) advocate the development of formal (or general) theories grounded in previously generated domain-specific (what they call substantive) analyses. They remind the reader that Glaser and Strauss (1967) not only urged the use of grounded theory in conjunction with qualitative and quantitative analysis, but also recommended its use to generate theory from substantive analysis (see Glaser and Strauss, 1967: 98).

Our purpose is to identify a set of relations that are both consistent with Barley's data and capable of generating the different patterns of interaction he observed. The translation of narrative data to a mathematical model results in a loss of richness and the ability to evoke important nuances in day-to-day experiences. The offsetting benefit is the ability to insure that our proposed theory can generate the dynamic behaviors that it purports to explain. To develop our model, we integrate three streams of current research in organization and social theory into a conceptual lens for viewing Barley's data.

Activities. Weick (1979), Orlikowski (2000) and others (Bourdieu, 1977; Giddens, 1984; Lave, 1988) have called attention to how daily activities and practices shape organizational and social patterns. The focus on activities is an important reminder of the agency of individuals and the dynamic nature of social environments. Focusing on how the CT scans were performed calls attention to two features of the interactions Barley observed. First, the nature of the scanning activity (and therefore the pattern of interaction) was quite different depending on whether or not doctors were in the room. When doctors were not present, technologists were forced to make numerous decisions related to the scan, presenting those results to doctors after the fact. During Suburban's second phase, this pattern of activity both reinforced technologists' claim to occupational knowledge and doctors' fear of norm-challenging role reversal, thereby enacting a pattern of limited interaction between the two groups (i.e., occupational separation). In contrast, during Phase 1 doctors were present and interactions between the two groups were far more frequent.

Second, even when doctors were present, the scanning activity differed significantly. In Phase 1 at Suburban even though doctors were present, technologists were still responsible for operating the machine and made a significant fraction of the operating decisions. When performed this way, the scanning activity led to a seemingly desirable pattern of interaction, doctors stated preferences and technologists worked to satisfy them in an iterative cycle of requests, learning, and execution (i.e., collaboration). In Urban's first phase, however, doctors made the majority of the operating decisions, either by issuing commands or simply operating the machine themselves, creating an environment that reinforced doctors' skill with and control over the CT machine, while limiting technologists' ability to cultivate useful skills (i.e., professional dominance).

Accumulations. A focus on activities highlights how differences in the conduct of scanning resulted in significantly different patterns of interaction between doctors and technologists. Such a perspective does not, however, explain why the scans were conducted differently during the different phases. To help answer this question, we turn to the stream of research that identifies how relative accumulations of knowledge, expertise, and power influence the relations between groups (Bourdieu and Passeron, 1970; Pfeffer and Salancik, 1974; Carlile, 2002). The type and amount of knowledge or expertise actors possess often determines who gets to do what in a given activity. Credentials and titles serve as proxies for legitimated accumulations of knowledge and power, often leading people to defer to those that have them. Further, because of previous accumulations some actors occupy a "relative position" that is more powerful than others in a given activity (Bourdieu, 1980).

Focusing on relative accumulations of knowledge and power highlights two features of the situation Barley studied. First, given their previous training and credentials, doctors were clearly in the more powerful position. Doctors are in this position because they have accumulated significant amounts of what we call *diagnostic knowledge*—the ability to recognize pathology—with the attendant social status that accompanies it, whereas technologists have no formal means of accumulating it. Because of their legitimated position, doctors could chose whether they were present when scans were conducted and who conducted the scan.

Second, as Barley clearly documents, while the two hospitals were similar on many dimensions, the relative accumulations of expertise in operating the machine, what we call *operating knowledge*, differed between the two hospitals. Suburban launched its scanning unit by hiring two technologists and one radiologist, all of whom had experience with body scanning. During

Suburban's first phase, these three people, along with the two inexperienced technologists transferred from other areas, collaborated and learned as the doctor stated preferences for the outcomes of a given scan and allowed technologists to cultivate their skill in producing those outcomes. In contrast, Urban started with two experienced doctors and eight technologists who, having previously worked in the head scanning unit, had never used a body scanner. During its first phase, Urban did not display collaboration and learning between the two groups. Instead, doctors gave directions or simply took over the controls.

Recursive Relations. Combining a focus on the activities of scanning with attention to the accumulation of knowledge and power takes us a long way towards explaining the patterns that Barley documented. Yet, at least two questions remain unanswered. First, while focusing on the relative distributions of expertise helps explain why the two hospitals started on different paths, it does not explain why they continued to diverge. For example, in Phases 2 and 3 at Urban, doctors, realizing that the lack of technologist skill was hurting performance, decided to stay in their offices to "encourage technologists to figure it out." Yet, as Barley (1986: 98) describes, the doctors' intervention—spending less time in the scanning area—made the situation worse rather than better. The dynamics at Urban appeared to preserve the patterns of interaction, despite doctors' attempts to change it. Second, the focus on activities and relative accumulation of knowledge does not explain why the same staffing change at both hospitals—rotating in the inexperienced doctors—produced such different outcomes (see Phase 2 at Suburban and Phase 4 at Urban in Table 1).

To answer these questions, we connect activities and accumulations of knowledge with the notion of recursion arising in the work of Giddens (1984) and Bourdieu (1980) and others (e.g., Bijker, 1987). Activities create additional accumulations of knowledge and current accumulations of knowledge determine who gets to do what in the scanning activity. Depending on the relative accumulations and the position of the actors, these interactions either "maintain" or “modify” (Barley, 1986) the current patterns as individuals draw upon their knowledge in meeting the demands of producing scans and diagnoses.

Weick’s (1990: 20-22) analysis of Barley’s data highlights how the initially collaborative nature of the scanning activity at Suburban was continually reinforced as doctors allowed the technologists to accumulate more operating knowledge. The increasing level of competence made doctors even more likely to let technologists operate the machine, creating a virtuous cycle of learning and collaborative interaction with doctors. Similarly, the initially dominant role of doctors in Urban’s phase 1 was also self-reinforcing.   As doctors took control of the machine, performing the scans themselves, they accumulated additional knowledge, making the technologists feel less competent and creating a vicious cycle of increasing frustration (among both groups) and declining collaboration.

Recognizing the recursive relationships between day-to-day activities and the accumulations of knowledge and power that both constrain and enable them suggests that each of the interaction patterns that Barley observed was self-sustaining. When doctors run the machine, they accumulate more knowledge while simultaneously restricting the learning of technologists, thereby reinforcing doctors’ initial desire to take control of the machine. Conversely, when technologists were initially allowed some latitude to make decisions, they accumulated expertise, making the less experienced doctors even more likely to relinquish control of the machine. Barley’s analysis does not, however, identify the conditions under which either of these two patterns of interaction is likely to arise. Only by integrating these insights, each of which focuses on only one pattern of interaction, into a single theory can we understand the complete set of dynamics that Barley observed.

INITIAL PATTERNS OF INTERACTION

To take the next step in understanding how the recursive relations connecting activities and accumulations create and sustain patterns of organizing, we turn to system dynamics as a tool for representing and analyzing a theory that explains the dynamics Barley observed. The system dynamics method provides a means to represent the interactions among activities and accumulations and analyze the resulting dynamics. We found it useful in explicating the relationships between activities undertaken in the CT area, accumulations of diagnostic and operational knowledge, and the hierarchical relationship between radiologists and technologists. We present our model in two pieces, focusing first on the structure required to explain the differing patterns that emerged when the CT machines were implemented at the two hospitals: collaboration and professional dominance. We then extend the model to account for the transformation that followed the introduction of inexperienced doctors in both hospitals.

Model Structure

Figure 2 shows an overview of the model. How the scanning activity is conducted is captured by the two variables at the center of the diagram, *Fraction of Operating Decisions by Doctors* and *Fraction of Operating Decisions by Technologists*, which always sum to one. For the moment, we assume that each scan can be conducted in one of two ways: (1) by doctors; or (2) by technologists with doctor supervision. In the next section we relax this assumption to account for the ability of doctors to exit the scanning room.

Figure 2 about here

Following the discussion above, the fraction of operational decisions made by each group is determined by that group's relative accumulation of knowledge related to operating the machine. We operationalize the links between accumulated knowledge and the scanning activity in the following fashion. First, we define operating knowledge as facility with a finite set of procedures relevant to performing a CT scan and represent it on a 0 to 1 scale (1 indicates skill with the complete set of relevant scanning procedures).[i] Using the convention common in system dynamics (e.g., Forrester, 1961; Sterman, 2000), the accumulations of knowledge are represented as *stocks* (denoted by rectangles). For the moment there are two stocks, *Technologist Operating Knowledge* and *Doctor Operating Knowledge*. Each knowledge stock is defined from 0 to 1 and represents the fraction of the total set of scanning procedures with which the particular group is skilled. Formally, a stock is the integration of its inflows less any outflows. Thus:

$$\text{Technologist Operating Knowledge}(t)=\int_t(\text{Technologist Operational Learning}(s))ds + \text{Initial Technologist Operating Knowledge} \quad (1)$$

$$\text{Doctor Operating Knowledge}(t)=\int_t(\text{Doctor Operational Learning}(s))ds + \text{Initial Technologist Operating Knowledge} \quad (2)$$

Stocks are critical to creating the dynamics of systems and represent the accumulated and enduring impacts of activities. In our case, the two stocks are increased by the flows (represented by arrows with valve symbols) of *Technologist Operational Learning* and *Doctor Operational Learnin*g respectively. The stocks of knowledge capture how activities undertaken in the past influence activities and interactions that occur today.

