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Learning Tradeoffs In Organizations: Measuring Multiple Dimensions Of Improvement To Investigate Learning-Curve Heterogeneity

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MEASURING MULTIPLE DIMENSIONS OF IMPROVEMENT TO INVESTIGATE LEARNING-CURVE HETEROGENEITY

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Learning-curve research has found that rates of learning can vary across similar settings, such that cumulative experience is a necessary but insufficient predictor of learning-curve slope. One explanation for this finding is that how the learning process is managed affects rates of learning. We investigate an additional possibility. At any point in time, organizations can learn along *multiple*, potentially competing, performance dimensions. In particular, we suggest that organizations adopting a new technology or practice can "learn" on more than one dimension at the same time, such that more than one meaningful learning curve may exist for the same learning challenge. Thus, by arguing that effort invested in learning on one dimension may inhibit learning on another dimension, we propose a new explanation of learning-curve heterogeneity across organizations. Using a sample of sixteen academic and community hospitals adopting a new surgical technology, we demonstrate a tradeoff in organizational rates of learning on two dimensions: improving proficiency in an existing application use of the technology (efficiency) and applying the technology to novel and more challenging uses (application innovation). Our results provide support for our proposed explanation of learning-curve heterogeneity and suggest the salience of both rate and direction (i.e., dimension) in learning. We also find that the goal orientation of the organization influences the direction of learning (efficiency vs. application innovation).

INTRODUCTION

Since the landmark finding of a relationship between experience and performance improvement in aircraft manufacturing (Wright, 1936), a large body of literature has explored the concept of the "learning curve." Learning-curve research has demonstrated that performance improves as a result of increased experience with a new technology, routine, and/or process. Remarkably robust, the experience effect has been reproduced in multiple business contexts, including both manufacturing and service settings. For example, learning curves have been found in nuclear power plants (Joskow & Rozanski, 1979), chemical processing (Lieberman, 1984), ship manufacturing (Rapping, 1965), truck production (Argote & Epple, 1990), cardiac surgery (Kelsey et al., 1984), and semiconductor manufacturing(Hatch & Mowery, 1998). Research in this area has found heterogeneity in learning curves across similar sites (Darr et al., 1995; Hatch & Mowery, 1998; Pisano et al., 2001; Edmondson et al., 2003), leading researchers to conclude that how experience is managed affects the rate of learning.

Several studies have investigated potential explanations for such variation in learning rates (Adler & Clark, 1991; Argote, 1999; Haunschild & Sullivan, 2002; Ittner et al., 2001; Lapre & Van Wassenove, 2001; Lieberman, 1987). Researchers have identified various factors explaining learning-rate heterogeneity, including properties of the knowledge being acquired, such as tacitness (Edmondson et al., 2003), stickiness (von Hippel, 1994), causal ambiguity (Szulanski, 1996), and other aspects at the team level, such as stability of team membership and quality of communication among team members (Edmondson et al., 2001).

Typically, prior work on learning curves has emphasized the comparison of learning rates among either organizational units or firms on a *single* dimension and a search for the underlying managerial causes of observed differences. In particular, most previous learning-curve studies have focused on improvements in efficiency, measured as a reduction over time in variables such as manufacturing costs or production time.

This paper extends prior research by examining learning rates in technology adoption across similar organizations on *multiple*, potentially competing, dimensions. In particular, we suggest that organizations adopting a new technology or practice can "learn" on more than one dimension at the same time, such that more than one meaningful learning curve may exist for the same challenge. For example, a manufacturing plant could focus on reducing costs or on increasing flexibility. From this perspective, a plant that focuses on reducing its manufacturing costs is not necessarily a better or worse learner than one that focuses on increasing its flexibility. If we were to measure the impact of cumulative experience only on costs, the first plant would appear to be a faster learner than the second, and vice versa.

In the case of new technology adoption, organizations often face two main learning hurdles: improving proficiency in the technology for a given application—what we refer to as *efficiency*—and trying out increasingly difficult or challenging applications for which the technology is appropriate—what we call *application innovation*. The former, using a new technology better or performing a task more efficiently with cumulative experience, is the common focus of the learning curve literature. An alternative to this dimension of learning is using the technology differently, either by modifying it or making use of it in a different way or in a different context from that which was originally intended by the manufacturer (as in the case of, for example, user innovations [von Hippel, 1988; 2005]).

Our suggested multi-dimensional perspective on learning invites analysis of not only difference in *rates* of learning across organizations, but also differences in the *direction* (i.e., dimension) of learning.[1] The existence of multiple dimensions of learning introduces another potential explanation for the observed heterogeneity in learning rates. If organizations can learn on more than one dimension, then what looks like "slow learning" on one dimension may be caused by effort invested instead in learning on another, unmeasured, dimension. Organizations may thus face a tradeoff in learning, as choosing to learn on one dimension may make it harder to simultaneously learn on another. A cross-sectional comparison of learning rates on a single dimension, which is the common approach used in learning curve studies,

[1] In this paper, we use the terms direction and dimension of learning interchangeably.

would not detect such a tradeoff. Differences in the *direction* of learning may explain observed differences in *rates* of learning.

We further explore the organizational attributes that may influence differences in the direction of learning. Two bodies of literature bear on this question. One is the strategy literature suggesting that product market positioning should influence investments in intangible assets, skills, and capabilities (Dierickx & Cool, 1989; Teece et al., 1997; Porter, 1991). A second body of work, rooted in psychology, argues that an individual's goal orientation, or the nature of the goals that an individual implicitly pursues (Dweck, 1986; Elliott & Dweck, 1988), is a robust predictor of behavior and performance in learning and achievement tasks. Given that a goal orientation may be prompted by situational factors (Button et al., 1996), an organization might implicitly or explicitly use situational cues to signal the goals and behaviors that are desired or rewarded to its members (Ames, 1992) and thus influence members' perceptions of the organization's learning climate and goal orientation (Ames & Archer, 1988; Button et al., 1996).

