Learning how and learning what: Effects of tacit and codified knowledge on performance improvement following technology adoption

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Abstract

This paper examines effects of tacit and codified knowledge on performance improvement as organizations gain experience with a new technology. We draw from knowledge management and learning curve research to predict improvement rate heterogeneity across organizations. We first note that the same technology can present opportunities for improvement along more than one dimension, such as efficiency and breadth of use. We compare improvement for two dimensions: one in which the acquisition of codified knowledge leads to improvement and another in which improvement requires tacit knowledge. We hypothesize that improvement rates across organizations will be more heterogeneous for dimensions of performance that rely on tacit knowledge than for those that rely on codified knowledge (H1), and that group membership stability predicts improvement rates for dimensions relying on tacit knowledge (H2). We further hypothesize that when performance relies on codified knowledge, later adopters should improve more quickly than earlier adopters (H3). All three hypotheses are supported in a study of 15 hospitals learning to use a new surgical technology. Implications for theory and practice are discussed.

Introduction

New technologies promise many advantages for organizations, such as improved operational efficiency or an ability to provide new services for customers. Yet the technology adoption process presents barriers to the realization of these advantages. Decision-makers first must become aware of and then commit to trying a new technology, and second users must understand it well enough to put it to productive use. Initial performance using newly acquired technology often may be inferior to existing processes, such that improvement is needed to ensure successful implementation. Technology implementation thus can be seen as an organizational learning process, in which the rate of performance improvement is an important determinant of user acceptance and implementation success. Neither organizational managers nor users will tolerate inferior performance for long. Organizational differences in rates of learning thus have both theoretical and managerial significance.

Researchers in both operations management and health care have found that performance on a new technology or procedure improves with increased experience (e.g., Ramsay et al., 2000). The implication of the so-called “learning curve” or experience curve is that “practice makes perfect” and organizations "learn by doing" (Pisano, 1996). Yet, some studies show homogeneous learning curves across sites (e.g., Wright, 1936; Baloff, 1970) and others show heterogeneity across sites (e.g., Dutton and Thomas, 1984; Argote, 1990; Hayes and Clark, 1985). These different results may be due to differences in the extent of social and organizational changes provoked by a new technology or practice, which give rise to differences in user acceptance and behavior (Barley, 1986; Orlikowski, 1993).

Using a new technology is difficult when the knowledge needed is “sticky” or embedded in an organizational context (von Hippel, 1994; Szulanski, 2000). Some technologies automatically convey the knowledge needed for their use when the physical object is transferred, but others require more subtle know-how to accompany physical transfer before a technology can be used easily or appropriately (Attewell, 1992). To realize performance improvements, existing routines may need to be revised or discarded to make room for new routines (Edmondson, Bohmer and Pisano, 2001).

Although the technology literature has noted that implementation is difficult when organizational routines are disrupted or when knowledge is sticky, effects of knowledge type on performance improvement following technology adoption have not been examined. This paper seeks to address this gap. Our aim is to draw from theories of knowledge management and technology implementation to propose implications for performance improvement curves in the aftermath of new technology adoption. In so doing, we contribute to both literatures by suggesting that knowledge type is a critical factor in new technology performance and implementation success.

To examine challenges posed by grappling with new technical and social knowledge in an organizational context, we studied a radical new surgical technology adopted in many United States hospitals starting in late 1997. Clearly, clinical effectiveness had to be demonstrated to gain user acceptance. To ensure ultimate implementation success in hospitals, however, performance improvement in both efficiency and breadth of use was necessary. For breadth of use, performance improvement utilized codified knowledge. For efficiency, tacit knowledge was required to improve. We compare rates of improvement for these dimensions and argue that the nature of the knowledge underlying performance on each affected whether rates of improvement across hospitals are heterogeneous or homogenous.

The Role of Knowledge in Technology Performance Improvement

Although adoption of a radical new technology can be disruptive, managers are willing to tolerate a period of adjustment before advantages are realized. Without demonstrated improvement, however, organizations are likely to revert to former practices or to a renewed search for alternatives. For example, physicians and hospital administrators will try out new technologies and techniques, track results for a period of time, and then evaluate whether the innovation provides tangible patient-outcome or cost benefits. Recognition of the need to allow time to come down the learning curve is an integral part of evaluating an innovation in health care (Pisano, Bohmer and Edmondson, 2001).

Clearly, at the point of exposure to a new technology, users lack full knowledge of how to use it to perform the tasks for which it is designed. They must therefore obtain or develop the knowledge needed to achieve proficiency and produce organizational benefits (Lapré, Mukerhee and Van Wassenhove, 2001). We argue that the degree to which the necessary knowledge is readily accessible or easy to develop will affect performance improvement rates heterogeneity.

The nature of knowledge

Research on the nature of knowledge articulates distinctions related to the degree to which knowledge is tacit or codified (Polyani, 1966; Nelson and Winter 1982) and to whether it takes the form of knowledge about the state of the world ("know what") or competence knowledge ("know-how") (Lundvall and Johnson, 1994). Codified knowledge refers to knowledge that is transmittable in formal, symbolic language, whereas tacit knowledge is hard to articulate and acquired through experience (Polanyi). Tacit knowledge is often rooted in action or context specific (Nonaka, 1994).

Tacit and codified knowledge exist along a spectrum, not as mutually exclusive categories. At one extreme, knowledge is predominantly codified; at the other extreme, knowledge is predominantly tacit (Polanyi, 1966). Tacit knowledge is characterized by the absence of an agreed upon language among an epistemic group, but may not be inherently or permanently tacit. For some knowledge, especially in medical practice, the difference between tacit and codified is temporal; much codified knowledge in medicine today was tacit in the past (e.g., Vosburgh and Newbower, 2002).

In general, social knowledge is more likely to remain tacit than technical knowledge because many aspects of behavior and coordination in organizations are not easily described in words or symbols. Social knowledge in organizations includes enacting reciprocal coordination (Thompson, 1967); this mutual adjustment is rarely reproduced the same way twice and thus eludes precise codification. Although, some collective routines in organizations are highly predictable and codified, as in pre-flight checklists in the cockpit (Gersick and Hackman, 1990), others require improvisation (Orlikowski, 2000). Social knowledge encompasses intuitive assessments of whom to trust (difficult to codify) (Edmondson, 2002) and awareness of who knows what (easier to codify) (Moreland, 1999).