The rates of doctor and technologist learning are determined by the character of the scanning activity, which, in turn, is determined by the relative accumulations of knowledge. We operationalize the recursive relationship among the accumulations of knowledge, the nature of the scanning activity, and the relative rates of learning (which change the accumulations of knowledge) by first assuming that there is no particular correlation between the procedures that doctors know and those that technologists know. We also assume that if both doctors and technologists know how to perform a specific procedure, then doctors defer to technologists. These assumptions yield the following equations for the fractions of the operating decisions made by doctors and technologists respectively:

$$\begin{aligned}&\text{Fraction of Operating Decisions by Technologists}\\&\quad=\text{Technologist Operating Knowledge} +\\&\quad(1 - \text{Fraction New Operating Decisions by Doctors})\bullet\\&\quad(1 - \text{Doctor Operating Knowledge})\bullet(1 - \text{Technologist Operating Knowledge})\end{aligned} \quad (3)$$

$$\begin{aligned}&\text{Fraction of Operating Decisions by Doctors}\\&\quad= \text{Doctor Operating Knowledge}\bullet(1 - \text{Technologist Operating Knowledge}) +\\&\quad\text{Fraction New Operating Decisions by Doctors}\bullet\\&\quad(1 - \text{Doctor Operating Knowledge})\bullet(1 - \text{Technologist Operating Knowledge})\end{aligned} \quad (4)$$

As the equations indicate, we model the process of determining who does what in two pieces. First, there are the procedures for which at least one of the two groups has the appropriate knowledge. We assume that technologists perform all of the scans for which they are qualified, hence the *Technologist Operating Knowledge* term in (3). Doctors, in contrast, perform only those scans for which they are qualified and technologists are not. Thus, the first term in their scanning equation (4) is *Doctor Operating Knowledge*•(1- *Technologist Operating Knowledge*). Second, there are the procedures for which neither group has the appropriate skills, represented by *(1- Technologist Operating Knowledge)•(1 – Doctor Operating Knowledge)*. How these are executed is important because it is through performing new procedures that doctors and technologists accumulate additional knowledge

How this set of procedures is allocated between the two groups is determined by the variable *Fraction of New Operating Decisions by Doctors*. We assume that the allocation of new procedures between doctors and technologists is a function of the relative knowledge of the two groups. As doctors know relatively more, they are likely to make more of the decisions for which neither group has the appropriate skill. Conversely, as technologists know relatively more, we assume that doctors allow them to execute a larger fraction of the procedures for which neither group has the appropriate knowledge. We operationalize these assumptions in the following two equations:

$$\text{Doctor's Knowledge Relative to Technologists} = \frac{\text{Doctor Operating Knowledge}}{\text{Technologist Operating Knowledge}} \qquad (5)$$

$$\text{Fraction of New Procedures by Doctors} = \frac{\text{Doctor's Knowledge Relative to Technologists}^{\alpha}}{1 + \text{Doctor's Knowledge Relative to Technologists}^{\alpha}} \qquad (6)$$

The variable *Doctor's Knowledge Relative to Technologists* is simply the ratio of the two knowledge stocks and thus represents a simple measure of the relative distribution of knowledge between the two groups. Equation (6) captures our assumption that as doctors know relatively more than technologists (as the knowledge ratio rises), they execute a larger fraction of the procedures for which neither group has the appropriate knowledge. Conversely, as technologists know more than doctors, they execute a larger fraction of the new procedures. The parameter α determines the strength of this bias. If α=1, decisions are allocated strictly in proportion to the stocks of existing knowledge (e.g., if doctors know 50% of the existing procedures and technologists know 25%, then doctors will execute two thirds of the new procedures). Values greater than 1 indicate a bias towards those with more knowledge, while if α<1, those with less knowledge make a larger fraction of the decisions for which neither group has the appropriate expertise. Following Barley's data, we set α=2, indicating a mild bias towards those having more knowledge. Such a bias was particularly prevalent at Urban, when doctors, frustrated with the technologists' lack of skill, would frequently usurp control of the machine.

The equations outlined so far describe how the relative accumulations of scanning knowledge determine how the scan is executed. To complete our model of the recursive relationship between activities and accumulations, we must also specify how the activity of scanning affects who learns what and, thereby, feeds back to the levels of accumulated knowledge. The equations for the inflows to the two knowledge stocks, *Technologist Operational Learning* and *Doctor Operational Learning* are:

Technologist Operational Learning =
(Fraction of Operating Decisions by Technologists – Technologist Operating Knowledge)/
Time to Accumulate Operating Knowledge (7)

Doctor Operational Learning =
(Fraction of Operating Decisions by Doctors – Doctor Operating Knowledge)/
Time to Accumulate Operating Knowledge (8)

Following Barley's description of the interactions between the CT-experienced radiologist and the CT-inexperienced technologists in Suburban's first phase (1986: 89), we assume that both groups learn when they execute new procedures. Thus both learning rates are proportional to the difference or gap between the fraction of scans currently being performed and those for which the group in question has existing expertise. How fast a technologist or doctor learns depends on the gap between what she is attempting to do and what she already knows how to do—a notion widely accepted in the literature on individual learning. It also takes time to accumulate knowledge—new procedures must be performed for some duration before one is expert in them. We capture this delay by dividing the gap by the *Time to Accumulate Knowledge*.

The equations outlined so far combine to produce a system characterized by two stocks (or state variables) and four important feedback loops (see Figure 2). The two balancing loops (B1 and B2) regulate the rates of learning, as the stocks of knowledge grow, the learning rates slow. The reinforcing loops (R1a, R1b, R2a and R2b) capture the interrelationship between learning and doing. As doctors learn more, they attempt new procedures, leading to additional learning and making it more likely that they will choose to control the machine (R2a and b). Similarly, as technologists learn more, doctors accord them more latitude to attempt new procedures, leading to additional learning for the technologists (R1a and b). Note, however, that these two processes do not operate independently. Rather, because who makes what decisions is a function of the *relative* accumulations of knowledge, the processes are highly interdependent. Technologists rely on doctors to acknowledge their abilities by allowing them to run the CT machine; doctors assess the technologists' competence in conducting scans. Moreover, because these two learning/doing processes are tightly intertwined, it is difficult to anticipate how they will interact to determine the system's dynamics. To understand their interrelationship, we turn to simulation.

Model Output

Simulating the model requires two additional pieces of information. First, we need to specify a time horizon for our analysis. Based on the duration of Barley's study, we simulate the model for 260 days. Second, we need to specify initial conditions for each of the stocks. As mentioned above, Suburban launched its scanning unit with one experienced radiologist, two experienced technologists, and two inexperienced technologists. To simulate Suburban's interactions we assume that the radiologist is skilled in 50% of the procedures while technologists have accumulated 30% of the available knowledge. Urban also launched its unit by hiring a radiologist with body scanning experience but did not hire experienced technologists, relying instead on technologists transferred from the head scanning unit. To simulate Urban's interactions we again assume that doctors begin knowing 50% of the procedures, but capture the relative inexperience of the technologists by assuming they know only 10% of the required knowledge. Figure 3 shows our model simulated under these two scenarios.

Figure 3 about here

Consider the dynamics at Suburban. Due to their relatively greater accumulation of experience (Figure 3a), doctors initially make the majority of the operational decisions (Figure 3c). However, technologists, because they have some knowledge, are allowed to execute an appreciable number of procedures. Consequently, they begin to accumulate additional operating knowledge (Figure 3a). As technologists accumulate knowledge, doctors allow them to make more decisions (Figure 3c), creating a self-reinforcing cycle of technologist learning and increasing authority. Moreover, as doctors cede operating authority, their learning rate slows (Figure 3a), further reinforcing the decision to allow technologists to operate the machine. Formally, under these conditions the technologists' learning loop *dominates* the behavior the system, meaning that it is the strongest of the different feedback processes. Here the system displays a *collaborative* pattern of interaction in which technologists, due to their accumulated experience, perform much of the scanning activity, allowing doctors to focus on diagnosis. By the end of the simulated period, technologists have learned to execute most of the scanning procedures and make essentially all of the operating decisions.

Urban displays different behavior. As Barley's data suggest, Urban starts with approximately the same level of experience among the doctors but with less experienced technologists. Doctors know *relatively* more and initially make a high proportion of the operating decisions (Figure 3d). In contrast to Suburban, the initial difference is not offset by the system's dynamics. Because they make more of the decisions, Urban's doctors learn faster than their suburban counterparts and their stock of knowledge continues to grow (Figure 3b). Technologists, meanwhile, are relegated to a supporting role, make few decisions, and, consequently, learn little (Figure 3b).

As doctors come to believe that technologists cannot produce the images that they themselves can, doctors are ever more likely to take control of the CT machine. At Urban, doctors' learning/doing process dominates the behavior of the system, reinforcing a pattern of interaction in which doctors make the decisions and technologists play a supporting role. Whereas Suburban's interaction evolved in a collaborative fashion, the dynamics at Urban reinforce a pattern of *professional dominance*: doctors come to dominate the technology and technologists offer relatively little.

Note that the structure of the system is identical in both scenarios. The only difference is that Urban's technologists begin with less accumulated experience. Yet, as the simulations demonstrate, the same model structure produces the qualitatively different patterns of interaction that Barley observed. One of the more compelling features of his study was that identical technology was implemented in both hospitals (in fact, each institution purchased exactly the same machine). Barley's data directly challenged the technological imperative model by showing that the same technology occasioned different structuring processes. Our analysis extends his insight by highlighting the differing initial accumulations of the technologists' knowledge of CT scanning at the two hospitals and showing how these differences combined with the feedback structure governing the character of the scanning activity to produce significantly different patterns of interaction.

INTRODUCING INEXPERIENCED DOCTORS

After deploying CT with experienced radiologists, both hospitals eventually changed their staffing plans by rotating inexperienced radiologists through the CT area and returning the CT-experienced doctors to normal duties in all of the scanning units. Remarkably, although the staffing change was virtually identical in both hospitals, it produced drastically different outcomes. At Suburban, which started on a highly collaborative path, introducing the inexperienced doctors changed the pattern of interaction for the worse. Doctors, fearing uncomfortable role reversals, retreated from the scanning area. And, while technologists gained almost total control over their daily activities, collaboration and learning between the two groups declined. At Urban, which started on an uncollaborative path, with doctors both performing and interpreting scans, the staffing change occasioned more collaborative interactions in which doctors and technologists mutually consulted one another. In this section we extend the model to account for these dynamics.

