KNOWLEDGE DRIVEN QUALITY IMPROVEMENT

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Abstract

Although the literature has suggested that both organizational learning and quality improvement are crucial for competition, the link between the two is ill-understood. We explore this link by studying 62 quality improvement projects undertaken in one factory over a decade. A factor analysis identifies three learning constructs that characterize the learning process: scope, conceptual learning and operational learning. We use OLS regressions to study the impact of these learning constructs on project performance. We offer explanations based on the organizational learning literature. The mix of conceptual and operational learning is found to play a crucial role in consistently improving quality, creating new technological knowledge, and changing factory personnel's attention. We formulate managerial recommendations and questions for future research.

(Quality, Organizational Learning, Technological Knowledge, Learning by Experimentation)

1 Introduction

In recent years, several experts have suggested that knowledge and information are increasingly becoming critically important assets for competitive success. In order to do well, firms have to explicitly manage organizational learning efforts directed at building knowledge and information they can use in the future. Though these ideas are becoming increasingly common in the literature, they have not been linked with the other critical basis for competition: relentless pursuit of quality.

A previous paper (Mukherjee & Van Wassenhove 1994) provided a first exploratory field research directed at filling this gap. In it, we identified two distinct dimensions of knowledge (experiential and formal) and discussed how they affected project level performance. That work helped us identify more objective measurements and clearer constructs about the learning process. In this paper, we report on this enhanced effort. We identify three dimensions of the learning process: scope, conceptual learning and operational learning. We show that these dimensions have differential impact on four different measures of performance and discuss why this happens.

In section 2, we explore the literature on organizational learning as we establish the need to link the pursuit of knowledge to the pursuit of quality. In section 3, we describe our research site, our data and its coding. In section 4, we use factor analysis to identify three latent characteristics of the learning process in the projects we studied: scope, conceptual learning, and operational learning. We also present OLS regressions that link our learning characteristics to four distinct - but related - project level measures of performance. We discuss the managerial implications of our findings in section 5 and the opportunities for future research in section 6.

At the outset, we note that throughout this paper, we will focus on the management of *technological knowledge*, which Bohn (1994, p. 62) defined as *"understanding the effects of the input variables [of a process] on the output."* Moreover, like Bohn, we use the following meanings for the terms *data, information, knowledge* and *learning.* Data are the qualitative and quantitative details firms collect about their products and processes. Information is refined data to which factory/firm employees ascribe value. Knowledge is the stock of information and learning is the process of acquiring data and creating information/knowledge in order to affect a factory's or a firm's performance goals.

cesses embody organizational knowledge/information (Allen 1977, Clark & Fujimoto 1991). Hence, if the knowledge/information possessed by a firm is sound, it will be well placed to create good products and processes (Bohn 1994). Consequently, systematic analyses about the "nature" of knowledge which supports quality could potentially reveal insights about the questions we raised.

Unfortunately, our understanding of knowledge management in manufacturing is quite limited. In recent years, Hayes & Jaikumar (1988), Zuboff (1989) and Adler (1989) have discussed the importance of the issue, particularly in environments dominated by computers. They have shown that technologies that "informate" are different from technologies that simply automate and that "intellectual assets" need to be explicitly managed. However, they have offered little research-based guidance on how firms should compete on the basis of knowledge. Bohn (1987, 1994) did address the costs and benefits of different strategies for managing experimentation on the shop floor and developed a qualitative scheme to measure the advancement of technological knowledge, but much work remains to be done.

We feel that there is significant value to be added by incorporating the research on organizational learning (see Hedberg 1981 and Huber 1991 for comprehensive reviews). As such, in this paper, we will draw upon aspects of this literature which discuss *how people learn in organizational settings* (e.g., see March & Olsen 1975, Kim 1993). From this perspective, learning becomes organizational when knowledge created or obtained by individuals is shared with others.

Organizations learn if they process information about events in their environment so as to change their range of potential behavior (Huber 1991). In its simplest form, this process begins with people experiencing and observing events. They then reflect on their observations and conceptualize appropriate responses. Finally, they test their concepts through implementation and thereby begin another learning cycle (Kim 1993).

The first problem that disrupts this simple cycle concerns people's inability to learn when their environments are turbulent or unstable (Hedberg 1981). Such environments

possess characteristics that Senge (1990) called detail and dynamic complexity and March & Olsen (1975) called ambiguity. (Detail complexity arises when the presence of too many variables makes it difficult to comprehend a problem in its entirety. Dynamic complexity arises when distance and time make cause-and-effect difficult to establish. Ambiguity refers to the simultaneous presence of equally plausible but mutually contradictory explanations of a situation.) These characteristics make it difficult for people to observe their environments, reflect on their observations and conceptualize and test possible solutions.

A related problem concerns people's ability to process data/information they acquire about their environments. People generally confuse data with untested generalizations of data (Senge 1990). Moreover, they attribute positive occurrences to actions they took in the past and negative occurrences to the actions of others (March 1981). Consequently, they produce "superstitious learning", (mis-attribution of cause-and-effect) and tend to create "myths" (potentially inaccurate beliefs based on subjective interpretations of data) (March & Olsen 1975, Hedberg 1981). While accurate feedback can overturn established myths when expected events fail to occur, the task is very difficult (Hedberg 1981). The difficulty is aggravated when the myths are held by powerful people (Duncan & Weiss 1979).