Knowledge type and ease of transfer. In the management literature, a central implication of conceptual distinctions about knowledge relates to the ease of knowledge transfer across individuals, groups, or organizations (Teece, 1977). When knowledge is codified, transfer across individuals involves transmission of documents or manuals. For codified *know-what*, transfer is complete with the acquisition of such materials; for codified *know-how* instructions also may require practice or discussion to capably execute prescribed tasks in a new setting, but transmission is still relatively straightforward. When knowledge is easy to transmit, in the form of journal articles or company documentation, users are able to acquire it quickly and likely to apply it similarly.

In contrast, when knowledge is tacit, it is often the case that proximity and interpersonal interaction are necessary for its transmission (Davenport and Prusak, 1998; Hansen, 1999; Sole and Edmondson, 2002; Szulanski, 1996). Hansen (1999) compared the transfer of complex knowledge (defined as tacit and context-dependent) to the transfer of simple knowledge (defined as explicit and context-independent) and found that relatively close relationships and personal contact were important for the former but not for the latter. Mechanisms for the transfer of tacit knowledge include mentorship, apprenticeship, and repeated practice over a period of time (Nonaka and Takeuchi, 1995; Spender, 1996). Similarly, in health care, medical practices that are dependent on subtle skills and judgment (tacit know-how) demonstrate substantial geographic heterogeneity (Wennberg, 1977). When knowledge is difficult to transmit – requiring physical proximity to see, understand, and practice the knowledge before it can be put to use – geographic variation in how knowledge is applied is likely.

The challenge of collective know-how. Much of the knowledge literature concerns knowledge used by individuals. Some researchers note that knowledge can be embedded in groups, or communities of practice (Brown and Duguid, 1991). When knowledge takes the form of collective *know-how*, or tasks executed by groups that require reciprocal coordination, the transmission problem is complex. The performance improvement path of a group learning a new task or set of tasks is likely to be heterogeneous and hence difficult to predict, in part because the exact combination of technical and social knowledge needed for the task is hard to specify. Further, if know-how is collective, the rate of performance is likely to be influenced by group membership stability (Moreland, 1999).

Knowledge underlying performance improvement

In this section, we consider differences in the nature of knowledge involved in distinct dimensions of improvement following an organization's adoption of a new technology. We then build on these arguments to suggest implications for rates of performance improvement across multiple organizations adopting the same technology.

Tacit versus codified. Some dimensions of technology performance rely on tacit knowledge. For example, when new technology requires a new way to coordinate actions across individuals, it is difficult to describe the knowledge needed for improvement. This *know-how* is rooted in action, improvisational (Orlikowski, 1993). Researchers thus emphasize the contextually embedded nature of knowledge about technology use in organizations (Orlikowski, 2000; von Hippel and Tyre, 1995). Technological knowledge developed through experimentation thus leads to performance improvement in some plants but not others, in part due to differences in management and interdepartmental relationships (Lapré, Mukerhee, and Van Wassenhove, 2001).

Tacit knowledge for using a new technology may include developing trust and awareness of how to respond to subtle cues from glances, body language, and other forms of nonverbal communication (Edmondson, Bohmer and Pisano, 2001). Learning new routines needed for a new technology necessarily means unlearning old routines (Hedberg, 1981), which are typically taken-for-granted and tacit, albeit potentially subject to codification by a careful observer (e.g, Barley, 1986). The taken-for-granted nature of existing practices makes unlearning them difficult (Gersick and Hackman, 1990).

Other dimensions of technology performance improvement rely on codified knowledge. For example, if users can be told what settings to use for optimal performance with certain equipment, they can put this knowledge to immediate use. Because codified knowledge can be transferred easily, improvement that stems from codified knowledge may follow a more predictable, homogeneous path than improvement that stems from tacit knowledge. We thus argue that similar organizations will show homogeneity in improvement rates for dimensions of performance that rely on codified knowledge, and build on this below to formulate hypothesis 1.

Transfer versus creation. The transferability of codified knowledge suggests that users, despite geographical distance, can be working with the same essential knowledge and can put it to use for improvement in similar ways. Codified knowledge can be found in technology suppliers' manuals, in technical literature (medical journals, for example), and in other users' reports of their experiences. In some cases, early users develop new knowledge that facilitates performance improvement and is easily codified for subsequent users to acquire and use without having to develop the knowledge themselves (Szulanski, 2000).

In contrast, when knowledge to improve performance cannot be obtained easily, users have to develop it themselves, through informal trial and error or formal problem solving. Sometimes performance improvement requires group practice, enabled by talking out loud about what is working and what is not. In these collective learning processes, groups develop "transactive memory" in which members have knowledge about who knows what, increasing the risk of group member substitution (Moreland, 1999).

Research on team and organizational learning has demonstrated substantial variance in experimentation or trial and error learning processes across groups (Edmondson, 1999; 2002) and organizations. The collective learning processes through which new know-how and tacit knowledge are developed in organizations are fraught with uncertainty and difficult to reproduce (Orlikowski, 1993). Stable membership thus promotes rapid performance improvement when learning a new group task (Moreland, 1999). Knowledge about how to execute interdependent tasks is tacit, action-based and difficult to transfer to new group members. Just as interpersonally intense forms of communication are needed to transfer tacit knowledge more generally, group stability is likely to aid performance improvement for new technology that relies on tacit knowledge.

Hypotheses. The above argument leads us to predict that multiple organizations simultaneously learning to use a new technology will show heterogeneity in rates of improvement for dimensions of performance that rely on tacit knowledge and homogeneity for dimensions of performance that rely on codified knowledge. Improvement rate heterogeneity is an informative dependent variable when studying a group of organizations adopting a new technology (e.g., Dutton and Thomas, 1984). Heterogeneity, or variance in rates of improvement, indicates that sites differ in how much they gain from similar levels of cumulative experience. Given the difficulty of transferring and using tacit knowledge described above, we thus posit a first hypothesis.

> Hypothesis 1 (H1): Variance in improvement rates across organizations will be greater for aspects of performance that rely on tacit knowledge than for aspects of performance that rely on codified knowledge.

