HOW INDIVIDUAL SKILL GROWTH AND DECAY AFFECT THE

PERFORMANCE OF PROJECT ORGANIZATIONS

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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

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Abstract

This dissertation describes a multi-disciplinary, multi-method inquiry into the effects of individual skill growth and decay on the performance of project-based organizations. It extends cognitive science literature by calibrating rates of skill growth and decay of individuals performing complex, cognitive tasks to quantify their effect on group learning within projects. Observations of student teams are used to quantify the growth and decay of individual knowledge in a project organization, depending on relatively controlled (OJT learning) vs. uncontrolled (forgetting due to *production breaks*) knowledge interventions. Findings suggest interventions at the individual level (e.g. role changes) will be reflected in the performance at the group level, but attenuated. Each level will also continue to learn and forget based on frequency of repetition and length of *production breaks* (Jaber and Sikstrom, 2004) in task performance. Group learning follows approximately the same pattern as individual learning; however, groups tend to learn and forget more slowly than individuals within the same knowledge environment. The analysis also indicates that an increase in trans-specialist knowledge, does not cause an increase in learning rate, but does cause an increase in decision making quality. This research develops a validated and calibrated simulation model that forecasts the organizational performance differences that occur as a result of individual growth and decay of cognitive skills. The simulation tool, POW-ER 3.2, is tentatively calibrated for cognitive skill, using data from student groups conducting a business strategy software exercise, (AROUSAL). The model is cross-validated against two other empirical data sets: a second round of

AROUSAL experimentation and from experimentation using the ELICIT Command and Control (C2) exercise. The second AROUSAL experiment also demonstrates the individual and combined effects of OJT, formal training and mentoring of individuals for a cognitive skill. Our intriguing findings suggest that, taken one at a time, formal training and mentoring each seem to cause a short term decrease in processing speed among individuals. However, these interventions ultimately lead to individual processing speeds that can surpass the processing speeds from OJT alone, based on our previously validated OJT learning rates of cognitive skills, and can also result in improvements in decision making quality.

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At the beginning of this process, I realized quickly that the decision to come to Stanford was not mine alone yet would have to be made with the consent of my darling wife Kathleen and our three daughters – Frances, Sarah, and the precocious Nora Clare. It is self evident that we chose the path of a Ph.D. from Stanford. It is with great pride and satisfaction that I therefore dedicate this doctorate and its requisite dissertation to my family - and especially to my courageous wife Kathleen. Her love, sparkle, and surpassing beauty will forever be a constant source of motivation and joy - and have now driven me to reach these great heights!

Finally, I am humbled by what God has done through his Son Jesus and the Holy Spirit. I will forever be His servant and count myself blessed to have reached this awesome achievement through – and only through – His constant help.

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Chapter 1: Introduction

Motivation

This research takes as its premise that science and engineering each consistently and successfully contribute to informing practice. Precise, explanatory mathematical flow models exist in the physical sciences such as fluid mechanics, electromagnetic wave propagation and light emissions. However, in stark contrast, organization theory and knowledge management researchers are currently hindered by the imprecise and ambiguous, natural language and textual descriptions of organizational knowledge flows (McKinlay, 2003).

Effective management of scarce resources—particularly knowledge—is critical to mission and project success. Learning and forgetting have been quantified at the individual level (e.g., Anderson, 2005 and Wixted, 2004) yet their combined effects have not been well understood at the group level, nor have their dynamic nature been analyzed to determine their cost and benefits to the project organization.

The goal of this research is to provide managers a method to determine optimal knowledge flow interventions for a variety of task and organizational contexts and to enable managers to identify where deficiencies in knowledge flows exist prior to project commencement, and to help them plan in advance for project success.

Sustained progress toward this goal will eventually enable managers to design more optimal knowledge management strategies for a variety of organizational designs in different environmental contexts. I calibrate and validate knowledge interventions that serve to change knowledge and commensurate skill level of agents (measured as processing speed). These findings can be used to inform managers how individual learning and forgetting rates can be used to generate reliable predictions of the effects of individually held knowledge at the organization level. This quantitative effort can afford a qualitative improvement over current best guess methods that managers currently employ toward managing the knowledge of their workers.

Research Questions

This research is organized by and explores the following questions:

Chapter 2: How can we predict the effect of individual learning and forgetting on organizational (or group) performance? Will a group of people exhibit the same sort of behavior as an individual does over time and can this be generalized to organizations? How does individual trans-specialist knowledge affect group performance?

Chapter 3: How can individual skill acquisition and decay be computationally modeled, calibrated, and validated? How are project organizations affected by the sum of the skill growth and decay of individual participants?

Chapter 4: How are project organizations affected by the sum of the skill growth and decay of individual participants? How are individual and group learning affected by formal training and mentoring? Will a group of people subject to formal training and mentoring, exhibit the same sort of behavior as those who learn through OJT, and can this be generalized to organizations?

Chapter Contents

Each chapter provides a foundation upon which ensuing chapters build. Each chapter contains some portions of summarized review from the preceding chapter to facilitate their future publication in different academic journals. The content of each chapter is described below.

Chapter 2 summarizes micro-behavior learning and forgetting rates found in cognitive science literature. The theory is compared to findings observed from two natural experiments that record observations from the business simulation AROUSAL. AROUSAL requires participants to compete a complex, cognitive task for eight iterations. I measure speed of processing and decision making quality at the individual and group level for each iteration. Chapter 2 also includes analysis of changing trans-specialist knowledge (Postrel, 2002). Findings from a Command and Control (C2) exercise entitled ELICIT are analyzed using AROUSAL findings.

Chapter 3 embeds calibrated and validated, individual, processing speed micro-behaviors from Chapter 2 into POW-ER 3.2. Output from a POW-ER 3.2 model of AROUSAL is calibrated using observations from the first AROUSAL experiment and validated using observations from the second AROUSAL exercise. Output from POW-ER 3.2 is also cross-validated against empirical findings of a third set of student groups conducting the ELICIT Command and Control (C2) exercise.

Chapter 4 continues my exploration of project team members learning a complex, cognitive task through the observations of participants using the second AROUSAL business simulation experiment. Chapter 4 builds on the previous chapters by quantitatively demonstrating the combined effects of OJT, formal training and mentoring of individuals for a cognitive skill in terms of processing speed and decision making quality along with role changes that increase trans-specialist knowledge (Postrel, 2002). Costs and benefits of OJT, formal training, and mentoring are discussed.

Chapter 2: Measuring How Individual Learning and Forgetting Affect Organizational Performance

Introduction

Effective management of scarce resources—particularly knowledge—is critical to mission and project success. Learning and forgetting have been quantified at the individual level (e.g., Anderson, 2005 and Wixted, 2004) yet their combined effects have not been well understood at the group level. This paper takes the initial steps of comparing extant research in cognitive psychology on learning and forgetting rates with findings from two experiments. These experiments - conducted one year apart with different participants - each recorded specialists' durations to prepare and integrate quarterly inputs of the AROUSAL construction business simulation exercise (Lansley, 1982). We observe that although group learning follows approximately the same pattern as individual learning, groups tend to learn and forget more slowly than individuals within the same knowledge environment. We also observe that an increase in trans-specialist knowledge (Postrel, 2002), does not cause an increase in learning rate, yet causes an increase in decision making quality.

We also suggest, using our findings, an explanation why learning does not occur for multiple rounds of the ELICIT exercise (Leweling and Nissen, 2007). ELICIT is a Command and Control exercise in which the length of time required for participants to develop a correct answer to a complex problem is measured. From these significant findings, we are able to extend our knowledge of group level learning and forgetting within an organization based on our understanding of individual learning and forgetting.

Background

Knowledge is a critical resource that must be managed and understood to improve the probability of success in any endeavor by an organization. The ability to understand and predict the diffusion of knowledge within the firm, considering knowledge as the supply or holdings of the firm within its employees, is thus a key factor predicting organizational success. In this paper, we seek to measure empirically the effects of three key factors relating to the flow of knowledge through an organization: knowledge learning rates, forgetting rates, and the influence of trans-specialist knowledge (Postrel, 2002).

It is important to define exactly what to measure in considering the ability of individuals to gain and lose knowledge and skill. We define data, information, and knowledge using a simple example. **Data** represent context-free descriptions of possible states of nature, for example, the specifications of different standard speaker components available from a manufacturer. **Information** places data in a specific context: e.g., a particular speaker that has been specified in a home audio system. And **knowledge** is applied to convert data into information: for example, the knowledge of how and why we selected the particular speaker for use in this project.

Knowledge itself can be epistemologically divided further into two types: *explicit* and *tacit* (Polanyi, 1966). Explicit knowledge is that which can be demonstrated or transmitted. Tacit knowledge is that which is held within the cognitive individual and “is deeply rooted in action, commitment, and involvement in a specific context” (Nonaka, 1994, p.16). We consider that the more an individual knows (either explicitly or implicitly), the greater is his skill. Trans-specialist knowledge refers to the level of knowledge shared by members of a group across specialties (Postrel, 2002).

Three sources (or inflows) of knowledge are available to transmit (or flow) knowledge into individuals within an organization. First, mentoring may provide the fastest means to provide knowledge inflow, but incurs a high cost of experts' time. Second, formal training may be employed. This is relatively inexpensive, but is somewhat slower. Finally, on-the-job training (OJT) is a slow but very inexpensive form of knowledge inflow that allows productive work to continue. Since OJT knowledge appears to be the knowledge inflow most relied upon and perhaps most analyzed within organizations (cf. Argote et al., 1995 and Epple et al., 1991), the remainder of this paper will focus on this knowledge transmission source.

Knowledge not only flows into people, groups and organizations; it also flows out. Such outflows represent subtractions from *knowledge inventory*. They arise from factors such as employee turnover, knowledge decay, and knowledge obsolescence. Employee turnover will cause all the tacit knowledge possessed by transferred employees to flow completely out of the transferring organization. Knowledge obsolescence may occur as a particular field grows and changes, such that old knowledge becomes less valuable. Finally, knowledge decay occurs through interference from other assignments or from infrequent practice or production breaks. Knowledge decay due to production break is the focus of this paper because we are interested in the way cognitive factors affect the learning and retention of specific knowledge within organizations over time.

To gain theoretical insight into knowledge flows, we began our research efforts by describing knowledge as a set of skills that grow and decay over time due to different environmental effects and managerial interventions (MacKinnon et al., 2005). We sought to understand how such skills can be managed to optimize organizational performance in different contexts. Specifically, we posited a model of knowledge as perishable inventory, whereby we discussed how parallel losses occur with respect to knowledge as a result of phenomena such as employee turnover, knowledge decay, and obsolescence, and how such a model aligned with inventory models for perishable, physical goods. However, the way in which knowledge is demanded and consumed differs considerably from the way that perishable goods are demanded and consumed in supply chains (MacKinnon et al., 2005). This suggested that an alternative approach might be more fruitful.

Here, we suggest a new empirically based approach to *knowledge inventory*, grounded in more micro-behavioral principles of learning and memory.

Knowledge flow: In the Individual and in the Organization

Individuals

Knowledge flows into individuals as they learn, and flows out as they forget, yet the psychological and neurological processes by which people learn and forget are extremely complex. We would be naïve to believe that we might explain all that there is to know about how humans learn and forget in a few short paragraphs. We will narrow our concern to the length of time required for an individual to complete a skill, or processing speed (e.g. Argote, 1999; DeKeyser, 1997; and Laird, Newell, and Rosenbloom, 1987), for the purpose of this study. Conceptually, we do not attempt to quantify knowledge directly, but instead measure skill completion time as a surrogate measure for knowledge held.

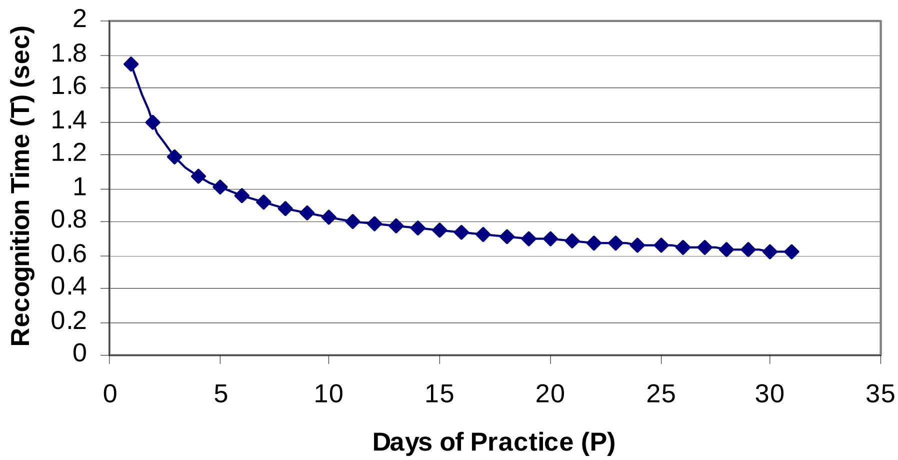

Figure 2.1: Power Law of Learning Over increasing days of practice, a simple recognition task (time required to recognize sentences) requires ever decreasing amounts of time (as found in Anderson, (2005)).

Skill completion - or response - time is typically modeled in terms of learning curves (Ebbinghaus, 1913; Anderson, 2005; Sikstrom and Jaber, 2002; and Wixted, 2004). Figure 2.1 illustrates the Power Law of Learning (Pirolli and Anderson, 1985) derived from empirical studies that appear ubiquitously in cognitive psychology texts (e.g. (Anderson, 2005)).

Time delay or *production breaks* (Jaber and Sikstrom, 2004) in between periods spent performing a task causes employees to forget. The rate at which forgetting occurs increases with task complexity and with simple failure to recall an item or procedure with some frequency (Jaber and Sikstrom, 2004). As with learning, forgetting follows a predictable function that can be described using a power law (e.g., Wixted, 2004; Wickelgren, 1974; and Ebbinghaus, 1913), e.g.: $R(t) = at^{-b}$ where t is time and a and b are scalars as shown below.

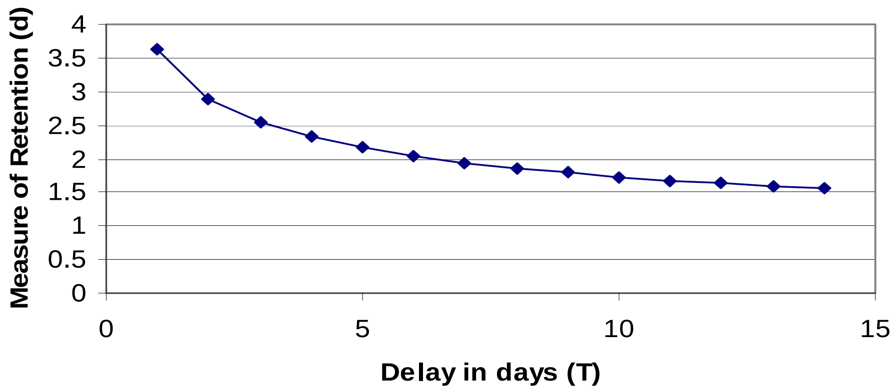

Figure 2.2: Power Law of Forgetting. Over time, what is known decays at a negatively accelerating pace. (Wickelgren, 1975; Wixted and Ebbesen, 1991)

While most work on forgetting has focused on relatively simple tasks, such as learning, where a participant is asked to recollect and recite memorized items from a list and, over time, begins to forget them (e.g., Anderson, 2005) similar effects can also be seen in the recall and performance of complex skills (Ericsson and Charness, 1994), such as forgetting in a practicing physician, (Smith, 1978) or skill decay in cardiopulmonary resuscitation (CPR); (McKenna and Glendon, 1985).

We will maintain our focus upon the learning and forgetting of a skill rather than simplified list learning. In the next section, we further narrow our scope toward analyzing skill learning and forgetting by categorizing different types of skill.

Skill Classification

Not all skills are learned by individuals with equal speed. Dar-El et al. (1995) classifies skills in the four following categories: (1) highly cognitive, (2) mostly cognitive, (3) mostly motor, and (4) highly motor, as shown below.

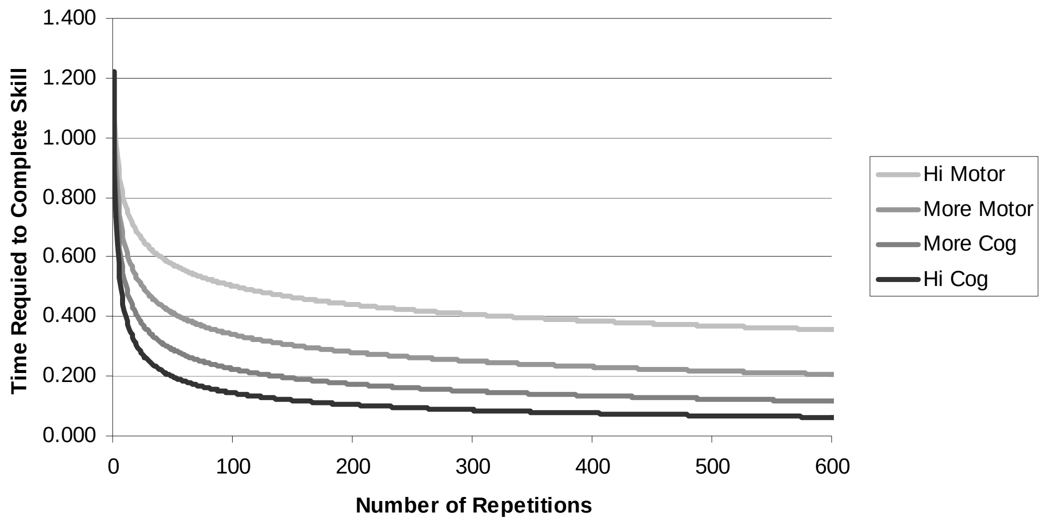

Figure 2.3: Learning Curves for Different Types of Skill (replicated from Dar-El et al., 1995). As skills become increasingly cognitive rather than motor, they tend to improve more over time.

Figure 2.3 illustrates the learning rate differences among four classifications of skill. Later, we will conduct an experiment whose empirical data will be plotted against these curves to attempt to classify the type of skill being used. We anticipate that this classification will further our understanding of skill learning when combined with forgetting. We will attempt to combine and build upon these theories by combining learning and forgetting with skill classification to improve our ability to forecast knowledge, or skill level, over time, and hence group performance.

We next discuss research about organization level skill loss and gain as we anticipate that individual learning and forgetting rates will have organization-level effects.

Organizations

There is a large body of literature on information flow in organizations, going back to the pioneering work of Herbert Simon and James March in the 1950's (Simon and March, 1958). However, the corresponding literature on the knowledge flow in organizations is only just emerging (e.g., Levitt et al., 1999; Nonaka, 1994; and Nissen, 2006) and remains inchoate.

A few studies have been published illustrating the gains and losses to projects as their employees learn and forget skills over time, or as they turn over during and between projects (Ibrahim, 2005). There have also been relatively few attempts to determine how to manage this knowledge in terms of interventions such as mentoring, training or OJT (listed from smallest to greatest levels of available research). For example, Carley and Svoboda (1996), as well as Carley (2001) using a model called ORGAHEAD, model individual learning computationally, and model organizations that can *adapt* (*hire, fire*, *redesign,* and *retask*) toward an increasingly optimal design to achieve maximum organizational performance. Carley also models how individual knowledge can become less valuable with new organizational structural changes.