A third problem concerns an organization's ability to change its range of potential behavior. Faced with problems or opportunities, organizations actively search for solutions in the vicinity of the problems or of existing approaches (Cyert & March 1963, Huber 1991). Note that by definition, all of the points of departure of such *focused searches* are determined by existing organizational practices. In other words, prevailing myths play a key role in directing behavior even as organizations try to solve problems that they might have created. One implication of this recurrent finding in the literature is that methods which can force organizational personnel to routinely undertake more wide-spread searches are, over time, likely to facilitate the challenging of myths. In fact, our field observations have convinced us that the real power of a new managerial paradigm like TQC comes from its ability to provide unconventional points of departure for solving existing organizational problems.

The conditions and problems discussed above are very common in modern factories (Jaikumar & Bohn 1992). Most factories have inter-locking technologies and systems which give rise to detail and dynamic complexity. Managers deal with these by decomposing the factory into manageable units like functional departments or cells. They then add organizational structures like cross-functional teams, hierarchies of quality control circles and the like to link the jobs of these departments (Juran & Gryna 1993). When contingencies –unexpected events which disrupt normal production activities– occur, factory personnel in these organizational settings have to learn to re-estabilish control (Mukherjee 1992). They might try to eliminate or minimize the impact of contingencies with adverse impact on performance or make routine contingencies with positive impact on performance. In either case, implicitly or explicitly, they have to deal with detail and dynamic complexity, ambiguity, the need to overturn myths and the difficulties of accurately processing data and information.

Given these conditions, what types of learning efforts do factory personnel undertake? Again, the organizational learning literature offers some insights. Kim (1993) distinguished between two types of effort, operational learning and conceptual learning. (Similar distinctions have been made by Hedberg (1981), Fiol & Lyles (1985) and Senge (1990)). Operational learning refers to the acquisition of know-how or the ability to act. The people involved observe and experience events and then try to deliberately implement their experience. When such implementation repeatedly succeeds in delivering the desired results, people acquire a know-how or a skill. Viewed from another perspective, operational learning is quintessential "learning by doing" (Arrow 1962). In contrast, conceptual learning is the acquisition of know-why. At its core is the development of understanding of an experience. Conceptual learning typically occurs when the people involved attempt to develop an abstract concept –a theory– to explain their experience.

In the rest of this paper, we will use statistical analyses to assess the use of these types of learning in the complex, ambiguous environment of a factory. We will also analyze the differences in performance that these types of learning can produce.

3 Research Design and Data Base

3.1 The Host Company

In order to establish links between learning and quality, field researchers must control for potentially confounding factors such as variations in product and resource markets, general management policies, corporate culture, production technology and geographical location. Moreover, they must delve into the details of product and manufacturing technologies, or they would be hard pressed to assert with any confidence that a specific bit of knowledge had a specific impact. Finally, they must have access to detailed data about the systems used to improve quality. The latter two requirements naturally raise questions about the safeguarding of potentially sensitive proprietary material.

These considerations convinced us to limit our study to a single firm, N.V. Bekaert, S.A., a Belgian multinational corporation. Bekaert is the world's largest independent producer of steel wire. In particular, its Steel Cord Division, which hosted our research, produces about one-third of the world's output of the steel wire (called "tire cord") used in the production of steel belted radial tires. Our project received the enthusiastic backing of then CEO Karel Vinck and current CEO Rafaël Decaluwé, providing us with unlimited access to people and documents.

During the 1980s, Bekaert's customers –tire manufacturers– experienced traumatic change, and responded by making simultaneous demands of high quality, short lead times, low cost and product line flexibility. Bekaert responded by initiating a pilot quality improvement program at its flagship Aalter plant (Belgium) in 1981. Through its joint venture with the Bridgestone Company of Japan, it had ready access to knowledge about Japanese quality control techniques. Nevertheless, ten years passed before it could claim to have deployed the TQC philosophy in most (but not all) of its Steel Cord plants. Its diligent efforts seem to have borne fruit, for in 1990, CEO Karel Vinck won the first European Forum for Quality Leadership Award. Many people believe that the jury was favorably impressed by his

vision for quality exemplified by the innovative practices at Aalter. Bekaert's second major recognition for quality came in 1992, when its Burgos plant won a European Quality Prize.

Thus, from the perspective of results, Bekaert is not a laggard in the area of managing quality. While it adopted the TQC philosophy late by Japanese standards, it was one of the first to do so in Europe and it probably has worked at it at least as long as (if not longer than) most well-managed American firms. So we believe that Bekaert's experiences can inform firms which are way behind in the quality race and can at least serve as an important point of comparison for the others.

3.2 The Production Process

Steel cord division factories are focused by product markets and technology (Skinner 1974). For most part, they produce tire cord for a handful of competing tire makers. Thus, at a macro level, product attributes, delivery/service requirements, quality levels, production technologies, etc. are all comparable. The few secondary products that are made use virtually identical production processes.

Bekaert's basic process flow is deceptively simple: Thick wire are pulled ("drawn") through dies which progressively reduce their diameter. Very thin wire ("filaments") are wrapped around each other to form tire cord. The simplest cord has two filaments; the most complex, hundreds.