Extended Model Structure

An overview of the extended model's structure is shown in Figure 4. As highlighted earlier, analyzing the system Barley studied in terms of the activities enabled by different accumulations of knowledge highlights the discretion doctors have in performing scans and being present in the scanning room. While our initial formulation captures who does what, it does not account for the possibility that doctors might choose to leave the scanning area altogether. To incorporate doctors' latitude, we add a new variable, *Doctor Participation in Scans,* representing the fraction of time doctors are present in the scanning room. Following Barley's data, we assume that doctors' decision to participate turns on the perceived threat of role reversals, occasions in which radiologists' lack of operating knowledge required them to ask technologists whether a CT image revealed a pathology (rather than about the machine's operation), thus creating discomfort for both groups. To reduce opportunities for awkward exchanges, the inexperienced radiologists "began to withdraw from the scanner's minute-by-minute operation to save face," retreating to their offices and leaving technologists with considerable autonomy in operating the scanner (1986: 94). The doctors saw the scans only once they were complete.

Figure 4 about here

Barley suggests that the uncollaborative behavior following the staffing change at Suburban was rooted in the diagnostic knowledge accumulated by technologists. Due to the initially collaborative nature of the interactions at Suburban, by the time the new doctors rotated into the scanning area, technologists had accumulated both knowledge in operating the CT equipment (i.e., operating knowledge) and some ability to recognize pathology (i.e., diagnostic knowledge). Pairing such knowledge with inexperienced doctors created situations in which technologists were required to assist doctors in diagnosis. While openly correcting an inexperienced doctor's off-the-mark question "would have been to risk affront and boldly invert the institutionalized status system" (Barley, 1986: 92), technologists often supplied corrective information, albeit in a deferential or tangential way. Such "Clandestine teaching threatened the institutionalized roles of radiologists and technologists," (Barley, 1986: 92). When doctors perceive their diagnostic abilities as inadequate, their primary form of power—the ability to make an accurate diagnosis—is threatened. To capture these dynamics, we assume that, along with operating knowledge, each group can, depending on the nature of the scanning activity, accumulate diagnostic knowledge. These accumulations are represented in our overview diagram as the stocks in the upper and lower right hand corners, labeled *Technologist Diagnostic Knowledge* and *Doctor Diagnostic Knowledge* respectively.

Following the convention used with operating knowledge, we represent diagnostic knowledge on a 0 to 1 scale. We then model the *Threat of Role Reversal* as the fraction of diagnostic knowledge technologists have that doctors do not:

$$\text{Threat of Role Reversal} = \text{Technologist Diagnostic Knowledge} \bullet (1 - \text{Doctor Diagnostic Knowledge}) \quad (9)$$

Following Barley's assertion that role reversals pose a significant challenge to the normal social order, we assume that the function relating role reversals to doctors' participation is steep and negatively sloped;[ii] just a few role reversals result in a significant decline in doctors' participation.

Including diagnostic knowledge in our analysis also requires modeling how it is acquired. We first assume that doctors enter the scanning area with a significant amount of diagnostic knowledge, accumulated either through medical training or work with other imaging technology, such as X-ray. Similarly, we assume that there is an upper bound on the diagnostic knowledge that technologists can acquire, since it is unlikely that any amount of on-the-job experience can provide the understanding of anatomy and pathology gained during medical school and residency. Given these constraints, we model diagnostic learning in a fashion similar to that used for operational knowledge. Technologists' diagnostic knowledge grows as they execute scans with doctor participation (this stock of knowledge represents only those skills that pertain to diagnosing the output of the CT scanner, not the full suite of skills associated with being a radiologist). Note we assume that technologists only accumulate additional diagnostic knowledge when they perform scans with doctor supervision. Similarly, we assume that doctors accumulate additional diagnostic knowledge only when they participate in the scanning process.[iii] The two flow equations are then:

Technologist Diagnostic Learning=
(Maximum Technologist Diagnostic Knowledge – Technologist Diagnostic Knowledge)•
Fraction of Scans with Doctor Supervision/
Time To Accumulate Diagnostic Knowledge (10)

Doctor Diagnostic Learning=
(Doctor Participation in Scans – Doctor Diagnostic Knowledge)/
Time to Accumulate Diagnostic Knowledge (11)

Incorporating diagnostic knowledge and the threat of role reversals adds several new feedback loops (see Figure 4). First, the balancing loops (B3 and B4) regulate the accumulation of diagnostic knowledge: as the stock of knowledge grows, the learning rate slows. Second, there is the reinforcing loop created by the participation of doctors in the scanning activity (R3): as doctors participate in scanning, they accumulate additional diagnostic knowledge, thereby reducing the threat of role reversals and making them more likely to participate in scanning. This loop is similar in structure to the reinforcing processes that arise from the accumulation of operating knowledge (R1 and R2). Finally, there is the loop connecting the participation of doctors in the scanning activity and the learning of technologists: as technologists accumulate diagnostic knowledge, the threat of role reversal *increases*, thereby reducing the participation of doctors and slowing the rate of technologist learning. Note that in contrast to the reinforcing loop driving the doctors' learning, the accumulation of diagnostic knowledge by technologists results in a *balancing* feedback process. This balancing loop is particularly important because, while all the other types of knowledge we study are embedded in self-reinforcing relationships (learning leads to opportunities for additional learning), technologists' diagnostic knowledge can be self-limiting. As technologists accumulate it, the threat of role reversals grows, causing doctors to retreat and reducing the possibility for collaboration and future learning. As we show below, this balancing loop plays a key role in creating the dynamics that Barley observed.

Switching Patterns

To simulate this system we maintain the assumptions used in the previous formulation. We further assume that doctors always enter the scanning room with at least 50% of the available diagnostic knowledge. Technologists, in contrast, start with zero diagnostic knowledge. To model Suburban's staffing change, at day 21 (the date it occurred in Barley's data) we reduce the level of doctors' operating knowledge by 83% to capture the introduction of the five radiologists lacking CT experience. We also reduce doctors' diagnostic knowledge.

Figure 5 about here

Figure 6 about here

Consider Suburban's dynamics first. The new rotation policy causes an immediate drop in doctors' accumulation of technical and diagnostic knowledge (Figures 5b and 5d). As a consequence, technologists immediately begin making a larger percentage of the operating decisions (Figure 6c). Technologists' greater discretion leads to additional learning, causing their stocks of operating and diagnostic knowledge to grow more quickly (Figures 5a and 5c). The new doctors, while learning little about operating the machine (since technologists now make most of the operating decisions), begin to accumulate additional diagnostic knowledge. These gains, however, are short lived.

The staffing change, by pairing experienced technologists—who accumulated a modest amount of diagnostic knowledge in the first twenty-one days—with inexperienced doctors, creates the threat of role reversal (Figure 6a). As Barley documents, the threat of role reversal causes doctors to reduce their participation in the scanning process (Figure 6b). Once doctors retreat to their offices, collaboration falls, slowing all forms of learning in the process. In this situation, the balancing loop created by the accumulation of technologists' diagnostic knowledge plays a dominant role, severely limiting collaboration. While Suburban started in a collaborative mode, following the staffing change it displays a pattern we label *occupational separation*; doctors, feeling threatened by the diagnostic knowledge of the technologists, actively separate themselves so as to minimize interaction.

Contrast this outcome with the dynamics at Urban. To model Urban's staffing change, at day 105 we introduce a similar change in doctors' knowledge stocks, and also *increase* technologists' operating knowledge by 50% to capture the departure of the four least-competent technologists. The results are shown below in Figures 7 and 8.

Figure 7 about here

Prior to the staffing change, the experienced doctors dominated the scanning activity, relegating technologists to a supporting role from which they could learn little. Doctors thus accumulated substantial amounts of both operating and diagnostic knowledge (Figures 7c and 7d), further reinforcing their dominance over the technologists, who made few decisions and accumulated little knowledge. Rotating in the four inexperienced radiologists significantly reduces the doctors' stocks of knowledge (Figures 7c and 7d). Technologists' experience a modest increase in operating knowledge, as the least competent of them are transferred to other areas (Figure 7a).

Figure 8 about here

The staffing change, by redistributing operating knowledge, causes an immediate increase in the fraction of the operating decisions made by technologists (Figure 8c). Since technologists now make most of the operating decisions, they do most of the learning and begin accumulating operating knowledge (Figure 7a). The new doctors, in contrast, learn relatively little about how to operate the machine (Figure 7c) because they make few of the operational decisions (Figure 8d). Note, however, that the change in the scanning activity does not cause Urban's doctors to retreat to their offices (Figure 8b). Prior to the staffing change, technologists were given few opportunities for learning, thus limiting their accumulation of diagnostic knowledge (Figure 7b). Consequently, when the new radiologists do arrive, the threat of role reversals is far smaller (Figure 8a). With little fear of role reversal, doctors remain in the scanning room (Figure 8b) allowing them to rapidly accumulate additional diagnostic knowledge through collaboration with the technologists (Figure 7d). While the staffing change moved Suburban from a desirable collaborative mode to a self-reinforcing pattern of occupational separation, rotating in the inexperienced doctors at Urban helps move the system from professional dominance to a collaboration. As Barley writes, the new rotation system "redistribut[ed] the relative balance of practical experience in favor of the remaining technologists." The resulting new patterns of interaction "inverted the interaction order established during Urban's earlier structuring…[as] radiologists now became seekers and technologists givers of directions" (1986: 99).