There is a nascent trend in the literature to view knowledge as a supply chain or knowledge chain (Holsapple and Jones, 2004 and 2005), yet these findings employ only qualitative, natural language descriptions. Kim (1993) also seeks to link individual learning to organizational learning via natural and metaphorical thinking and examples. However, his efforts do not extend to quantifying the effects of individual learning on project outcomes. We will extend this portion of the literature by stepping away from the current natural language descriptions and toward a more quantitative computational perspective that has the potential to produce new understanding in determining how to forecast, and perhaps manage, knowledge inventory more optimally in project teams.

Schreiber and Carley (2004) using CONSTRUCT, modeled individual knowledge as both cognitive and *transactive*. Transactive knowledge refers to the "meta-knowledge" of where or with whom different kinds of knowledge reside. They seek to determine the impact that database use and data type have on organizational performance in terms of levels of group interactions and knowledge sharing. Our research has a similar goal, but will take a different approach. We seek to improve project organizational outcomes by determining the impact of individual learning.

Postrel (2002) considers an alternate approach of analyzing when trans-specialist knowledge has a positive impact on organization performance. In his conclusion, he challenges researchers to allow learning to take place within projects that involve trans-specialist knowledge. We are motivated by this challenge.

We offer a quantitative study of how dynamic, individual knowledge, both with and without trans-specialist knowledge, will manifest itself at the organizational level. We anticipate that each agent's dynamic, skill completion time speed and trans-specialist knowledge will have far-reaching implications throughout the organization that will directly affect expected project duration, cost, rework volume and quality risk.

So far, learning and forgetting curves are averages of individual performance.

Research Questions

1. How can we predict the effect of individual learning and forgetting on organizational (or group) performance?
2. Will a group of people exhibit the same sort of behavior as an individual does over time and can this be generalized to organizations?
3. How does individual trans-specialist knowledge affect group performance?

Approach and Methodology

We began by considering how we might measure knowledge level among individuals. We first decided to implement a *problem based learning* (PBL) experiment rather than a purely synthetic or laboratory experiment. A laboratory experiment allows for stricter experimental control, however, the PBL experiment provides for greater realism (Zolin, Fruchter, and Levitt 2003) while still providing for considerable environmental control. This type of experimentation seemed a better fit for what we wish to explore. Second, we determined that the clearest indication of knowledge level is though measurable performance. We will therefore measure how long it takes each participant to perform a complex skill during each iteration of a simulated construction business exercise. We expected to replicate the power law of learning and forgetting and to measure the effect of trans-specialist knowledge on individual and group learning.

We selected a business case simulation, entitled *AROUSAL* (Lansley, 1982) where participants were asked to provide quarterly plans for a simulated business. A class of 31 Master of Science students was asked to participate in a business case simulation where they manage a virtual construction company. Each participant was randomly placed in a group and given a role to perform. These roles consisted of either: marketing-sales, operations, human resources, or finance. There were four participants per group and the groups decided who would take each role. One group consisted of only three participants, so its data are not included in this paper. Each participant was directed to develop his/her individual quarterly business plan. Each group was then directed to convene to integrate these plans. Integration was not trivial because each individual competed for limited group resources. For instance, the budget of each group had to be allocated among initiatives related to marketing, hiring new people, and writing proposals (bids) for new construction jobs.

The simulation ran for eight quarters (Q1 through Q8). After four quarters, the groups were asked to stop playing and resume some time later, approximately three days, at their discretion. Three of the seven groups exchanged roles to provide an opportunity to measure their trans-specialist knowledge. The remaining four groups maintained their roles throughout the game, providing them more cycles to learn their skill. The first quarter's inputs were pre-specified for each group to provide software training, so its data are not considered.

We asked each participant to voluntarily sign a release form under appropriate protocol, notifying them of the anonymous nature of the recorded data as well as their voluntary participation in this study. They were then asked to self-report their background or Knowledge Inventory (KI). They were also asked to self-report both their time spent on their individual task each quarter, and the time their group spent integrating its plans for that quarter.

AROUSAL Measurements

We measured how long it took for participants to accomplish a recurring skill (i.e. a specific functional portion of a quarterly business plan), and then measured how long each group required to integrate these plans. We also measured how trans-specialist knowledge changed individual and group performance as we compared the groups who changed roles with those who did not. We measured this for seven iterations.

We measured this to understand the rate at which individuals and groups learn so that we might embed these learning and forgetting rates into an agent-based, project organizational simulation so that the simulation model could reliably simulate learning in other organizational contexts.

Cognitive Measurements

Each participant also voluntarily participated in a short, cognitive test of text reading and comprehension to determine relative cognitive ability (Sternberg, 1995). The test required single strings of text to be read and remembered. After each text string was read and understood, the participant was asked to depress the shift-key to reveal the next text string. After each set of five strings were read, a true or false question about comprehension was asked. Ten sets of strings were used in total. Times, measured in milliseconds, via DMDX software (Forster and Forster, 2002), were recorded for the time required to read or answer each text string or question. Correct responses were also recorded. The findings of this test are discussed along with the findings of the Arousal exercise.

Our Hypotheses

We considered the participants' required time to develop and then integrate their business plans with a production break of several days between Q4 and Q5, in the exercise. We also considered the monetary success of each group. We formed three hypotheses.

<u>Hypothesis 1a</u>: Participants will decrease their time required to develop the next business case following a learning curve. Because these cases are conducted for four quarters in each work session, and a production break occurs after Q4, they will spend more time in Q5 to overcome what they have forgotten since Q4, based on what they have learned in the past four quarters.

<u>1b</u>: Individuals who exchanged roles at the one year mark will take more time (knowledge decay) due to learning a new role, than those who remain in the same roles, as shown in figure 2.4.

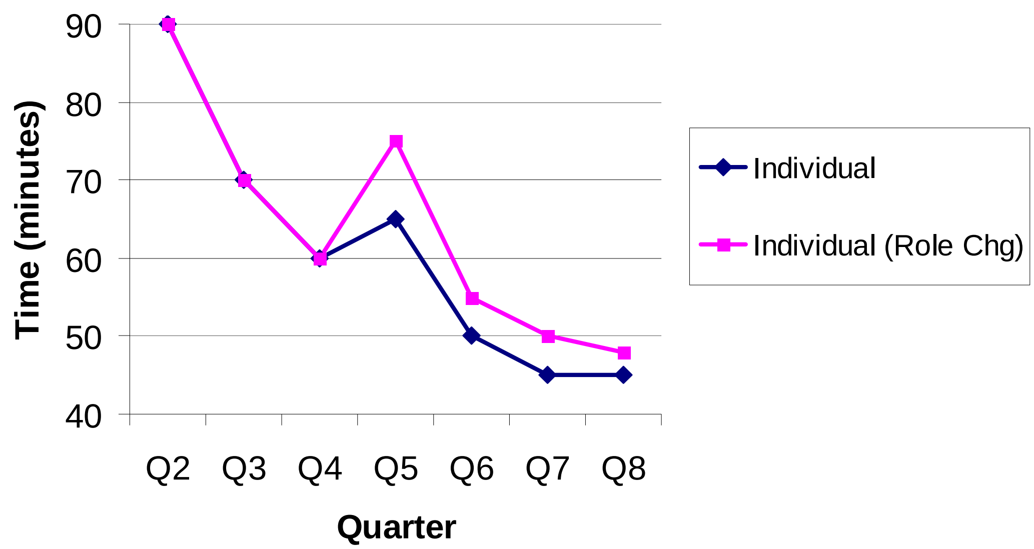

Figure 2.4: Hypothesized Time Spent on Individual Preparation showing the hypothesis about average time each student spends in preparing their portion of the business case, comparing those individuals who changed roles (dashed line) with those who did not (solid).

<u>Hypothesis 2a</u>: Groups will show a decrease in their time required to integrate each successive business case following a learning curve. Since these cases are conducted four quarters per meeting, and a production break occurs after Q4, they will spend more time in Q5 to overcome what they have forgotten and to implement what they have learned in the past four quarters.

<u>2b</u>: The groups who change roles at the one year mark will encounter an even greater time requirement afterward than those groups who maintain their original roles, due to learning new roles.

<u>2c</u>: The groups who change their roles will overcome this initial deficit over the final three quarters because of increased trans-specialist knowledge of each other's skills. This will result in decreased time for required group integration, as shown in figure 2.5.

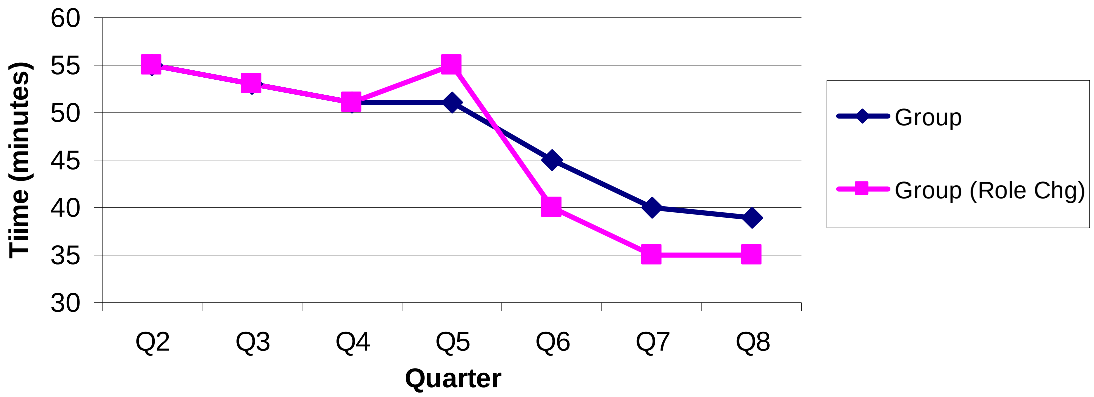

Figure 2.5: Hypothesized Time Spent on Group Preparation comparing groups who changed roles (dashed line) with those who did not (solid).

<u>Hypothesis 3a</u>: All groups will increase in their net worth in the next business cycle following an inverse learning curve. Since these cases are conducted four quarters in each session, they will not improve as much in the fifth quarter because of what they have forgotten in the past four quarters.

<u>3b</u>: Individuals who change roles at the one year mark will encounter greater decision making quality, shown through profit growth, than those groups who maintained their original roles. This will be due to improved trans-specialist knowledge and improved decision making, as shown in figure 2.6.

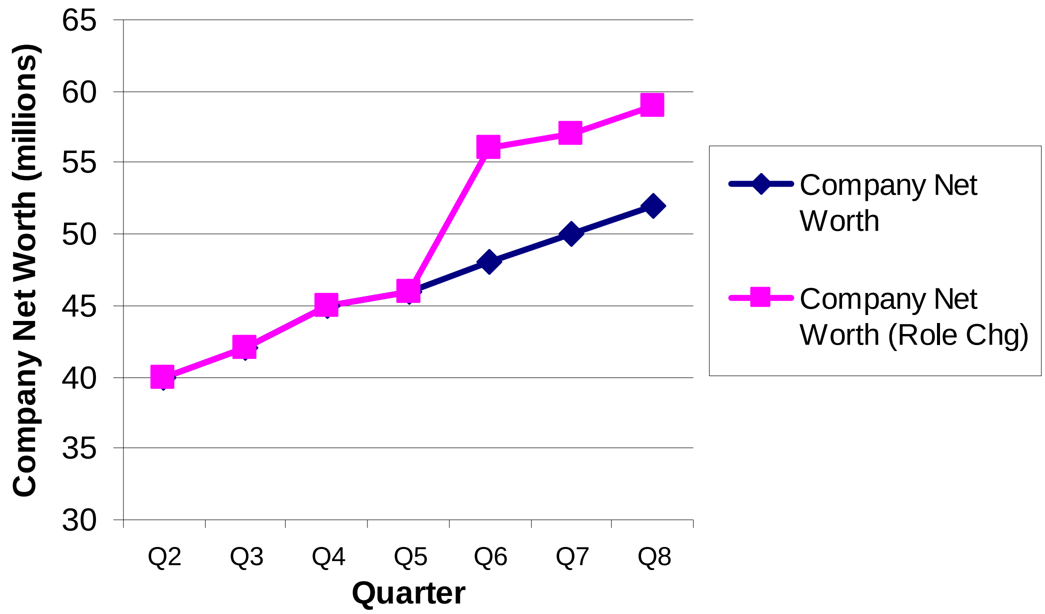

Figure 2.6: Hypothesized Company Net Worth Over Two Years comparing groups who changed roles (dashed line) with those who did not (solid).

Results

Individuals and groups exhibited learning and forgetting effects as shown in the averaged processing times below.

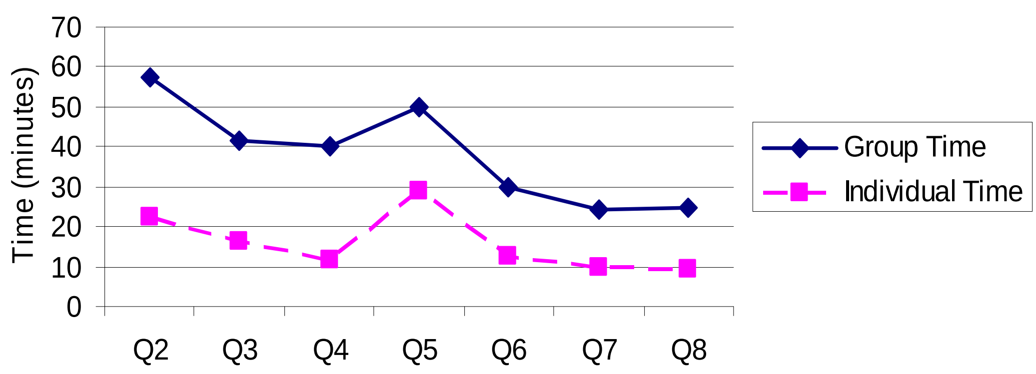

Figure 2.7: Aggregated Group (solid) and Individual (dashed line) Learning Over Time which shows a consistent time requirement decrease after the second quarter, except at Q5 where participants were asked to introduce a production break in their work prior to the final four quarters.

The individuals and groups each exhibited the hypothesized learning behavior in their skill completion time during the first three quarters. Q1 data is not included because its input was provided to each individual for simulation training. As predicted, groups and individuals each showed a marked increase in required time for Q5. This seems due to the three to four day production break in performing the simulation. The increase in time for the fifth quarter indicates the skill decay that took place as a result of the production break.

Forgetting seems to occur less drastically among the groups than the individuals as seen in figure 2.7, yet both the groups and the individuals swiftly regain their skill level after just two quarters. We also found that the length of the production break was a significant variable. For every day of production break that groups waited to commence the final four quarters, the time required for the group to integrate their business plans grew by about 7.4 minutes as shown below.

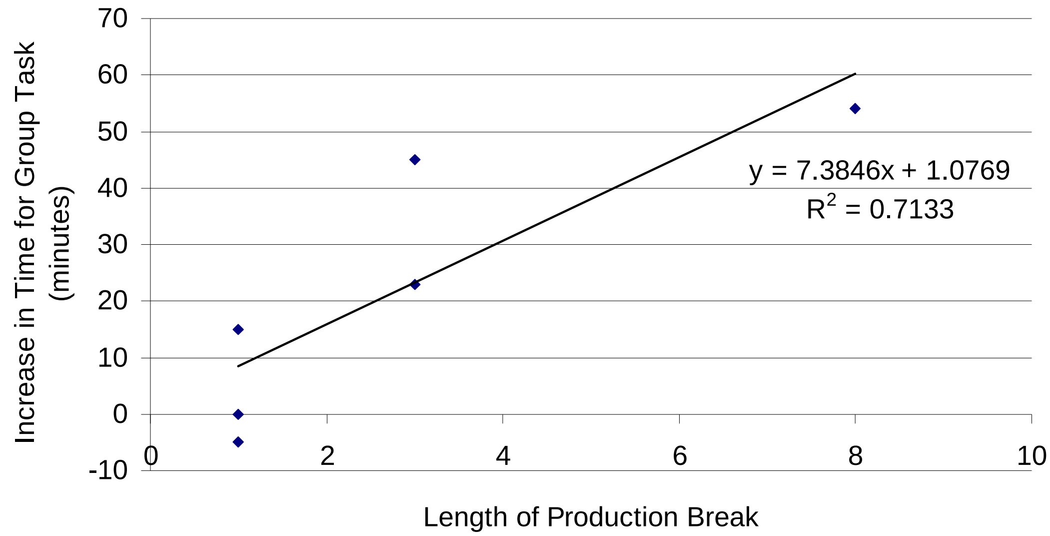

Figure 2.8: Forgetting Correlation for Aggregated Group Data which shows the relatively high correlation between length of production break and increase in time to complete the cognitive task.

From this figure and its included regression trend line, we note that approximately 7.4 extra minutes are required to complete the task for every day of production break between tasks (R^2=0.7133), (*p* = .0344). The group task required 39 minutes on average to accomplish before the break. From this we infer that for every day in production break, each group loses approximately 19% of its skill in terms of average processing speed (7.4/39 minutes). Data from one of the groups is not included due to their taking two breaks instead of one.

Next, we show how the data compares to the skill classification learning curves (Dar-El et al., 1995). Times shown are normalized to provide comparison.

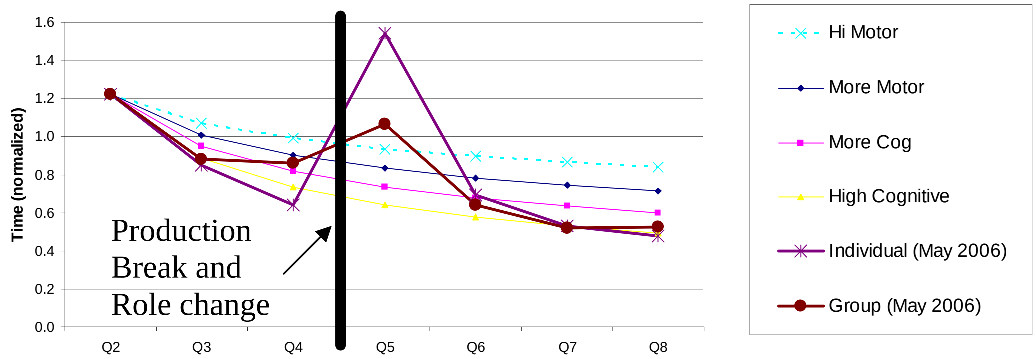

Figure 2.9: Dar-El et al. Learning Curves with Individual and Group Learning Rates Aggregated Over Time which shows the replication of cognitive learning plus the reacquisition of the curve after a production break - which is denoted by the vertical bar.