Of course, reality is much more intricate. First, each plant has a handful of huge drawing machines upstream and hundreds of small drawing and filament wrapping machines downstream. The upstream machines handle continuous inputs of thick wire while the downstream machines individually process small spools. Second, swimming pool sized pits supply lubricant (for the dies) to the drawing machines downstream. Thus, while these machines run independently, the soap circuits link them to each other. Third, the wire is heat treated at two intermediate points to make it ductile. At one of these points, a chemical process also coats the wires with brass. Despite the use of sophisticated controls, wires which are

heat treated and coated together do not have identical properties. Fourth, even for similar cord, different customers demanded customized product properties. Fifth, Bekaert's suppliers, which included some of the best known steel companies in Europe and Japan, could not guarantee homogeneity of properties across the thousands of tons of wire they sold.

As a result, plant personnel have to contend with very high levels of detail and dynamic complexity (Senge 1990). The former arose from the need to coordinate the large numbers of machines and the different technical skills required at the different stages. The latter arose from the ease with which effects of problems experienced at any machine or production stage could be transmitted to other machines and stages. In other words, Bekaert's factories readily fit Jaikumar & Bohn's (1992) definition of dynamic production environments.

3.3 Total Quality Control at the Aalter Plant

TQC efforts at the Aalter plant were initiated in April 1981 when a project team responded to extraordinarily high levels of fractures in two complex spiral wrapped cords. It created, set and enforced Standard Operating Procedures (SOP's); educated the workers about variability, process capability, control charts and Ishikawa diagrams; and created an information system which provided plant personnel with performance data on a daily basis. Within 6 months, the level of fractures dropped by a factor 10. Over the next ten years, Aalter:

- Trained its managers about concepts in problem solving and the need to ensure process capability. The SCRA (symptom-cause-remedy-action) approach became a standard tool (1981).
- Invested heavily in training of plant personnel (throughout the 1980s).
- Created a functional TQC organization, consisting of a plant level TQC steering committee and departmental TQC teams. The TQC teams solved chronic problems relying on the experience of their members, brainstorming and the Seven Statistical Tools (1983).
- Introduced SPC for the control of a few key parameters and attributes (1983).

- Added accuracy (C_A) and precision (C_P) indices to the existing Bekaert Quality Index (BQI) (1983).
- Trained foremen in creating, establishing and monitoring SOP's and so, reduced variances attributable to idiosyncratic work practices (1984).
- Installed a new information system which economically provided standardized daily, weekly and monthly production and quality data (1985).
- Incorporated process capability measures (C_{PK}) in the BQI and specified the minimum acceptable level as a C_{PK} of 1.33 (i.e., less than 6 rejects per 100,000) (1986).
- Implemented SPC for virtually all product and process variables (1986).
- Established a "model line" for an important, representative product and asked its personnel to create fundamental process control knowledge without sacrificing the production of saleable wire. The model line routinely used natural and controlled experiments to solve problems (1988).
- Set up quality control circles with voluntary membership (1989).
- Started emphasizing the behavioral (instead of the technical) component of TQC (1991).

These methods are both used by most quality-minded firms around the world and recommended in the literature quoted in section 2.

3.4 The Projects

The literature on quality distinguishes two types of projects (e.g. Deming 1982, Imai 1986, Juran & Gryna 1993). "Breakthrough" or "common cause" projects deal with issues of potentially wide-ranging impact, which may be able to improve performance dramatically. *Kaizen* or "special cause" projects are undertaken in the spirit of continuous improvement. While they do not have significant impact individually, cumulatively they can propel firms to very high levels of performance.

Bekaert uses the term IKZ (the Flemish acronym for TQC) to describe *Kaizen* projects.

These projects deal with problems of internal product failure and process capability, safety, housekeeping, ergonomics, maintenance and productivity (see appendix A). They are managed by foremen or supervisors. Typically, intra-departmental in scope, they embody the SCRA and Plan-Do-Check-Act methodologies. Participants first define the problem and agree upon a goal. They then collect and analyze data using the Seven Statistical Tools, brainstorm about their experiences and knowledge and determine the issues they should tackle. Next, they develop and test remedies. Finally, they act on their decisions, cycling back to refine their analyses whenever necessary.

Bekaert calls common cause projects key projects. Managed by engineers, they seek major improvements and are often interdepartmental in scope. They usually meet the criteria for unstructured or poorly structured problems (see e.g. Daft & Macintosh 1981, Smith 1988). In other words, well defined problem solving methods often do not exist, conflicting tradeoffs have to be made, solutions cannot be recognized until they are reached and not all problem transformations and states are known.

We had unlimited access to all of Aalter's records on improvement projects undertaken throughout the 1980s. From these, we selected projects undertaken between 1982 and 1991 that sought to improve product attributes or process control (as opposed to say, housekeeping). We then eliminated projects that had not progressed (at least) past the testing stage and that had not been adequately documented. This selection left us with 55 IKZ and 7 key projects.

3.5 Project Data and Coding

We coded the projects on eight questions which dealt with their execution ("learning process") and four questions which dealt with their performance (see Appendix B). We structured these questions on the basis of our experience with an earlier exploratory research (Mukherjee & Van Wassenhove 1994).