Our analysis thus answers the questions raised by Barley's data by highlighting how the relative accumulation of expertise interacts with the feedbacks governing the conduct of the scanning activity to determine which patterns of interaction are realized. When doctors have more operating knowledge than technologists, they are likely to usurp control, leading to additional learning for the doctors and reinforcing a pattern of professional dominance. Conversely, when technologists' diagnostic knowledge challenges doctors' diagnostic authority, doctors minimize contact, reinforcing a pattern of occupational separation. Only when expertise is relatively balanced and consistent with social norms (i.e., when doctors know more about diagnosis than technologists), does the system produce collaboration between the two groups. Ironically, because Urban started on an uncollaborative pattern that limited technologists' learning, rotating in the inexperienced doctors changed the system for the better. In contrast, because Suburban started out in a collaborative mode in which technologists could learn, rotating in the inexperienced doctors pushed the system towards a pattern of occupational separation.

Note the key role of the non-separability of technical and diagnostic knowledge (Barley, 1996). Following the argument above, one might conclude that the ideal situation is one in which technologists have ample technical knowledge but little diagnostic knowledge while doctors have the opposite distribution. In imaging technologies that preceded CT such a separation was possible. For example, with X-ray images, technologists required little diagnostic understanding to competently create usable images and often could not recognize even rudimentary elements of pathology (Barley, 1986, 1988). Doctors, on the other hand, usually had some knowledge of how to operate imaging equipment, though they seldom exercised it. With the introduction of computer-dependent modalities, however, the clear separability between scanning and diagnosis begins to disappear. Computer-aided tomography, like ultra-sound technology, provides more complicated, three-dimensional images of the human body. Producing images that aid doctors in providing accurate diagnoses requires some knowledge of what the scan reveals (i.e., diagnostic knowledge). One type of knowledge cannot be accumulated without the other; physicians who learn to diagnose pathology using CT images will also learn something about operating the machine, while technologists who learn to operate the machine will also accumulate some diagnostic capability.

Such non-separability is critical to the dynamics we study because, while the two types of knowledge cannot be accumulated independently, they are nonetheless considered to be the rightful province of two different groups: doctors are supposed to do diagnosis, technologists are supposed to operate the machine. Because such knowledge is non-separable, the likelihood of interactions that challenge normal roles and responsibilities is high. And, as our analysis shows, when such interactions occur, the structure of the system reinforces rather than offsets the initial imbalance. When doctors know more than technologists in the technologists' realm of expertise, doctors act in ways that restrict technologists' learning. Conversely, when technologists challenge doctors in the doctors' realm, doctors retreat from the interaction, effectively limiting the learning of both groups and ensuring that the initial imbalance is not corrected.

The upshot of this set of dynamics is that ongoing collaboration between professionals and technologists, when the operation and use of the technology cannot be cleanly decoupled, requires a specific set of conditions, mainly a relative balance of experience between the two groups. Consider the following set of simulation experiments (which cover conditions that Barley did not observe). Here we systematically vary the initial accumulations of knowledge for both groups. To assess the outcomes that these different initial conditions produce we report *Practical Knowledge*, defined as the sum of doctors' diagnostic knowledge and technologists' operating knowledge, relative to potential (which is 2), at the end of nine months.

Table 2 about here

As the table highlights, the system displays the highest levels of expertise when the initial accumulations of knowledge on either side of the doctor-technologist boundary are relatively balanced. Regardless of whether initial knowledge is low or high, if the two groups start with similar levels of experience, by the end of the nine-month period, technologists have nearly mastered using the CT machine, and doctors have learned almost all they can about interpreting CT scans. In contrast, when doctors initially know more than technologists, (the cells below the diagonal) the doctors often produce the scans themselves. Practical knowledge is lower with these initial conditions because technologists have little access to the activities that generate learning. Conversely, when technologists start with more experience than doctors, the cells above the diagonal, doctors reduce their participation, thereby limiting both their ability to accumulate additional diagnostic knowledge and the ability of technologists to learn to produce better scans.

DISCUSSION

The ever-increasing advancement of information technologies suggests that many, if not most, organizations will continue to face the challenge of implementing new technologies that blur the boundaries between occupational groups (Zuboff, 1988; Barley, 1996). Recent examples range from new methods of cardiac surgery that require doctors and nurses to interact in different ways (Edmondson, Bohmer and Pisano, 2001) to simulation tools used to develop new products that necessitate different modes of communication between design and manufacturing engineers (Carlile, 2002). Barley's careful analysis of Urban's and Suburban's experience implementing CT technology provides compelling evidence that such technologies can occasion very different patterns of organizing depending on the context in which they are implemented. His pivotal work left us with two main questions: (1) Why did the introduction of the new technology produce such different outcomes; and (2) why did the identical intervention, rotating inexperienced radiologists into the CT department, also produce different outcomes? More generally, can we move beyond situated descriptions of contextual complexity and mutual adaptation to operational characterizations of the interactions that generate the dynamics occasioned by new technologies, characterizations that are both testable and provide guidance to practitioners? Our answers to these questions build on three findings.

First, our analysis highlights the critical role that relative expertise plays in the dynamics occasioned by the introduction of new technology. Barley (1986: 107) anticipated the importance of relative expertise when he concluded his analysis by writing:

> …to devise a theory of how technology alters radiological work, one would need … to account for relative distributions of expertise…to explain how distributions of relative expertise can be accommodated differently in daily interaction.

While studies of technology implementation have historically analyzed the ability of users to interact with technology, often focusing on their raw skill level (e.g., Repenning and Sterman, 2000), our study suggests that, while the absolute level of a users' knowledge is important, differences in the accumulations of expertise of actors who must collaborate also play a key role in determining the dynamics of implementation. The distribution of knowledge affords each actor a “relative position” (Bourdieu, 1983) that shapes the current patterns of a given activity. Yet despite the importance of such initial conditions, they do not necessarily explain which patterns are observed. Our analysis suggests that the system’s dynamics do not always preserve the initial distribution of knowledge. Sometimes the initial distribution is reinforced, as in the early days of Urban; other times, however, it is transformed, as in the opening efforts of Suburban.

Our second contribution comes in identifying how differences in relative expertise interact with the feedbacks governing participation, learning and social norms to determine the pattern of interaction. Specifically, our characterization of the dynamics surrounding the interaction between technologists and doctors in the presence of a new technology suggests that the resulting system has three possible patterns: collaboration, professional dominance, and occupational separation. When expertise is both relatively balanced between the two groups and consistent with established social norms, both groups can participate in the activity according to their occupational expertise; the likelihood of role-threatening interactions is small. Such a state is likely to result in a collaborative pattern in which occupational boundaries overlap (Barley, 1996: 436) and mutual learning allows the two groups to best utilize the technology to generate a good diagnosis. When doctors know more than technologists in using the technology, however, they are likely to dominate the technology, accumulating more operating knowledge at the expense of technologists’ learning and improvement. Conversely, when technologists’ capability and skill challenges the doctors’ capability in their professional realm (i.e., diagnostic knowledge), doctors separate themselves, reinforcing their perceived inadequacy and diminishing the possibility of collaboration and learning across occupational boundaries.

Finally, our third contribution comes in highlighting the role of the non-separability of occupational knowledge in creating undesirable patterns of interaction. As recognized by Barley (1996) and others (Zuboff, 1988) many work relations are becoming less vertical (Taylor, 1911) and more horizontal, making boundaries between occupations more problematic. When technical and professional knowledge can be cleanly separated, it is relatively easy to achieve a successful pattern. Pairing relatively new professionals with experienced technologists is not particularly problematic as long as, in the process of becoming knowledgeable about the technology, technologists have not also accumulated some knowledge that is considered to be the domain of the professionals. X-ray technologies allowed for the separation of knowledge and execution between x-ray technologists and doctors; successful outcomes could be produced with little or no interaction, creating an "industrial atmosphere" (Barley, 1996: 435). In contrast, producing CT scans and sonograms require overlapping occupational boundaries (Barley, 1996: 435) and "discretion" to produce "good scans" (Barley, 1988). When overlapping technical and professional knowledge is essential to reap the full benefit of a new technology, achieving the necessary balance of expertise becomes a significant challenge. This has broad implications for different occupational groups or knowledge communities who must collaborate to create a product or service. The point here is not that groups collaborating across functional boundaries should have similar accumulations of their "specialized" knowledge, but that each group should have similar accumulations of knowledge in the tools they use to collaborate (Carlile, 2002).

Taken together, these three insights produce a striking implication: When implementing new technology more knowledge does not necessarily produce a better long run outcome. Consider, for example, how many organizations launch new information systems designed to support busy professionals. Having invested substantially in developing such systems, senior managers are understandably anxious to deploy the system to those who can use it. Hiring experienced technologists to support the implementation seems like a logical way to speed deployment. Yet our results suggest that such a strategy, while possibly producing short-run gains, runs the risk of creating occupational separation rather than collaboration. Professionals, fearing uncomfortable challenges to their authority, may actively separate themselves from the technologists and the technology. More generally, our analysis shows that the collaborative outcomes cannot be achieved from every set of initial conditions. Practitioners would be wise to consider the relative distribution of expertise when implementing new technology (see Table 2). In many cases, organizations would be better off launching a technology with less, but balanced expertise, rather than risk undesirable patterns that can arise from significant differences.

There are, of course, numerous limitations associated with our findings. Not only do we study only two implementation episodes, but in building on someone else's study and translating that data into a formal model we lose contextual details. Thus, even within the confines of the setting studied, the generalizability of our results is limited. Moreover, the results are closely tied to a specific feature of the hospital setting: the clear hierarchical boundary between doctors and technologists. The pathological outcomes we identify arise from the doctors' ability to determine both who does the scan and who is present. Professional dominance arises when doctors usurp control, while occupational separation results from doctors choosing to "hide in their offices." This nascent theory is silent on questions of what happens when the power differential is far less significant, or when more than two groups are involved. Our analysis thus offers only a few of the hypotheses that might eventually comprise a theory adequate to the complexity of the phenomenon. Future work is required.