Above, we compare both the individual data and the group data with the theoretic categorized skill curves of Dar-El et al. (1995). We observe that our data plot along the cognitive curve for both the individual and the group data for the second and third quarters which support hypotheses 1a and 2a. Q5 shows a significantly increased time requirement for both individuals and groups, with the individuals' amount of time increased more than the group time. This is due to the production break taken between simulation runs (and due to the exchange of roles within three of the groups). The impact of the exchange of roles is discussed in the trans-specialist knowledge analysis section below.

We also observe that both the individuals and the group times return quickly to near their original trend - and again track along the cognitive curve. In replicating the findings of Dar-El et al., we provide compelling evidence that predictions of individual knowledge can be validated and perhaps calibrated for use in predictive organizational models of cognitive skill.

We observe that group learning follows qualitatively the same pattern as individual learning; however, groups tend to learn and forget more slowly than individuals within the same knowledge environment. This qualitative finding supports the notion that groups, rather than individuals, might provide a preferred echelon of learning because of the retained knowledge revealed through reduced levels of forgetting.

Our cognitive testing of individuals revealed no significant correlation between cognitive ability and time to complete tasks either for individuals or groups. Our cognitive testing data did not correlate with groups who performed better or worse than others in terms of "company" performance in the exercise. This may be explained by the observation that the range of cognitive abilities for this group of Civil and Environmental Engineering, Master of Science students is relatively small.

In this next section we discuss our observations and findings of the effects of trans-specialist knowledge (Postrel, 2002).

Trans-Specialist Knowledge Analysis

Our experimental design allowed us to collect data on individuals and groups who exchanged roles after four quarters of the simulation to examine the effects of trans-specialist knowledge (Postrel, 2002). Trans-specialist knowledge refers to knowledge that is "shared across specialties" (p.303). This kind of knowledge seems helpful within a group task for which roles are relatively interdependent with one another, by helping individuals understand and anticipate the constraints and requirements of other individuals operating within the same team.

Within the AROUSAL experiment, three groups exchanged their four roles at the halfway point through the experiment while participating in the remaining four groups kept the same roles. This exchange only took place once and coincided with a planned break in the simulation, after which roles remained fixed for the remaining four quarters.

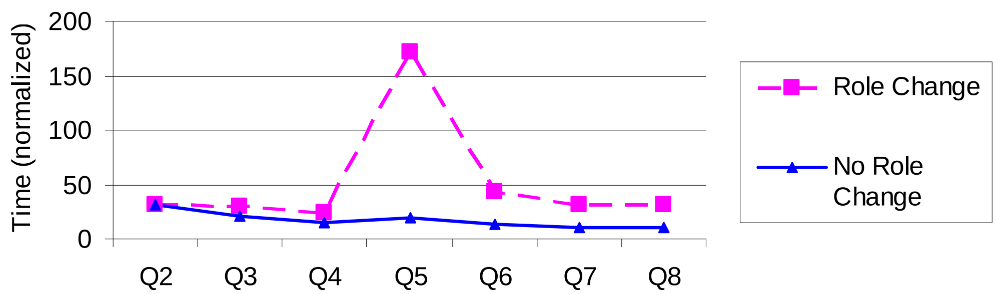

Figure 2.10: Averaged Individual Time Required for Each Quarter with Role Changes which shows the relatively large increase in time requirement (skill loss) when roles were exchanged.

Figure 2.10 shows the normalized averaged individual time required to develop each quarterly business plan. Individuals who exchanged roles are shown with a dotted line. The two sets of individuals initially required different amounts of time in Q2, therefore the data are analyzed and shown normalized for comparison of learning rates. Note that after Q4, individuals who exchanged roles required a substantially longer amount of time than those who did not exchange roles. This results in a statistically significant difference (p =.004). This increase begins to be decrease in the next quarter, yet the difference (44 versus 13 minutes) remains statistically different (p =.016) as both sets of individuals continue to develop their individual business plans. Q7 and Q8 each remain statistically different, p = .019 and p = .017, respectively. It appears that the increase in required time is caused primarily by the exchange in roles.

Hypothesis 1b is supported since the data for Q5 through Q8 are statistically distinguishable. There is an increased amount of time required by those individuals who exchanged roles compared to those who did not, and it persists for the remainder of the exercise.

These findings suggest that individuals who change roles might experience a greater effect from a production break than their fixed-role counterparts. This increased time requirement seems to have been caused by learning a new skill rather than forgetting a previously learned skill. This suggests that individuals who exchange roles may require more time in learning new skills yet, may better prepare a group to accomplish novel tasks found in a more dynamic environment.

Figure 2.11 shows the average amount of time required by the two sets of groups in each quarter. This graph shows approximately the same effect of role changes for groups as it did for individuals - an increase in time required by those groups who exchanged roles over those who did not. We note that the time required for the first two quarters is higher for the no-role-change groups. This is attributable to other group characteristics not characterized by our data. We therefore analyze and illustrate this data as normalized to compare rates of learning.

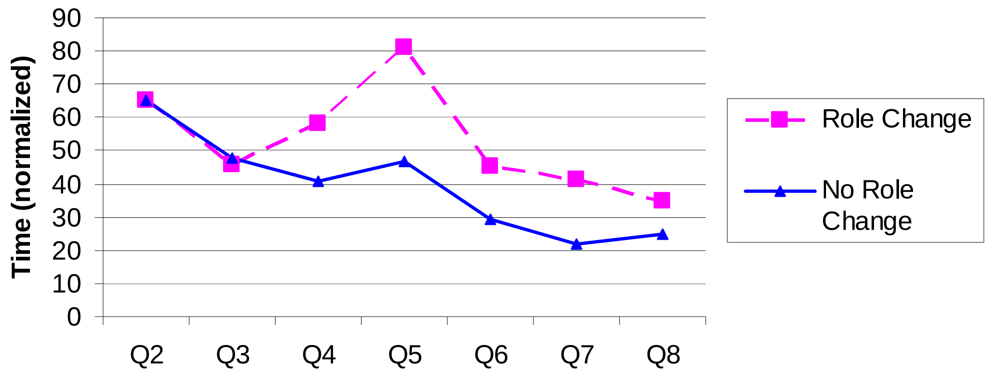

Figure 2.11: Normalized Average Group Time Required for Each Quarter with Role Changes which shows an increased time requirement for groups whose individuals exchanged roles.

Q5 again shows a marked increase perhaps caused by production break forgetting and the exchange of individual roles. The time difference for those groups who exchanged roles before Q5 is statistically different than those groups who maintained their original roles (p = .014). Q6 through Q8 also remain statistically different, p = .015, .003, and .029 respectively. Hypothesis 2c is not supported in that the difference in group times is not recouped after the production break during which roles are exchanged between individuals.

It seems that groups who exchanged roles required more time from Q5 through Q8, and that time spent in learning new skills began to decrease over the remaining three quarters. The groups who exchanged roles show a continuing steeper downward trend in required time. We theorize that this trans-specialist knowledge, caused by role exchanging, may provide increased flexibility for future group assignments. We would expect that the groups would not recover their uninterrupted learning rates as modeled by Dar-El with a production break interposed, so these results are not surprising. The effect of the production break appears initially to outweigh the effects of higher trans-specialist knowledge due to role swapping.

There is a strikingly qualitative difference in performance, as demonstrated through group profit gained, between groups who exchanged roles and those who did not as shown in figure 2.12. However, their difference is not statistically significant, given the relatively large standard deviations and the relatively small sample sizes. Specifically, the three groups who exchanged roles began to earn profits only after the role change and completed the exercise with a cumulative net worth of $615K with a standard deviation of $425K. The five groups who did not exchange roles ended with a cumulative net worth of $214K with a standard deviation of $266K. A pair-wise comparison, pooled variance t-test of the final three quarters indicates that the difference at Q6 is not statistically different (p = .127, yet the difference in net worth between those who exchanged role and those who did not is significantly different for Q7 and Q8. p= .038 and .017 respectively.

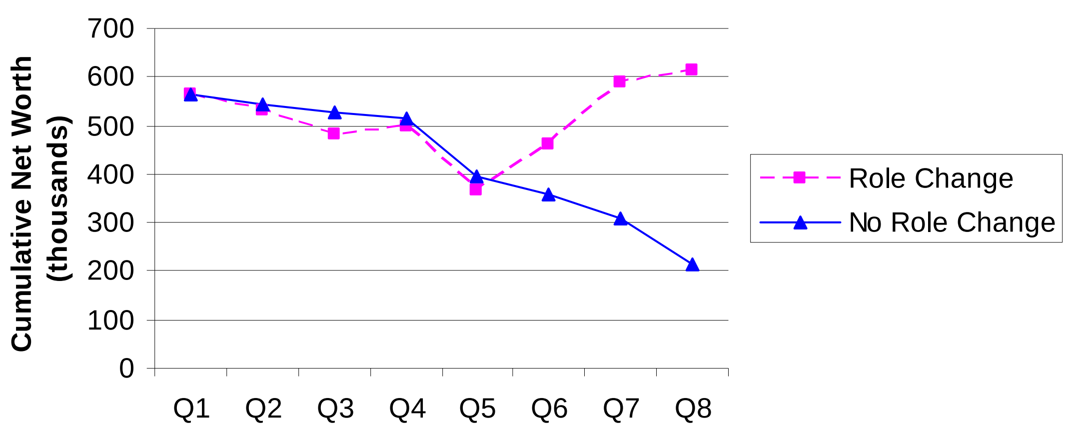

Figure 2.12: Normalized Averaged Differences in Cumulative Net Worth Between Role Change and No Role Change Groups which shows that groups who exchanged roles performed better thereafter.

Hypothesis 3 is supported in that this divergence took place after Q5. We theorize that there is a qualitative difference in decision making ability between the groups given their difference in trans-specialist knowledge.

The role exchange caused a greater difference at the individual level than at the group level. In both cases the increased skill completion time began to be overcome at each level in the following quarter. This seems reasonable because exchanging roles causes individuals to acquire new knowledge, while the group integration time might only increase slightly, yet allow for improved decision making due to the increase of specialist knowledge.

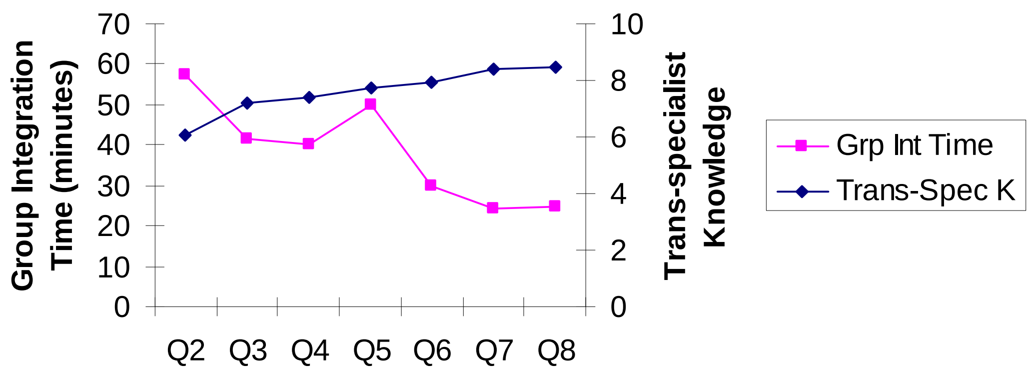

Figure 2.13: Aggregated Group Time with (self reported) Trans-Specialist Knowledge which shows that as time continues groups tend to require less time in skill performance as their trans-specialist knowledge improves. The trans-specialist scale represents an aggregate, self-reported level of knowledge of other's roles on a scale from 0-10, where 10 represents perfect knowledge of the other's role.

Here, we compare the time required by all groups with the self-reported level of trans-specialist knowledge at each quarter. There is a negatively accelerating increase that mirrors the reduction in time required by each group, with the exception of quarter five, when exchanges and production breaks took place. This symmetric and opposite difference may support a method of calibration of group learning via the level of trans-specialist knowledge they obtain over time.

It seems that trans-specialist knowledge (Postrel, 2002) learning could be qualitatively calibrated via the kinds of data collected in the AROUSAL experiment, but our sample sizes in this experiment were too small. A control mechanism for all groups was produced since learning was demonstrated through decreased time requirements by all groups during the first three quarters before any roles were exchanged. After the role exchange, the individuals who changed roles experienced a decrease in the aggregated average time required to develop individual plans that kept pace with their previous trend after one time period of learning their new skill. The time required at the group level for integrating plans decreased faster for those whose group's changed roles, yet the reduction was not statistically significant and resulted in their regaining their previous trend. The difference occurred in the group's decision making ability to make decisions. Since the groups with a role change increased their profits significantly more than those groups who did not, this suggests that trans-specialist knowledge may have a significant effect on team performance and can be qualitatively calibrated. More data from future experiments of this type will be needed to explore these tentative findings and confirm or reject them.

A Second AROUSAL Experiment

A second AROUSAL experiment was conducted one year later, using 41 student participants. Each group again temporarily stopped the exercise after the fourth quarter (Q4) for 3.1 days and each group exchanged roles at that time. The following figure illustrates our observations.

The data shown in figure 2.14 again indicate the average amount of time required for individuals to develop their individual quarterly business plans. We observe that the individual times for the second round of AROUSAL, conducted May 2007, confirm and validate our observations taken one year earlier. The data have one anomaly. Average individual (but not group) times increase in Q4, but not by much.

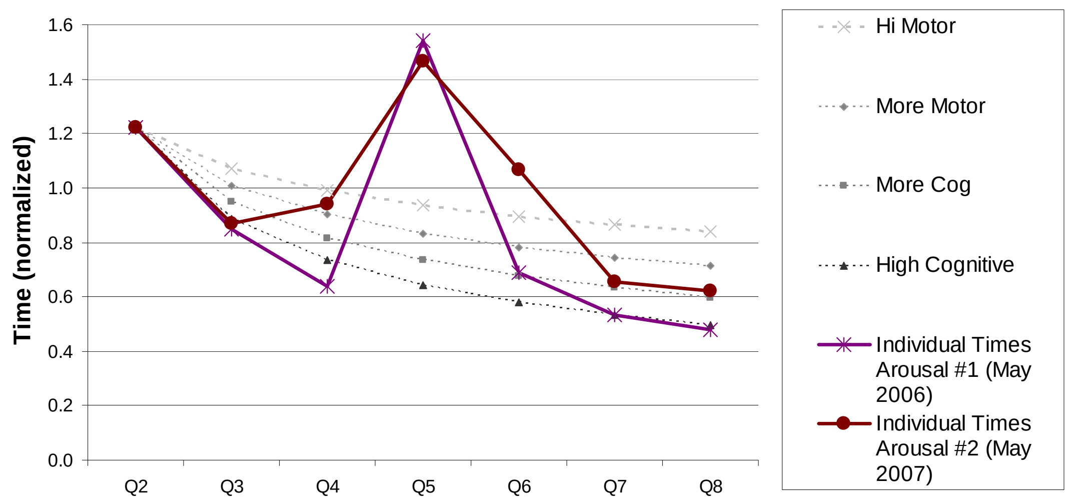

Figure 2.14: Combined AROUSAL Individual Times showing the similarity between separate rounds of AROUSAL.

Group integration times also show a strong similarity between AROUSAL cases for nearly all quarters (see figure 2.15).

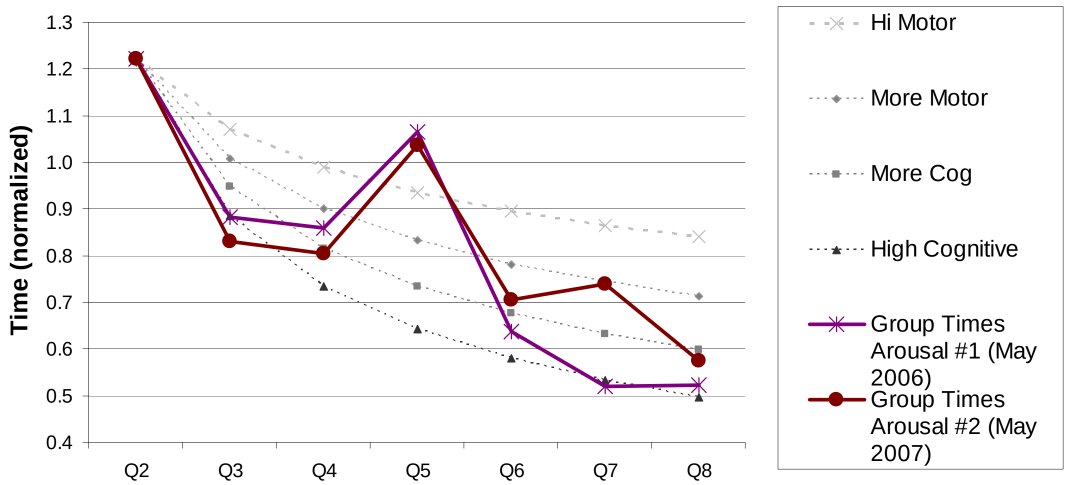

Figure 2.15: Combined AROUSAL Group Times showing the similarity between separate rounds of AROUSAL.

Net worth for each quarter was again observed and is illustrated in figure 2.16 below. AROUSAL #1 groups tended to lose money on average compared to AROUSAL #2 groups. This may have resulted from experimental interventions and from a slight variation in the AROUSAL #2 software. The AROUSAL software version implemented in the May 2007 exercise was altered slightly through the updating of available market data to 2007 and 2008, in which demand was much higher than in the 2003-2004 data used by groups in the first experiment.

Our comparison of the net worth for the two AROUSAL cases indicates that quarters Q2 through Q6 (average *p*-value .009) and Q8 (p = .024) are statistically different; Q1 was the fixed starting point for all groups and the average net worths in Q7 are not statistically different, p=.109.

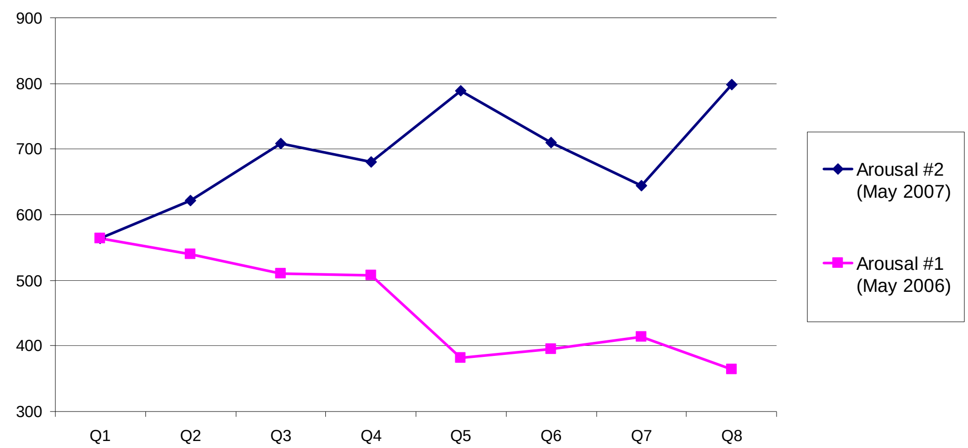

Figure 2.16: Combined AROUSAL Net Worth showing the difference between the separate AROUSAL experiments. All data are normalized for Q1.