Two of the learning process questions dealt with the use of cross-functional teams in

problem solving and implementation of project results. While such teams have widely been identified as critical for success in product development, evidence of their efficacy in pure manufacturing problems is less clear. For example, locally directed quality control circles helped many Japanese firms achieve success, but failed in many US firms (Ishikawa & Lu 1985, Shea 1986). A third question - on the focus of the project - addressed the oft repeated assertion of the organizational learning literature that firms tend to search for new solutions in the neighborhood of existing problems or solutions (Cyert & March 1963). A question on the use of statistics addressed the view that the use of statistical tools was always desirable (Deming 1982, Wadsworth et al. 1986).

Case analysis of fifteen key projects at Bekaert had led Mukherjee (1992) to suggest that scientific inputs, which he called "high formality mode," made problem solving effective. A fifth question addressed this issue. The question on the number of levels in the Ishikawa diagram sought to capture the degree of realism of the models plant personnel used. It was suggested by Senge's (1990) findings that when they tried to learn, people viewed the problem through the lenses of models and data. In contrast, the question on the modification of action variables dealt with steps actually taken by the project team during the project. Finally, the question on follow-up of experimental results was based on the observation that factories have high levels of both detail and dynamic complexity. Consequently, it was reasonable to assume that in the absence of rigorous follow-up, experimental findings could well be ephemeral.

Our four measures of performance were related to each other, but dealt with unique issues. First, we checked whether a project achieved its stated goal. Typically, TQC projects begin with clearly specified objectives, e.g., "Reduce wire fractures from 5 per ton to 3.5 per ton." Such goals may have no relation to process capability and hence, may be very easy or unrealistically ambitious. Nevertheless, field observation suggests that project goals typically call for incremental improvement. Second, we checked whether a project produced consistent improvement regardless of whether it achieved its stated goal. For example, a

project which sought to reduce wire fractures from 5 per ton to 3.5 per ton could achieve only 4 per ton. By their very formulation, both these performance measures implicitly focus on "know-how" (Kim 1993, Leonard-Barton 1990). No effort is made to determine whether the project team developed any knowledge of cause-and-effect and the conditions under which the causes could produce these effects.

A broader measure of performance is captured by the question "Ability to specify impact of variability of known causal variables." This question addresses whether the project team could predict how quality-related performance would vary if changes were made in the levels of a given set of process parameters (e.g., speed of drawing of wire through a die). In the context of typical projects at Bekaert, these parameters would typically be elements of Ishikawa diagrams or models developed during execution. This question directly addresses Bohn's (1994) definition of technological knowledge. Bohn identifies eight stages of technological knowledge ranging from complete ignorance to complete understanding. While the low end of our coding scale corresponds to the first three stages, level 4 (empirical equation) corresponds to Bohns stage 6 and level 5 (scientific model) corresponds to Bohn's stage 7 (scientific formulae and algorithms).

Our broadest and deepest measure ("Degree of change in attention as a result of the project") sought to evaluate whether the project team could actually prescribe changes in organizational behavior. Our scale covered the complete range from a total inability to change the organizational focus to major changes in the variables normally monitored by the plant. The foundation for this question lies in the organizational learning literature. March & Olsen (1975) assert that it is possible for the beliefs or actions of members of the organization not to affect the actions of the organization. They call a breakdown between individual beliefs and individual action "role-constrained experiential learning" and a breakdown between individual action and organizational action "audience experiential learning." The TQC literature also recognizes the importance of uniform adoption of changed behavior. For example, the ISO 9000 standards make a virtue of assiduously recording all changes in

procedures and following all such changes. Thus, the ability of a learning/quality project to change a factory's focus of attention is of critical importance.

For the IKZ projects, one of us coded the responses to these questions either on a 5-point Likert scale or in absolute terms. He based his assessments primarily on the final project reports, which under a management edict, contained fairly detailed information in a standardized format. Additionally, he relied on any available interim reports. Finally, he resolved any ambiguity by discussing the affected project with the plant's TQC coordinator, who had not only participated in all of the IKZ projects, but had maintained his own notes about them.

Data on the key projects came from a prior research effort undertaken by one of us (Mukherjee 1992). He had conducted over 100 hours of formal, semi-structured interviews at Aalter and at Bekaert's corporate R&D and engineering centers (Belgium). He had also collected archival data on the projects and cross-referenced these with the interview data. The person who coded the IKZ projects used these data to code the key projects, seeking clarifications –when necessary– from the collector of the data set.

It is important to appreciate that our coding and analysis treated each project as an independent data point and ignored possible interactions among them. For example, at different points in time and in different parts of the plant, Bekaert personnel executed projects aimed at reducing different types of wire fractures. We chose not to evaluate in this paper the impact that the projects executed earlier had on those which followed.

4 Latent Characteristics of Learning and Their Effect on Quality Performance

We applied factor analysis to our process related questions to identify latent characteristics of learning. The largest eigenvalues obtained from the evaluation of the 62 projects were: 4.0, 1.3 and 0.8. Normally, these figures would lead to the retention of only 2 factors. However,

since we had only eight variables (questions) in our data base, we used this "eigenvalue criterion" as a starting point and extracted an additional factor (Hair, et al. 1992, Kim & Mueller 1978, Stewart 1981). These factors explained 76.3% of the variance in the coded data (Table 1). Moreover, as is apparent from the communality estimates, the three factors –after Varimax rotation– explained between 65% and the 91% of the variation in the responses to the questions.