Our results do, however, offer a number of implications for how such studies might be performed. Most generally, our results further confirm the utility of conceptualizing organizational patterns as the product of recursive interaction among activities and the accumulations of knowledge and power they generate. Whereas a static approach suggests that technology determines behavior, theorists taking a more dynamic, recursive view (Barley, 1986; Orlikowski, 1992) soundly refuted this explanation. Our analysis extends these insights not only by highlighting the central role that recursive relations play in creating organizational outcomes, but also by concretely specifying a set of recursive relations among activities and accumulations sufficient to generate the behavior of interest. Despite the limitations of this study, our explanation adds additional support to the claim that a dynamic, recursive view of organizing leads to a qualitatively different perspective on the phenomenon of interest.

Yet, taking a recursive view on organizational phenomena does pose a substantial analytic challenge. If features of organizational life normally conceptualized as static are themselves part of a larger dynamic system, theorists may find themselves helplessly lost in a world of endless interconnections, lacking the ability to identify which interactions are particularly important to generating the phenomenon of interest. If everything is connected to everything else, can we move beyond general statements concerning mutual adaptation to operational characterizations of structuring processes? Consider for example the hierarchical relationship between doctors and technologists that is so central to our analysis. Is not the power relationship between technologists and doctors itself the outcome of the ongoing interactions between the two groups and the accumulations of expertise that such activities enable? Our analysis is thus premised on a seeming contradiction. On the one hand, we represent the process of *structuring* whereby the knowledge about and authority over the operation of the scanner evolved over time. On the other hand, however, we capture this evolution by appealing to seemingly fixed social *structures* such as the authority that doctors have over technologists.

The resolution lies in the logic of accumulation and contains perhaps the most important component of our analytic approach. As Giddens argues, some institutional norms prove far more resistant to change than others (Giddens, 1984). Put more simply, all structures are subject to ongoing change, but not at the same rate. The authority of doctors over technologists is not an immutable feature of the environment but is itself an outcome of previous structuring. It is, however, the product of accumulations that change much more slowly than the patterns of interest in the implementation of CT technology. The differing rates of change between the patterns of interaction in the scanning operations and the authority relationship between doctors and technologists allow us to assume that the power relations in the model are part of the "deeper structure" that shapes the interactions at each hospital. By this we mean that the institutional norms dictating who is in charge of making a diagnosis change on a longer time scale than temporal patterns related to implementing CT technology. The authority of doctors over technologists is the outcome of at least a century of structuring and accumulating knowledge and power across a set of social institutions. This certainly changed little over the year Barley performed his study.

That which is considered the transient outcome of “structuring” and that which is considered “structure” is, in the end, a temporal distinction, referring to how rapidly the phenomenon of interest changes. While this point may seem trivial at first glance, we believe it is fundamental to improving how we conceptualize recursive organizational phenomena. Viewing the world as an interconnected set of activities and accumulations could suggest that we will be hopelessly unable to understand it. But, because not all accumulations change at the same rate, it is not necessary to identify every interconnection to understand a given pattern of organizing. Recognizing that social structures change at different rates provides a way to clarify and focus both theoretical and empirical efforts. Understanding factors that shape the evolution of the traditional relationship between physicians and non-physician staff is a fascinating question, but its dynamics do not need to be explicated to understand the patterns of organizing “triggered” by the implementation of CT technology at Urban and Suburban. A principal benefit of focusing on patterns of organizing that play out over explicitly specified time scales (e.g. weeks, months, years, decades) is that it allows the theorist to determine that which is dynamic and thus must be thought of in terms of *structuring processes* and that which is not and can, therefore, be thought of as stable *structure* for the purpose of the study at hand.

Finally, our approach highlights how formal models can be used as representational tools to bridge the thick descriptions common in ethnographic accounts and the complex conceptualizations found in Giddens and Bourdieu. As we noted earlier, most work applying the structuring approach is characterized by rich descriptions of specific instances (Barley, 1986; Orlikowski, 1992). Operationalizing such perspectives or drawing clear inferences from them, however, pose significant challenges. In particular, a “narrative” text provides a limited medium in which to represent the dynamics generated by recursive interactions between action and social structure. We have tried to illustrate how empirically-rooted mathematical formalization can be a valuable complement to empirically-rooted textual descriptions as both are engaged in theory development and testing.

Mathematical models do, of course, have a long history in organization studies (e.g. Cyert and March, 1963; Nelson and Winter, 1982), often providing a critical perspective on the dynamics of organizational processes (e.g., Levinthal and March, 1981). These models do, however, represent relatively general inquiries. Our analysis suggests that formal modeling may also add value as a tool for more focused inquiries into specific episodes of organizing, providing a critical step between rich data and broader theoretical generalizations. This was clearly recognized by Barley at the conclusion of his 1986 piece:

> Technologies do influence organizational structure in orderly ways, but their influence depends on the specific historical processes in which they are embedded. To predict a technology’s ramifications for an organization’s structure therefore required a methodology and a concept of technical change open to the construction of grounded population-specific theories (107).

As evidenced by our use of Barley’s data, our analytic approach is not a substitute for either thick description or powerful conceptualization, but rather is a useful link between the two.

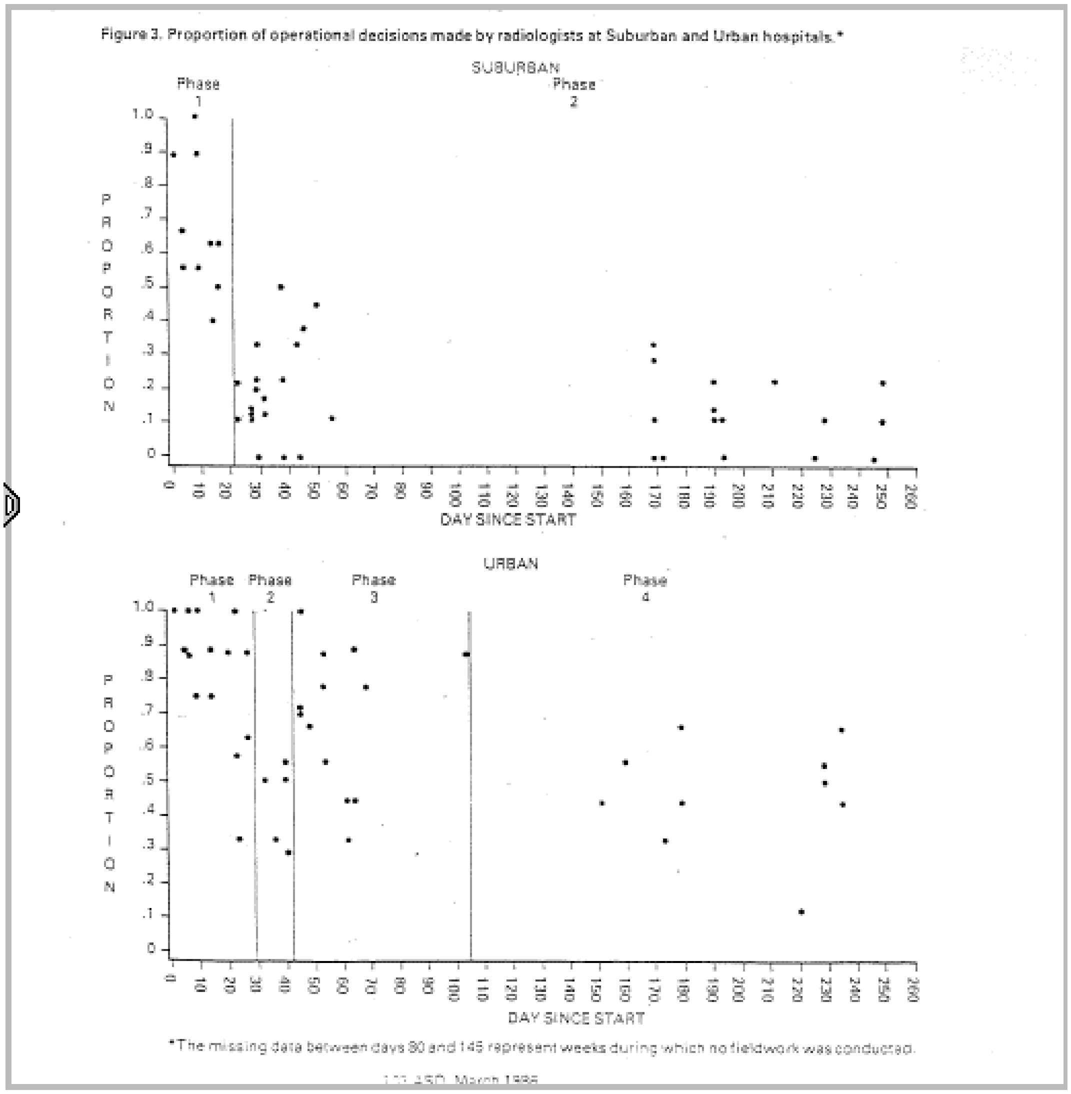
Table 1: Summary of Barley's Observations at Two Hospitals and Characteristic Organizational Patterns for Each Phase