We empirically investigate learning tradeoffs with data on hospitals adopting a particular new technology for cardiac surgery, referred to here as Minimally Invasive Cardiac Surgery, or MICS. Using data on all 679 patients who underwent operations in 16 hospitals that were learning to use the technology between 1996 and 1998, we analyzed whether hospitals exhibited learning on two distinct dimensions. One dimension of improvement was to reduce the time required to complete the procedure, a vital measure of efficiency in surgery. The second dimension for improvement was to use the procedure for more difficult operative cases or patient conditions, an important form of application innovation in healthcare delivery. We estimated learning curves for hospitals along both of these dimensions of performance improvement. We then analyzed whether different improvement strategies had a different impact on performance and whether these differences were associated with broader institutional goals.

This paper extends the current understanding of learning curves in two main ways. First, it expands beyond the study of efficiency to include a new dimension, application innovation, and investigates the potential tradeoff between the two dimensions on learning outcomes. Second, this study explores what influences such a tradeoff to occur by examining the link between organization type and learning orientation. Our findings suggest that organizations should explicitly determine which dimension is of greatest strategic importance to them so as to enable initial focus and potential competitive advantage.

THEORETICAL BACKGROUND AND HYPOTHESES

The tradeoff between two competing learning dimensions

Research on organizational learning has distinguished between learning processes that refine and improve current capabilities and learning processes that discover and develop new capabilities because they will likely have an impact on performance. Labeling the former “exploitation” and the latter “exploration,” March (1991) suggested that sustained performance results from the ability of an organization to balance the two. Although it is possible for a firm to be “ambidextrous” and excel at both (Tushman & O'Reilly III, 1996), exploitation and exploration are often competing strategies, as the resources of time and focus are limited and decisions about what to learn may impact each other. In fact, exploitation strategies tend to limit the amount of firm exploration; similarly, exploration strategies tend to limit the amount of firm exploitation (March, 1991). Also, the two strategies often compete for limited resources within the firm and are associated with opposite organizational structures and cultures. As such, companies that pursue both strategies are viewed as lacking focus and internal fit (Miller & Friesen, 1986).

In essence, organizational research has observed several tensions in firms trying to engage in high levels of both exploitation and exploration. We propose that an analogous tension is faced by organizations that learn in the wake of new technology adoption. Specifically, technology adoption poses two learning challenges. The first is what we call “application innovation,” or the expansion of the use of a technology beyond its initial applications. When a technology is new, it is often not clear ex ante to which applications it is best suited. A key aspect of innovation is experimenting with and exploring alternative and more challenging applications for the technology (e.g., von Hippel, 1988; 2005). Application innovation plays a critical role in the diffusion of technology and it is one of the two learning dimensions we refer to in our study.

A second learning challenge of technology adoption is to become proficient in the use of the technology for a given application. This often means becoming more efficient (e.g., lower costs, increased speed) or achieving more consistent outcomes. This second learning challenge has been the focus of the extensive learning-curve literature cited earlier and it is the second dimension of learning we investigate in this paper.

Both dimensions of learning—finding more difficult applications and improving efficiency—can potentially benefit from cumulative experience. The empirical and causal link between efficiency or proficiency and experience has been well documented (see, for instance, Adler & Clark, 1991). However, the search for new applications for a technology can also benefit from experience, as this process also consists of trial and error. Limited resources and pre-existing organizational cultures and routines are likely to constrain multiple options for learning; thus, for any particular organization, the rate of learning on one dimension is likely to differ from that on another dimension.

We can think of an organization as "consuming" its cumulative experience of a new technology in one of two ways: it can deepen its proficiency in a given application of the technology, or it can expand its ability to use the technology in different applications. Because limited resources and pre-existing organizational cultures and routines are likely to constrain multiple options for learning, for any particular organization, the rate of learning on one dimension is unlikely to be the same as the rate of learning on another dimension.[2] Drawing from the work cited above, we expect there to be a tradeoff between the rates of learning along these two dimensions. Specifically:

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[2] The presence of multiple dimension of learning at the organizational level would extend the results on learning tradeoffs demonstrated at the individual level. Research in psychology has found that, in individual learning, people tend to trade speed for accuracy, or vice versa; the more rapidly an individual performs a skill, the less accurate it becomes (see, for example, MacKay, 1982). This well-established finding in the psychology literature is known as the speed–accuracy tradeoff (Fitts, 1954; Woodworth, 1899).

Hypothesis 1: The speed of learning on the efficiency dimension will be inversely related to the speed of learning on the application innovation.

Several factors might determine the dimension on which an organization learns. First, the observed direction of learning might be the result of a deliberate strategic choice when the capability being learned is central to the firm's competitive advantage (Argote & Ingram, 2000; Teece & Pisano, 1994). Hence, firms competing on the basis of differentiation would choose to learn along dimensions that promote (application) innovation, whereas firms competing on price would choose dimensions of efficiency. Second, resource constraints might determine the direction of learning. Attention to one dimension of improvement may reduce the time and resources available to improve on another dimension; because employee effort is finite, improvement in one area may come at the expense of improvement in another area. Third, learning may be path dependent. An organization's prior experience, culture, and existing routines may predispose it to focus on one kind of performance improvement, such as efficiency, rather than another, such as cost (Tripsas & Gavetti, 2000). Those already competing on the basis of application innovation might be more likely to improve on this dimension than would those competing on cost, and vice versa. Finally, the observed direction of learning might depend on the organization's goal orientation. We explore this possibility next.