Next, given the advantages of proximity and mutual interaction and adjustment for technological performance that relies on tacit knowledge, membership stability in a group of interdependent users is likely to predict rates of performance improvement. This hypothesis presents an opportunity to test, in a field setting, previous laboratory research on transactive memory in groups.

> Hypothesis 2 (H2): Group membership stability will predict improvement rates for dimensions of performance that rely on tacit knowledge.

Finally, we argue that when knowledge needed for performance improvement is codified, later adopters can benefit from the experience of earlier adopters because the knowledge developed by the pioneers can be readily transferred to those starting later, helping them to move along the learning curve more quickly. In contrast, for knowledge that is non-codified, late adopters are not likely to have a performance improvement advantage. Instead, they must start from scratch, learn through their own trial and reflection process, with starting points and early rates of performance improvement that are similar to those of earlier adopters.

> Hypothesis 3 (H3): When performance relies on codified knowledge, later adopters should improve performance more quickly than earlier adopters.

Implementing New Technology in Health Care Delivery

In health care, many new technologies are adopted quickly. Knowledge about a new technology's advantages relative to an existing approach diffuses readily among the community of users in the health care industry, in part due to the powerful role of opinion leaders, leading to widespread adoption and use of preferred approaches (Soumerai and Avorn, 1986; Greer, 1988). Another factor is that some aspects of medical knowledge are well-codified; many medical or surgical procedures are thus easy to transfer across sites, with cumulative experience proving an accurate predictor of performance for adopting practitioners (Kopacz, Neal, and Pollock, 1996). The more an individual does of a given, well-specified procedure, the better he or she becomes.

Operational or process knowledge in health care, in contrast, is generally not well codified and, indeed, geographic variation in operational process is well documented (O'Connor, et al., 1999). Unlike processes in most manufacturing environments, coordination tends to be worked out relationally and interpersonally, in action (Gittell, 2002). Introducing process changes thus tends to be fraught with uncertainty and uneven success (Westphal, Gulati and Shortell, 1997). Therefore, when performance using a new technique rests upon codified medical knowledge, we argue that improvement rates will be predictable and similar across practitioners. When the knowledge is largely tacit and operational, or related to how to coordinate tasks across disciplines (as in the care of diabetes patients whose treatment involves multiple specialties loosely coordinated over time), performance improvement is likely to be difficult to predict and to vary across practitioners. These predictions apply hypothesis 1 to the health care context.

To test our hypotheses, we use data from implementation a particular new technology referred to by the pseudonym, Minimally Invasive Cardiac Surgery (MICS). Introduced in the U.S. market in 1996 by a company we call Minimally Invasive Surgical Associates (MISA), the technology was an innovation for coronary artery bypass graft (CABG) surgery. MICS allowed surgeons and operating room (OR) teams to conduct the CABG procedure through a set of small incisions instead of the invasive practice of splitting open the patient's breastbone. The means of accessing a patient's cardiac vessels for surgical repair thus was different, but the repair itself was essentially the same. (See the appendix for more detail.) Because splitting open the chest creates a large and slow healing wound, MICS promised patient benefits in the form of shorter recovery time and more rapid return to normal activities. These benefits could offer a competitive advantage for hospitals in terms of attracting patients who wished to have this innovative, less invasive experience; it also promised the opportunity to generate cost savings through reduced length of stay in the hospital.

The advantages for individual patients could be realized almost immediately, because surgeons took the extra time they needed to conduct each operation safely and to achieve a quality of cardiac repair equivalent to the standard operation. For early patients, achieving equivalent surgical outcomes involved significantly more time in the operating room – itself an expensive resource – in addition to the extra time of an entire OR team to achieve what was essentially an equivalent surgical outcome to conventional CABG. Therefore, although patients were only at minimal added risk when subject to initial uses of the innovation, the hospitals took on considerable extra expense and constraints in the short term.

Improving efficiency. Cost advantages could be realized only after substantial performance improvement in procedure time. With increasing experience, operating room teams indeed could conduct the operation more quickly by speeding up coordination of the different activities through which patients were prepared for the actual stitching of grafts. To do this, new team routines to support the new technology had to be developed by each team through trial, reflection, repetition, and practice (Edmondson et al, 2001). Knowledge of how to communicate, build trust, and become more efficient in reciprocal coordination cannot easily be communicated from external sources such as other teams, medical publications, or vendor sales representatives. Given this context, efficiency improvement for MICS clearly relied on tacit knowledge.

Improving breadth of use. A second critical dimension of improvement was expanding MICS use from more simple to more complex procedures. In advance of surgery, cardiologists or cardiac surgeons diagnose patients as needing repair of one or more cardiac vessels. As surgeons became more experienced with and comfortable using the new technology, they began to apply it to patients with a greater number of coronary vessels needing repair (called *grafts*). Thus, initial operations might be limited to one or two grafts, but later operations might include quadruple and quintuple bypass—up to a maximum of six grafts. Increasing the number of grafts for MICS expanded the number of potential patient referrals, which was important for the ongoing viability of the technology in the hospital. All surgeons studied were experienced with multiple grafts, but initially had not conducted multiple grafts using MICS. The variable, grafts, thus provides an index of performance capturing breadth of use.

Patients needing more grafts presented greater technical challenge for the surgeon but did not affect the team coordination process. Performance improvement on breadth of use thus involved using existing competencies (the surgeon already knows how to do multiple grafts, routinely doing this with the old technology) in a new setting (within the confines of a smaller incision). This type of improvement was thus possible as soon as surgeons became aware that multiple vessels could be grafted using the small incision with no harm to the patient and with minimal changes in stitching technique. They could discover this knowledge themselves, or learn it from others' reports at conferences or in the literature. In short, the knowledge required to increase number of vessels grafted was codified and consisted of two components: knowledge that a given target (number of grafts) was both possible and safe, and knowledge of simple pointers on technique that facilitated access to the additional vessels in a smaller surgical field.

Although patient outcomes were a critically important index of performance, this variable was unlikely to vary significantly across hospitals because surgeons had many ways to ensure the best possible patient outcomes for a given patient. In the case of MICS, surgeons either took additional time to ensure quality of surgical repairs, as noted above, or remained conservative in terms of patient conditions they were willing to take on with MICS. Therefore, performance improved over time in efficiency and breadth of application, but tended to remain stable (and uniformly excellent) in terms of patient outcomes as measured by mortality and complication rates. We report on all three dimensions of performance below.