ELICIT

ELICIT is a computer-based, small group, Command and Control (C2) exercise. It requires that a group of 17 participants piece together disparate sentences (factoids) to determine the *who*, *what*, *when*, and *where* of a fictitious terrorist plot. This exercise is typically conducted using four teams, organized using two different organizational forms. These two forms are "hierarchy" and "edge" (Alberts and Hayes, 2003). Hierarchy organizations are a more prevalent type of organization with one person who is in overall charge. The person in charge has four people who report to her. One of these four is tasked to learn "what"; a second "where"; a third "who"; and the fourth "where." Each of the second level personnel has three individuals who report to him. Hierarchy organizations are specialized, as in this case; and they flow their knowledge from, and maintain their decision rights in a centralized headquarters where the overall leader resides. The edge organization, alternatively, can be compared metaphorically to a “networked” organization in which there is no specialization of members and no particular leader. All of the workers are interconnected and therefore able to communicate with each other. Knowledge and decision rights reside at this one – and only – level. The other difference among the two organizational forms is their ability to assess available knowledge bases (or synthetic websites for posting and retrieving of factoids). Only the Overall Coordinator in the hierarchy case can access all of the knowledge bases, whereas the remaining agents are only permitted to access their team-specific knowledge base. All agents in the edge organizational form have access to all knowledge bases. Participants were tasked with the same goal of producing the correct “who, what, when, and where” identification of the simulated terrorist plot.

External Validity

In this next section we focus upon the output from the ELICIT Command and Control exercise in which multiple rounds of the exercise revealed the following average duration times for each organizational form (Leweling and Nissen, 2007).

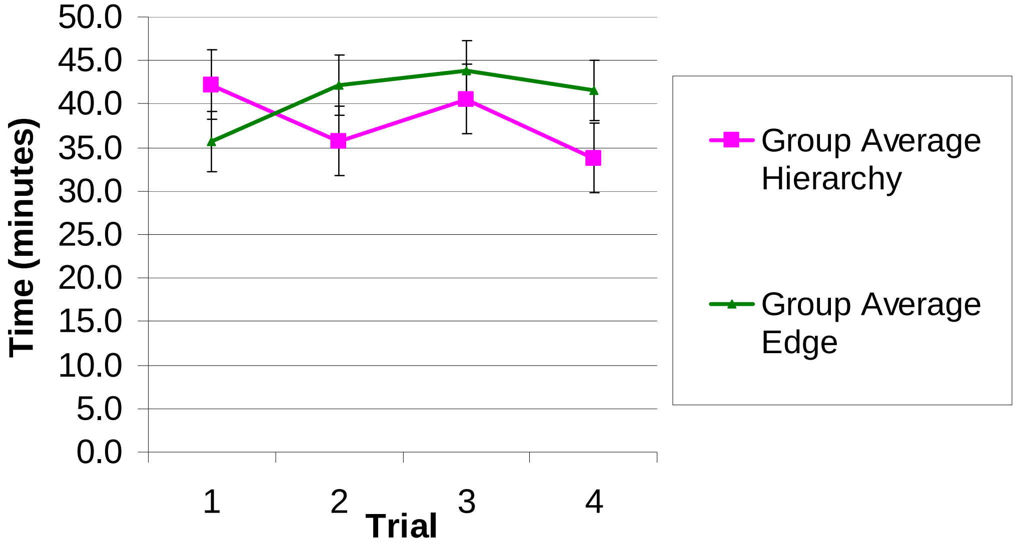

Figure 2.17: ELICIT Empirical Hierarchy and Edge completion times showing participant's average time to achieve the correct answer.

The data observed from the edge groups does not exhibit learning. It trends upward indicating that more time is required for each successive round. The data from the hierarchy groups demonstrates high variability between successive rounds with a slight downward trend on average. Variation in the empirical data is partially explained by the authors through slight variations among different ELICIT trials and slight unforeseen changes in personnel participating in the exercise (Leweling and Nissen, 2007). The authors also indicate that the time between runs is approximately three and a half days. Our findings from the AROUSAL exercise indicate that for a complex, cognitive task, successive repetitions, without a break in between are required to provide the opportunity for individuals to learn. It seems that in the ELICIT case, a series of single rounds that require one hour on average to complete is insufficient for learning to be demonstrated, given the production breaks of three and a half days. It seems that individual participants are forgetting the knowledge of the skill they have practiced.

Conclusions

Our goal was to determine how to calibrate the skill growth and decay of individuals to determine their effect on group learning and performance within projects. We therefore, analyzed the growth and decay of individual knowledge in the project organization, based learning via OJT and production breaks.

Our analysis suggests that perturbations at the individual level (e.g. production breaks and role changes) will have quantifiable and predictable effects. These same effects are also quantifiable and predictable at the group level, yet to a lesser extent. Each level learns and forgets based on frequency and length of production breaks in task performance. Our analysis also suggests that increasing trans-specialist knowledge at the individual level by rotating roles provides improved quality at the group level yet costs the organization a statistically different amount of time in speed of processing. Our analysis indicated that this lost time may be recouped faster at the group level than at the individual level.

We observe that group learning follows approximately the same pattern as individual learning, but groups tend to learn and forget slower than individuals within the same knowledge environment. We also observe that an increase in trans-specialist knowledge by rotating roles (Postrel, 2002), does not cause an increase in skill. However, it causes an increase in decision making quality. From these significant findings, we are able to extend our knowledge of group level learning and forgetting within an organization.

Both rounds of AROUSAL serve to support our proposed hypotheses as summarized in the table below.

Table 2.1. Hypothesis Results Summary The three proposed hypotheses are summarized below. Statistical significance is given where appropriate.

Hypothesis Summary	Results	Level of Significance
Hypothesis 1a: Individuals will decrease their task accomplishment time following a learning curve except in Q5 after a production break occurs.	1a: Supported by the data. Individuals follow a cognitive learning curve except after Q5.	1a. Q5 durations are significantly higher than Q4 durations for all individuals and groups.
1b: Individuals who exchange roles will encounter a greater time requirement due to learning a new role than those who remain in the same role.	1b: Supported by the data. There is an increased amount of time required by those individuals who exchanged roles, and it persists for the remainder of the exercise.	1b: Difference at Q5 between individuals who exchanged roles is significant (p=.004). 1b: Afterwards, Q6 to Q8, remain statistically different.

Hypothesis 2a: Groups will decrease their task accomplishment time following a learning curve except in Q5 after a production break occurs. 2b: Groups whose individuals exchange roles will encounter a greater time requirement due to learning a new role than those who remain in the same role.	2a: Supported by the data. Groups followed the cognitive learning curve through Q4 when the production break occurred. 2b: Supported by the data. Groups with role change showed a statistically significant increase in time compared to those groups who did not exchange roles.	2a and b: Difference at Q5 between groups whose individual exchanged roles is significant (*p*=.041).
2c: The groups whose individuals exchange roles will overcome this initial deficit during the final four quarters because of increased cross-team knowledge of each other's skills. This will result in decreased time for required group integration.	2c: Not supported by the data. Groups who exchanged roles required statistically more time in Q5 through Q7, but not in Q8. Time spent in learning new skills was not recouped over the remaining three quarters. Note that groups who exchanged roles show a continuing downward trend in required time. We also theorize that that this trans-specialist knowledge may provide increased flexibility for future group assignments.	2c: Afterwards, Q6 to Q7, remain statistically different (p = .014, .015, .003 respectively) Q8 difference is not statistically different (p = .053) from groups whose individuals exchanged roles with those who did not.
Hypothesis 3a: Group net profit per period will rise as time required for skill decreases, except in Q5 after a production break. 3b: Individuals who exchange roles will achieve greater decision making quality shown through increased profit.	3a and b: Supported by the data. Groups whose individuals exchanged roles began to earn more profit after Q5. We theorize that there is a qualitative difference in decision making ability between the groups because of their difference in trans-specialist knowledge.	3a and b: Q8 cumulative net profit: [$M (sdev)] - Groups with fixed roles: $214K (266) - Groups who exchanged roles: $615K (425); statistically different, (p =.017).

These experiments have brought us closer toward our goal of "engineering" knowledge management solutions in organizations. This effort will eventually provide managers a method to determine more optimal knowledge flow interventions for a variety of task and organizational contexts.

Anticipated Impact on Practice

Our overarching goal is to enable managers to identify where deficiencies in knowledge flows exist prior to project commencement, and to help them plan in advance for project success.

Sustained progress toward this goal will eventually enable managers to design more optimal knowledge management strategies for a variety of organizational designs in different environmental contexts. In calibrating and validating knowledge interventions that serve to change knowledge and commensurate skill level of agents (measured as processing speed), these findings will be used to inform managers how individual learning and forgetting rates can be used to generate reliable predictions of the effects of individually held knowledge at the organization level. This quantitative effort will afford an improvement over current best guess methods that managers currently employ toward managing the knowledge of their workers.

Next Steps

Next, we will leverage and integrate these cognitive psychology experiments and embed the calibrated empirical findings as micro-behaviors in POW-ER

(Ramsey et al., 2006), a previously validated computational model of project organizations. Chapter 3 describes how we first model the AROUSAL exercise to calibrate POW-ER 3.2, followed by modeling the second AROUSAL case and the ELICIT exercises to calibrate POW-ER 3.2. This extended model should enable progress toward an improved understanding of how changes in knowledge levels of individuals over time affect project outcomes.

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Chapter 3: Computationally Modeling How Individual Skill Growth and Decay Affect the Performance of Project Organizations

Summary

This chapter leverages results of our literature review and experimentation from Chapter 2 to calibrate and validate a computational model capable of predicting organization-level outcomes based on learning and forgetting of skills by computational agents. Learning and forgetting have been quantified at the individual level (e.g., Anderson, 2005 and Wixted, 2004) yet their combined effects have not been well understood at the group level. We now take the next step of embedding empirically grounded learning and forgetting behaviors into an agent-based model (Levitt et al., 1999) to compare model predictions with empirical findings from a classroom experiment in which specialists' durations to prepare quarterly inputs in eight successive trials of the AROUSAL business simulation exercise (Lansley, 1982) were recorded.

The model, POW-ER 3.2 (Project Organization Workflow model for Edge Research), embeds empirically calibrated knowledge growth and decay micro-behaviors in its computational agents. The team completing eight rounds of the AROUSAL exercise is then modeled as a project in order to validate the new learning and forgetting micro-behaviors by comparing the model's meso- and macro-predictions to the empirical meso- and macro-data from a round of the AROUSAL empirical exercise. This chapter provides further calibration and validation for the learning extensions to the POW-ER computational organizational simulation model through comparison of individual and team-level model

predictions to data from a second set of AROUSAL student team data; and it tests for external validity of POW-ER 3.2 (MacKinnon and Levitt, 2007) by comparing POW-ER 3.2 predictions to findings from a different set of experiments using student group data from the ELICIT exercise (Leweling and Nissen, 2007) conducted by our collaborators at the Naval Postgraduate School. This further bolsters the validity of the POW-ER 3.2 model.

Practically, our findings, predict the impact on project duration that can be anticipated by project managers whose workers learn and forget. Theoretically, we are able to extend our knowledge of group level learning and forgetting within an organization based on our observation and subsequent modeling of agents' learning and forgetting in project teams.

Motivation

The goal of the research described in this paper is to enhance our capability to model, simulate, and eventually optimize, work and knowledge flows in organizations. It presents results of a validation study in which:

- Individual learning and forgetting micro-behaviors observed in a student team completing a business simulation exercise (AROUSAL) are embedded in to the computational agents of an organization simulation model (POW-ER 3.2);
- Output from a POW-ER 3.2 model of the AROUSAL exercise are then compared with a second round of empirical data on the performance of the student teams engaged in the AROUSAL exercise as well as empirical data

available from an outside study conducted using the ELICIT Command and Control exercise. This effort enables us to calibrate and validate the POW-ER 3.2 model twice.

We then use this calibrated model to examine the performance differences between static skill for computational agents versus dynamic skill for “learning and forgetting” computational agents engaged in equivalent project-oriented tasks. This POW-ER 3.2 model thus enables us to quantify and report the impacts of individual learning and forgetting on organizational performance outcomes.

Background

Efficient knowledge management is critical to mission and project success (Cole 1998, Grant 1996, and Spender, 1996), yet few studies have explored the organizational effect of individual skill learning as a project continues and its participants improve their skills through repeatedly performing the task. This research explores and compares organizational effects of individual learning and forgetting over time for simulated runs of the AROUSAL business exercise. These calibrated micro-behaviors, when embedded into POW-ER 3.2, enable a necessary next step toward quantifying the results of individual learning and forgetting, instead of just speculating qualitatively about their importance.

Work and Knowledge flows

A large body of research exists on *information* flow in organizations, commencing with Herbert Simon's (1958) groundbreaking research. However, the corresponding literature on *knowledge* flow in organizations is only just emerging (e.g., McKinlay, 2003; Nissen, 2006 and 2002; and MacKinnon et al., 2005) and remains more qualitative than quantitative. Other researchers have analyzed and attempted to explain individual and organizational levels of information and knowledge flows (Simon, 1950; Argote, 1999; and Nissen, 2006). Knowledge can also be viewed as *inflows* and *outflows* (Dierickx and Cool, 1989). These inflows and outflows are metaphorically viewed as water entering and exiting a "bathtub." In this sense, the level of water is viewed as the level of available knowledge to the organization and the amount of water entering and exiting the bathtub is seen as the amount of knowledge gained or lost, respectively.

We consider that the flow of knowledge of an organization can be modeled as the learning and forgetting of skills that occur for all of its individual participants. When those individuals frequently exercise their skills, there is no loss of knowledge and potentially some growth. Yet when skills remain unused or dormant, knowledge erodes over time. We conceptualize that the current level of knowledge for an individual is measured (inversely) as the required time for the individual to accomplish a specific skill-based task. We consider that, as knowledge level improves, a concomitant increase in skill processing speed —i.e., a decrease in duration of tasks that employ that skill— will also occur, as well as improvements in project quality.

We can, thus, envision a method to advance from qualitative to quantitative analysis of the effects of organizational knowledge flow: we will analyze the organizational effects of individual learning and forgetting in terms of their effects on task and project duration, and on a set of numerical process quality metrics. We use an organization simulation model that extends concepts first modeled in the "Virtual Design Team" (VDT) (Jin and Levitt, 1996), presently named "POW-ER" Version 3.2, to demonstrate the impact on project duration and quality as the levels of skill of individual participants change due to learning and forgetting.

Learning and Forgetting

Few studies have been published illustrating the gains and losses to projects as their employees learn and forget skills over time, or as they turn over during and between projects. A notable exception is Ibrahim (2005). There have also been few attempts to determine how to manage this knowledge in terms of interventions such as mentoring, training or OJT (listed from smallest to greatest levels of available research).

For example, Carley and Svoboda (1996) and Carley (2001) model individual learning computationally, and model organizations that can *adapt* (*hire, fire, redesign,* and *retask*) toward an increasingly optimal design to achieve higher levels of organizational performance. Carley also models the reduced impact of individual knowledge on performance with organizational structural changes.

There is a nascent trend in the literature to view knowledge as a supply chain or knowledge chain (Holsapple and Jones, 2004 and 2005), yet research to date is qualitative, using only natural language descriptions. Kim (1993) also seeks to link individual learning to organizational learning via natural and metaphorical thinking and examples. However, Kim's research does not extend to quantifying the effects of individual learning and forgetting on project outcomes.

We will extend this portion of the literature by stepping away from the current natural language descriptions and toward a more quantitative computational perspective that has the potential to predict and ultimately manage knowledge inventory more optimally in project teams. We seek to improve project outcomes by determining the specific, quantitative impacts of management decisions that cause individual learning and forgetting on organizational performance.

Ramsey et al. (2006) extended POW-ER to add learning and forgetting capabilities. During 2005-06 we obtained theoretical learning and forgetting rates from Cognitive Science literature (MacKinnon et al., 2006) as reported in Chapter Two. We anticipate that each agent's task completion time, which varies inversely with the dynamically changing skill level of the agent, will directly affect expected project cost, length, rework and project quality risk. Thus, we want to calibrate these learning and forgetting rates for use in POW-ER against the actual task and project completion durations and quality outcomes of humans engaged in modern organizational knowledge-work tasks. Once these calibrated learning and forgetting behaviors rates are implemented in POW-ER, we can more confidently begin to quantify how dynamic, individual knowledge will affect performance outcomes at the organizational level.

Points of Departure

Organizational theory explores and analyzes how organizations achieve their goals. Human knowledge and its management are critical to mission and project success (Burton and Obel, 1995; Grant, 1996; Nissen, 2006; Spender, 1996; Cole, 1998; and MacKinnon, 2005). We seek to calibrate and validate a model that will combine organization theory with agent-based modeling. Computational models, such as OrgCon (Burton and Obel, 2004) and the Virtual Design Team (VDT) model (Levitt et al., 1999; Jin and Levitt, 1996) are currently used to conduct virtual computational experiments that explore the performance of novel, structural designs, as well as many other variables affecting the performance of organizations, including agent culture (Horii, 2006) and agent turnover (Ibrahim, 2005). VDT is a finer grained simulation framework than OrgCon, which models entire enterprises. VDT models projects in which the user can input the skill level of each agent. However, VDT sets each agent's skill level at the beginning of the simulation, and it remains fixed for the entire project. This paper reports on our efforts to embed more dynamic learning and forgetting agent micro-behaviors into POW-ER 3.2, to assess their impact on organizational performance.

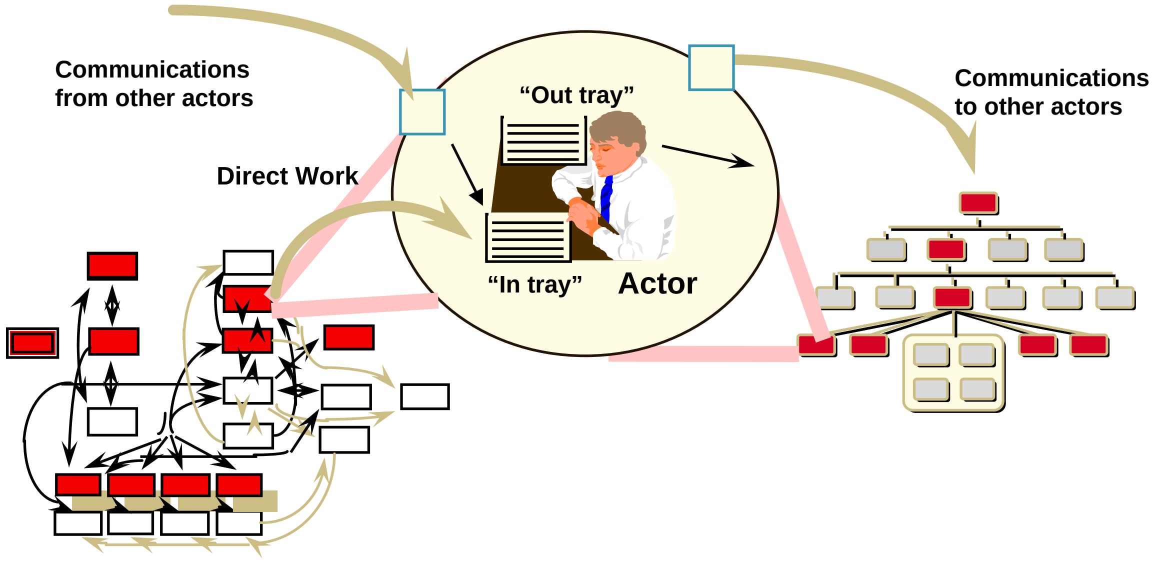

Figure 3.1: VDT information and work processing showing how direct work, communication, exceptions and rework are processed and accumulated via in- and out-boxes by each actor. (Source: Jin and Levitt, 1996). Note: Actors in VDT are assigned a skill level (no, low, medium, or high) for one or more skill types, which remains fixed over the entire project duration.