The impact of learning orientation on learning outcomes

Research in psychology has identified two distinct behavior patterns that individuals use in achievement situations, namely mastery (or learning) goal orientation and performance goal orientation (Dweck & Leggett, 1988; Ames & Archer, 1988). Individuals who are learning goal oriented are willing to work hard to "master" a skill or concept. They tend to persist in the face of difficulty, and they generally take risks and try new things they don't already know how to do. On the other hand, individuals who are performance goal oriented work toward the goal of appearing competent or at least avoiding appearing incompetent. As a result, they are less likely to persist if they make an error or have to put forth a lot of effort. They prefer to perform tasks that they know they can do; they're not willing to take risks, and they want to do better than everyone else (Dweck & Leggett, 1988; Ames & Archer, 1988).

Prior studies have also found that the type of goal toward which a person is working greatly influences how they pursue the goal, as well as how much they learn and how well they perform on the learning task (see, for instance, Kaplan, Middleton, Urdan, & Midgley, 2002). Thus, at the individual level, goal orientation influences learning processes and outcomes.

Although the research on goal orientation has been conducted mostly on individuals in experimental settings, the results might be generalizable to organizational settings. An organization may use situational cues to influence its members' perception of the learning climate's emphasis on learning versus performance goals (Ames & Archer, 1988). As occurs at the individual level, an organization's different emphasis in goal orientation may result in different learning outcomes and, specifically, may affect the speed of learning on various dimensions. In particular, because the emphasis of mastery goal orientation is on development of skills, knowledge, and competence (Bunderson & Sutcliffe, 2003), mastery-goal-oriented organizations might be more concerned with application innovation than with efficiency. On the contrary, because the emphasis of performance goal orientation is on demonstrating competence and avoiding failure (Bunderson & Sutcliffe, 2003), performance-goal-oriented organizations might give priority to efficiency. This reasoning led to the following hypothesis:

Hypothesis 2: The speed of learning on the efficiency dimension versus the application-innovation dimension will be related to the organization's goal orientation.

RESEARCH DESIGN

Context: Medical technology

Since the first antibiotics were introduced more than a hundred years ago, the development and dissemination of new technologies has been of central concern in the field of healthcare. Within an overall context of steady improvement in treatment options for patients, healthcare managers confront a tension between 1) focusing on streamlining existing technologies and practices to enable treatment of increasing numbers of patients more efficiently (e.g., O'Connor et al., 1996) and 2) applying resources toward developing innovative approaches to treat previously untreatable patients (e.g., Barnard, 1967; Druker et al., 2001). Indeed, society expects the healthcare sector simultaneously to develop innovative technologies *and* make them widely available (Wilensky, 1990).

Although some medical technologies, by design, can only be used in one way or for one task, others may be used in many different ways to accomplish many different goals. The same drug may be used to treat multiple conditions and the same device for several procedures. Moreover, the full range of a medical technology's use may not be fully specified at the time of its release to market. A medical technology innovator may not have fully characterized all of the possible ways in which a technology can be used before taking it to market,[3] leaving it to expert clinicians not only to learn through experience how to use the technology for its specified use (faster, better, cheaper), but also to learn the range of uses to which the technology might be put—to explore the boundaries of its technological potential.

Minimally Invasive Cardiac Surgery. In this study, we used the adoption of Minimally Invasive Cardiac Surgery (MICS) technology to investigate separate dimensions of learning among cardiac surgery units. This technology was developed by a private company and received FDA approval in 1996. Hospitals adopting MICS faced a substantial learning challenge. First, initial procedures took much longer than the conventional approach. Longer operations not only put patients at greater risk, but also are extremely costly for hospitals, as cardiac operating rooms are an expensive resource and are generally capacity constrained. Second, initial procedures were limited to a small subset of cardiac patients: relatively healthy patients and those requiring simple cardiac procedures on the front of the heart (Galloway et al., 1999). Widening the population of patients for whom this procedure could be used could affect the hospital's ability to gain a competitive advantage from it. In essence, while the first form

[3] In the pharmaceutical industry, the huge costs associated with clinical trials and FDA approval provide an incentive for firms to be highly selective in their choice of indications. Practicing physicians are not, however, restricted to only using a drug for those uses approved by the FDA.

of learning was measured by rates of efficiency improvement, the second was captured by the possibility of expanding the range of patients to whom MICS techniques could be applied.

As a research context for investigating multiple dimensions of learning, MICS offered several advantages. First, as noted above, the technique was a dramatic departure from conventional surgery and required substantial learning. It required significant changes in the roles and tasks of individual operating room team members and in their working relationships. Initially, these changes required longer procedure times, as noted above. Whether and how to use the technology for very difficult patient cases represented another substantial opportunity for learning. Second, MICS was a recent innovation, thereby allowing data collection from the original adopting surgeons and operating room teams. Third, all cardiac surgery operating room teams employ similar technology and surgical routines, minimizing *a priori* differences that might affect ease of learning. Finally, the company that developed and marketed the equipment for MICS established a database of detailed patient-level data—including measures of efficiency, patient severity of illness, and complexity of the surgical procedure undertaken—for all MICS cases performed at adopting hospitals.[4] These data were conducive to analyzing hospital-specific learning curves.