Method

Data sources

We obtained data on all coronary artery bypass graft (CABG) operations conducted with the MICS technology in cardiac surgical units in 16 hospitals, during the initial period of the new technology's use in the US. These data were collected by each hospital and provided to MISA. We asked MISA to identify a subset of the 150 adopting hospitals in the US that would be representative of their customer base (i.e., would include academic and community hospitals, differences in size, location, and resources) and would be willing to be studied. For convenience, we over-sampled hospitals in the region near our university; nonetheless, the sample of 16 was roughly representative of the population of hospitals that had adopted MICS. Although the data set, compiled for clinical study purposes, had gaps, we were able to obtain missing data directly from the hospitals.

For each institution, we assembled a case series that spanned the first CABG performed with the new technology at that hospital through the last performed as of October 1998. We eliminated one of the hospitals in the data set because its surgical team performed only 2 CABG procedures. Of the remaining 15 hospitals, nine were academic medical centers ("teaching hospitals") and six were non-academic ("community") hospitals; all were non-profit entities. Total annual cardiac surgery volumes ranged from 400-3500 cases per year; average annual volume was 1400. Most hospitals had extensive experience adopting new cardiac surgery innovations, and all surgeons had substantial experience with conventional cardiac surgery before exposure to MICS.

The average number of CABG procedures performed at each of the 15 sites was 20.7 (with a range of 5 to 48). Table 1 presents descriptive statistics for the 15 hospitals. The number of cases varied due to differences in the exact time of adoption (influencing number of cases performed by October 1998) and surgeon choice about whether and when to use the new technology. In all hospitals, a single surgeon or pair of surgeons performed all MICS cases, such that surgeon and hospital were confounded. The resulting data set included standard controls for studying cardiac surgery – including patient characteristics (e.g., age, sex, height and weight), health status prior to the operation (e.g., presence of diabetes or chronic lung disease, assessed by a standard risk variable called the "Higgins" score), and type and number of grafts; it also included operation date, the ordinal sequence a case represented for the hospital (first case, second case, etc.), times required to complete various phases of the operation, and patient outcomes including the presence of surgical complications and mortality.

Table 1 about here

Preparatory analyses

We checked for differences across sites in patient outcomes by comparing rates of surgical complication. One of the authors, a physician, combed through all of the surgical data for evidence of complications and found that they were extremely rare and showed no differences across sites. Simultaneously, other researchers reported that mortality rates for MICS were approximately 1-1.5% or slightly lower than the 2-2.5% for standard CABG (Galloway, et al, 1999). This finding does not necessarily indicate that patients were better off with MICS because surgeons may have been conservative in their use of MICS, applying it to less sick patients. Thus, patients did well and surgical outcomes did not differ across sites, allowing the other two dimensions of performance – efficiency and breadth of use – to be meaningfully compared without controlling for patient outcomes.

We analyzed the two dimensions of performance improvement as follows. Efficiency improvement was measured by reduction in time required to perform the operation (procedure time), adjusted for individual case complexity, as described below. The second measure of performance improvement is the number of grafts undertaken in successive CABG procedure. This captures increase in breadth of use of the new technology. As noted above, surgeons in this sample (as experienced cardiac surgeons) were already skilled at performing multiple grafts in conventional CABG.

We created a measure of adoption timing, separating the sites in our sample into earlier and later adopters. As shown in Table 2, all 15 hospitals performed their first minimally invasive CABG procedure during the first 17 months of the 25-month study. Nine of the sites, Hospitals A through I, started during the first seven months, right after FDA approval. The other group, six hospitals (J through O), started more than nine months after Hospital A. There was a larger gap between I and J (83 days) than between any other two consecutive hospitals (average 26.4 days, excluding the last adopter, which started more than a year after its predecessor). We designated the first group “early adopters” and second "late adopters."

Tables 2 and 3 about here

Other measures

To assess team membership stability, we interviewed operating room team members participating in MICS implementation at the participating hospitals, in all sites including at least one member of each of the four disciplines (surgery, anesthesia, nursing, and perfusion), often interviewing two from each discipline. We remained blind to hospital identity in the clinical data set throughout site visits and interviews. The responses of multiple informants from each site were used to create one hospital-level measure of team stability.

We asked two related questions: we first probed team members for an explicit or implicit strategy related to team stability or to the addition of new team members and, second, asked how many operations the original team that went to training conducted together before changing team composition. We coded informants' responses as representing one of four categories: (4) deliberately kept the team stable for at least 10-15 cases before adding or substituting additional team members, (3) kept the team stable with staged inclusion during early cases, (2) allowed immediate inclusion of new members, and (1) allowed immediate substitution of new members. Two to four of the authors were present at each interview, and in no case did we disagree on the coding of an informant's response. Table 3 shows summary statistics and correlations for all variables.

The interviews also allowed us to assess the nature of the knowledge needed for improving efficiency and breadth of use. These data inform the description of the technology and learning challenge provided above. Finally, in the discussion section, we again draw from the qualitative data to shed light on the quantitative analyses.

Results

Comparing models for efficiency improvement and breadth of use

The first model isolated effects of cumulative volume on total CABG procedure time, controlling for factors expected to have an effect on time in the medical literature. Its form is,

$$\begin{aligned}\ln(\text{ProcTime}_{ij}) = \beta_0 + \beta_1 \text{Grafts}_{ij} + \beta_2 \text{Hospital}_i + \beta_3 \ln(\text{CumVolume}_{ij}) + \\ \beta_4 \text{Hospital}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \tag{1}$$

where i is an index of hospitals and j is an index of patients at hospital i. Variables are:

ProcTime_{ij}	Time in minutes required to perform the MICS CABG on the j^{th} patient and hospital i.
Grafts_{ij}	A control variable indicating the total number of sites where veins or arteries were stitched to the cardiac arteries being bypassed on the j^{th} patient at hospital i.
Hospital_j	A vector of i dummy variables.
CumVolume_{ij}	The number of prior cases of the MICS CABG procedure performed at hospital i when patient j had his or her operation.