Table 1 about here

Not unexpectedly, the questions on the use of cross-functional teams, interdepartmental implementation and project focus loaded on to the first factor. Since these questions captured the degree of cross-functionality of a project, we labelled the factor "scope."

The questions on the use of statistics, use of science and the levels of the Ishikawa diagrams loaded on to the second factor. These tools enable project teams to formulate their problem and conceptualize potential solutions. They enable project teams to develop deep understanding of the cause-and-effect of contingencies, knowledge which can potentially be used to improve performance. We labelled this factor "conceptual learning" in recognition of Kim's (1993) equation of the term with the understanding of an experience, the development of a theory and the acquisition of know-why.

The questions on the modification of action variables and follow-up of experimental results loaded on to the third factor. We labelled this factor "operational learning" in recognition of Kim's (1993) equating the term with the implementation of a concept and observation of the results. As we noted earlier, this type of learning has long been recognized as "learning by doing." We emphasize that such learning has great importance in manufacturing since in factories knowledge has value only to the extent that it can be applied. From this perspective, the two questions which loaded on to the third factor assured project teams that their ideas and findings would work.

Table 1 shows that while each of the questions loaded high on one of the three factors, four of the questions showed moderate to high degree of cross-loading. The high cross-loading of

the question on the modification of action variables on to the conceptual learning factor can be explained in the context of the discussion in the prior paragraph: in factories, knowledge has value only to the extent that it can be applied. The other cross-loadings can be explained by a common cause uncovered by our field data from Bekaert (including that collected during a prior research effort (Mukherjee 1992)): dynamic production environments. First, the questions on the use of science and levels of the Ishikawa have high cross-loadings on to scope. In dynamic production environments characterized by incomplete technological knowledge, cross-functional problem solving using scientific tools works particularly well for complex projects characterized by deep Ishikawa diagrams. Second, project focus has a moderate cross-loading on to conceptual learning. Conceptual learning aims at creating know-why. In dynamic production environments know-why cannot be created by looking at a single production stage only: larger project focus is called for.

The data in Table 2 compares the mean factor scores of the IKZ and the key projects for the constructs identified above. Factor scores, by construction, indicate how a given project scored on a specific factor. As the mean value of all scores is normalized to 0, positive scores show a high degree of the identified construct and negative scores show a low degree. Thus, the data in Table 2 establishes that the key projects scored higher on scope and conceptual learning. The difference on scope reflects our original description of Bekaert's approach to the two types of projects – IKZ projects typically were intra-departmental while key projects were not. The difference on conceptual learning suggests that when problems are complex and unstructured, factory personnel do introduce conceptual learning into their efforts. Overall, both types of projects relied on operational learning equally, suggesting that in dynamic production environments, the proof of the pudding is indeed in the eating.

Table 2 about here

The next question that arises is whether the different degrees of reliance on scope and operational and conceptual learning actually affect performance. Table 3 presents the results of OLS regressions of the factor scores of the three learning constructs on our four performance

measures. Since we are conducting exploratory empirical research, there exists no theory which can guide the formulation of the OLS models. Hence, in the interest of parsimony, we have simply treated our three factors as linearly additive.

Table 3 about here

Column 1 shows that goal achievement is enhanced by increased scope and much more importantly, operational learning. To appreciate why this result is plausible, recall our obervation that quality improvement projects often focus on creating know-how. They rely more heavily on hands-on experiential knowledge than on scientific or engineering principles. For example, at Bekaert, it would be very unusual to find an IKZ project on reducing wire fractures which used finite dimensional stress analysis to determine root cause. In contrast, every project would utilize knowledge such as "As the level of wire on a spool decreases, the probability of fractures increases" and "As the level of wire on a spool decreases, tension in the wire increases." Under the circumstances, operational learning, with its emphasis on manipulating controls and observing the resultant impact –a process that Bohn (1987) calls ad hoc experimentation– has a beneficial effect. Problem solving progresses by the effectiveness of experience-based trial-and-error experimentation rather than on the rational assessment of cause-effect relationships. The role of scope is closely related. Projects with a larger scope involve more people with different experiences. This variety not only enables project teams to consider a more diverse set of options, but also exposes them to cross-departmental consequences of their actions. Team members in different departments can track the effects of changes they recommend. These factors are important for success in an environment dominated by both detail and dynamic complexity.

Column 2 shows that achieving consistent improvement also requires increased scope and operational learning. The reasons are identical to the ones given above. In addition, however, conceptual learning becomes important. The reason is that empirical evidence produced by operational learning is subject to superstitious learning (March & Olsen 1975). Project personnel can confuse correlation with causality. This is particularly true since in

the turbulent environment of the factory, experimental conditions can change too rapidly for people to conduct meaningful experiments (Hedberg 1981). As such, *consistently* maintaining a level of performance requires some appreciation of the drivers of that performance. Such an appreciation comes from efforts directed at conceptual learning, i.e. application of science, engineering and statistics.

Column 3 shows that a project team's ability to specify the impact of changes in known causal variables increases with increased project scope, improved conceptual learning and to a lesser extent, operational learning. The positive impact of scope confirms the findings of an in-depth case study of two projects in our data set (Mukherjee & Jaikumar 1993). Production processes (like Bekaert's) which are characterized by dynamic complexity cannot be decomposed optimally. Successful assessment of cause-and-effect therefore requires cross-functional linking of product, process and environmental variables. Projects with broad scope are better positioned to pinpoint, monitor, understand and manipulate potentially important variables.