The MICS procedure. A conventional cardiac surgical procedure comprises three phases: (1) cutting open the chest and splitting the breastbone, then connecting the patient to a heart-lung bypass machine, and clamping the aorta to prevent blood from flowing backwards into the heart while the surgeon operates, (2) stitching to repair diseased components, and (3) restarting the heart and weaning the patient from the bypass machine, then closing the chest. MICS changed this process in two important ways. First, under MICS, the breastbone is not split. The surgeon instead gains access to the heart through a small incision between the ribs, and therefore lacks the same level of access to the heart and the same level of visual and tactile information about the state of the heart available in a conventional procedure. Second, instead of an external clamp, a small catheter with a balloon at its tip is fed into the aorta to stop the blood flow. Although the surgeon directs the positioning of the balloon clamp,

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[4] This patient registry was maintained by an independent contract research organization; details that could identify patients (name, date of birth, social security number) were removed.

monitoring its stability requires coordinated action from an anesthesiologist and a perfusionist (the technician who runs the heart-lung bypass machine). When the technology was first being used, these changes, physical constraints, and extra tasks led to very long MICS procedures, lasting four to twelve hours, compared to the two to six hours characterizing a conventional procedure.

Dimensions of learning in MICS technology adoption

Hospitals and surgeons have powerful incentives, both medical and financial, to reduce cardiac surgical procedure times. Long operations are associated with an increased risk of postoperative complications, particularly strokes (Ricotta, Faggioli, Castilone, & Hassett, 1995). Furthermore, neither hospitals nor surgeons receive additional compensation for longer time spent in the operating room, and, in this setting, MICS operations reduced the number of cases that could be done in a single operating room from three to two per day.

At the same time, there is a range of patient severity and operation types in cardiac surgery. The MICS technology offered an innovation in its method of gaining access to the heart. It had the potential to be used for the same range of cardiac operations as the conventional "open" method; however, with its restricted access to the heart and chest cavity, certain operations were far more technically difficult using MICS than using conventional technology.[5] Being able to use MICS for a wider range of cardiac operations of varying difficulty meant that a surgeon could treat more patients with the MICS approach, which might allow both the hospital's reputation and referral pool to expand if nearby hospitals were unable to do the same. We therefore concluded that for cardiac surgery teams adopting the MICS technology, two dimensions of potential learning were present: increasing efficiency, measured by reductions in procedure time, and increasing application innovation, measured by increases in case difficulty.

[5] In particular, procedures in which the surgeon needs access to the back or sides of the heart, such as in multiple graft CABG (e.g., quadruple bypass) and those in which operating through a narrow opening in the chest poses particular limitations (e.g., multiple concurrent valve replacements), were far more challenging technically than standard CABG and valve replacement.

Academic and community hospitals. The data set comprised both academic and community medical centers (AMCs and CMCs). These two types of hospital have differing resources, competencies, primary missions, and goals, which may incline them to learn on different dimensions as they adopted MICS. The primary role of a community center is to serve its local community's medical needs. Compared to academic medical centers, community hospitals rely more heavily on revenue from clinical operations than from teaching and research. Thus, community hospitals might be labeled "performance goal oriented." The reduced surgical capacity resulting from initially long MICS procedure times (a proxy for efficiency) would thus be particularly significant for community hospitals.

In contrast, AMCs undertake research and teaching in addition to providing clinical care and derive additional revenue from these activities. Moreover, they benefit from publications in leading journals and are often the developers of, and the testing grounds for, medical innovations. Lastly, AMCs have a more heterogeneous pool of patients than community centers, one that includes both routine cases and severe illness or esoteric conditions. Thus, academic hospitals might be labeled "mastery goal oriented." Given their patient diversity, AMCs are likely to derive competitive advantage from increasing procedural difficulty with MICS (a proxy for application innovation), as it can increase the number of potential patients on whom the new technology can be used. The ability to conduct difficult procedures also can promote academic prestige and serve as a differentiator in attracting residents (surgeons in training) who must choose which training program to attend.

Hence, because of strategic considerations related to their differing goals and resource constraints related to their different income sources and referral pools, we expected academic and community hospitals to learn on different dimensions. Specifically, for the specific context under study, Hypothesis 2 was formulated as follows:

Hypothesis 2a: Relative to community hospitals, academic hospitals will learn more rapidly along the dimension of application innovation, captured by technical difficulty.

Hypothesis 2b: Relative to academic hospitals, community hospitals will learn more rapidly along the dimension of efficiency, measured by procedure time.

Academic hospitals draw on a more diverse patient-referral population than community hospitals and are more likely to be able to withstand a short-term revenue loss during MICS adoption. Both factors allow academic hospitals to experiment with new uses for MICS in the absence of an imperative to shorten operation time. Moreover, academic hospitals could benefit—by gaining prestige and by serving patients others were unable to serve—from learning to offer the MICS procedure to more difficult patient cases. This benefit may be realized in patient care revenue and/or future research funding. By way of contrast, not only are community hospitals unlikely to realize benefits from becoming adept at difficult cases, but they also do not have the diverse referral pool from which to draw patients requiring more technically challenging operations. Instead, they are more likely to increase volume by increasing efficiency; by getting faster, they would be able to serve more patients in the same amount of time.

METHODS

Sample

The study sample comprised sixteen cardiac surgical units across the United States, nine academic medical centers and seven community hospitals. A geographically diverse sample of sites was selected from the 108 hospitals that had purchased the MICS technology prior to August 1997 to include both academic and community hospitals. The average hospital in the sample undertook a fairly high volume of cardiac surgeries on an annual basis (approximately 1,400 cases/year, ranging from 400-3,500 cases/year). Most of the hospitals had extensive experience adopting new cardiac surgery innovations, and all had at least some prior experience with innovation. The company introducing the technology had targeted these institutions because they were considered to have "first-tier" cardiac surgery departments (with moderate to high total case volumes, highly regarded surgeons, and a reputation for high-quality care and excellent clinical outcomes). The company that developed the technology provided introductions to these sites, all of which agreed to participate in this research.

