The Impact of Technology on the Learning Curve of Service Organizations

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Abstract

The learning curve has been an important tool in the management of manufacturing operations since mid-century. Considerable empirical evidence documents the existence of learning curves in a variety of firms and industries. The efficiency gains captured by the learning curve are generally considered to stem from, in part, from technology improvements. However, research into the dynamics of the learning curve in service operations has been limited. And, research into the effects of process technology changes on learning in service organizations has been even more limited. This study examines productivity changes in a professional service organization over a ten-year span, in order to determine the magnitude and significance of the learning curve in this environment. The results indicate the presence of a significant, albeit shallow, learning curve. Additionally, the results indicate that whether technology improvement has an effect on the rate of learning is contingent on the type and use of the technology. Technology improvements that monitor and control the process have no significant effect on organizational learning, while technology improvements in the process lead to significant improvements in the rate of learning.

1 Introduction

Why do some organizations learn faster than others? The consequences of faster - or more effective learning have given rise to the paradigm of "the learning organization. This increased awareness of the learning organization has been fueled by a realization that effective and efficient learning - both by individuals and organizations is a critical organizational imperative.

Operations management researchers, in particular, have traditionally modeled the learning phenomenon through learning or experience curves. Since its discovery, arguments have been advanced, in the organizational, operations, and the systems dynamics literature on what drives learning rates, i.e. the slope of learning curves. Among the most common drivers, the literature suggests, are organizational structure, strategy, environment, culture, and technology (Dutton and Thomas, 1984). Our focus is the impact of information technology on the rate of learning in a service organization.
This study examines data on learning -- and the impact of information technology on it -- in a service organization over a ten-year span. The data permits analysis of learning in service organizations over a longer term than has been undertaken in past research. The study examines whether a perceptible and significant learning curve can be detected within the time frame under study. Additionally, since the accurate measurement of technological impact warrants a long time frame, the data permits a more precise analysis of the effect of information technology on the learning curve.

This research has a few distinctive features. First, this paper represents one of a few studies examining the rate of learning in professional service organizations. Second, the service "products" produced by the professional service organization under study are heterogeneous. Past research into learning in services has examined organizations producing homogenous outputs. The thinking has been that there will be little demonstrable learning in organizations with high variety or heterogeneous outputs. However, heterogeneity is a hallmark of services, and understanding whether learning may occur with heterogeneous outputs may be representative of more service organizations. Third, and perhaps most important, the research investigates the impact of two different types of information technologies, one that monitors the process (akin to Zuboff's (1988) "informate" idea) and one that changes the process (the traditional "automate" concept). Past research, in manufacturing organizations, has indicated that the rate of learning can be altered by technological innovation. Service organizations have invested relatively heavily in information technology over the past several years -- about $750 billion during the 1980s. Consequently, the results of this study will indicate whether those investments are likely to accelerate learning rates. If so, then the findings have important implications for the role of technology in managing learning in services.

2 Data and Analysis

Data for this research were collected from a large multi-disciplinary engineering organization. The organization is comprised of four departments: architects, electrical, mechanical and civil engineers. The organization operates in a project-process environment, creating drawings, technical specifications and cost estimates to meet customer requirements. The projects are highly variable, ranging from very simple designs, such as the installation of a single piece of equipment, to very complex designs, such as the complete design of a building.

Two separate information technology innovations were introduced into the organization during the time frame covered by the sample. The first was a project monitoring system (PMS) -- a computer-based database system -- that was used to collect information on design projects. This system, installed in 1989, replaced a manual system. The PMS system required every engineer to enter into the computer several pre-specified pieces of information -- such as man-hours expended, start,
finish dates etc. -- on the projects they were managing. The PMS system provided a centralized database containing information on all projects.

The second information technology was a personal computer (PC) based AutoCAD system, installed in mid-1993. The AutoCAD system was installed on PCs on every engineer's desk. After the installation of AutoCAD, all engineers and architects were required to complete drawings using the technology.