Objectives and Approach

We set out to embed individual learning micro-behaviors into an agent-based simulation model (POW-ER) based on the Virtual Design Team (VDT) methodology. Efforts to date to extend the basic information processing behavior of VDT agents (based on Galbraith's (1974) information processing and exception processing metaphor) have added: inter-agent coordination costs (Cohen, 1988 and Christensen, 1994), different goal emphasis among agents (Thomsen, 1995 and Salazar-Kish, 1999), dynamic work processes (Fridsma, 1996), time-of-day and day-of-week contextually driven behaviors (Cheng Cain 1999), knowledge networks (Lambert, 1999, Buettner, 2002 and Nissen, 2006), institutional costs (Mahalingham, 2005; Orr, 2005; Taylor, 2005; and Horii, 2006).

Starting in 2004, Ramsey et al. (2005) began developing a new project organizational simulation framework (POW-ER) that replicates many of VDT's agent micro-behaviors and adds several new kinds of behaviors, including the ability for the agents to learn and forget.

Organizations can be viewed as processors of information (Galbraith, 1974), that must either evolve to improve their capacity to process more information or must search for opportunities to decrease their information processing demand (Galbraith, 1974). Agents in a VDT simulation mimic information processing by receiving: direct work, communications, rework, and *exceptions* from other workers who require assistance. The processing speed at which the agent resolves and accomplishes these types of work is determined by a designated skill level: unskilled, low, medium, and high. These speeds remain fixed for the simulation at present.

In a typical project, agents are able to learn so that they can accomplish frequently utilized skills with greater speed, while not improving or actually decreasing their processing speed for those skills which are seldom required. Our conceptual model below illustrates how we conceive of an improvement to this method by moving from fixed assignment of skill level to a dynamic skill level that changes as a result either recurring or lack of performance of the skill.

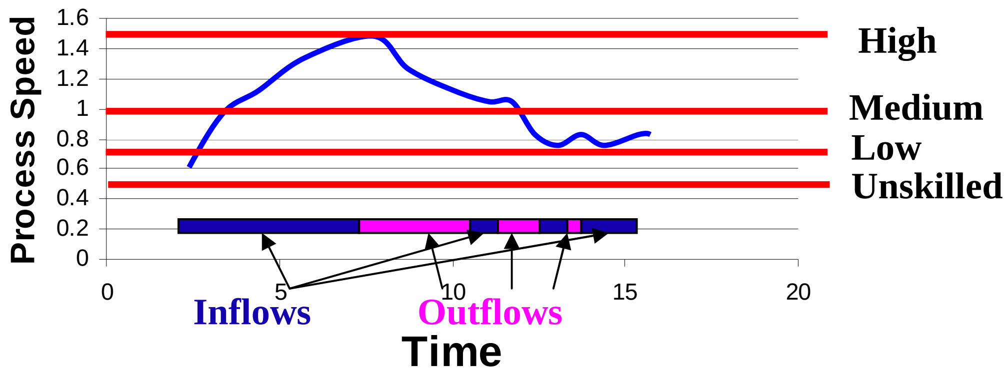

Figure 3.2: Our conceptual model of knowledge inflows and outflows that cause each actor's processing speed to either increase or decrease accordingly, as shown by the blue curve. Current, static levels of processing speed are shown by the horizontal red lines.

Our approach is to observe participants whose skill level both increases and decreases in a project environment and measure the time empirically required by the participants to accomplish a given skill. We will then mathematically model these observations to develop and embed an algorithm in VDT to replicate the observed individual learning rates and determine their organizational effects.

Research Questions

1. How can individual skill acquisition and decay be computationally modeled, calibrated, and validated?
2. How is the performance of project organizations affected by the sum of the skill growth and decay of individual participants?

Scope

Many researchers have proposed different methods for characterizing and modeling knowledge. It is important that we explain what our research will not include and how it differs from previous work.

This research will not extend the ideas of knowledge networks nor *transactive* knowledge (Wegner, 1995; Weick and Roberts, 1993; and Nissen, 2006) as developed through improved interactions between agents or individuals (cf. Carley, 2001). Transactive knowledge refers to the meta-knowledge of knowing *who knows what* and gives rise to knowledge specialization in groups and to group members' understanding of knowledge networks.

Carley and Svoboda (1996) model organizational structure adaptation to improve performance. Our efforts will follow the VDT organization analysis methodology (Jin and Levitt, 1996); that is, we confine our experiments to predicting project outcomes given static structures. We model only one kind of learning (and forgetting): an increase (or decrease) in skill level, which is measured quantitatively by a reduced (or increased) duration for completion of a task requiring that skill.

We do not model the search for ideal or better-adapted organizational structures that emerge through individual learning. Efforts by Carley (2001) take a *bottom-up* approach that allows for computational agents to learn by making interconnections between many bits of information and via exposure to other agents. This in turn, provides the opportunity and the motivation for the organization structure to *adapt*, allowing for improved knowledge flow. Alternatively, KHosraviani (2005) takes a *top-down* approach toward organizational adaptation, leveraging Genetic Programming evolutionary programming techniques (Koza, 1992) to evolve optimal organization structure from given fitness functions that can give different emphases to project schedule, cost, and quality outcomes.

Instead, we explore the ramifications for a project organization that is already in place when its members learn or forget a skill over time due to different knowledge interventions such as on-the-job training (OJT), formal training or mentoring. We seek improved methods for predicting the outcome of projects with a given sequence of tasks and a fixed structure, using embedded learning and forgetting micro-behaviors within individual agents in the agent-based, organizational simulation "POW-ER 3.2" (Ramsey and Levitt, 2005).

We do not improve or leverage methods from Artificial Intelligence (AI) nor do we contribute toward improved cognitive architectures —e.g., *chunking* as in *SOAR* (Laird, Newell, and Rosenbloom, 1987). Our research models learning much more abstractly, as improvements in individual processing speed caused by varying knowledge interventions that lead to improved organizational performance. This empirically based, individual learning methodology – once calibrated – hews more closely to the "boundedly rational" information processing abstraction used in Galbraith's framework (1974), VDT and POW-ER, rather than semantically richer models of actors and work used in SOAR or elsewhere within the field of AI.

We began our research by considering that management science inventory control methodology might perhaps provide a clear and insightful approach for quantitative analysis of learning in organizations, viewing knowledge as perishable inventory (MacKinnon et al., 2005). Yet, knowledge has the quality of a public good. It can be used by many people and not be depleted, making *knowledge inventory* difficult to quantify. Certain kinds of (especially explicit) knowledge exhibit the trait of a *public, collective, nonrivalrous* or *nonexcludable good* and exhibit the quality of *jointness of supply* “in that partner’s uses of the good are noncompeting” (Monge, Fulk, et al., 1998, p. 411). We do not intend to pursue this line of thinking further.

Alternatively, other kinds of (especially tacit) knowledge cannot easily be shared at all. This difference is best resolved, it seems, by considering the bounds of the organization (Grant, 1996). For instance, if an individual belonging to an organization shares knowledge within the organization (or partner organizations), the organization has not lost its competitive advantage gained by his expertise. Indeed, such advantage would likely increase as the shared knowledge expands its reach through the organization. Yet if s/he shares this knowledge outside the organization, a potentially damaging loss has occurred. This loss can be prevented or at least made illegal through the use of non-disclosure statements, patents, and copyrights. This research will not extend beyond the boundaries of a single organization and will be limited to project-based work processes and organization structures.

Validating Computational Emulation Models

Validation is a challenging, yet necessary problem in computational organization theory research. We will follow an accepted framework (Thomsen et al., 1999) to validate whether “computational emulation” of agents’ micro-behaviors can replicate observed micro-behaviors and macro-outcomes. The evaluation trajectory set forth by Thomsen et al. (1999) for computational models of organizations illustrates a methodology for developing sequential validation experiments for new or extended models as shown below. The three required steps of Thomsen's validation sequentially validate: reasoning, representation, and usefulness. As the first step, the reasoning assumptions of the simulation model must be validated. Specifically, the micro-theories derived from observable micro-behavior must match the agent micro-behaviors in the simulation.

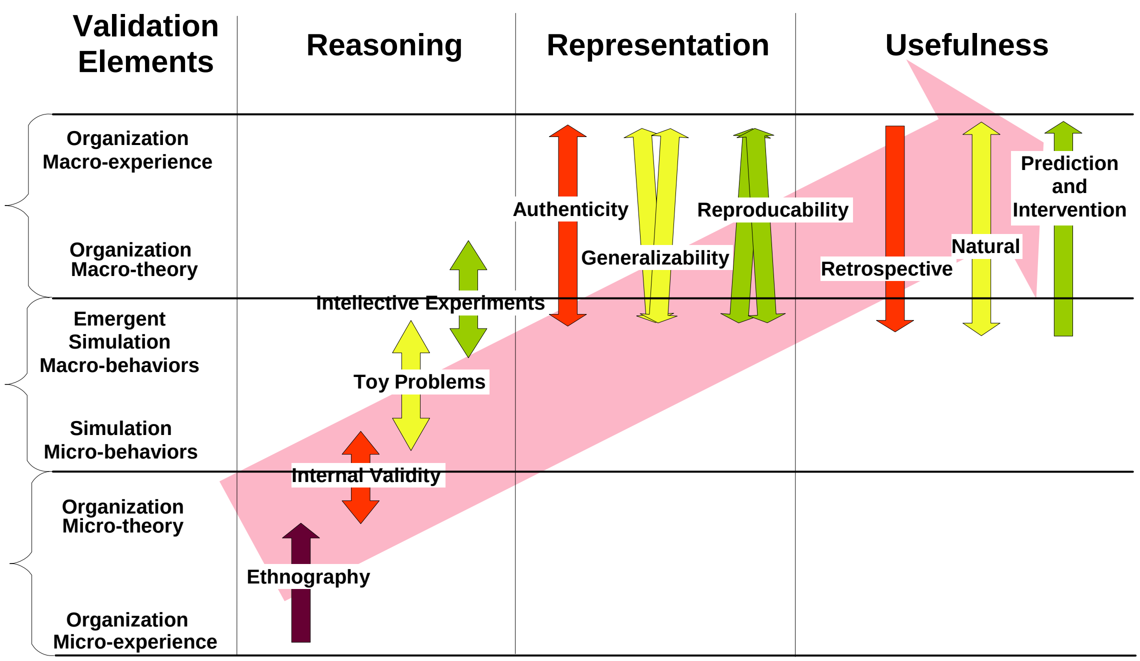

Figure 3.3: A validation methodology for model development showing successive steps toward model validation using intellective and emulation (retrospective, natural and prospective) experiments to validate model output against theory and data from real projects (Thomsen et al, 1996)

This research commenced with our first paper (MacKinnon, 2007), which gathered and analyzed ethnographic data that was compared to the cognitive psychology literature. This provided the basis for our understanding and provided a comparison for internal validity for our initial reasoning — i.e., our mathematical models of individual learning. Intellective experiments to validate the reasoning in POW-ER were carried out by Nissen et al (ref) in comparing idealized hierarchical versus power-to-the-edge organizations, but the version of POW-ER used in those experiments lacked the learning capabilities that we can now exploit. We previously conducted "toy problem" experiments and intellective experiments with POW-ER 3.2 to validate its learning and forgetting reasoning, but these are not reported here. We continued to follow the validation framework and conducted a set of two retrospective validation experiments to demonstrate the usefulness of POW-ER 3.2. These experiments are described in the remainder of this chapter.

Calibrating Learning

We began by considering how we might measure the dynamic knowledge level of individuals. It seems that one clear measure of knowledge level is the time required to complete a complex skill-based task. To validate learning and forgetting of POW-ER for a complex, cognitive, group task, we selected a computational business simulation entitled AROUSAL (Lansley, 1982), where 31 students were asked to provide individual as well as integrated quarterly business plans for a hypothetical construction company and choose from among an array of possible managerial interventions.

The four roles in each team were: marketing-sales, operations, human resources, and finance. Each participant was randomly placed in a four-person group and given one of these roles to perform. (One group consisted of only three participants;

its data are not included in our analysis.) Each participant was directed to develop his/her individual quarterly business plan and recommended set of interventions with justifications for them. Each group was then directed to convene to integrate these plans and choose coordinated interventions. Integration was non-trivial because each role competed for limited group resources. For instance, each group's budget for each period had to be divided among ongoing operations, marketing expenses, hiring staff, and writing proposals (bids) for new construction jobs.

The simulation ran for eight quarters. The first quarter was used to provide the players with training in how to analyze outputs and how to input a fixed set of interventions, so we have not included data from this quarter in our analysis. After the 4th quarter (Q4), the groups were asked to stop the exercise and resume it some time later — approximately three days— at their discretion. This production break introduced an opportunity for us to measure "forgetting" of previously acquired skills in playing each role.

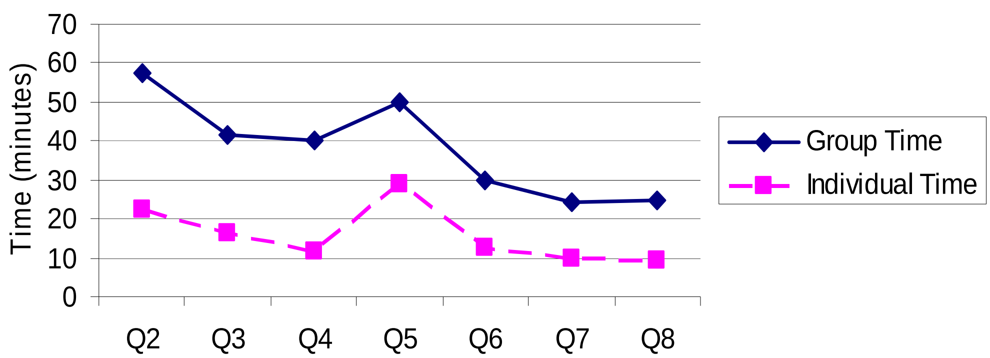

Figure 3.4: Empirical AROUSAL empirical data illustrating the time required for the average individual and group to prepare and integrate, respectively, a quarterly business plan. Note the increase in the time required after the fourth quarter, when a production break of approximately 3.3 days was introduced.

The figure above illustrates the aggregated learning and forgetting among the individuals and groups who took part in the AROUSAL exercise. We note the decrease in time required in successive quarters for each team to accomplish its tasks. The rise in time required in Q5 is attributable to the production break of 3.3 days on average after Q4 as each group took a break from performing the exercise.

We introduce the notion of skill classification (Dar-El et al., 1995) which will help in our effort to calibrate our POW-ER 3.2 model for learning as we further narrow our scope toward analyzing skill learning and forgetting by categorizing different types of skill.

Skill Classification

Not all skills are learned by individuals with equal speed. Dar-El et al. (1995) classifies skills in the four following categories: (1) highly cognitive, (2) mostly cognitive, (3) mostly motor, and (4) highly motor, as shown below.

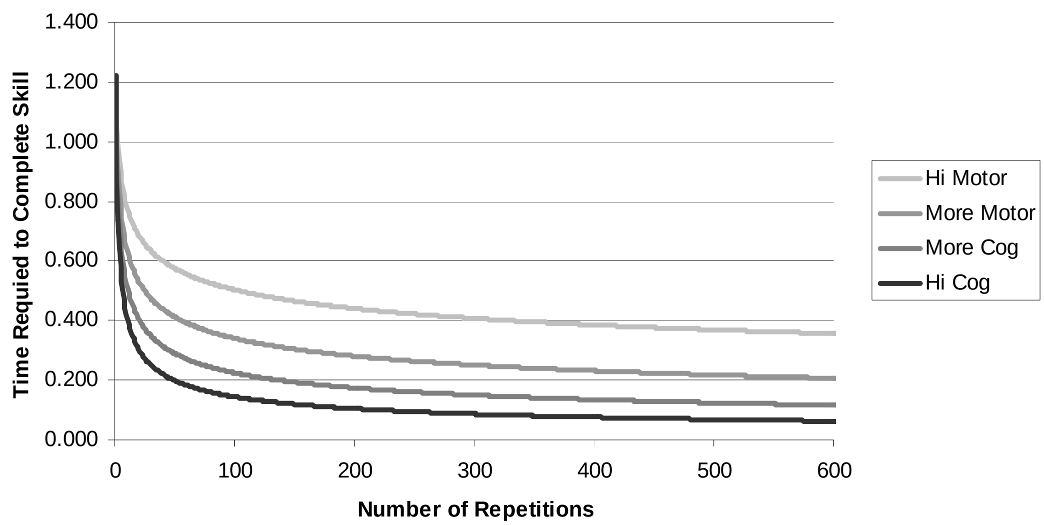

Figure 3.5: Learning Curves for Different Types of Tasks (replicated from Dar-El et al., 1995). As skills become increasingly cognitive *vs.* motor, the amount of learning (the reduction in time required to complete the task) that occurs on each trial increases.

The previous chapter showed how we validated our observations of the student teams against these curves to identify and replicate Dar-El's findings using the AROUSAL exercise. We hypothesized that the AROUSAL exercise requires cognitive skill given that the exercise is completely computer-based and requires each participant to read and select the required best business options.

We then took the next step of extracting the first seven data points from the skill classification curve above and graphed both the averaged individual and group required times from the AROUSAL exercise to show how the data compare to the set of four learning curves (cognitive to motor). Our empirical AROUSAL data are normalized against the Dar-El data based on the time for the first iteration.

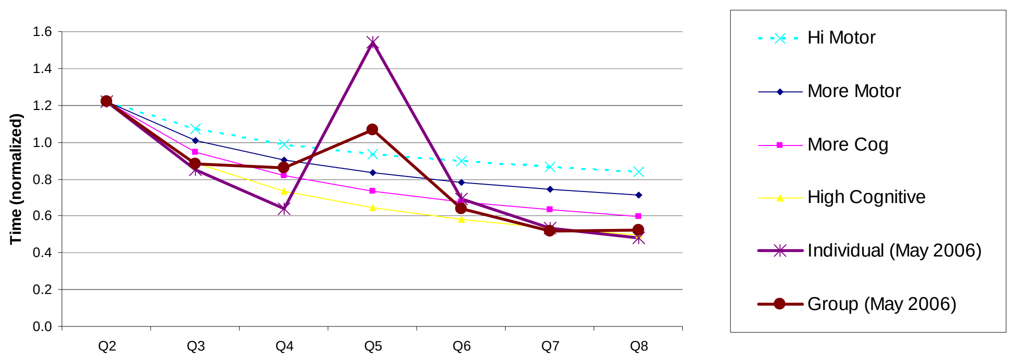

Figure 3.6: Dar-El et al. Learning Curves with Individual and Group Learning Rates Aggregated Over Time which shows the replication of cognitive learning plus the reacquisition of the curve after a period of skill usage production break.