Data sources

All hospitals provided data for every MICS operation performed, including data on the type of cardiac operation performed, procedure time, and information about each patient's clinical condition. This was our primary data source. In cases where patient data was missing, we collected the missing data directly from the hospital's internal databases or original medical records. The final data set contained every MICS operation performed at each of the sixteen sites from their first case (April 1997 or later) until December 1998. During this time interval, each of the selected sixteen institutions contributed between 9 and 92 cases, totaling 679 cases. Differences in number of cases performed across sites were generally the result of two factors. Although all 16 hospitals in our sample were considered "early adopters" because they adopted MICS within the first year of FDA approval, the exact time of adoption differed, thus influencing the number of cases performed by November 1998. In addition, sites also varied in the rate (number of cases per month) at which they were able to do the procedure (due to the availability of appropriate patients and the interests of the adopting surgeon).

In addition to patient-level data, two or three of the authors conducted a site visit at each hospital. We interviewed all those connected with the adoption of MICS, including surgeons, anesthesiologists, scrub nurses, perfusionists, referring cardiologists, and administrators. Over a five-month period during the time of adoption, we conducted 165 interviews, an average of 10.2 per site. We used the interviews to obtain background about why the hospital adopted the new technology, informants' descriptions of the implementation process and its challenges, and insight into the learning goals that each site might hold.

Measures

For each patient, we collected two measures that allowed us to construct hospital-specific learning curves for two dimensions of performance improvement: the technical difficulty of the surgical procedure undertaken and the efficiency, in terms of time, with which it was executed.

Application innovation. To measure application innovation in this setting, we used expert ratings of technical difficulty, a core aspect of application innovation in this context. We interviewed four surgeons about this challenge and obtained their ratings of the relative difficulty of each of the twelve types of cardiac procedure that occur in the data set. We asked them to asses the difficulty of performing each procedure, creating four groups of procedures: those with 1) the least technical difficulty, 2) less than average technical difficulty, 3) higher than average technical difficulty, and 4) the greatest technical difficulty. The surgeons were asked to concentrate on the additional technical difficulty imposed when performing these procedures via MICS, rather than the technical difficulty of the procedures themselves, with which all of the surgeons were highly competent. Using the means of the surgeons' standardized scores for each procedure, we divided the procedures into four groups by placing group boundaries at relatively large jumps in the scores. We then interviewed a fifth surgeon, highly expert in MICS, to get feedback on our final ratings. He approved of the classifications, which are shown in Table 1.

Insert Table 1 about here

Although this classification was determined based on the opinions of only five surgeons, we believe that it is robust for two reasons. First, there was a very high degree of agreement between the surgeons' opinions. The kappa statistics for inter-rater reliability among the first four surgeons of 0.75 ($p < 0.0001$) indicates "substantial" agreement (Cohen, 1960; Landis & Koch, 1977). Second, there is an intuitive basis for this classification, which thus has face validity. Lay descriptions of the twelve procedures, shown in Table 2, clarify the increase in difficulty from one group to the next.

Insert Table 2 about here

Efficiency. Our measure of efficiency, procedure time, is the time it took for a surgical team to complete the operation. This time, known colloquially as "skin-to-skin time," is the time between the first surgical incision and the last stitch. Because it does not include the time spent preparing the operating room (by setting up the instruments) or preparing the patient with initial anesthesia, procedure time measures the time the cardiac surgical team is working together as a core unit.

Statistical models and analysis

In this section, we estimate models for both application innovation and efficiency. The former uses data on how technical difficulty changed with cumulative experience; the latter uses data on how procedure time changed.

Application innovation. To compare the rates at which hospitals improved along the dimension of application innovation, assessed as technical difficulty, we modeled the probability that a surgical team would perform a more difficult procedure via the MICS approach. For this model we used a cumulative, ordinal logit because our dependent variable comprises four, ordered categories of increasing technical difficulty. Our model is:

$$\log\left(\frac{P(\text{more difficult procedure})}{1-P(\text{more difficult procedure})}\right) = \alpha_0 + \beta_0 Hospital_i + \beta_1 \log(CumVolume_{ij}) + \beta_2 Hospital_i \times \log(CumVolume_{ij}) + \varepsilon_{ij} \tag{1}$$

where *i* is an index of hospitals, and *j* is an index of patients at hospital *i*. $Hospital_i$ represents a vector of dummy variables for the individual hospital sites, and $CumVolume_{ij}$ is the number of prior MICS operations performed at hospital *i* when patient *j* had his or her operation. We use the log of cumulative volume, following the conventional form of learning curves. No patient-specific control variables are included in the model because it is not sensible to predict the difficulty of the procedure undertaken as a function of patient severity of illness; further, this would risk circularity. Instead, we are specifically modeling the choice to use the MICS approach for procedures that present different levels of technical difficulty.

The coefficients in the model capture the effect of each variable on the log odds that a procedure would be in a higher category of difficulty. β_2 relates to the slope of learning curves for procedure difficulty. It is a vector that captures how much the rate of learning at a given hospital differs from the average rate for all hospitals.

Table 3 shows our results. The model provides a significant fit to the data, using the likelihood ratio chi-square. Maximum likelihood estimators for all hospital-specific coefficients are not shown. Here we indicate the statistical significance of the entire vector.

Insert Table 3 about here

As can be seen from the results for model 1 in Table 3, hospitals differ in the mean technical difficulty of the procedures they chose for MICS. In model 3, by adding an interaction term, *Hospitalxlog(CumVolume)*, we tested for differences in the slope of hospital-specific learning curves. We found that these slopes, corresponding to the *rates* at which hospitals increase or decrease technical difficulty with cumulative experience, differ from the 16-hospital average. They also differ from each other (Wald $\chi^2 = 38.3$, $p < 0.001$).