Conceptual learning helps project teams apply scientific principles to develop falsifiable hypotheses and models of cause-and-effect. These models can help the teams to determine key variables, time frames for data collection and the like. Moreover, the application of statistics enables the project team to appreciate the key role of variability in determining subjectively observed reality. Under these conditions, the ubiquitous ambiguity and detail and dynamic complexity of factories do not create major impediments to the project teams' efforts to improve performance. A collateral –but important– benefit is that implementation is no longer a means for learning, but a means for validating the appropriateness of the models. This assertion is supported by our present finding that operational learning is of lesser importance than conceptual learning for specifying the impact of changes in known causal variables.

Mukherjee (1992) and Mukherjee & Jaikumar (1993) documented and discussed these issues. In one project they studied (which is also in our data base), the project team

developed a model of how wire reacted chemically with the soap used for its lubrication and developed experiments about the temporal and thermal conditions which promoted the reaction. These models and experiments enabled the team to define dramatically different operating policies even though routinely collected data were shrouded in ambiguity. Such practices are in sharp contrast to the execution of most IKZ projects. In these, action variables are modified once and the effects of such modifications are followed up. Rarely are efforts made to define the "boundary conditions" under which the modifications deliver results.

Conceptual learning is also important at the organizational level when (as is true for our research) the projects involve technical problems governed by objective and relatively immutable laws of nature. Under these conditions, conceptual learning can reduce the potential for superstitious learning and the development of erroneous myths. On the one hand, project teams employing this technique will be looking for scientific support for their findings. Thus, they are less likely to make erroneous links of cause-and-effect. On the other hand, faced with evidence supported by science, defenders of subjectively perceived, experience-based myths are likely to experience significant difficulty in disputing new findings of cause-and-effect (see also Mukherjee 1992).

Finally, column 4 shows that the our broadest and deepest measures of performance –the ability to change attention rules– is very strongly affected by both conceptual and operational learning. The role of conceptual learning in affecting this measure is identical to the one we advanced for the prior performance measure. Nevertheless, we observed that while conceptual learning enabled project members to overturn myths, by itself it could not force factory personnel to change behavior. When the overturned myths are supported by (i) observable changes in action variables and (ii) follow-up of experimental evidence (i.e., the components of operational learning), even the most skeptical of factory personnel have to face up to the possibility of an improved method for production. Consequently, we find that a judicious mix of conceptual and operational learning is important for convincing non-project

members to change their behavior.

In line with the previous argument it not surprising that scope had no statistically significant impact on the ability to change attention rules. Regardless of the scope of a project, it takes empirically proven understanding to change behavior. For example, local IKZ project teams that solved problems by developing both the know-why and the know-how did not need scope to change attention rules. Conversely, some key projects that failed to develop such empirically proven understanding did not change attention rules despite their large scope.

5 Discussion of Results

Our research findings suggest that in modern factories, the management of quality might well require an approach that is (at least) somewhat different from current norms. We will support this assertion by first discussing the nature of typical quality related learning effforts and then relating these to our findings and managerial recommendations.

Quality improvement efforts often take two forms. On the one hand, they require plant managers to seek quick, easily implementable solutions to problems identified by workers. They experience and observe events, relate their observations to strongly held beliefs of what works (i.e., myths), tentatively implement one or more (uncontrolled) changes, observe the effects and either label the problem as solved or cycle back to try another change. Such efforts are generally and pejoratively called "fire fighting." On the other hand, they require plant personnel to identify problems using Statistical Process Control, assess their magnitude with Pareto analyses, determine possible causes using Ishikawa diagrams to structure strongly held beliefs of cause-and-effect (i.e., myths), tentatively implement one or more (uncontrolled) changes, observe the effects using scatter diagrams and SPC charts and either label the problem as solved or cycle back to try another change. Such efforts are generally lauded as quintessential examples of TQC and kaizen implemented by empowered workers.

Admittedly, both our descriptions are stereotypical and there is a world of difference

between them. Today, practitioners and academics alike decry the first sequence and unequivocally advocate the adoption of the second. *Nevertheless, at their core, both sequences of problem solving/learning apply what we have called "operational learning."* Both sequences apply *ad hoc* experimentation (Bohn 1987) to understand their world. Both rely on and engender experience-based know-how to nudge it towards preferred directions. If anything, the "TQC/*Kaizen* sequence" actually de-emphasizes the role of engineering and science as it emphasizes the importance of the line operators' understanding of their machines and environment.

We do not discount the importance of operational learning. Factory personnel typically have to solve the specific problems they face. They do not have to develop generalized solutions that would be applicable everywhere. Know-how based operational learning can and does deliver results at this level. Moreover, as we have noted earlier, it is a well known fact that solutions which work in theory, in laboratories or even in pilot plants often do not work in full scale manufacturing. Hence, the ultimate test of the applicability of a proposed solution to an industrial problem is in its implementation. This is precisely the approach operational learning takes.