The coefficients in this model can be interpreted as follows. β_2 is a vector of coefficients that captures how the average CABG procedure times vary by hospital. β_3 represents the average impact of case volume experience on procedure time across all institutions and is expected to have a negative sign because procedure times generally fall with experience, holding other variables constant. β_4 is a vector of coefficients that captures the extent to which the slope of the performance improvement curve for a given institution varies from the average. As a first step in testing H1, that performance improvement that relies on tacit knowledge will be more heterogeneous than performance improvement that relies on codified knowledge, we checked the F-statistic to find that individual coefficients for all hospital-specific estimates were significantly different from the average. The Higgins score (shown in Table 3) was originally included in the model but because its coefficient was insignificant and R-squared was unchanged by its inclusion, it was not included in the final specification.

As shown in Table 4, Model 1 shows that number of grafts and cumulative volume predict procedure time; Model 2 shows that hospitals differ in mean procedure times, and Model 3 demonstrates that hospitals differ significantly both in initial procedure time, estimated by the intercept, and in the rate at which procedure time improves with cumulative experience, estimated by the interaction term.

Table 4 about here

The regression model of the number of grafts takes the form,

$$\begin{aligned}\text{Grafts}_{ij} = \beta_0 + \beta_1 \text{Hospital}_i + \beta_2 \ln(\text{CumVolume}_{ij}) + \\ \beta_3 \text{Hospital}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \qquad (2)$$

where *i* is again an index of hospitals, *j* is an index of patients at hospital *i*, and variables are as described above. No additional control variables were included because our intention is to model the isolated effect of cumulative volume on grafts using MICS; unlike procedure time, graft is a surgeon choice, which is not influenced by the control variables used above.

The coefficients in this model can be interpreted as follows. β_1 is a vector of coefficients that captures how the number of grafts varies across institutions. β_2 captures the average impact of case volume experience on graft number across all institutions, and is expected to have a positive sign because surgeons are likely to increase grafts with experience. β_3 is a vector of the coefficient that captures the extent to which the slope of graft increase for a given institution varies from the average; consistent with H1, slopes are homogenous across sites, in contrast with those in Model 3 for efficiency improvement.

As shown in Table 5, Model 2 shows that hospitals do differ in their average number of grafts—such that some sites tend in general to have more difficult cases and patients with worse disease than other sites—and that case volume is a strong predictor of an increase in grafts. This means that doing more cases tends to push surgeons toward using MICS toward on patients with a larger number of grafts. Thus, with practice, surgeons tended to improve on breadth of use in a way consistent with the general notion of a learning curve. Model 3 shows homogeneity across sites in rate of graft increase.

Table 5 about here

Models for team stability

To test H2, we estimated the effect of team stability on rates of performance improvement for both outcome measures. For procedure time, we added team stability to the first model estimating procedure time, equation (1) above, to estimate the rate of performance improvement in procedure time for different levels of team stability, controlling for number of grafts:

$$\begin{aligned}\ln(\text{ProcTime}_{ij}) = \beta_0 + \beta_1\text{Grafts}_{ij} + \beta_2\text{TeamStability}_i + \beta_3\ln(\text{CumVolume}_{ij}) + \\ \beta_4\text{TeamStability}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \quad (3)$$

The new variables is:

TeamStability_i a four-point measure of OR team stability at hospital *i*.

The coefficients in this model can be interpreted as follows. β_2 estimates the difference between the average CABG procedure times at hospitals with different levels of team stability. β_4 captures the extent to which the slopes of the performance improvement curves for hospitals with different levels of team stability.

Model 6 in Table 4 shows that team stability is a significant predictor of the rate at which hospitals improved procedure time. The negative coefficient supports H2, that greater team stability is associated with lower procedure times, controlling for experience and the number of grafts. All predictor variables in this model are significant. (Model 5 shows that team stability negatively predicts average procedure time in hospitals, as expected, because hospitals improving faster should have lower average times for the overall time period).

As a comparison, we assessed the effect of team stability on breadth of use; we thus estimated number of grafts as a function of team stability and cumulative case volume:

$$\begin{aligned}\text{Grafts}_{ij} = \beta_0 + \beta_1\text{TeamStability}_i + \beta_2 \ln(\text{CumVolume}_{ij}) + \\ \beta_3\text{TeamStability}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \tag{4}$$

Results show that, unlike equation (5) above, which modeled procedure time, team stability was not a significant predictor of the rate of improvement in number of grafts. As shown in Table 5, Models 4 and 5, team stability does not predict either the average number of grafts at hospitals, nor the rate at which operating room teams increase the number of grafts in CABG procedures.

Models for late and early adopters

To test H3, we compared two groups of hospitals—early adopters and late adopters—for improvement in breadth of use. As a comparison, we also examine effect of late adoption on efficiency improvement. For procedure time, our model was identical to the model estimating procedure time for different hospitals, above, but using adoption group as the basis for comparison:

$$\begin{aligned}\ln(\text{ProcTime}_{ij}) = \beta_0 + \beta_1\text{Grafts}_{ij} + \beta_2\text{LateAdopter}_i + \beta_3 \ln(\text{CumVolume}_{ij}) + \\ \beta_4\text{LateAdopter}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \tag{5}$$

The new variables is:

LateAdopter_i	Dummy variable indicating whether hospital *i* was a late adopter of the technology.

The coefficients in this model can be interpreted as follows. β_2 estimates the difference between the average CABG procedure times of the two groups. β_3 estimates the average impact of case volume experience on procedure time across both groups. β_4 captures the extent to which the slopes of the performance improvement curves for each group differ.

The regression results, in Table 4, Model 8, do not identify a difference for early and late adopters in the rate at which they improve procedure time, estimated by β_4. The model shows that the estimated difference in the slopes of the procedure time improvement curves is not significant.

The estimated intercepts for the two performance improvement curves—the sum of estimated average procedure times for each group and the intercept for the entire set—also do not differ significantly.