Efficiency. We compared the rates at which different hospitals reduced procedure time using the following model:

$$\begin{aligned}\log(ProcTime) = \alpha_0 + \beta_0 Difficulty_k + \beta_1 Hospital_i + \\ \beta_2 \log(CumVolume_{ij}) + \beta_3 Hospital_i \times \log(CumVolume_{ij}) + \varepsilon_{ij}\end{aligned} \tag{2}$$

where *i* is again an index of hospitals, *j* is an index of patients at hospital *i*, and *k* is an index of the four categories of technical difficulty. Because of the possibility that more technically difficult procedures take longer, we use the four-score procedure difficulty, $Difficulty_k$, described above, as a control variable for procedure type. We use the log of procedure time and of cumulative volume, following the conventional form of learning curves. The first coefficient, β_0, captures the mean effect of procedure difficulty on procedure time; β_1 is a vector of coefficients that capture how average procedure times differ across hospitals; β_2 captures the average effect of cumulative volume on procedure time; and β_3 is a vector of coefficients that capture how much the slope of the learning curve of a given hospital differs from the average learning curve slope for all hospitals.

Results from the regression for procedure time are shown in Table 4. Individual coefficients for hospital-specific estimates are not shown. Vectors for these parameters are significantly different from zero.

Insert Table 4 about here

Model 1 in Table 4 shows that, controlling for technical difficulty, hospitals differed in their mean procedure times. As expected, the statistical significance of the *Difficulty* coefficient confirms that technical difficulty is indeed a significant predictor of procedure time. Model 2 incorporates cumulative volume into the model. Here we find—again controlling for technical difficulty—that the effect of cumulative volume varies significantly across hospitals ($F = 11.04$, $p < 0.001$). With the addition of an interaction term, *Hospitalxlog(CumVolume)*, model 3 tests the extent to which hospitals differ in the *rates* at which they increase or decrease the efficiency of the MICS procedures with cumulative experience. Results show that the vector of coefficients corresponding to the interaction term is statistically significant. Further, by calculating an F statistic from the vector of coefficients for β_{3j}, we find significantly different learning curves across hospitals ($F = 3.3$, $p < 0.001$).

Trade-offs. To test our first hypothesis, that there is a tradeoff between the rates of learning in these two dimensions, we calculated the correlation between the slope coefficients for every hospital, derived from the models described above. The Spearman rank correlation coefficient was 0.55 ($p < 0.05$), indicating a *negative* correlation between the rates of learning for procedure time and technical difficulty.[6] The correlation is negative because faster learning in the dimension of procedure time is negative (time

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[6] We used Spearman's rank order correlation coefficient because it does not require assumptions about the distribution of the population from which the samples were taken and is particularly well suited to small samples and data for which the distribution is not necessarily normal (Saslow, 1982). Although Pearson's correlations can inflate the degree of association between two variables of this kind if there are a few extreme values, Spearman's coefficient solves this problem by correlating the rank order between two variables.

decreases) while faster learning in the dimension of technical difficulty is positive (difficulty increases). Therefore, as postulated in Hypothesis 1, those hospitals whose efficiency in performing MICS procedures became faster (negative procedure-time learning-curve slope) tended not to take on more technically difficult cases. Conversely, hospitals that increased the technical difficulty of their MICS cases (positive technical-difficulty learning-curve slope) tended not to get faster, even controlling for difficulty. This evidence is consistent with the proposition that there are tradeoffs in improvement trajectories at the hospital level, confirming Hypothesis 1.

Learning dimension and hospital goal orientation. To explore whether these patterns of learning might be related to hospital goal orientation, we divided the sample into two subgroups based on hospital type (AMC or CMC). To compare the rates of learning between these two groups, we re-estimated models (1) and (2), replacing the *Hospital* dummy variable with a new, binary dummy variable *Academic* to indicate whether the hospital was an AMC. These two new models tested for the difference between procedure-time learning-curve slopes and technical-difficulty learning-curve slopes at the academic and community hospitals in the sample.

Results of the difficulty model are shown in Table 5. The mean difficulty of MICS procedures performed at hospitals in the sample was higher at academic than at community hospitals. The mean procedure difficulty score at academic hospitals was 2.2 versus 1.8 ($p < 0.001$) at community hospitals. Further, the new model for technical difficulty indicated a significant difference between academic and community hospitals in the rate at which they increased the difficulty score of their procedures. As shown in model 1 in Table 5, the slope coefficient for the rate of increase in procedure difficulty was higher ($p < 0.01$) at academic centers than at community hospitals. That is, academic centers increased the difficulty of the procedures they performed using MICS at a greater rate than their community counterparts. Results were not sensitive to the decreasing quantity of data at higher cumulative volumes.

Insert Table 5 about here

Results of the model for procedure time are reported in Table 6 and show that the community hospitals in the sample were faster learners when it came to decreasing operative times, or efficiency. As can be seen in Table 6, the slope of the learning curve for academic hospitals was higher than that of community hospitals ($p < 0.05$). After controlling for technical difficulty, community hospitals were able to reduce their MICS procedure times faster than the academic hospitals in the sample. Again, these results were not sensitive to the decreasing data at higher cumulative volumes.

Insert Table 6 about here

The two models described above confirm Hypotheses 2a and 2b. They show that there were significant differences in the rates of learning between the academic and community hospitals in the sample. These groups of hospitals differed in the rates at which they improved efficiency and in the rates at which they increased application innovation through procedure difficulty. Additionally, community hospitals were faster learners on the dimension of efficiency; academic hospitals were faster learners on the dimension of application innovation.