<table>
<tr><td colspan="5" align="center">Suburban</td></tr>
<tr><td></td><td colspan="2" align="center">Phase 1</td><td colspan="2" align="center">Phase 2</td></tr>
<tr><td>Staffing change</td><td colspan="2"></td><td colspan="2">Inexperienced radiologists added on day 21</td></tr>
<tr><td>Experienced with CT</td><td colspan="2">1 of 1 radiologists
2 of 4 technologists</td><td colspan="2">1 of 6 radiologists
4 technologists</td></tr>
<tr><td>Scripts</td><td colspan="2">Unsought validation
Anticipatory questions
Preference stating</td><td colspan="2">Clandestine teaching
Role reversal
Blaming the technologist</td></tr>
<tr><td>Organizational Pattern</td><td colspan="2">Collaboration</td><td colspan="2">Occupational Separation</td></tr>
<tr><td colspan="5" align="center">Urban</td></tr>
<tr><td></td><td align="center">Phase 1</td><td colspan="2" align="center">Phases 2 and 3</td><td align="center">Phase 4</td></tr>
<tr><td>Staffing change</td><td></td><td colspan="2">Radiologists stay in office to encourage technologists to “figure it out”</td><td>Inexperienced radiologists added in day 105, and least competent technologists transferred out on day 105</td></tr>
<tr><td>Experienced with CT</td><td>2 of 2 radiologists
0 of 8 technologists</td><td colspan="2">2 of 2 radiologists
0 of 8 technologists</td><td>2 of 6 radiologists
4 of 4 technologists</td></tr>
<tr><td>Scripts</td><td>Direction giving
Countermand
Usurping the controls
Direction seeking</td><td colspan="2">Unexpected criticism
Accusatory questions</td><td>Technical consultation
Mutual execution</td></tr>
<tr><td>Organizational Pattern</td><td>Professional Dominance</td><td colspan="2">Professional Dominance</td><td>Collaboration</td></tr>
</table>

Table 2: Practical Knowledge After 9 Months

Doctors' Initial Knowledge \ Technicians' Initial Knowledge	Low (O 0.1 D 0.0)	Medium (O 0.5 D 0.18)	High (O 0.9 D 0.35)
Low (O 0.1 D 0.5/0.1)	.99	.55	.75
Medium (O 0.5 D 0.5/0.3)	.56	.98	.85
High (O 0.9 D 0.5/0.45)	.55	.81	.96

Figure 1: Barley's Original Plots of the Proportion of Operational Decisions Made by Doctors at Suburban and Urban



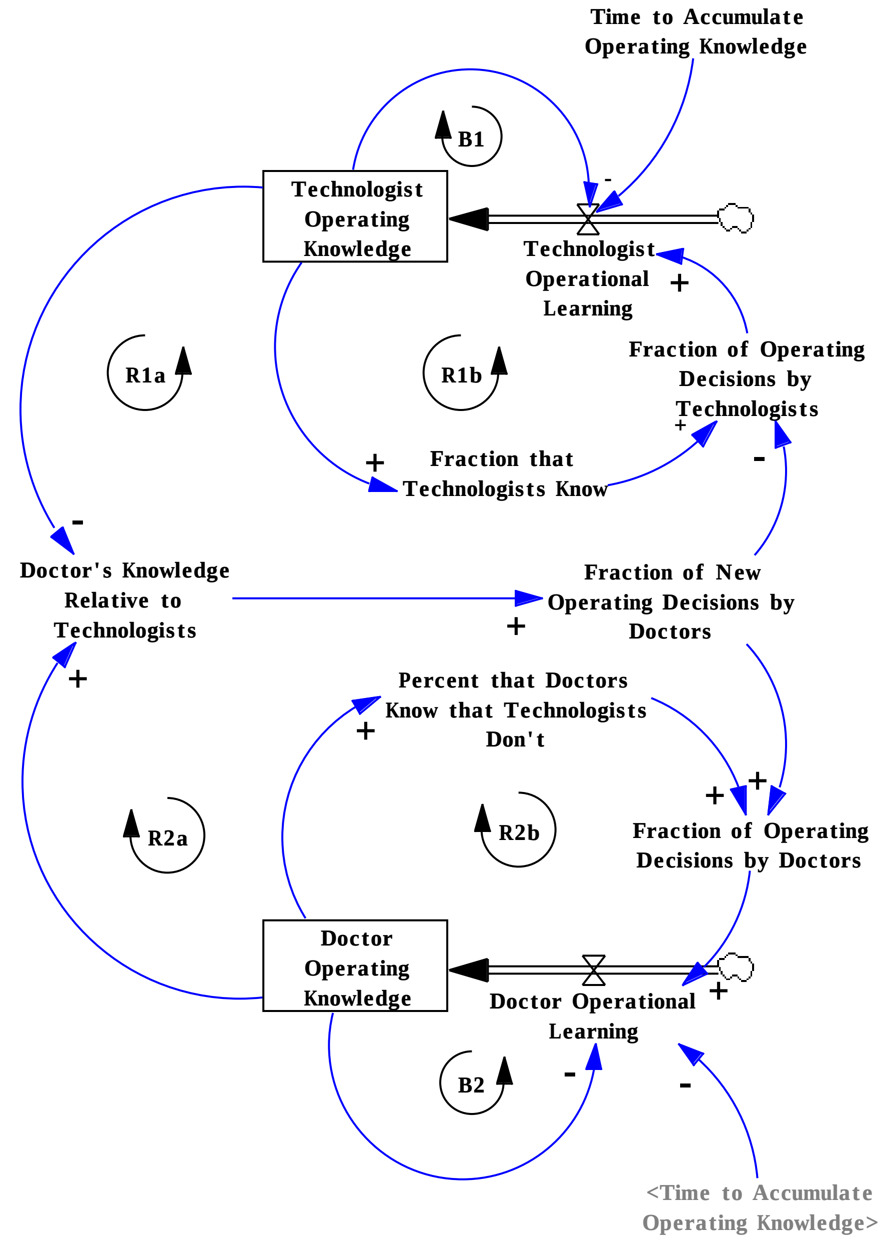
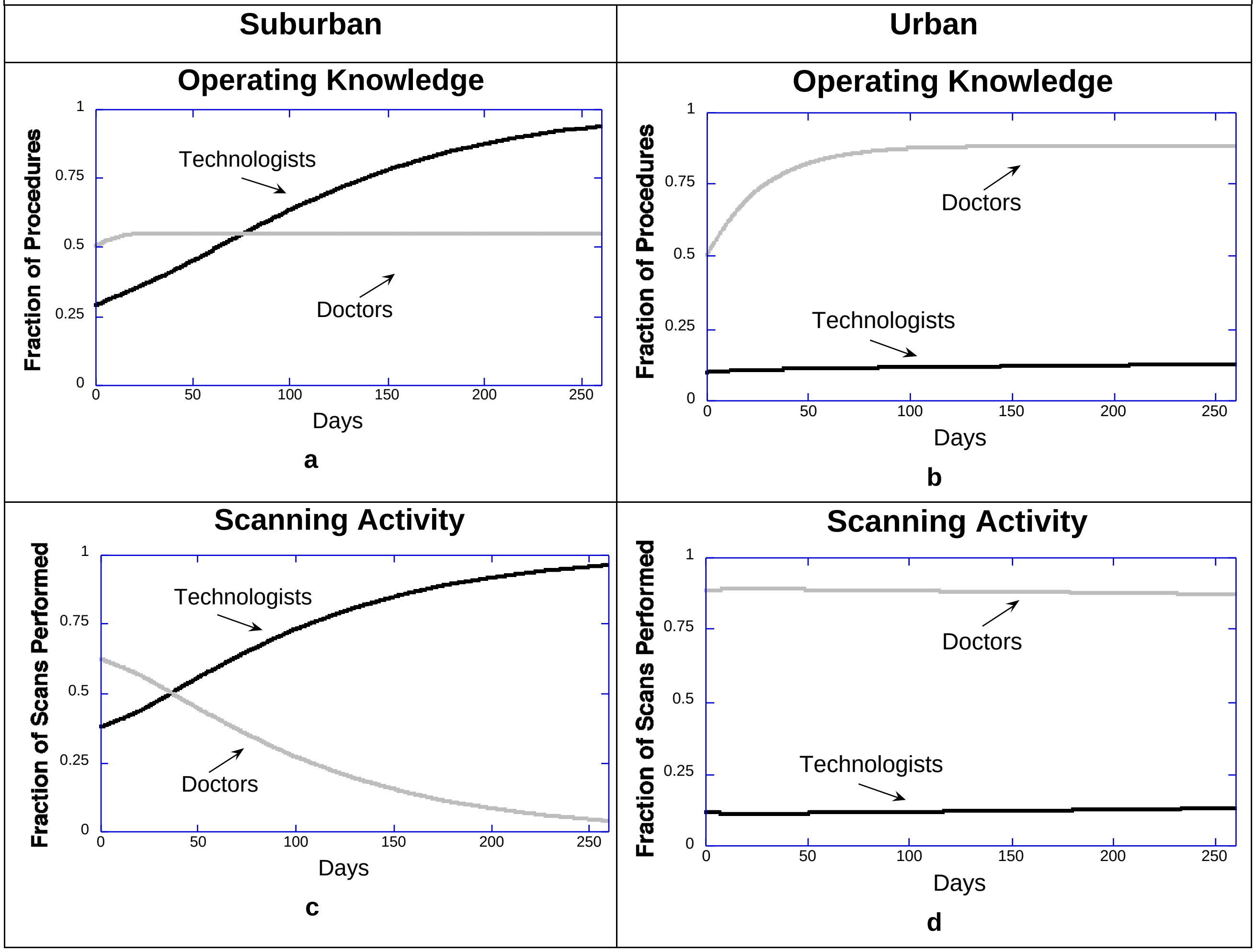


Figure 2: Overview of Initial Model Formulation. Signs ('+' or '-') at arrowheads indicate the polarity of causal relationships: a '+' denotes that an increase in the independent variable causes the dependent variable to increase, ceteris paribus (and a decrease causes a decrease). That is, $X \xrightarrow{+} Y \Leftrightarrow \partial Y/\partial X > 0$. Similarly, '-' indicates that an increase in the independent variable causes the dependent variable to decrease; that is, $X \xrightarrow{-} Y \Leftrightarrow \partial Y/\partial X < 0$. Boxes represent stocks; arrows with valves represent flows. A stock is the accumulation of the difference between its inflows and outflows. See Sterman 2000.