The model for the number of grafts performed by early and late adopters takes the form,

$$\begin{aligned}\text{Grafts}_{ij} = \beta_0 + \beta_1 \text{LateAdopter}_i + \beta_2 \ln(\text{CumVolume}_{ij}) + \\ \beta_3 \text{LateAdopter}_i * \ln(\text{CumVolume}_{ij}) + \varepsilon_{ij}\end{aligned} \tag{6}$$

In contrast to the procedure time regression results, Model 7 in Table 5 shows differences for number of grafts, based on adoption timing. The estimated difference between the intercepts—the number of grafts for each group's first procedure—is 1.4, $p<0.001$. The slopes of performance improvement curves for each group also differ significantly ($p<0.05$). This finding supports the argument that the almost three months lag time separating the two groups allowed the knowledge that earlier adopters were using MICS for multiple grafts to spread and be put to use by later adopters. Conversely, later adoption did not accelerate procedure time reduction with its dependence on tacit knowledge.

Discussion

Data from multiple hospitals learning to use a new technology showed, first and most important, that patients did not suffer unduly when hospitals took on this implementation challenge. As noted above, complication and mortality rates were no higher than the very low rates found in conventional cardiac surgery, nor were there differences across sites in either outcome. This homogeneity of surgical outcomes could be attributed to surgeons' ability to sacrifice other dimensions of performance – notably efficiency and breadth of use – to ensure patient well-being. Second, we found support for all three hypotheses. Organizational performance improvement in efficiency and breadth of use was indeed related to the type of knowledge involved, as described below.

Knowledge type and performance improvement

Data analyses supported the predicted relationship between knowledge type and performance improvement heterogeneity during implementation of a new technology. Consistent with H1, hospitals show far greater heterogeneity of improvement for efficiency than for breadth of use. Procedure time reduction, a measure of efficiency improvement, required the development of new social knowledge about how to coordinate actions in the operating room – knowledge that was difficult to codify and correspondingly difficult to transfer across hospitals. Each team, no matter when they adopted the technology, had to figure out how to get faster— going through their own, local learning process. The significant differences in efficiency improvement slopes are indicative of these unique learning journeys. In contrast, graft increases represented a form of improvement triggered by codified knowledge, easily transferred across hospitals.

Consistent with the result that rates of efficiency improvement differed significantly across sites, team members were unable to describe to other sites precisely what they did to get faster. As one anesthesiologist we interviewed commented after visiting another site, "I saw how good we were." His awareness of his team's superior coordination performance did not help him explain to other hospitals how to achieve this; knowledge about how to get faster developed well *within* a team through informal interaction. To illustrate, a team member from the hospital with the fastest procedure time reduction described the ongoing informal sharing of subtle techniques that allowed them to improve, using his hands to illustrate how the catheter can go in too far:

> Everyone would talk in the hall and say ‘this is a problem or that’s a problem or this is working or that is working,’ and we’re always talking in the OR too. For example, if we put the coronary sinus catheter in too far, you pass a main branch, so if you let it down while shooting you can see the back flow. You can see if the position works, so that gets passed on to others [within the team]. If I thought of something, I’d pass it on too. For example, [I told others] ‘you can use the other end of the wire like *this* to compensate for that additional flexibility.’… It’s all anecdotal and passed on.

In contrast, rates of improvement in breadth of use, measured by number of grafts, did not differ across sites, suggesting a high degree of transferability of this codified knowledge and an ability to facilitate improvement in other sites. Thus, consistent with H3, improvement that relied on codified knowledge was greater for hospitals adopting the technology later, compared to those adopting earlier. Hospitals were able to quickly apply codified knowledge received from other sites. As reported by team members in interviews, once a surgeon learned that other surgeons were doing additional grafts, increasing the number of grafts at his site was not difficult. One surgeon explained that he saw a colleague present results of doing multiple grafts at a surgical conference, and immediately “we talked to the [company] representative and made the decision [to do the same thing].” Similarly, another surgeon found that multiple grafts could be undertaken more easily by using additional pieces of equipment—easily reported to others—thus adding to codified knowledge needed for increasing breadth of use.

Contributions to research on innovation

Although research has investigated conditions organizations under which organizations adopt innovations (e.g., Rogers, 1983) and shown that new technologies are not always successfully implemented (e.g., Attewell, 1992), we know less about factors that shape performance improvement during implementation. This study thus contributes to the innovation literature by demonstrating that when tacit knowledge is required for improvement, heterogeneity of performance improvement can be expected; in contrast, when codified knowledge is available, improvement is likely to be homogenous. When improving performance with a new technology relies heavily on tacit knowledge, we suggest that organizations should expect uneven and unpredictable improvement paths. When knowledge is or can be codified, improvement is likely to be more predictable and easily transferred across individuals and organizations.

Previous research has examined the transferability of knowledge, but not studied its effects on performance improvement rates. This paper extends research on knowledge management by suggesting that the availability of codified knowledge increases the ability of managers or researchers to predict and plan subsequent performance improvement. One implication of this finding is that expectations related to the timing of improvement should be adjusted based on the type of knowledge involved. By calibrating expectations, managers can make more informed decisions about whether or when to abandon a new technology or other process innovation. Equally important, as discussed below, a different management approach may be required for innovations that involve tacit knowledge compared to those presenting a higher degree of codified knowledge.

Finally, this study adds to the learning curve literature by suggesting a variable – knowledge type – that may help explain discrepancies in past research, in which learning curves vary across organizations in some studies and in other studies are consistent across sites. We suggest that the degree to which knowledge required for improvement is codified will be associated with similarity across organizations in rates of improvement. Performance improvement following technology implementation represents one way that organizations adapt to changes in the external world or competitive landscape. Technology learning curves thus capture an important form of organizational learning, and by connecting knowledge type to learning curves we suggest that codified knowledge not only spreads more easily but also affects performance improvement.

Contributions to research on team learning

Regression analyses integrating surgical and interview data supported H2, that teams with greater membership stability would increase efficiency more quickly than those with less stability. Because it required tacit, social knowledge about how to coordinate, teams were able to decrease procedure time more rapidly when membership was stable, as indicated by the significant negative coefficient for team stability shown in Table 4. As depicted in the earlier quotation, by working closely together, team members developed ways of talking and coordinating that were difficult to codify.

This finding extends laboratory research on transactive memory in teams by finding evidence of the benefits of stability for real, cross-disciplinary teams facing a new task for which the development of social knowledge and interdependent *know-how* was an imperative. For managers deciding how to staff improvement projects, these results suggest a need for initial team stability that when tacit knowledge is involved, such as when news tasks involve reciprocal coordination. At the same time, membership stability may not matter for performance improvement when tasks are highly codified, such as when the need for reciprocal coordination is low. In these cases, the convenience of more flexible staffing can be realized.