DISCUSSION

Previous learning-curve studies have examined the *rate* of learning on a single dimension without attention to choices about the *direction* of learning. This paper analyzes longitudinal data from sixteen hospitals implementing a new technology to show that these organizations could learn along two distinct, potentially equally important, performance-improvement trajectories: efficiency (how to do a basic procedure more quickly) and application innovation (how to do more technically difficult procedures).

The present study focuses on these two key dimensions of learning and examines their impact on learning outcomes in surgery, where the tension between the two is particularly critical. Learning tradeoffs also are fundamental to settings outside the realm of healthcare, and are of particular relevance to the field of operations management and operations strategy. For example, most operations management scholars define operations strategy according to the relative weighting of four basic manufacturing capabilities: low cost, quality, flexibility, and delivery (Schmenner and Swink 1998; Ward, McCreery, Ritzman and Sharma, 1998). These scholars suggest that firms must make tradeoffs between these capabilities based on their relative importance to the organization (see, for instance, Boyer and Lewis, 2002). This well-established perspective in the operations strategy literature is known as the tradeoff model (see Skinner, 1969; 1974). In essence, organizations must choose a manufacturing priority first and then allocate their time and scarce resources accordingly (Hayes and Wheelwright, 1984; Garvin, 1993).

Overall, the group of hospitals studied became both more efficient and more adept at performing difficult cases as they accumulated experience. However, some hospitals moved more quickly along the efficiency improvement curve, while others moved more quickly along the application-innovation curve. A negative relationship between the slopes of these curves for the full sample supported the notion that learning on one dimension could inhibit learning on the other dimension, suggesting that it can be difficult to learn on more that one dimension simultaneously, most likely because each dimension requires an investment of effort and resources from a limited pool. We also found that academic and community hospitals have significantly different tendencies in their learning dimensions that correspond to differences in their organizational environments, strategies, and goal orientation. These findings support the idea that goal orientation at the organizational level shapes learning investments and outcomes.

This paper contributes to the learning-curve literature in two primary ways. First, it extends previous research by including a new dimension of learning, application innovation, and examining whether this dimension conflicts with learning on the efficiency dimension, the form of learning commonly investigated in the literature. Prior work has emphasized that learning must be managed; differences in managerial effectiveness might explain why some organizations learn faster than others. Our findings suggest a second fundamental explanation for learning-curve heterogeneity across organizations: some organizations may learn more slowly on a particular observed dimension of learning because they are investing in a different, potentially contradictory dimension of learning. In our study's setting, hospitals that focused on increasing the technical difficulty and innovativeness of their use of a new technology were less likely to increase efficiency as quickly as those that were focused on efficiency. Had the study only assessed efficiency, as most prior studies of learning curves have done, this explanation would have been overlooked.

Our second contribution is the identification of a factor that might contribute to the tradeoff between the two learning dimensions, namely an organization's goal orientation. Based on the organization type and learning climate, we made inferences about the organization's goal orientation and examined its impact on learning outcomes.

Theoretical implications

Previous work has shown that deliberate management of the activities and roles related to learning can improve an organization's rate of learning (Baloff, 1970; Dutton & Thomas, 1984). This paper suggests further that organizations working with a new technology or process may learn on more than one meaningful dimension, each of which may contribute to improving firm performance. Thus, the present study adds to the ongoing discussion of whether organizations can excel in all areas by providing evidence of the difficulty of such agenda. When resources are limited, organizations face a tradeoff between what should be learned; thus, managers may need first to select the most important dimension of performance along which to manage learning. Even those organizations that are held up as models of excellence in all areas (e.g., Toyota) might experience tensions during the adoption of new technologies or practices. For example, a close examination of Toyota's production system reveals that the company very carefully plans the sequence in which it implements improvements (Spear and Bowen, 1999). In a new Toyota plant, the first emphasis is on quality—that is, "how to get it right" (Mishina, 1995). Once both systems and employees excel on the dimension of quality, the plant works on improving efficiency.

Finally, when the plant reaches a certain efficiency threshold, it adds capability for producing application innovation, for example by increasing complexity and technical difficulty (Spear and Bowen, 1999). Our findings similarly suggest that organizations should explicitly identify the learning dimension of greatest strategic relevance to them and focus initially on this dimension.

As noted above, our study suggests a possible omission in previous learning-curve studies. If some users, when learning to use a new technology, use it "differently" rather than more efficiently, then cross-sectional comparisons of learning-curve slopes for efficiency would be likely to show heterogeneity, not due to less effective learning but due to the fact that learning occurred on another dimension. We thus raise the possibility that organizations identified as having slower rates of learning than others may be focusing on learning along a dimension other than that which was measured.

Limitations

The learning-curve analyses presented in this paper have some limitations. First, the analyses are sensitive to a hospital's initial starting point. Those hospitals that did not deliberately select less challenging operations for their early experiences with MICS may have been more likely to reduce procedure difficulty with experience. Second, although we found that academic hospitals were more likely to improve in difficulty and community hospitals more likely to improve in efficiency, we cannot tell if this was the result of the different capabilities, resources, or strategic choices of each group.

Finally, it is possible that our finding is specific to the healthcare context. Healthcare technologies often enter use before their full range of applications has been determined. For patients whose health problems have no well-agreed, single solution, healthcare is somewhat experimental. Practitioners continually test out new solutions to such health problems, particularly at academic hospitals. Thus, exploring the range of use of an innovation is a common practice in healthcare—hence, the need to learn along this dimension—but may not be the case in other industries. Given the specialized context of this study in cardiac surgery organizations, we believe that future research on learning trajectories and possible tradeoffs in other contexts is needed to assess the generalizability of these conclusions.

We suggest that additional research on the topics explored in this paper will provide valuable insights for both scholars and practitioners interested in learning. We hope that this paper stimulates further work that looks at learning during the acquisition of new technologic capabilities.