We note that for quarters two and three, the empirical AROUSAL data for both individuals and groups closely follow the cognitive curve from the Dar-El study. We also note in Q4, that the groups required only slightly less time than the third quarter. After Q3, most groups in the exercise began to lose significant amounts of money as they attempted to complete projects for which they had bid too low. We, therefore, believe that the anomaly in our Q4 group learning data occurred from longer group discussions about how to address their mounting losses and taking more time to integrate their individual plans. In Q5, following a 3.3 day break, we observe that both individual and group durations increased significantly; in fact, individuals, on average, required more time than originally required in Q2. Both curves over the ensuing quarters show that learning recovered rapidly toward the cognitive curve.

The qualitative and reasonably explained Q4 anomaly in the data was excluded in developing an equation for learning and forgetting. To obtain learning rates for our agent learning micro-behaviors, we used the replicated Dar-El cognitive skill curve to develop a learning equation. The resulting cognitive individual learning equation is:

$$T_n = -1.2222\ (r_n^{.4639}) \quad ; \quad T_n = \text{time required to perform the skill}$$
$$; \quad r_n = \text{repetition number}$$

Calibrating Forgetting

A production break in between periods spent performing a task causes employees to forget. The rate at which forgetting occurs increases with task complexity and with simple failure to recall an item or procedure with some frequency (Jaber and Sikstrom, 2004). As with learning, forgetting follows a predictable function that can be described using a power law (e.g., Wixted, 2004; Wickelgren, 1974; and Ebbinghaus, 1913), e.g.: $R(t) = at^{-b}$ where t is time and a and b are scalars as shown below.

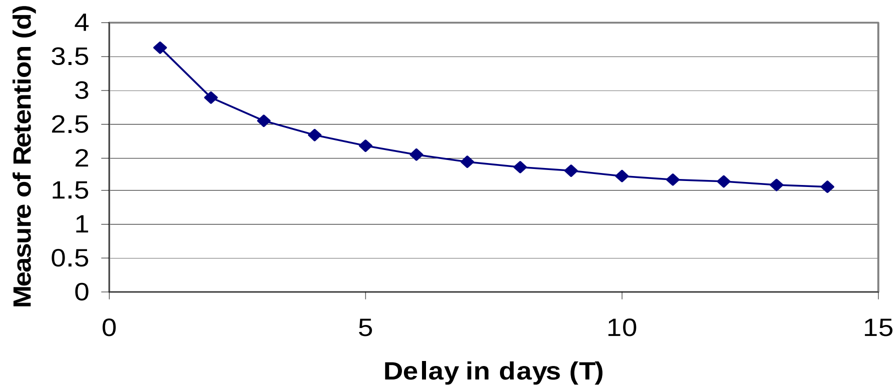

Figure 3.7: Power Law of Forgetting. Over time what is known decays at a negatively accelerating pace. (Wickelgren, 1975; Wixted and Ebbesen, 1991)

Most work on forgetting has focused on relatively simple tasks, e.g., where a participant is asked to recollect and recite memorized items from a list and, over time, begins to forget them (e.g., Anderson, 2005). Similar effects can also be seen in the recall and performance of complex skills (Ericsson and Charness, 1994), such as forgetting in a practicing physician, (Smith, 1978) or skill decay in cardiopulmonary resuscitation (CPR); (McKenna and Glendon, 1985). We will maintain our focus upon the learning and forgetting of a skill rather than simplified list learning.

We will follow the reasoning that "the performance time on the learning curve equals that on the forgetting curve at the point of interruption" (Sikstrom and Jaber, 2002, p.121) to develop our forgetting curve. In other words, the forgetting curve will commence and be of the same, but oppositely rising shape, at the point in time the players stop performing the skill. Forgetting seems to occur less drastically for groups than for individuals as seen in figure 3.6, yet both the groups and the individuals swiftly regain their skill level learning rates after just two additional quarters. The amount of skill loss was found to be proportional to the length of the production break between Q4 and Q5. For every day of production break that groups waited to commence the final four quarters, they grew in the time required for the group to integrate their business plans as shown below.

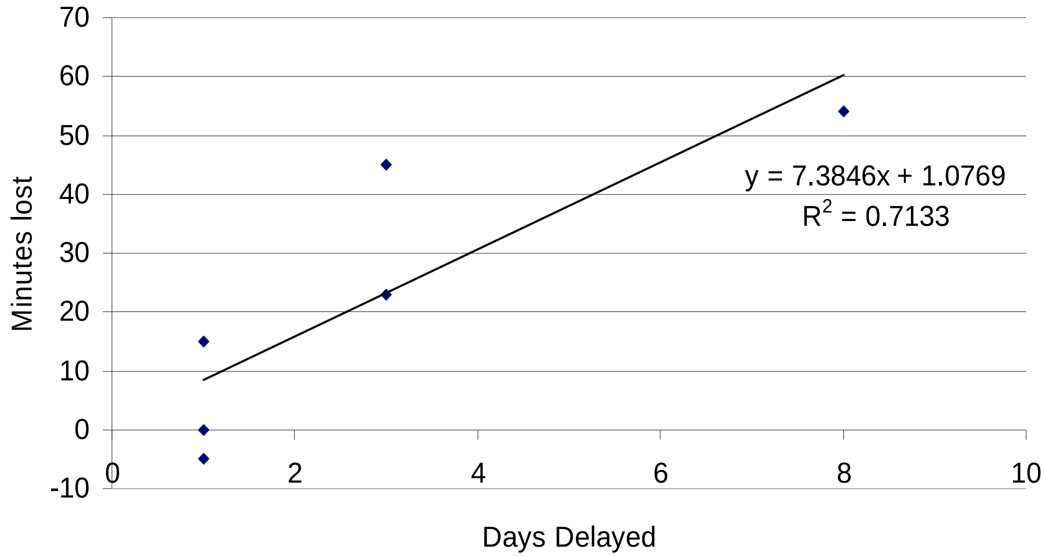

Figure 3.8: Forgetting Correlation for Aggregated Group Data which shows the relatively high correlation we found between a given length of production break vs. the skill loss — i.e., the increase in time to complete the task.

From the regression for these data, we note that task duration increases by about 7.4 minutes for every day of production break between tasks (R^2=0.7133). The group data indicates that the group integration task requires 39 minutes on average to accomplish. From this, we infer that for every day in production break, each group loses approximately 19% of its skill in terms of average processing speed (7.4/39 minutes). (One group showed skill improvement after a one day production break which resulted in negative time lost. Data from another group is not included due to their taking two breaks instead of one.) We again found compelling evidence to support our use of this aggregated finding to calibrate delay-based forgetting of cognitive skills in our POW-ER model because of this high observed correlation between time delay and the increase in task duration.

Our empirical data from the AROUSAL exercise demonstrates that the skill learned by the agents is virtually forgotten after a production break of 3.3 days. Our dynamic skill curve returns to its original point of *low* skill indicating that the expected time to process the skill is equal to the first attempt without prior experience. This occurrence follows the findings and assumptions of other learning and forgetting models (Sikstrom and Jaber, 2002 and Jaber and Bonney, 1997). This skill is performed four times in approximately four hours which is followed by a production break of approximately 3 days in which no skill is performed. The skill is then performed for another four times for approximately four hours. Our forgetting curve which implements and follows the line of theory that "the performance time on the learning curve equals that on the forgetting curve at the point of interruption" (Sikstrom and Jaber, 2002, p.121) is supported by our data. We use this as further evidence to support the use of this type of forgetting curve in our embedded agent micro-behaviors.

POW-ER 3.2 Model

POW-ER 3.2 provides us the opportunity to replicate the AROUSAL exercise explicitly as seen in the figure below.

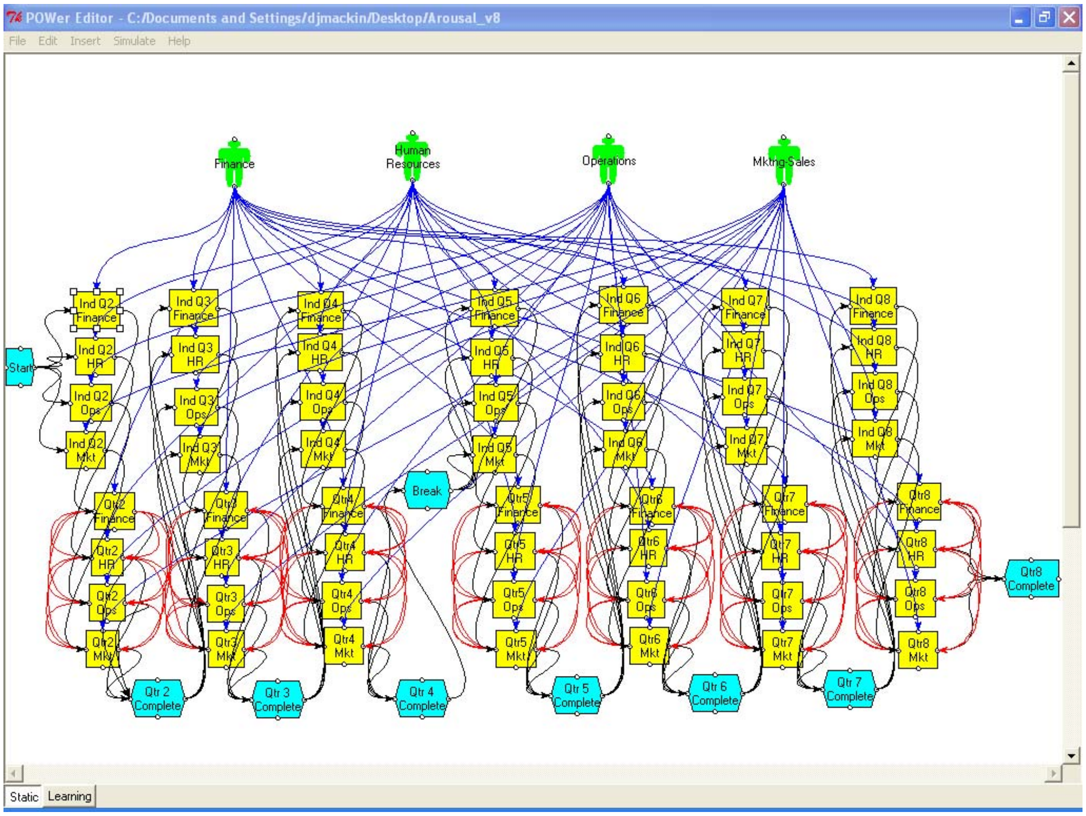

Figure 3.9: AROUSAL POW-ER 3.2 Model. This model shows each agent (people icons) and each quarterly task (boxes). Individual plans are completed first (uppermost four boxes) followed by group meetings modeled as four integrated tasks, one per player (lower four boxes) which require rework links (recurring arcs in the lower four tasks) as decisions are made about limited resources. Each quarter ends with a hexagonal milestone icon. For additional details about POW-ER models see Ramsey et al. (2006).

Each of the teams of four participants (agents) is indicated by a green agent icon shown at the top of the figure. Each agent is assigned via blue assignment arrows, to each quarter's individual plan developments as well as each quarter's group integrations. Q1 is not included because its fixed are provided as a training period to the participants. The model illustrates the start of the simulation using a blue milestone icon to the left, followed by four parallel tasks which indicate individual plan development. Each of these tasks are followed a set of group integration tasks which are reciprocally interdependent (Thompson, 1967). The red *rework* links, present for this phase of each quarter, indicate that the group must integrate and mutually adjust their individual plans. Groups must consider how to optimize their available, yet limited, funds and personnel to achieve maximum profitability for the entire exercise. The goal for each group is end the exercise having earned the most money. In the middle of the game, teams were asked to stop playing for a period of 3 to 4 days, and to resume their play afterwards. The exercise ends when the eighth quarter is complete.

POW-ER 3.2 had the ability for agents to be assigned a static skill (unskilled, low, medium or high). In this research we embedded the aforementioned learning and forgetting algorithm that allows the skills of an agent to change dynamically up or down based on the frequency and recency of completing a task that uses the skill of the agent. We executed the simulation with each agent starting at the unskilled level and allowed each agent to learn and forget using the algorithm explained above.

Results

We modeled the AROUSAL exercise with and without learning by our computational agents. Table 1 compares our empirical data with our synthetic experiment predictions.

Table 3.1. AROUSAL: Empirical Data vs. POW-ER Model Output The individual and group duration data shown were normalized for the Quarter Two (Q2) durations of Empirical data and the POW-ER model in the "without learning" case. In the "learning-enabled" case, the individual empirical data *vs.* the individual POW-ER predictions of total duration differ by only 1.8% and the group empirical vs. computational model data differ by a miniscule 0.5%.

Metric	Individual Data		Group Data	
	Empirical	**POW-ER 3.2**	**Empirical**	**POW-ER 3.2**
Summed individual durations (based on initial period, assuming no subsequent learning)	161 days	161 days	406 days	406 days
Duration (with learning)	106 days	103 days	235 days	233 days
Percent Savings from Learning	34.2%	36.0%	42.1%	42.6%

The 161 *days* duration shown for the "no learning" case was determined by multiplying the original average exercise time required by the number of quarters to be played — in this case seven — (= 23 * 7). Student teams performed each subsequent quarter requiring less time than the previous quarter (with the exception of the quarter that followed the production break). The average total time required by the individuals was 106 days or a 34.2% savings resulting from learning. Groups required 58 days each quarter, for a total of 406 days (= 58 * 7).

The POW-ER model was calibrated to begin with the same required time. With the learning and forgetting micro-behavior embedded, it forecasted a savings of 36.0% over the seven quarters. The very small difference between the empirical data and the model output in the learning case may be accounted for by differences among teams of individuals.

The smallest “clock-tick” in POW-ER’s discrete event simulation framework is currently one minute. Exception handling times, waiting time-outs for “delegation by default” decision making, and other simulation parameters were originally developed and have been extensively calibrated for tasks with durations from one day to several days. The AROUSAL exercise is typically conducted in about 90 minutes depending on the team’s ability. So, for this experiment, we scaled our assigned work within the POW-ER model up from *minutes* to *days* and then scaled days of output back down from days to minutes. Ultimately POW-ER will be recalibrated, and its minimum clock-tick reset, to allow for tasks of arbitrary length.

We next discuss the POW-ER 3.2 predictions for the AROUSAL exercise vs. empirical AROUSAL 2 student team data for individual and group quarterly durations.

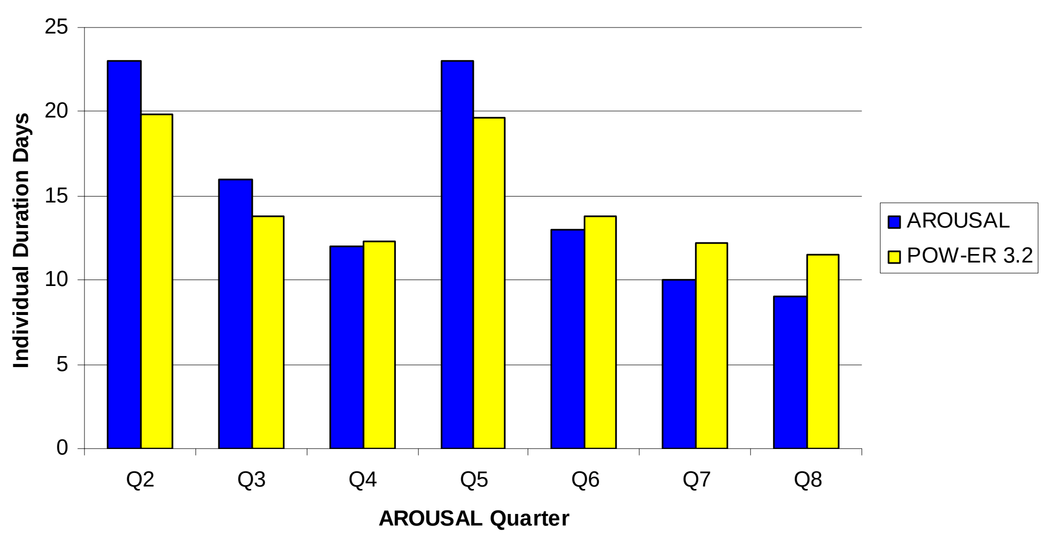

Figure 3.10: POW-ER 3.2 Predicted vs. Actual Individual Task Durations for Each Quarter which shows the relatively high correlation between the empirical data and simulation model output.

Individual quarterly predictions from our POW-ER 3.2 model output are highly correlated with the empirical findings of the AROUSAL exercise. We ran 100 trials of the POW-ER model and there were seven groups who played the AROUSAL exercise. We compared the empirical results of each quarter with our computed predictions using a pooled variance t-test. We note that the empirical and computed durations of each quarter are statistically indistinguishable. We can reject the null hypothesis there is a difference between the individual empirical data and the POW-ER 3.2 computational predictions (alpha = 0.05).

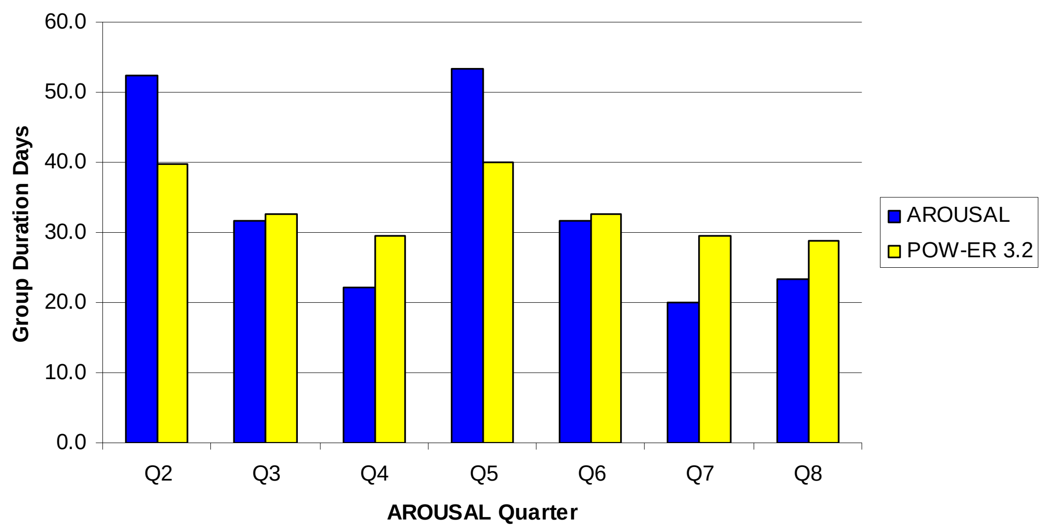

Figure 3.11: POW-ER 3.2 Predicted Group Durations for Each Quarter which also shows the relatively high correlation between the empirical and synthetic output.