In service organizations that operate around the clock, team stability is sometimes impractical; staffing multiple shifts with individuals from multiple disciplines is challenging even without constraints related to keeping certain individuals together. Moreover, some turnover in team membership is necessary to train additional organizational members in the new practices and give them an opportunity to work closely with experienced team members.

If a new technology is to become accepted practice in an organization, all members, not just those involved in an initial implementation project, have to be trained.

Implications for theory and practice in performance improvement

We draw from these results to suggest a need for contingent thinking related to achieving improvement with new technologies or new practices. One perspective in the research literature has suggested that performance improvement in operations is best achieved by accurate copying of existing best practices – a transfer approach (Szulanski, et al., 2002). From this perspective, the not invented here syndrome (Katz and Allen, 1988), in which organization members resist externally developed practices, appropriately can be deemed evidence of irrational resistance or hubris. Another perspective, in contrast, portrays performance improvement efforts as inherently local, situated in unique organizational contexts, eluding transfer, and therefore best approached through trial and error, or learning by doing (Pisano, 1996; Tyre and von Hippel, 1997). This paper suggests that both perspectives may be appropriate – under different conditions. When new practices rely on codified knowledge, transfer and accuracy are likely to be key determinants of successful performance improvement elsewhere. When new practices rely on tacit knowledge, then an improvisational learning-by-doing strategy may be the best route to performance improvement.

Interestingly, the technology we studied later failed in the market—despite stunning successes in some of the hospitals studied—in part because only the explicit aspects of performance improvement were able to diffuse easily through the community of users. The tacit dimension of how to use the technology more efficiently was extremely slow to spread —ultimately residing in only one or two organizations that had focused on developing this knowledge locally while others remained frustrated by the difficulty of improving its efficiency. Over time, most hospitals abandoned the effort. Accustomed to relying on weak ties (journal articles, opinion leader endorsements) to transfer codified medical knowledge, the surgeons studied were not sensitive to the importance of collective tacit knowledge for performance improvement with the new technology. Although medical education anticipates the need for mentorship and oversight for learning new techniques as individuals, effects of collective tacit knowledge have not been emphasized in health care or innovation research.

Conclusion

The ability to anticipate the rate of performance improvement is important for management decision-making and planning when considering the adoption of a new technology. This paper demonstrates that performance improvement that relies on tacit knowledge varies significantly across organizations adopting the same technology. We further demonstrated that performance improvement that relies on codified knowledge was accelerated in later adopters of the same technology, because they can obtain useful knowledge from early adopters that can be readily translated into performance gains.

This study suggests that a new technology with proven advantages can fail in the market—despite stunning successes of some adopting organizations—when tacit knowledge is needed for performance improvement. Successful implementation of this and other technologies that involve tacit knowledge can require intense communication among past and future users, perhaps involving moving people around so that new users can work closely with more experienced users. Managers making decisions about implementation must allocate sufficient time and resources to the development of this tacit, social knowledge –

such as by supporting learning-by-doing in initially stable groups of users. By engaging in a process of learning to work together effectively to accommodate a new technology, organizations can increase the chances of achieving the performance improvement that is essential to the innovation's successful implementation.

As new technologies in many industries become more complex and more likely to be used by interdependent users, the need for teamwork is increasing. The challenge of learning as teams and developing tacit knowledge needed for performance improvement is thus likely to become increasingly relevant. Understanding how new technologies in health care and elsewhere can be more successfully implemented—and how they rely on team and organizational learning to realize performance advantages—remains a critical area for research. The study presented here suggests that this future research must take into consideration the distinction between codified and tacit knowledge.

Appendix: A New Technology for Cardiac Surgery

In the most common cardiac surgical procedure, a coronary artery bypass graft (CABG), a blocked artery is bypassed with either a vein taken from the leg or an artery dissected from the inside of the chest wall. The operation starts with splitting open the breast bone (called the *median sternotomy*) to gain access to the heart. The most important difference between the minimally invasive and conventional technologies for CABG is that the breastbone is not split apart. Instead, the heart is accessed through a small incision between the ribs using specially designed equipment. The new technology thus posed both *technical* (learning to use new equipment) and *process* (or organizational) challenges. The core process challenge was that the operating room (OR) team had to learn new routines.

The team. An operating room team for cardiac surgery consists of four roles, the surgeon, anesthesiologist, nurses, and perfusionist (a technician who runs the heart-line bypass machine). Across hospitals of varying size, location, history, and academic status, the structure of cardiac surgery departments—especially as manifested in roles and relationships in the operating room (OR) team—are remarkably consistent. This team routine transcends institutions. Professional training in surgery follows widely accepted protocols and uses standard technology, both derived from the research literature with which physicians are expected to remain current. This promotes homogeneity across hospitals. Acting within prescribed roles, team members are able to act in perfect concert without discussion; conversation that does occur is typically about an unrelated subject, such as last night's baseball game. As an informant in our study explained, "In [CABG surgery], you look at the surgeon and you know the body language, and you act." The OR team in a typical cardiac surgery department is likely to perform one or two, and sometimes three, open-heart operations each day and, therefore, hundreds each year. All members of the surgical department are assumed to be equally capable of doing the work of their particular discipline, and team members within a discipline are readily substituted for each other. This consistency of practice reduced the likelihood of differences in preexisting routines across sites and thus made it an ideal context in which to investigate whether differences in the collective learning process occurred and whether this affected the implementation success of a new technology.

The task. Conventional cardiac surgical procedures have three phases. First, the surgeon cuts open the chest, splits apart the breastbone (the "median sternotomy"), and stops the heart. The surgeon then directs the nurse and perfusionist to connect the patient's vessels to a heart-lung bypass machine that regulates oxygenation and blood pressure while the heart is stopped. In the second phase, a clamp is placed on the aorta to prevent blood from flowing backward into the heart while the surgeon repairs diseased components ("stitching"), and in the third, the surgeon restarts the heart, which then fills with blood, allowing the patient to be weaned from the bypass machine and the chest to be closed and stitched by the surgeon. The role of each team member in this routine is well established. Further, because everyone has direct visual access to the heart, each team member can monitor the progress of the operation and anticipate what actions will be needed. For instance, the clamping of the aorta is visually apparent to everyone in the operating room and is a signal to the scrub nurse that the surgeon will soon begin stitching.