3 Method

Our analysis estimates the relationship between monthly productivity and experience using least-squares regression. The variables used during the analysis are as follows:

- \( i_t \) the index for the department in which the project was performed.
- \( q_{it} \) the number of projects completed by department \( i \) in month \( t \)
- \( Q_{it} \) the cumulative number of projects completed by department \( i \) through \( t \)
- \( l_{it} \) the number of labor hours expended on projects completed by department \( i \) in month \( t \)
- \( o_t \) the number of projects completed by the organization in month \( t \)
- \( O_t \) the cumulative number of projects completed by the organization through month \( t \)
- \( S_{it} \) the cumulative number of projects completed by department \( i \) in month \( t \) after the implementation of the process monitoring system
- \( C_{it} \) the cumulative number of labor hours expended on projects by department \( i \) in month \( t \) after the implementation of the AutoCAD system
- \( \epsilon_t \) estimation errors, assumed to be normally distributed

\( Q_{it} \) is used as an indicator of departmental experience or learning. \( O_t \), on the other hand, represents the organizational experience or learning.

The first of model tests for the significance of departmental and organizational experience before the implementation of the PMS system or the AutoCAD technology. This model estimates the relationship between organizational and departmental experience and monthly productivity. Our method is similar to that used by several researchers (see for example Baloff, 1971 and Argote, Beckman, and Epple, 1997). We fit a logarithmic model, as do the above mentioned research papers, to measure the relationships between organizational, departmental experience and monthly departmental productivity while controlling for labor hours and overall organizational workload. Specifically, we test two basic models -- Model 1A & 1B. The only difference between the two models is that in Model 1A, we introduce a dummy variable \( D_i \) which takes the value one if the project under consideration is part of department \( i \), else it is zero. The intention here is to see if the originating
department has any predictive effect. As the ensuing discussion will show, the department of origin is not a significant predictor of productivity, and hence we chose Model 1B for all future analysis.

$$\text{Model 1A: } \ln(q_{it}) = \beta_0 + \beta_1 \ln(l_{it}) + \beta_2 \ln(Q_{it}) + \beta_3 \ln(O_{it}) + \beta_4 \ln(o_{it}) + \beta_5 D_i + \epsilon_i$$  

(1)

and,

$$\text{Model 1B: } \ln(q_{it}) = \beta_0 + \beta_1 \ln(l_{it}) + \beta_2 \ln(Q_{it}) + \beta_3 \ln(O_{it}) + \beta_4 \ln(o_{it}) + \epsilon_i$$  

(2)

The second model, shown below, incorporates the use of the PMS technology. The goal is to determine whether department experience with the process monitoring system is a significant predictor of productivity. In order to isolate the effect of the process monitoring system, the analysis evaluates data after the implementation of the system and before the implementation of the AutoCAD system. The model tested is:

$$\text{Model 2: } \ln(q_{it}) = \beta_0 + \beta_1 \ln(l_{it}) + \beta_2 \ln(Q_{it}) + \beta_3 \ln(O_{it}) + \beta_4 \ln(o_{it}) + \beta_5 \ln(S_{it}) + \epsilon_i$$  

(3)

The third model examines the relationship between productivity and the use of the AutoCAD technology. The goal is to determine whether department experience with the AutoCAD system is a significant predictor of productivity. In order to isolate the effect of the AutoCAD system, the analysis evaluates the data on projects completed after the implementation of the AutoCAD system. The model tested is:

$$\text{Model 3: } \ln(q_{it}) = \beta_0 + \beta_1 \ln(l_{it}) + \beta_2 \ln(Q_{it}) + \beta_3 \ln(O_{it}) + \beta_4 \ln(o_{it}) + \beta_5 \ln(C_{it}) + \epsilon_i$$  

(4)

4 Results and Discussion

Table 1 presents the results of all our analysis. The findings indicate that experience is a significant predictor of productivity, even in an organization with considerable process variability. After controlling for the labor hours and number of projects, there are a couple of primary findings. First, the cumulative number of projects completed by the department and the cumulative number of projects completed by the organization are both significant predictors of departmental output. However, they have opposite effects on productivity. Departmental experience tends to be associated with increases in the departmental output. Organizational experience tends to be associated with decreases in departmental output.