However, our findings show that operational learning, by itself, is likely to be ineffective at dealing with quality in dynamic production environments characterized by detail and dynamic complexity and ambiguity. Without adequate support from know-why based conceptual learning, quality personnel will not be able to maintain consistent levels of improvement, develop valid statements of cause-and-effect or overturn received wisdom on appropriate manufacturing practices.

The main benefit of conceptual learning lies in its ability to provide what Kim calls "...a coherent structure to our observations" (1994, p. 2). Thus, it can enable people and their organizations to explore root causes of problems and "...therefore to see new possibilities for shaping the future" (Senge 1990, p. 12). A second important benefit for organizational learning is that conceptual learning provides a framework for organizations to integrate

knowledge created by their members. Both these characteristics become important as the pressures of short product life cycles force the introduction of new technologies at low-to-moderate stages of knowledge (Jaikumar & Bohn 1992). They also become important as the power of computer-based technologies necessitate the complete procedural controls assumed at the highest stages of knowledge.

Thus, our first recommendation for practice is for managers to abandon an uncritical reliance on the *Kaizen* style quality management. Instead, they should explicitly consider questions like: Where are we on the stages of knowledge and where do we want to be? How dynamic/complex/ambiguous is our environment? Hence, how well do we truly understand our technology? What types of problems (vis-a-vis the measures of performance studied in this paper) are we trying to solve? The answers to these questions might suggest a need for a more balanced mix of operational learning and conceptual learning.

Our second recommendation for practice is a warning. Firms which identify a need to incorporate higher levels of conceptual learning might not find it easy to make the transition. Both earlier research at Bekaert and organizational learning research indicate that conceptual learning is difficult to apply, particularly if the organization has so far mainly relied on operational learning (Hedberg 1981, Senge 1990, Mukherjee 1992). The literature on knowledge management in technological settings suggests that the appropriate communication channels, organization structures and culture might be absent (Henderson & Clark 1990, Hayes & Jaikumar 1988, Mukherjee 1992).

Our third recommendation concerns the sequence of application of conceptual and operational learning. It is possible to view our research as a confirmation of the ideas repeatedly presented by Deming and Juran about the critical role that management plays in addressing 80-85% of quality problems. Such a perspective would relate conceptual learning to breakthrough or focus on breakthrough versus routine. A more productive view might be to look at the problem at hand and assess what type of knowledge is required to solve the problem. People with different types of training and experience generally possess different types of

knowledge and a key managerial challenge is to determine when each type of knowledge should hold center stage.

Our fourth recommendation concerns the scope of a quality improvement effort. Our findings suggest that in dynamic production environments a cross-functional project team is in a better position to (i) control contingencies, and (ii) create technological knowledge. Consequently, if the interactions among production stages are poorly understood, local problem solving is likely to produce sub-optimal solutions.

6 Avenues for Future Work

A first piece of future research that could follow our work concerns the applicability or generalizability of our single firm research. As we noted in section 3, Bekaert is definitely not a laggard with respect to quality and in fact could offer valuable insights for others. But are insights from the wire drawing industry relevant elsewhere? In the discussion of our findings we did not tie explanations to Bekaert specific factors. Instead, we tied our explanations to characteristics inherent to dynamic production environments with incomplete technological knowledge like detail and dynamic complexity (Jaikumar & Bohn 1992, Senge 1990). We would therefore expect our findings to be relevant in process industries with dynamic production environments. Nevertheless, we readily acknowledge that his assertion should be subjected to an empirical test. Reproduction of our work in other settings or well-designed cross-industry studies would make for important research.

A second piece of work should focus on developing more rigorous definitions (and instruments) of the constructs of operational and conceptual learning. We essentially defined these constructs in terms of know-how and know-why respectively. It is important to recognize that virtually all of the existing definitions of these terms (e.g. Leonard-Barton 1990) are verbal and subject to ambiguity. To deal with this problem, we used statistical data from a factory. Nevertheless, we believe that the quality of future work –and reproducibility of research– will depend heavily on clearer articulation of these constructs. They are admittedly

multi-faceted constructs. What facets, other than those that we have addressed, should be covered in future research? What other constructs (and related instruments) do we need? Can we develop scales which will measure progress over time along the stages of knowledge (Jaikumar & Bohn 1992)?

A third important area of research should focus on the impact of learning characteristics on long-term performance of a factory. In this paper, we have focused on project-level performance. We have not addressed the cumulative impact of operational and conceptual learning on the evolution of quality measured at the level of a factory. Such research, would open up the black box of the learning curve, explicitly introducing the idea of knowledge acquisition. Moreover, it would help develop an understanding of the dynamic nature of learning. For example, do factories need to emphasize different types of learning at different points in time? Such research could offer normative advice to managers developing TQC programs about the proper sequence of sub-programs.

A fourth important area of research would involve determining the appropriate tools and systems for producing and supporting conceptual and operational learning. Mukherjee (1992) and Mukherjee & Jaikumar (1993) used in-depth case studies from Bekaert to show that different "paradigms" of process control required different information systems, organizational structures and even training. They simply scratched the surface. Future research could identify the design for a managerial system that consistently produces and supports learning. We believe that the answers to these questions will increasingly enhance firms' efforts to manage learning to improve quality.