CONCLUSION

This paper argues that organizations face more than one way to improve when implementing a new technology, manufacturing a new product, or facing some other significant trigger of process change. We argued that learning on one dimension in such situations—efficiency or cost improvement being the most frequently studied in prior research—comes at the cost of learning on another dimension, such as innovation or difficulty. Data from sixteen hospitals implementing a new technology for cardiac surgery supported this core proposition. We also found that these organizations tended to improve along learning dimensions consistent with their goal orientation and strategic operational position.

Table 1
Technical Difficulty Scores for Cardiac Operations Using MICS

	1 Least Technical Difficulty	**2 Less Than Average Technical Difficulty**	**3 Greater Than Average Technical Difficulty**	**4 Greatest Technical Difficulty**	**Mean Standar-dized Score**
Type of Procedure:					
ASD	•				-1.75
CABG without proximals	•				-1.10
AV Replacement		•			-0.65
MV Replacement		•			-0.42
Valve/ASD Combination		•			-0.20
CABG with proximals		•			-0.01
Redo Valve			•		0.21
MV Repair			•		0.44
Redo CABG				•	0.71
Double or Triple Valve				•	0.89
CABG/Valve Combination				•	0.89
Maze				•	1.30

CABG = coronary artery bypass graft; ASD = atrial septal defect repair; MV = mitral valve; AV = aortic valve; Redo = repeated operation; Maze = focal destruction of electrical impulse conducting cells within the heart.

Table 2 Descriptions of Cardiac Procedures		
Procedure	**Description**	**Notes**
ASD	Closure of a small hole between the right and left atria.	Although it is within the heart, the ASD is easy to reach and closure is usually achieved with a few simple stitches.
CABG without proximals	Bypassing diseased coronary arteries with another artery taken from the inside of the chest wall.	Procedure is undertaken entirely on the exterior of the heart, usually its front. Artery is attached directly to the coronary artery with precision suturing.
AV Replacement	Aortic valve replaced with a prosthesis.	Replacing a valve through a small opening is harder than suturing. The aortic valve is close to the front surface of the heart.
MV Replacement	Mitral valve replaced with a prosthesis.	Mitral valve deeper within the heart.
Valve/ASD Combination	Replace the aortic or mitral valve and close a small hole between the right and left atria.	Relatively simple, additional procedure performed with valve replacement.
CABG with proximals	Bypassing diseased coronary arteries with a piece of vein, taken from the leg.	Vein must be attached at both ends, to the proximal aorta and the coronary artery. Often requires working on the back of the heart which is difficult through a small opening.
Redo Valve	Removal of a failing valve prosthesis and replacement.	Repeat operations are substantially complicated by the presence of scar tissue left over from the preceding operation.
MV Repair	Repair of diseased mitral valve	Valve repair is more difficult than replacement. It requires a more surgical judgment and decisions and also very delicate stitching in a restricted space.
Redo CABG	Bypassing diseased coronary bypasses usually with another vein taken from the leg.	Repeat operations are substantially complicated by the presence of scar tissue left over from the preceding operation.
Double or Triple Valve	Replacing two or three of the mitral, aortic, and tricuspid valves concurrently.	Combination procedures are typically more difficult.
CABG/Valve Combination	Replacing one of the mitral, aortic, or tricuspid valves concurrent with a coronary artery bypass.	Requires surgery on the inside and exterior of the heart.
Maze	Series of cuts made in the wall of the atrium to interrupt abnormal pathways of electrical conduction.	Cuts made in the internal or external wall of the atrium. Extensive manipulation of delicate tissues required. Understanding of the key elements of this procedure is still evolving.

Table 3
Ordinal Logistic Regression Models Describing the Probability that Procedures with Higher Complexity are Done Using MICS

	null	*Model 1*	*Model 2*	*Model 3*
Hospital		***	***	*
log(CumVolume)			0.04	0.26
Hospital□log(CumVolume)				***
-2 log likelihood	1708.5	1533.4	1533.1	1487.1
χ^2		175.1***	175.4***	221.4***
N		679	679	679

*** p < 0.001
** p < 0.01
* p < 0.05

Table 4
Estimated Coefficients for Procedure Time Models (standard error in parentheses)

	Model 1	*Model 2*	*Model 3*
Intercept	6.14*** (0.074)	6.24*** (0.079)	6.25*** (0.167)
Difficulty	***	***	***
Hospital	***	***	***
log(CumVolume)		-0.041*** (0.012)	-0.048 (0.062)
Hospital×log(CumVolume)			***
N	679	679	679
F statistic	19.14***	18.99***	12.6***
R^2	0.34	0.35	0.40

*** p < 0.001
** p < 0.01
* p < 0.05

Table 5
Ordinal Logistic Regression Models Describing the Probability that Procedures with Higher Complexity are Done Using MICS, Comparing Academic to Community Hospitals (standard error in parentheses)

	null	*Model 1*
Academic		-0.17 (0.23)
log(CumVolume)		0.070 (0.07)
Academic×log(CumVolume)		0.191** (0.73)
-2 log likelihood	1708.5	1665.6
χ^2		42.9***
N		679

*** p < 0.001, ** p < 0.01, * p < 0.05

Table 6
Estimated Coefficients for Procedure Time Models, Comparing Academic to Community Hospitals (standard error in parentheses)

Intercept	5.61*** (0.063)
Difficulty	0.078*** (0.013)
Academic	0.087 (0.078)
log(CumVolume)	-0.048** (0.016)
Academic×log(CumVolume)	0.041* (0.025)
N	679
F statistic	41.49***
R^2	0.20

*** p < 0.001, ** p < 0.01, * p < 0.05

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