These findings may be indicated by inter-organization dynamics. Within-department affiliations are much stronger than organizational affiliation. Departmental experience may be more significant because workers within each department share the same skills and knowledge sets. Information is shared informally within departments. Typically, workers go to others within their same departments with questions or concerns. Brown and Duguid (1996) define learning as becoming part of
a community, as becoming “enculturated.” The findings suggest that within the organization studied, employees become a part of their departmental communities. This may be due, in part, to the specialized knowledge within the departments.

**Table 1: Results**

<table>
<thead>
<tr>
<th></th>
<th>Model 1A</th>
<th>Model 1B</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor hours ($\beta_1$)</td>
<td>.330 (.000)</td>
<td>.328 (.000)</td>
<td>.172 (.000)</td>
<td>.355 (.000)</td>
</tr>
<tr>
<td>Cumulative department output ($\beta_2$)</td>
<td>.777 (.000)</td>
<td>.749 (.000)</td>
<td>.615 (.001)</td>
<td>.902 (.000)</td>
</tr>
<tr>
<td>Cumulative organization output ($\beta_3$)</td>
<td>-.931 (.000)</td>
<td>-.902 (.000)</td>
<td>-.005 (964)</td>
<td>-.1591 (.001)</td>
</tr>
<tr>
<td>Number of projects ($\beta_4$)</td>
<td>.381 (.000)</td>
<td>.384 (.000)</td>
<td>.377 (.000)</td>
<td>.272 (.000)</td>
</tr>
<tr>
<td>Department ($\beta_5$)</td>
<td>.005 (.709)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative department output with monitoring technology ($\beta_5s$)</td>
<td></td>
<td></td>
<td>-.002 (.359)</td>
<td></td>
</tr>
<tr>
<td>Cumulative department experience with AutoCAD ($\beta_6$)</td>
<td></td>
<td></td>
<td>.002 (.004)</td>
<td></td>
</tr>
<tr>
<td>Constant ($\beta_0$)</td>
<td></td>
<td></td>
<td></td>
<td>1.446 (.198)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.814</td>
<td>.813</td>
<td>.697</td>
<td>.654</td>
</tr>
<tr>
<td>Number of Projects</td>
<td>246</td>
<td>246</td>
<td>94</td>
<td>152</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>210.39</td>
<td>263.89</td>
<td>40.97</td>
<td>55.50</td>
</tr>
</tbody>
</table>

Organizational experience has a negative effect on productivity. The organizational experience variable may be capturing information regarding the overall bureaucracy in the organization. In addition, the findings suggest that the mechanisms for sharing information and task knowledge between departments within the organization are relatively weak.

The findings also indicate that information technology innovations can have a significant positive impact on productivity. The relationship, however, appears to be contingent on the type and use of the technology. Process monitoring technology – technologies that only seek to informate do not seem to have a significant effect on productivity. This makes sense as this technology does not alter the process, but simply gathers information on projects. However, Huber (1991) considers that knowledge acquisition and information distribution are important dimensions of organizational learning. This suggests that the organization may not be gathering the appropriate information, or the organization may not be transforming the information in a way that creates knowledge.
Experience with the AutoCAD technology, which can be thought of as a process-changing technology, is associated with increases in productivity. However, the magnitude of the effect of this technology is relatively small. In the realm of the service industry, this study is perhaps one of the few that show that process-changing information technology is, unequivocally, a significant predictor of productivity. This could be due to the long time frame we have chosen, indicating that investment in information technology could have “long-term” benefits.

5 Summary and Conclusions

At the outset, we had two primary objectives. First, recognizing that there is a dearth of research in evaluating the learning curve in service industries, we sought to investigate if there exists an appreciable learning curve in the professional service industry. We have based our analysis from data over a ten-year period in order to determine the magnitude and significance of the learning curve in this environment. The results indicate the presence of a significant, albeit shallow, learning curve.

Our second contribution was to see if technological improvements had a significant impact on the rate of learning. The results indicate that whether technology improvement has an effect on the rate of learning is contingent on the type and use of the technology. Technology improvements that monitor and control the process have no significant effect on organizational learning, while technology improvements in the process lead to significant improvements in the rate of learning.

References