Figure 3. Initial Patterns and Suburban and Urban



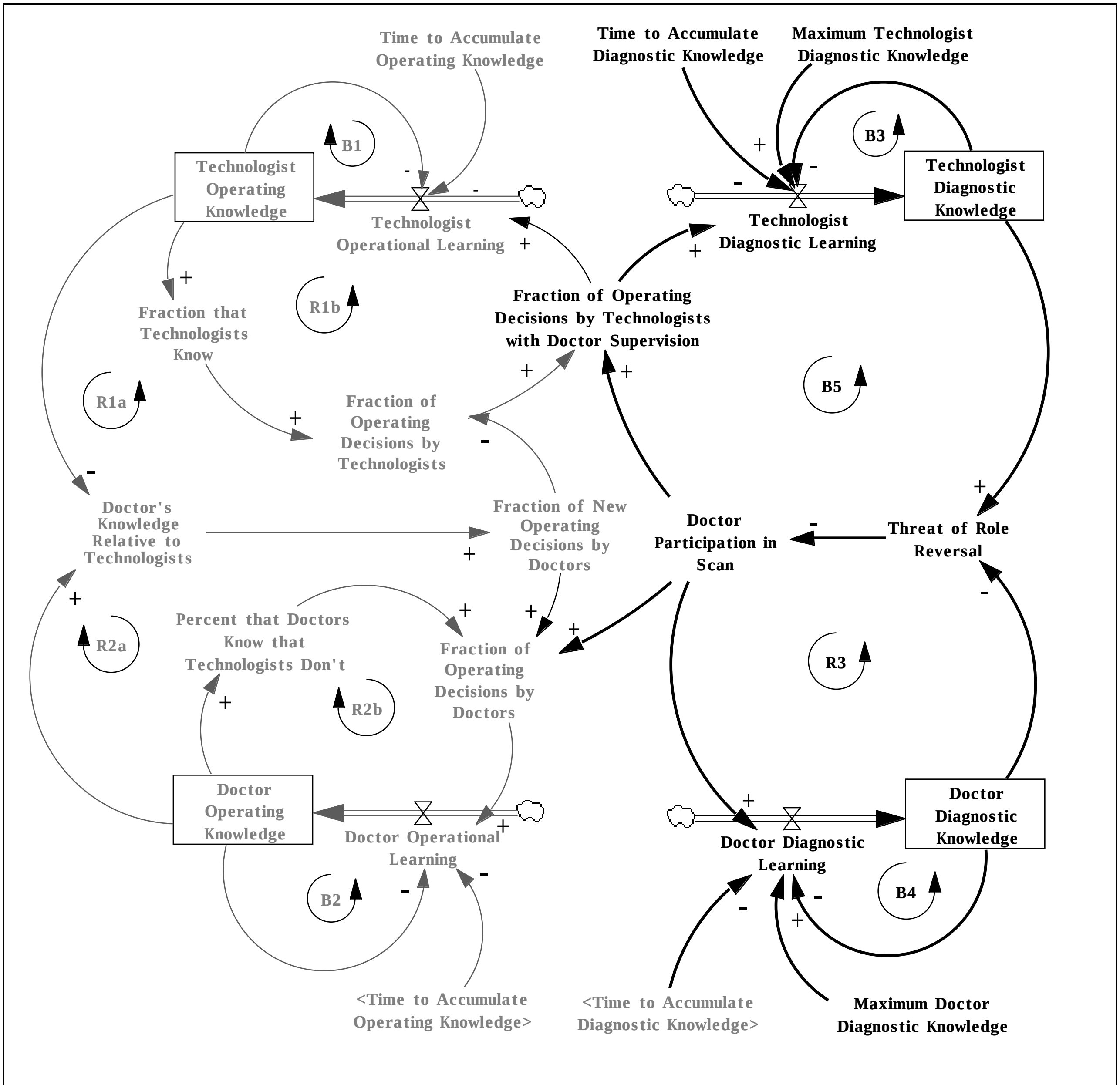


Figure 4: Overview Diagram of Extended Model

Figure 5: Knowledge Accumulation at Suburban

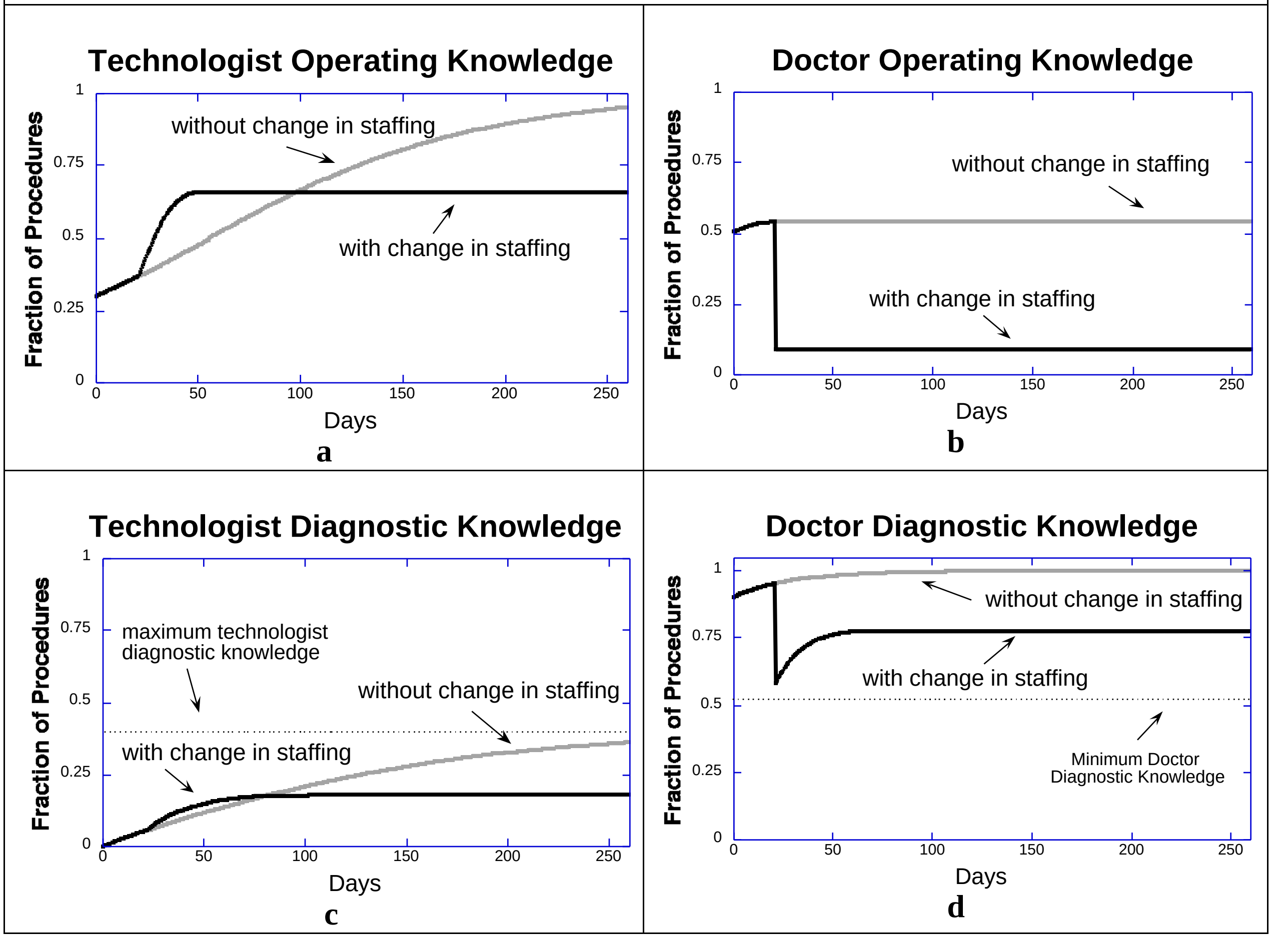


Figure 6: Scanning Activity at Suburban

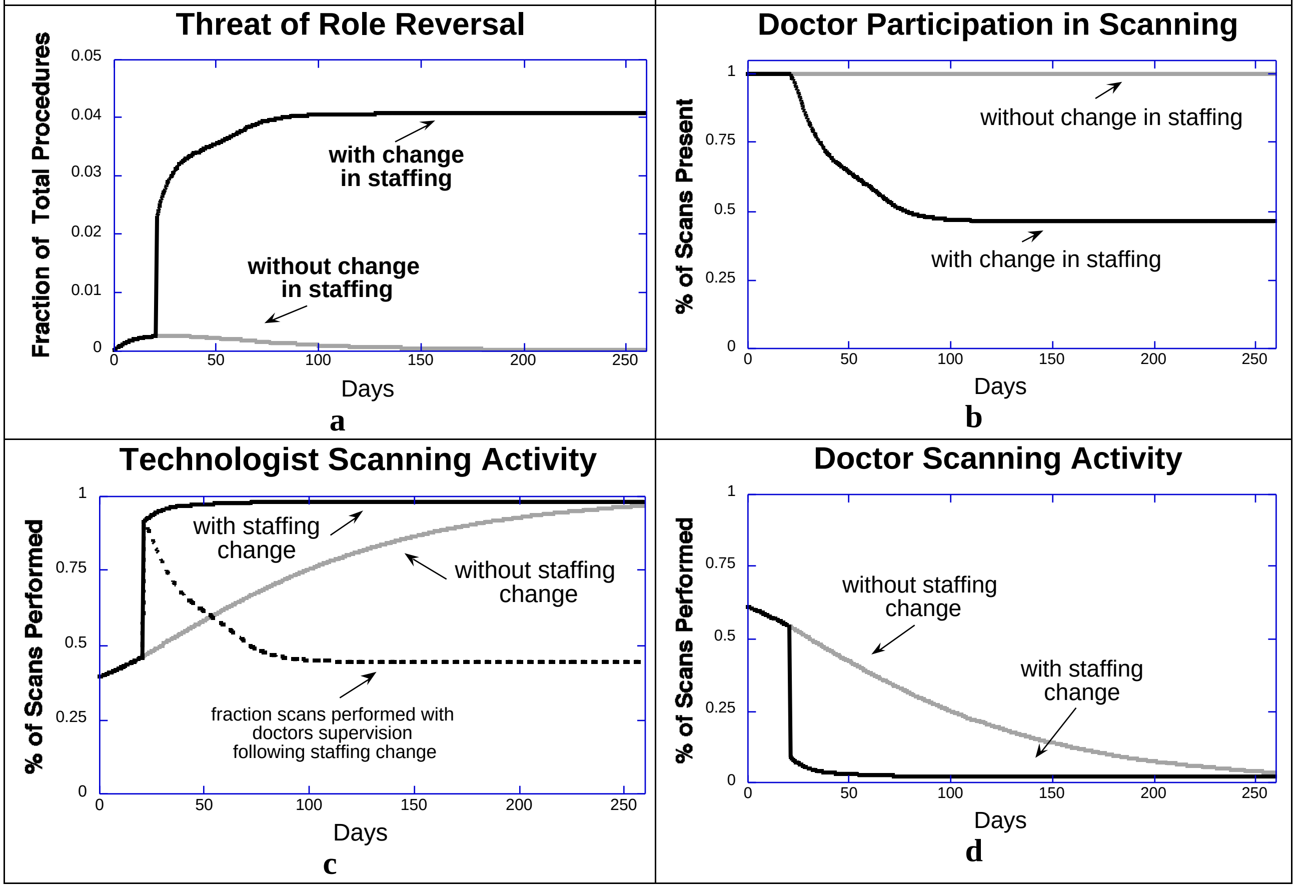


Figure 7:
Knowledge Accumulation at Urban

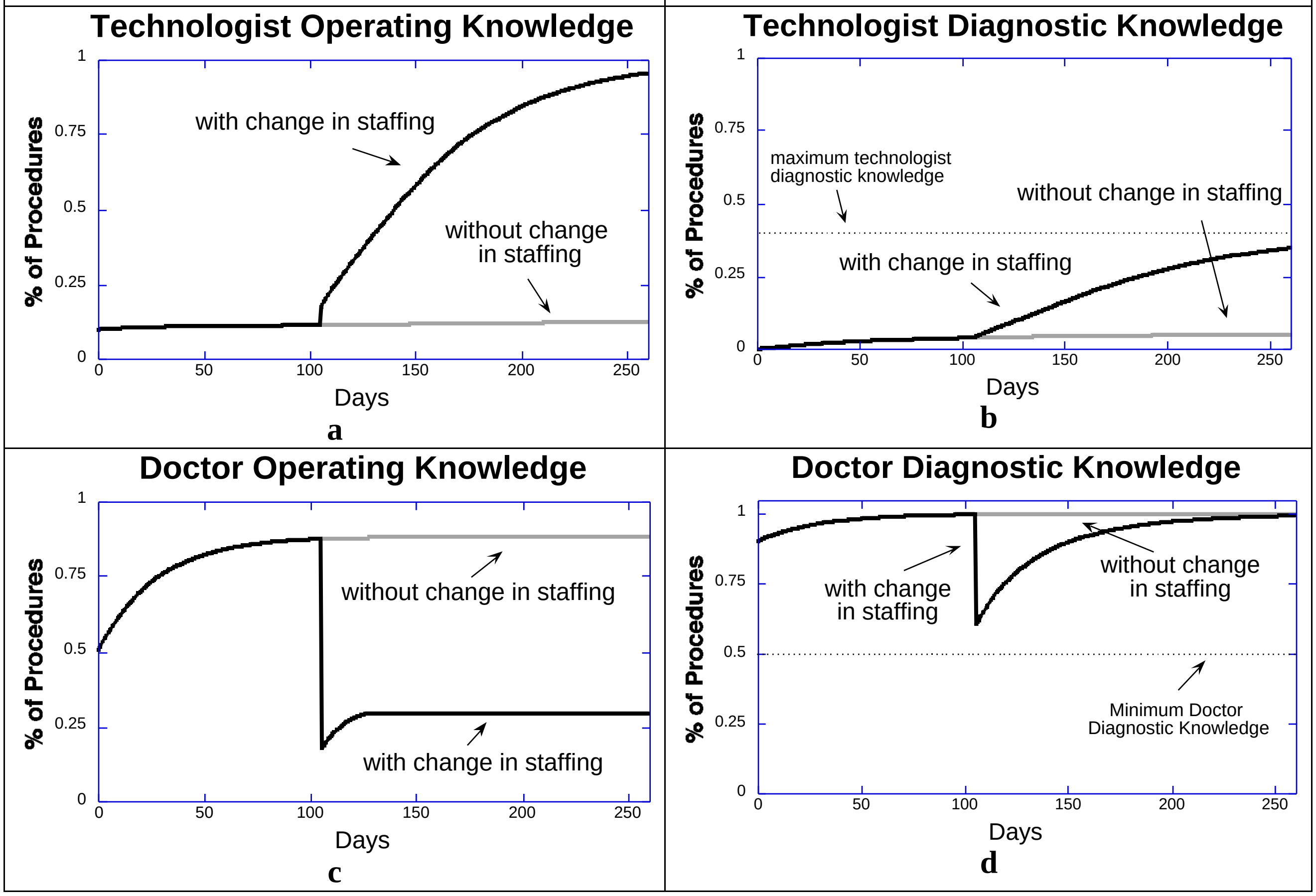
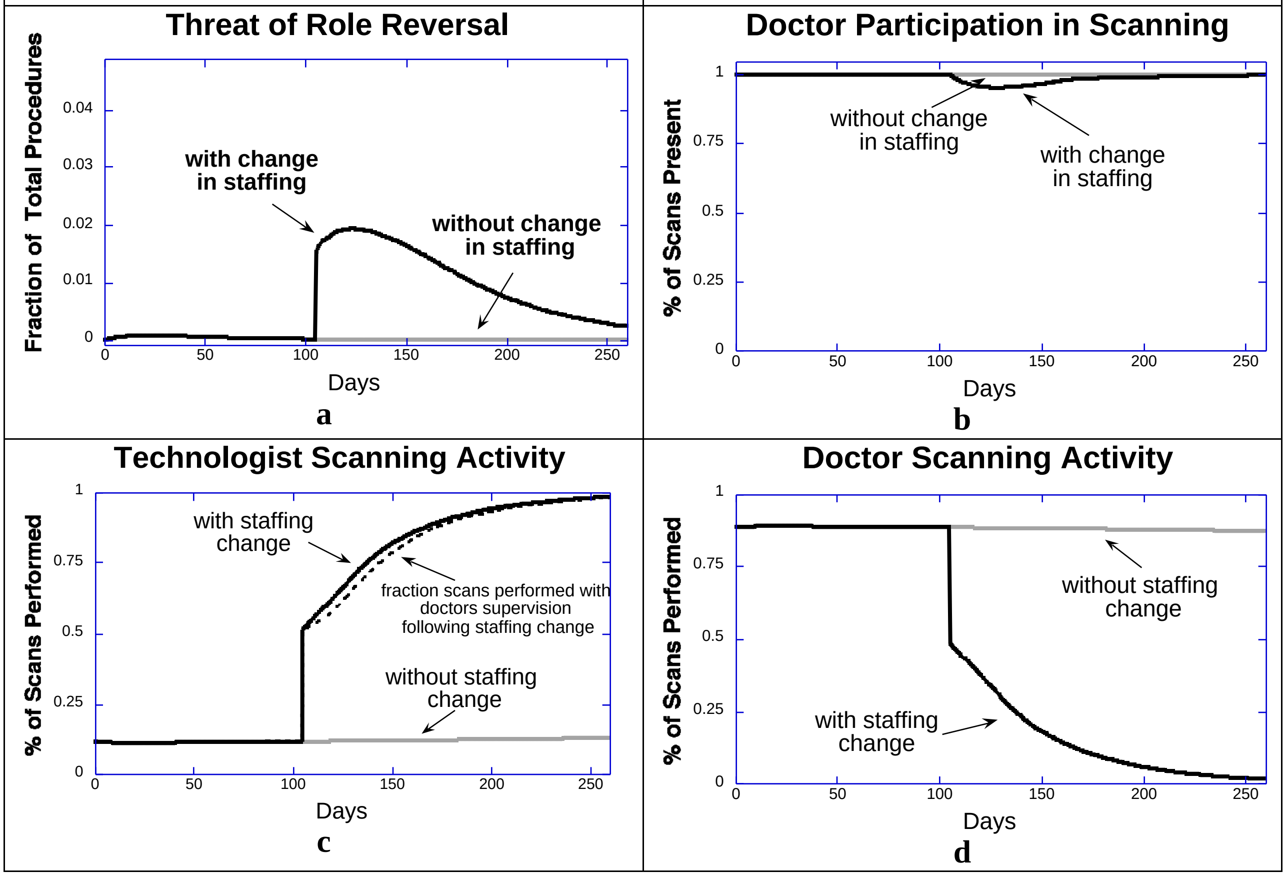


Figure 8: Scanning Activity at Urban



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[i] . Note that this formulation precludes the discovery of new ways to use the machine. Our model could be easily extended to capture this feature, however we leave it for future work.

[ii] . A technical appendix containing complete model documentation and instructions for replicating the results in the paper can be obtained at http://web.mit.edu/nelsonr/www/. A working version of the model in Vensim is also available.

[iii] . There are of numerous other ways for doctors to accumulate additional diagnostic knowledge, such as attending training or conferences, that we do not capture in the model. We omit these other sources of learning because, while they may be effective, they are likely to proceed on a far slower time scale than we consider in our analysis.