The group durations also fit the relative trend of the empirical data well. Again we statistically tested the group empirical results of each quarter with computed predictions using a pooled variance t-test. We note that each quarter is statistically indistinguishable so we can reject the null hypothesis that there is a difference between the group empirical data and the POW-ER 3.2 computational predictions (alpha = 0.05) except for Q7 and Q8 (p = .169 and .179 respectively). Our computed predictions in these two quarters are higher than empirically observed, resulting in a more conservative overall prediction for project duration.

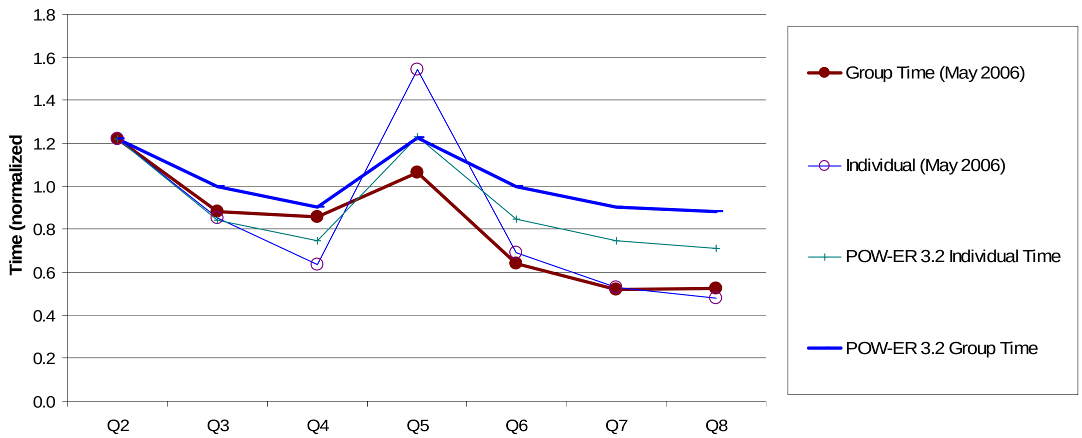

Figure 3.12: Empirical Curves vs. POW-ER 3.2 curves which shows the relatively high correlation between the empirical data and simulation output.

From these results, we claim that the learning and forgetting micro-behaviors in POW-ER 3.2 are validated and tentatively calibrated to reasonable rates of individual learning and forgetting for cognitive tasks at both the individual and group levels.

We next compare our POW-ER 3.2 model quarterly predictions to the empirical AROUSAL data using Dar-El's (1995) skill classification.

Comparisons using Dar-El Skill Classification

Our data demonstrate an excellent fit to Dar-El's et al. (1995) findings for "Highly cognitive" skill learning as shown in the mean processing times for both individual and group learning and forgetting. The individuals and groups each exhibited learning behavior in their task completion time during the first three quarters. (Recall, Q1 data is not included because it is a training trial.) Groups and individuals each showed a marked increase in required time for Q5 due to a three to four day production break between performing the first three and second four sets of simulation runs. The magnitude of increase in time for Q5 indicates the level of skill decay, or forgetting, that occurred as a result of the production break. But the curves rapidly converged back to the Dar El "high cognitive" learning curve after a few more periods of practice (see figure 3.13).

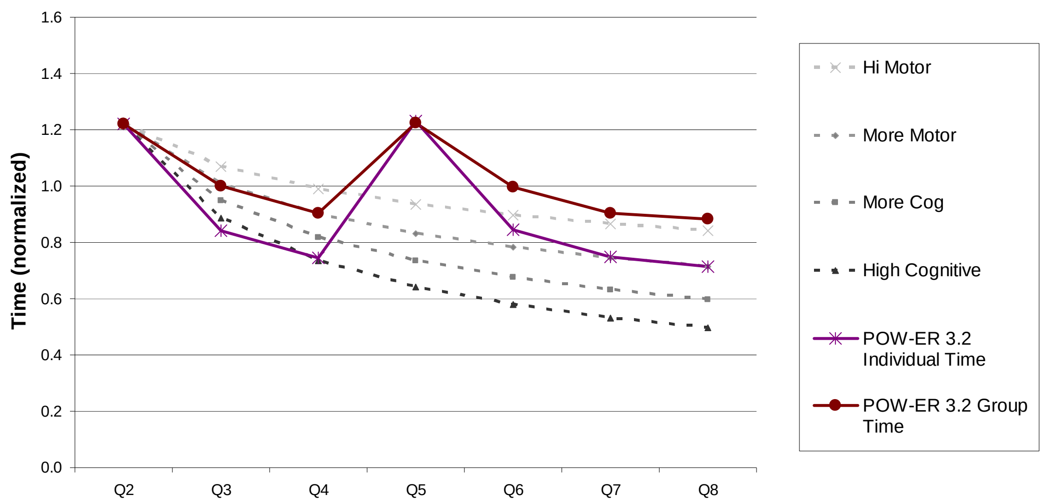

Figure 3.13: Dar-El et al. Learning Curves vs. Normalized AROUSAL Individual and Group Learning Rates from POW-ER 3.2 Project Prediction Aggregated Over Multiple Trials show the effects of cognitive learning, the effects of forgetting caused by a production break after trial Q4, plus the reacquisition of skill following the production break. Note the excellent fit between our POW-ER 3.2 model output for individual time in Q2 through Q4 and the Dar-El "Hi Cog" curve.

We note that our empirical data shown in Figure 3.12 plot along the "cognitive skill type" curve for both the individual and the group data for the second and third quarters. Our individual computational data in Fig 3.13 also plot along the "cognitive skill type" for Q2 through Q4 and return to same maximum amount of time required empirically in Q5. In Q6, the computational data plots in a decreasing direction yet in the remaining quarters, does not return to the cognitive line. As expected, the production break causes an enduring loss of skill in subsequent periods relative to the uninterrupted learning trials modeled by Dar-El.

After the production break, the computational individual predictions never fully regain the cognitive curve that they would have tracked without the delay. Computational group times similarly follow a downward trend yet demonstrate a more conservative decrease over time than the empirical group times over Q2 through Q4. At Q5 the computational group time returns to the normalized average time. In the ensuing quarters, Q6 though Q8, the group curves continue to follow a downward but again reduced slope. Although the Dar-El curves claim only to represent individual learning rates, it appears that group learning exhibits relatively similar behavior.

In replicating the theoretic findings of Dar-El et al. for individual learning for the first three quarters, we provide compelling evidence to validate the Dar-El "High Cognitive" learning rates that we had embedded in POW-ER 3.2 for learning of cognitive skills. It seems correct that there would be some lingering effect of the production break, so that both the individual and group learning continue to lag the theoretical learning curve following the production break. The close fit between the individual empirical data with the POW-ER 3.2 predicted learning and forgetting curve, supports our claim of calibration and validation for the POW-ER 3.2 model.

Having calibrated the POW-ER 3.2 model against this first set of AROUSAL data, we next compare our POW-ER 3.2 model quarterly predictions to a second round of empirical AROUSAL data to strengthen our claim of external validity. We follow this discussion with a section that compares empirical data from a third experiment —the ELICIT exercise— to POW-ER 3.2 output derived from a model of the ELICIT exercise. This final comparison provides a second round of validation.

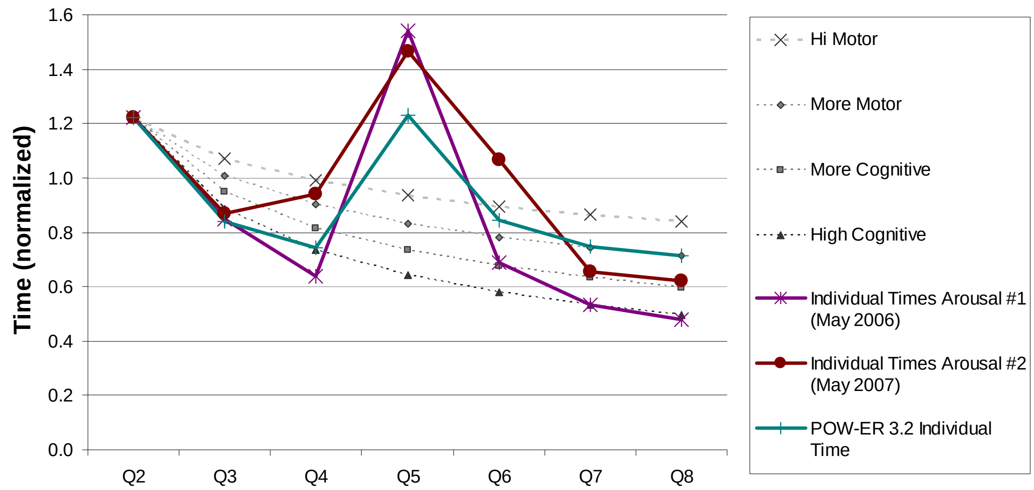

Figure 3.14: Dar-El et al. Learning Curves vs. Normalized AROUSAL Individual Learning Rates with POW-ER 3.2 Project Predictions for Multiple Trials. Note the similarity between different rounds of AROUSAL held in May 2006 and May 2007 and the excellent fit of the POW-ER 3.2 model output for these data as well as the Dar-El High-cognitive skill curve.

We replicated the experiment using the AROUSAL exercise in May 2007, with some additional interventions described in Chapter 3. We found that the average individual and group learning behaviors were almost identical. Above we note the similarity between individual learning rates in the two separate rounds of the AROUSAL exercise as well as the close fit to the POW-ER 3.2 model output. In our next graph we compare the group times for the second round of the AROUSAL exercise.

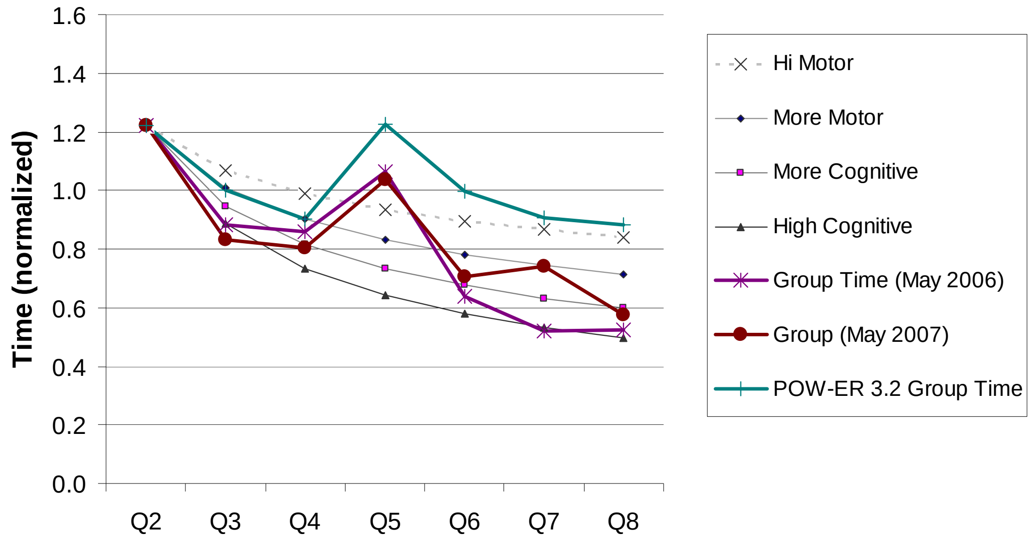

Figure 3.15: Dar-El et al. Learning Curves vs. Normalized AROUSAL Group Learning Rates with POW-ER 3.2 Project Prediction Aggregated Over Multiple Trials showing the similarity between different rounds of AROUSAL held in May 2006 and May 2007 and qualitative fit of the POW-ER 3.2 model output for cognitive skill.

We observe the replicated findings for group level learning for the second round of the AROUSAL exercise held May 2007. The POW-ER 3.2 group learning curve remains conservatively higher than may be practically expected even allowing for the production break (see periods Q3 and Q4 prior to the break). We note that Dar-El et al. (1995) make no claim about their learning curves ability to predict group level learning. We use their curves for consistency of comparison. We model individual agent micro-behaviors for learning and forgetting; group-level "learning" is an emergent result of our simulation of individual agents..

A Second External Validation Experiment: ELICIT

ELICIT is a small group synthetic Command and Control (C2) exercise. It requires that a group of 17 participants piece together disparate sentences (factoids) that are provided to them over time to determine the *who, what, when,* and *where* of a fictitious terrorist plot. This exercise is typically conducted using four teams who are organized in two different organizational forms: hierarchy and edge (Alberts and Hayes, 2003). Hierarchy organizations are a more traditional C2 type of organization with one person in overall charge. Four second level managers report to her or him. Each second level manager has individuals who report to them. Hierarchy organizations flow their knowledge from, and maintain decision rights in, a centralized headquarters where the overall leader resides. The edge organization, in contrast, is an interconnected, single level, "networked" organization in which there is no specialist or defined leader. Knowledge and decision rights reside at this one – and only – level.

We are able to model these two forms using identical numbers of agents[1] who learn and forget and whom are tasked with the equivalent amounts of work to perform. The other difference among the two groups, besides organizational forms, is their ability to communicate with available knowledge bases. Only the overall coordinator in the hierarchy case can access all of the knowledge bases, whereas the remaining agents are only permitted read and write access to their team-specific knowledge base. All agents in the edge organizational form have read and write access to all knowledge bases. The two POW-ER 3.2 models are shown below.

[1] "Numbers of agents" refers to the consistent number of student participants in each ELICIT exercise. Both hierarchy and edge organizational POW-ER models implement 17 participants, or 17 FTE's, each.

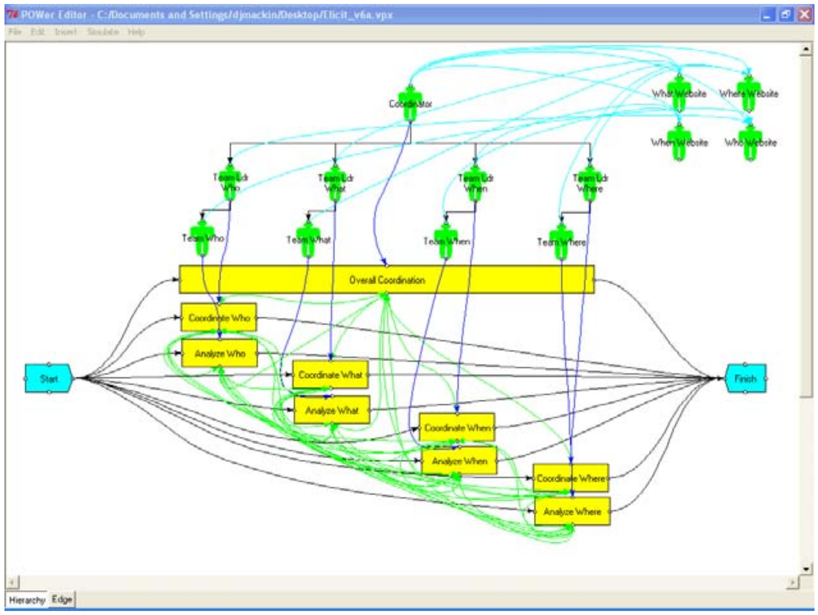

Figure 3.16: POW-ER 3.2 ELICIT Hierarchy Organization showing the agents (people icons) and tasks (boxes) and their connectivity to knowledge bases (upper right). Each team (who what, when, where) has 3 FTE's (Full Time Equivalent) for a total of 17 FTE's.

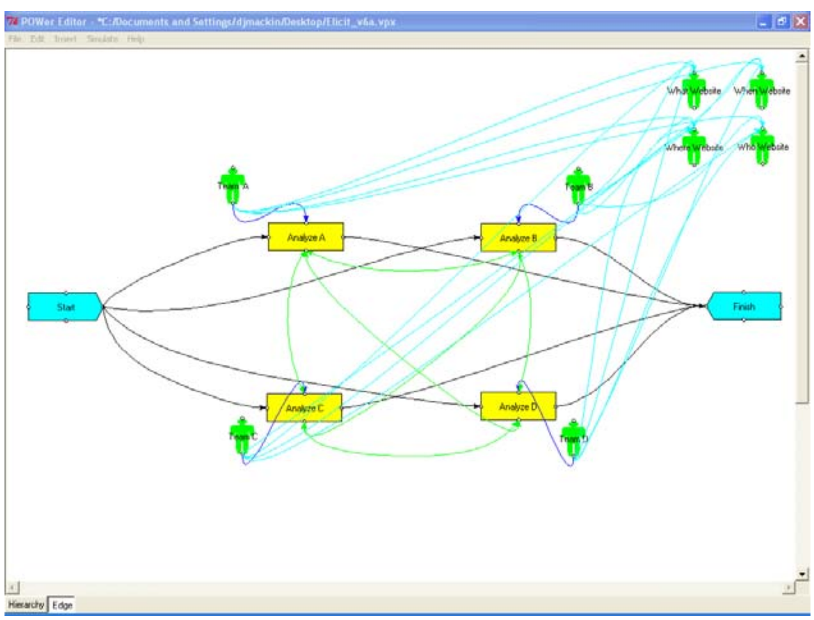

Figure 3.17: POW-ER 3.2 ELICIT Edge Organization showing the agents (people icons) and tasks (boxes) and their connectivity to

knowledge bases (upper right). The four teams (A, B, C, D) have 5, 4, 4, and 4 FTE's respectively, for a total of 17 FTE's.

ELICIT Findings

In this next section, we will focus upon the output from the ELICIT exercise. This second source of validation data strengthens our claim of external validity for POW-ER 3.2. We compare our POW-ER 3.2 hierarchy model output of project duration with the empirical data from an ELICIT small group exercise (Leweling and Nissen, 2007).

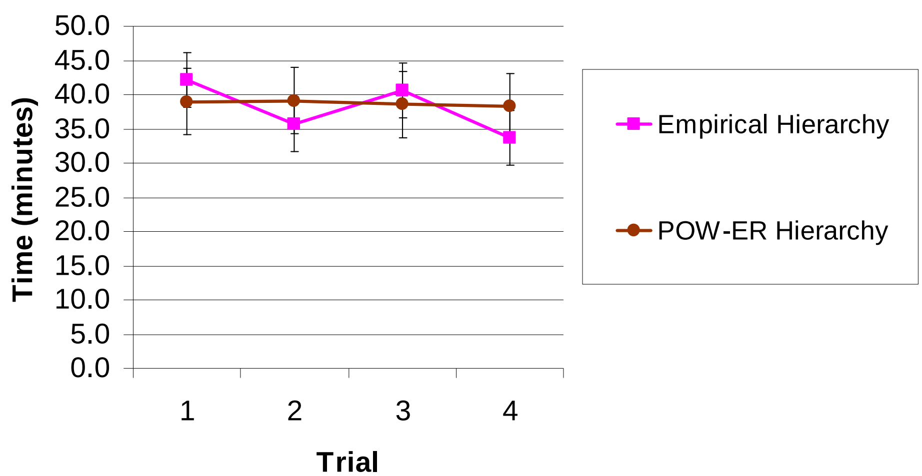

Figure 3.18: Empirical vs. POW-ER 3.2 Hierarchy Individual Learning Times comparing the average time required to complete a complex skill. Note that very little learning occurred across the four trials in both cases.