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Appendix A. Summary of the Final Report of a Typical TQC Project

Project Name: Inversions $3 \times 0.22 + 9 \times 0.20 + 1$ HT

When Executed: December 1988 until May 1989

Project Team: Supervisor, foreman, an engineer and 4 workers

Symptom Inversion means that one of the three 0.22 mm core filaments which should have been in the core of the cord had switched places with one of the 0.20 mm which should have been on the outside. In November 1988, 2.85% of the production was rejected because of inversions. The team set a goal of 0%. The problem was believed to have occurred because of a rapid introduction of the (new) cord. Normally, new cords were tested for long periods before being mass manufactured.

Cause Data analysis showed that 78% of the inversions were caused by two 0.20 mm filaments which got entangled before entering the cabling die. Brainstorming produced an Ishikawa diagram which listed eleven main causes. The team voted to rank incorrect pay-off tension as the principal cause of the problem and the shape of the distribution piece as the second cause.

Remedy The team proposed dealing with the pay-off tension by securing the pay-off tension more often and increasing the pay-off tension by 20%. It chose to recommend a new design for the distribution piece.

Action Operators on machines KGLT 24 to 33 secured pay-off tension every week. After five weeks, rejects were still at 2.79% (compared to 3.56% for the other machines). On machines KGLT 29 to 46, the team increased the pay-off tension for the 0.22 mm filaments by 20%. Reject rates averaged 3.69%, compared with 3.56% for the other machines. The team abandonned all actions related to pay-off tension.

A test on a single machine equipped with the new distribution piece yielded 0% rejects. When 18 machines were modified, 0.06% rejects occurred against 1.25% on the other

machines. Finally, implementation on all 39 machines resulted in 0% rejects for three consecutive months.

In October 1992 there were 0.38% rejects due to inversion.

Appendix B. The Questionnaire

Questions are coded by giving either a number of items or a response on a 5 point Likert scale. For each question we indicate below which number, or we give typical examples for the extreme answers (1 or 5) on a Likert scale.

The Learning Process

1. Cross-functional team

   Number of departments (production and support functions) involved in the project

2. Interdepartmental implementation

   Number of other production departments involved in implementing results

3. Scope addressed by the project

   1 one product, one department ...5 all products and/or all departments

4. Use of statistics in the project

   1 none

   2 moderate use of 7 statistical tools

   3 extensive use of 7 statistical tools and/or ad hoc experiments

   4 natural experiments

   5 controlled experiments

5. Use of scientific models and/or R&D/engineering staff

   1 none ...5 extensive

6. Number of levels in the Ishikawa diagram used in the final solution

7. Degree of modification of action variables or Ishikawa diagram

   1 no change ...5 major change/primary variable dropped or added

8. Follow-up of experimental results

   1 no sufficient follow-up nor improvement in the mean or the variance ...

   5 for sufficient follow-up a distinct improvement in the mean and/or the variance

Performance Measures

1. Degree of goal achievement

   1 no improvement ... 5 goal 100 % achieved or, if no goal is stated, order of magnitude improvement

2. Ability of the output to consistently change the level of contingencies

   1 no improvement ... 5 level of contingencies consistently at the level aimed at

3. Ability to specify impact of variability of known causal variables

   1 none ... 5 scientific model

4. Degree of change in attention as a result of the project

   1 no change ... 5 major changes in the set of variables routinely monitored

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Variable \ Factor	**Scope**	**Conceptual Learning**	**Operational Learning**	Communality
Cross-functional team	**0.92**	0.15	0.06	0.88
Interdepartmental implementation	**0.81**	0.06	0.22	0.72
Project focus	**0.71**	0.38	0.02	0.65
Use of statistics	0.10	**0.81**	0.15	0.69
Use of science	0.50	**0.70**	0.16	0.77
Levels of the Ishikawa diagram	0.51	**0.65**	0.15	0.71
Follow-up of experiments	0.25	0.12	**0.91**	0.91
Modification of action variables	-0.07	0.60	**0.66**	0.79
Variance explained	2.61	2.12	1.38	6.12
Variance explained (%)	32.7	26.3	17.3	76.3

Table 1: Factor Analysis for 62 projects

	Key project mean	IKZ project mean	t-statistic
Scope	1.65	-0.21	4.61*
Conceptual Learning	1.36	-0.17	3.80*
Operational Learning	0.09	-0.12	0.52
Sample size	7	55	

(* signifies significant at 0.05% in a 1-tail test.)

Table 2: Mean factor scores for key projects vs. IKZ projects

	Goal Achievement	Consistent Control of Contingencies	Ability to Specify Impact	Change in Attention Rules
Constant	3.69***	3.05***	1.85***	3.16***
	(0.13)	(0.10)	(0.10)	(0.15)
Scope	0.29**	0.25**	0.55***	0.15
	(0.13)	(0.10)	(0.10)	(0.15)
Conceptual Learning	−0.09	0.26**	0.50***	0.77***
	(0.13)	(0.10)	(0.10)	(0.15)
Operational Learning	0.84***	1.24***	0.19*	0.65***
	(0.13)	(0.10)	(0.10)	(0.15)
Adjusted R^2	0.43	0.73	0.47	0.40
Sample size	62	62	62	62

(Standard errors in parentheses. * signifies significant at 10% in a 2-tail test. ** signifies significant at 5%. *** signifies significant at 0.01%.)

Table 3: OLS: Impact of Learning Constructs on Project Performance