The new technology. Minimally invasive cardiac surgery (MICS) differs from the conventional approach in that the patient's breastbone is not split apart. This reduces the extent of pain and recovery time for patients, such that they are able to resume normal activities more quickly than after conventional cardiac surgery. Using special new equipment, the heart is accessed through small incisions between the ribs, and the patient is connected to the bypass machine through the artery and vein in the groin. A tiny deflated balloon, threaded into the aorta and then inflated to prevent blood from flowing backwards into the stopped heart, replaces the traditional clamp inserted directly into the chest.

Balloon placement is the critical challenge the technology imposes on the OR team, requiring coordination among all team members. The balloon's path must be carefully monitored with specialized ultrasound technology, because there are no direct visual and tactile data to help guide the process. Tolerances on balloon location are excruciatingly low, and correct placement is critical. Team members must then continue to monitor the balloon to make sure it stays in place. Thus, unlike conventional surgery, in which surgeons rely on direct sensation, MICS calls for team members to supply the surgeon with vital information displayed on digital and visual monitors.

In conventional surgery, each team member's role is well established. The open chest provides direct visual access, allowing team members to monitor progress of the operation and to use visual cues to anticipate what actions will be needed. In contrast, when using the new technology, the small incision requires an OR team to coordinate their actions carefully, real time. For instance, in conventional CABG, the clamping of the aorta is visually apparent to everyone and is carried out by the surgeon with no need for communication. In contrast, the new technology involves clamping the aorta using an internal balloon, requiring team members to coordinate their actions while monitoring this device with imaging technology called trans-esophageal echo (TEE). Correct placement of the balloon requires intense, real-time sharing of information among team members. Only after the balloon is properly placed and inflated can the surgeon perform the coronary artery bypass grafts; problems occurring when placing the balloon thus lead to longer operations. And, similarly, problems keeping the balloon in place can emerge if team communication is poor.

Before operating on patients, all adopting teams were required to undergo a rigorous three-day training that imparted technical skills and emphasized teamwork. However knowledge of how to coordinate and how to become more efficient at doing so was difficult to communicate, even through a well-designed and intensive training program.

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Table 1: Date of first, date of last, and total number of CABG procedures in data set, by hospital

Hospital	Date of first CABG	Date of last CABG	Number of CABGs performed	Hospital	Date of first CABG	Date of last CABG	Number of CABGs performed
A	Oct-96	Jul-97	33	I	Apr-97	May-97	5
B	Dec-96	Jul-97	6	J	Jul-97	Jun-98	18
C	Dec-96	May-97	48	K	Jul-97	Jun-98	35
D	Jan-97	Mar-98	12	L	Jul-97	Oct-98	40
E	Jan-97	Dec-97	23	M	Aug-97	Oct-97	14
F	Jan-97	Sep-97	26	N	Sep-97	Aug-98	17
G	Feb-97	Mar-98	13	O	Feb-98	May-98	12
H	Apr-97	Jun-98	9	*Total*	Oct-96	Oct-98	311

Table 2: Dates of first CABG procedures and number of days since first case at hospital A

Hospital	Month of First CABG at each Hospital	Number of Days Since First Case at Hospital A
A	Oct-1996	0
B	Dec-1996	48
C	Dec-1996	58
D	Jan-1997	87
E	Jan-1997	93
F	Jan-1997	94
G	Feb-1997	118
H	Apr-1997	164
I	Apr-1997	189
J	Jul-1997	272
K	Jul-1997	273
L	Jul-1997	275
M	Aug-1997	302
N	Sep-1997	343
O	Feb-1998	492

Table 3: Summary statistics and correlation matrix.

	Mean	Standard Deviation	Procedure Time	Number of Grafts	Higgins Score	Early Adopter	Team Stability
Procedure Time (minutes)	290.7	99.9	—	0.421***	-0.061	0.093	-0.276***
Number of Grafts	2.50	1.43		—	-0.031	-0.213***	-0.076
Higgins Score	0.94	1.22			—	-0.058	0.068
Early Adopter	0.56	0.50				—	-0.326***
Team Stability	2.81	1.22					—

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

Table 4: Regression models that estimate procedure time.

	Regression Models							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
R^2	0.154	0.199	0.425	0.493	0.250	0.278	0.222	0.223
F	56.25***	38.32***	13.61***	9.08***	34.07***	29.51***	29.2***	21.91***
Explanatory Variables	Regression Beta Coefficients							
Intercept	5.365***	5.593***	5.843***	6.236***	5.768***	5.344***	5.620***	5.595***
Number of Grafts	0.099***	0.105***	0.101***	0.096***	0.100***	0.101***	0.113***	0.113***
ln(CumVolume)		-0.081***	-0.067**	-0.230*	-0.073***	0.067	-0.080***	-0.072**
Hospital			***	**				
Hospital□ln(CumVolume)				**				
TeamStability					-0.067***	0.089		
TeamStability□ln(CumVolume)						-0.051***		
LateAdoptor							0.111**	0.051
LateAdoptor□ln(CumVolume)								0.020

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

Table 5: Regression models that estimate number of grafts.

	Regression Models						
	1	*2*	*3*	*4*	*5*	*6*	*7*
R^2	0.013	0.288	0.321	0.020	0.021	0.056	0.059
F	3.93*	7.94***	4.59***	3.11*	2.18	9.21***	6.43***
Explanatory Variables	Regression Beta Coefficiets						
Intercept	1.996***	1.425***	1.660	2.244***	2.563***	2.36***	2.64***
ln(CumVolume)	0.168*	0.318***	0.217	0.178*	0.073	0.159	0.069
Hospital		***	‡				
Hospital□ln(CumVolume)			‡				
TeamStability				-0.100	-0.217		
TeamStability□ln(CumVolume)					0.038		
LateAdoptor						0.602***	1.076
LateAdoptor□ln(CumVolume)							0.157*

*** p < 0.001
** p < 0.01
* p < 0.05
‡ not significant