This graph compares the empirical data from four rounds of the ELICIT exercise to the forecast duration data from the same exercise modeled using POW-ER 3.2. The POW-ER 3.2 output data (n = 100 runs) plots close to the randomly varying times taken by the hierarchy organizational groups in ELICIT (Leweling and Nissen, 2007). Standard deviations for each datum are indicated by the perpendicular line segments. Each set of data shows a slight trend downward caused by the net learning of individuals in each organization. Variation in the empirical data is partially explained by the authors as due to slight variations among different ELICIT trials and slight unforeseen changes in personnel participating in the exercise (Leweling and Nissen, 2007).

Next we compare the ELICIT "edge" organization with the POW-ER 3.2 edge model output in the figure below.

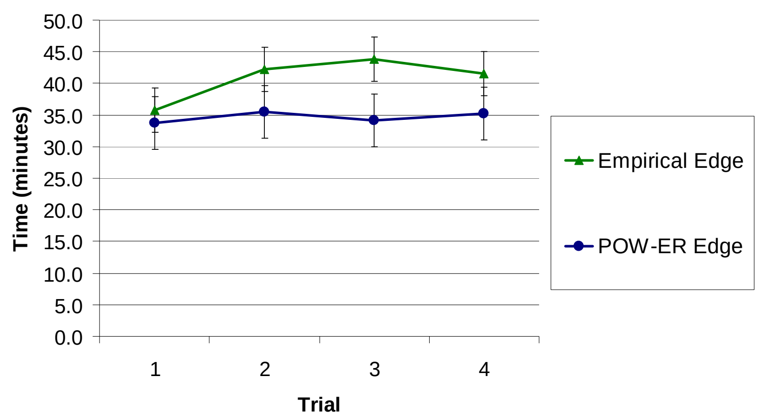

Figure 3.19: Empirical vs. POW-ER 3.2 Edge Learning Times for Individuals comparing the average time required to complete a complex skill.

This graph illustrates the difference between the empirical and the forecasted edge organization performance data. The empirical data indicate that more – not less – time is required after each interval. The experiment's authors theorize that this is due to differences between the four version of the ELICIT exercise or perhaps it is from a slight turnover of personnel participating in each trial. POW-ER 3.2 output however, indicates that the reason for the absence of net learning is that the trials are limited to 60 minute durations, yet occur after successive production breaks of up to seven days, which offset any learning from repetition of the exercise. It seems that little net learning has occurred in either hierarchy or edge organizational forms due to the lack of recency and frequency of exercises rather than differences among trials or slight variations in participants. Forgetting, it seems, is causing this lack of sustained learning among participants.

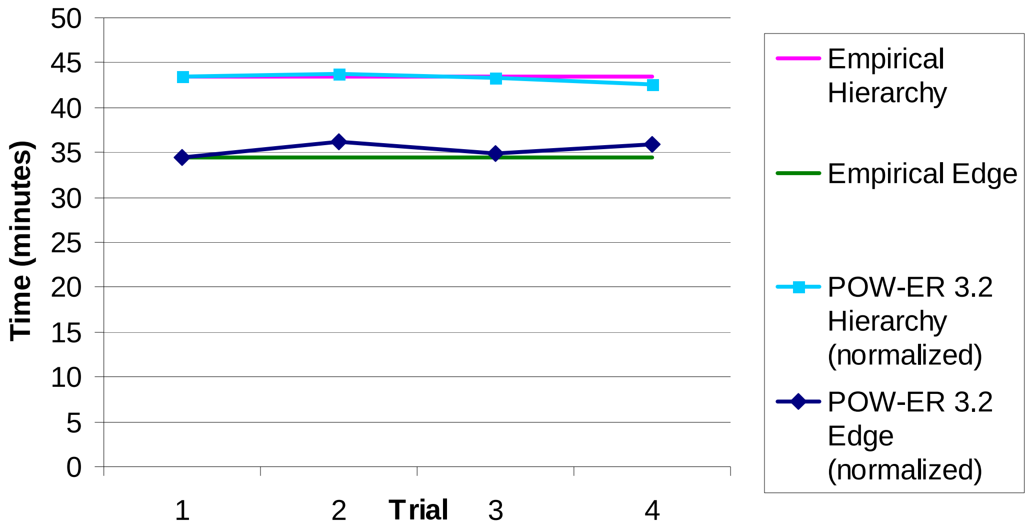

Figure 3.20: Normalized Empirical vs. POW-ER 3.2 Project Duration Times comparing the average time required to complete a project using the two organizational forms.

The normalized graphs (with simulated Edge and Hierarchy durations normalized to first period ELICIT empirical durations) above compares our POW-ER 3.2 output with the average Edge and Hierarchy ELICIT exercise observations (Leweling and Nissen, 2007). We note that the empirical findings indicate that edge organizations should perform better, in terms of project duration, than hierarchy organizations. Our POW-ER 3.2 concurs qualitatively with these findings, yet is different in terms of magnitude. The empirical data indicates a time performance difference of approximately 15%. The POW-ER 3.2 model indicates a difference of approximately 7% between Hierarchy and Edge structures for this exercise.

We normalize the POW-ER 3.2 simulation output in figure 3.20, to compare it to the empirical output of the empirical ELICIT data. We note no significant difference between the output and the empirical data ($p = .310$). The face validity of these findings (MacKinnon et al., 2007) was confirmed by the authors of the ELICIT experiment (Leweling and Nissen, 2007). The data from this experiment demonstrate that the parameters in the learning and forgetting micro-behaviors in POW-ER 3.2 appear to have replicated the offsetting effects of learning and forgetting accurately. Thus, this experiment provides additional support for our claim of external validation for the POW-ER 3.2 organization, simulation model of learning and forgetting.

Discussion

Comparisons are made between empirical AROUSAL output and POW-ER 3.2 simulation output for both a single trial (no learning) and multiple trials (with learning) as shown in the Results section above. This is supported by two forms of validation of the workflow model in POW-ER 3.2 and of the learning micro-behaviors that have recently been embedded in POW-ER 3.2. We note that POW-ER 3.2 output is statistically indistinguishable from the Dar-El high-cognitive curve until the production break occurs after Q4. We note that the empirical and POW-ER 3.2 computed durations of each AROUSAL quarter are statistically indistinguishable at the individual level, yet are statistically different (higher) for predicting group durations for Q7 and Q8 (p = .169, .179 respectively).

At this time we claim only face validity for comparability between the POW-ER model and the AROUSAL exercise it is attempting to emulate. We claim to have obtained plausible qualitative agreement of model predictions from one experiment, given the current implementations and limitations of AROUSAL and POW-ER. The validation against ELICIT showed good agreement of the POW-ER 3.2 model for two organizational forms forecasting the offsetting effects of individual learning and forgetting.

Conclusions

This paper reports on our continuing efforts to understand the organizational performance effects that occur as a result of individual learning and forgetting in project teams. We described our continuing research on specifying key variables that effect work flow, knowledge flow and organizational learning and provided a quantitative analysis of how micro-behaviors (learning and forgetting) affect organizational performance of project teams.

The experiments reported here cross-calibrated data on learning and forgetting from the cognitive science literature, results from three empirical group tasks involving both learning and forgetting, and predictions of a computational modeling experiment. The set of cross-validation experiments employed synthetic group experiments and organizational simulations of AROUSAL both with and without learning by agents, to cross-validate, calibrate and refine POW-ER 3.2 agent learning and forgetting parameters. This effort is bolstered by a second round of validation, leveraging findings from the ELICIT command and control exercise conducted by our collaborators at the Naval Postgraduate School.

This research has thus taken the necessary next step of merging the theories of learning and forgetting found in the cognitive science literature with research on computational modeling of organizations. Through an extension to the POW-ER model framework, we captured the dynamics of individual knowledge gained and lost in organizations and are thus able to extend our ability to model organizational learning and forgetting.

These experiments provide new evidence for some of the predicted performance differences found as a result of individual learning and forgetting both empirically and synthetically, and contribute toward an improved knowledge of organization knowledge flow effects (Nissen, 2006). The research has also provided a validated and calibrated tool to develop and test individual knowledge flow impacts on novel organizational forms and can determine contingently-based costs and benefits of individual skill growth and decay interventions (such as training or production breaks in performing tasks) for managers of project organizations.

Future Research

We intend to further validate and calibrate POW-ER through additional experiments, so that researchers will be able to use POW-ER to generate, model, and test novel hypotheses about traditional and novel organizational forms—such as "Power to the Edge" organizations (Alberts and Hayes, 2003). We will also begin to model and, validate and calibrate knowledge management interventions such as training and mentoring (described in Chapter 4) to further explore the costs, benefits, and effects of such organization investments.

In situations for which learning and forgetting of skills by agents are believed to have significant impacts on team performance, the extended POW-ER model will eventually allow managers to explore the impacts of knowledge management interventions such as task repetition, formal training, mentoring, rotation of employees through different tasks, and different schedules for production breaks on team performance.

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Chapter 4: The Effect of Formal Training and Mentoring on Individual Learning

Summary

Organizational knowledge is a critical resource that must be managed and understood to improve the probability of success in any endeavor. Understanding and predicting individual and group knowledge growth, decay and diffusion within the organization is a key factor in determining organizational success, yet is hindered by imprecise measurements and analyses based on earlier natural language descriptions.

The quantitative impact of dynamic individual knowledge flows has been informed through modeling and simulation of learning and forgetting at the individual and group level through our efforts. This chapter builds on the prior research of the author by focusing on the quantitative and combined effect of on-the-job-training (OJT), formal training, and mentoring, along with role changes to increase trans-specialist knowledge (Postrel, 2002).

The analysis indicates that training and mentoring do not cause an immediate improvement in processing speed but can eventually surpass the growth in processing speed from OJT learning alone, and can cause improvements in decision quality.

The results of this research extend our knowledge of individual and group-level learning and forgetting effects within an organization to incorporate formal training, mentoring and rotational assignments as potential managerial knowledge flow interventions.

Background

Organizational knowledge is a critical resource that must be managed and understood to improve the probability of success in any endeavor. Knowledge held by individuals and its effective management has been scrutinized from many perspectives, almost exclusively using qualitative, natural language approaches (Holsapple and Jones, 2004 and 2005; Kim, 1993; and Nissen, 2006).

Understanding and predicting individual and group knowledge growth, decay and diffusion within the organization is a key factor in determining organizational success, yet the “qualitative ambiguity” arising from indeterminate outcomes of sometimes opposing effects of multiple variables in prior work hinders the progress of researchers; and it prevents practitioners from understanding the payoff of interventions aimed at growing individual knowledge on project organizational performance.

A common framework used to explain the flow of knowledge has been seen through one, two and three dimensional graphs that attempt to explain its *explicitness* (Polanyi, 1966), *reach* (Nonaka, 1994), and *lifecycle* (Nissen, 2006). Knowledge has been viewed as a source of competitive advantage (Senge, 1990) and its value has been viewed from the perspective of something that is derived from information (Nissen, 2006) and that can be grown (Dierckx and Cool, 1989 and Nonaka, 1994). Knowledge itself can be epistemologically divided further into two types: *explicit* and *tacit* (Polanyi, 1966). Explicit knowledge is that which can be demonstrated or transmitted. Tacit knowledge is that which is held within the cognitive individual and “is deeply rooted in action, commitment, and involvement in a specific context” (Nonaka, 1994, p.16). We consider that the more an individual knows (either explicitly or tacitly), the greater is his skill level.

Emerging research describes the tension between learning and performance (Singer and Edmondson, 2006) where learning seems to occur at the cost of performance. This effort has underscored the need for more research in this area. Much research and practical experience confirms qualitatively that individual knowledge must be acquired and retained within the organization (e.g. Argote, 1999). However, we find a lack of quantitative analysis to help determine the effect of individual skill growth and decay on short term, project organizations. Our efforts are inspired by these prior qualitative efforts.

We theorize that the level of knowledge held by the individual can be inferred from the directly observable processing speed demonstrated by an individual conducting a complex task (Jin and Levitt, 1996). The quantitative team-level impact of dynamic individual knowledge has recently been informed through modeling and simulation of learning and forgetting at the individual and group level through our efforts in Chapter 3. This chapter builds on our prior research by addressing the quantitative effect of formal training, and mentoring, along with role changes to increase trans-specialist knowledge (Postrel, 2002) on team performance, in addition to learning from on the job training and forgetting due to production breaks that we previously addressed.

We assert that, once learning (and forgetting) rates can be verified and calibrated, they can be embedded as agent micro-behaviors into an agent-based computational organizational simulation such that their combined effects can be understood at the organization-level of a project.

In this paper, we focus on three sources (or inflows) of knowledge that are available to transmit (or flow) knowledge into individuals within an organization. First, <u>on-the-job training</u> (OJT) is a slow but very inexpensive form of knowledge inflow that allows productive work to continue. Second, <u>formal training</u> may be employed. This is relatively inexpensive, but also somewhat slower and usually takes participants away from doing direct work for the duration of the formal training. Finally, <u>mentoring</u> may provide the fastest means to provide knowledge inflow, but it incurs the high cost of the time of experts who provide the mentoring to novices. We have previously conducted an experiment that involved only OJT knowledge growth and decay as discussed in Chapters 2 and 3. We now turn our attention to including different mixes of all three types of knowledge flow interventions.

AROUSAL is a construction business simulation team exercise that provides the opportunity to observe participants performing a task requiring a complex, cognitive skill (management) and provides the opportunity to observe the effects of knowledge inflows of OJT, formal training, and mentoring. We selected this type of exercise because it implements a realistic *problem-based learning* (PBL) experience rather than the contrived tasks used in most synthetic or laboratory experiments. A laboratory experiment allows for stricter experimental control, however, the PBL experiment provides for greater realism (Zolin, Fruchter, and

Levitt 2003) while still providing for environmental control. This type of experimentation seemed a better fit for what we wish to explore.

Participants in AROUSAL are randomly placed in groups of four. These four individuals fill the roles of: marketing-sales, human resources, operations, and finance. Each group must decide how it will use limited funds and people, and determine how to compete for construction jobs. To do this, each participant must first develop her own functional plan and plan justification according to the functional role assigned, and then engage in a discussion with other group members to integrate that plan with the functional plans of the other three members of the group.

Groups typically require 90 minutes to develop individual and group plans for each quarter. AROUSAL runs for eight, successive, simulated business quarters. This provides a researcher the opportunity to observe changes in processing speed and decision quality over time. Each group is asked to temporarily stop their execution after the first four quarters to allow for rest and a one-time role exchange. The AROUSAL exercise then continues until all eight quarters are complete.

Individual and group plan development time as well as cumulative net worth of the simulated business are recorded for each quarter. The instructor also assigns grades to each team based on the rigor of its team members' justifications for their decisions made.

We previously modeled teams engaged in the AROUSAL exercise using POW-ER 3.2 to calibrate micro-behaviors of learning and forgetting as discussed in Chapter 3. This inquiry extended, calibrated and validated organization simulation research conducted by the Virtual Design Team (VDT) research group (Jin and Levitt, 1996) via a new simulation framework, POW-ER (Project Organization Workflow model for Edge Research) (Ramsey, MacKinnon, and Levitt, 2006). VDT agents have static knowledge levels for each skill type modeled as an ordinal variable (None, Low, Medium, or High) (Levitt, et al., 1999). The improved POW-ER framework provides development of a finer-grained, numerical skill metric, and simulates additions and deletions to agents' knowledge as knowledge *inflows* and *outflows (*Dierickx and Cool, 1989) that occur as a result of task repetition and breaks in task performance, respectively.

This paper continues our exploration of project team members learning a complex, cognitive skill through the observations of participants using the AROUSAL business simulation. Our previous findings are summarized below, followed by our present hypotheses about how formal training and mentoring might affect speed of processing.

This next section discusses a benchmark finding from cognitive science research on learning against which to compare our learning observations. We will use the skill classification graph (Dar-El et al., 1995) below for this purpose.

Skill Classification

Not all skills are learned by individuals with equal speed through repetitive performance. Dar-El et al. (1995) classify skills in the following four categories: (1) highly cognitive, (2) mostly cognitive, (3) mostly motor, and (4) highly motor, and show their respective rates of learning in terms of time to complete a task requiring that skill type as a function of the number of repetitions of the task, as shown in figure 4.1.

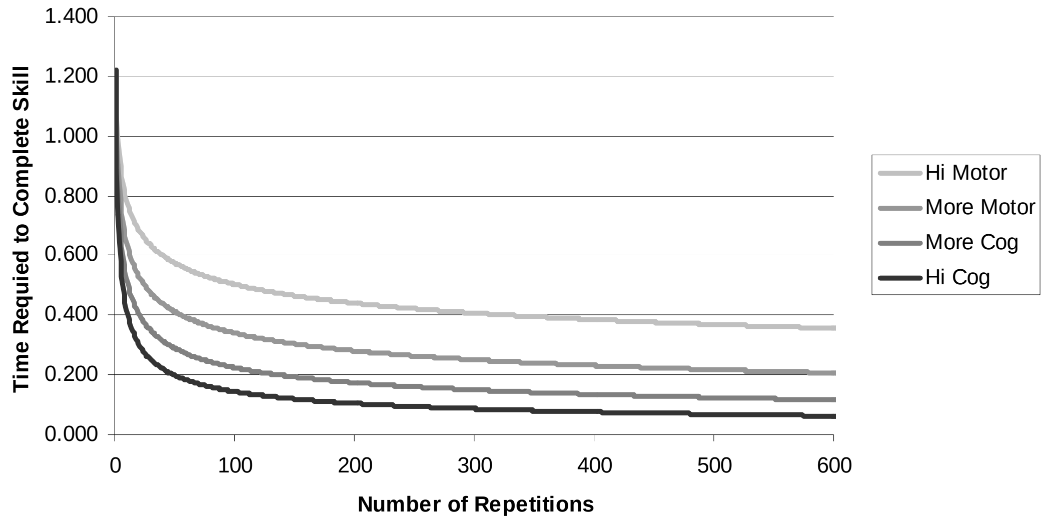

Figure 4.1: Learning Curves for Different Types of Skill (replicated from Dar-El et al., 1995). As skills become increasingly cognitive rather than motor, they tend to improve more over time.

Figure 4.1 illustrates the learning rate differences among tasks requiring four types of skill. We anticipate that this classification will further our understanding of skill learning when combined with forgetting. We will attempt to combine and build upon these theories by combining learning and forgetting with skill classification to improve our ability to forecast knowledge, or skill level, over time, and use this as our initial basis of comparison between and among different experiments.

Our previous findings are summarized below and provide the basis for comparing our current observations.

Summary of our Previous Findings

Our earlier efforts are summarized below. These findings will be compared with the findings from the experiments conducted in this paper. Again, we will use the skill classification learning curves (Dar-El et al., 1995) to provide a consistent benchmark which to compare experimental output. Times shown are normalized to provide comparison.

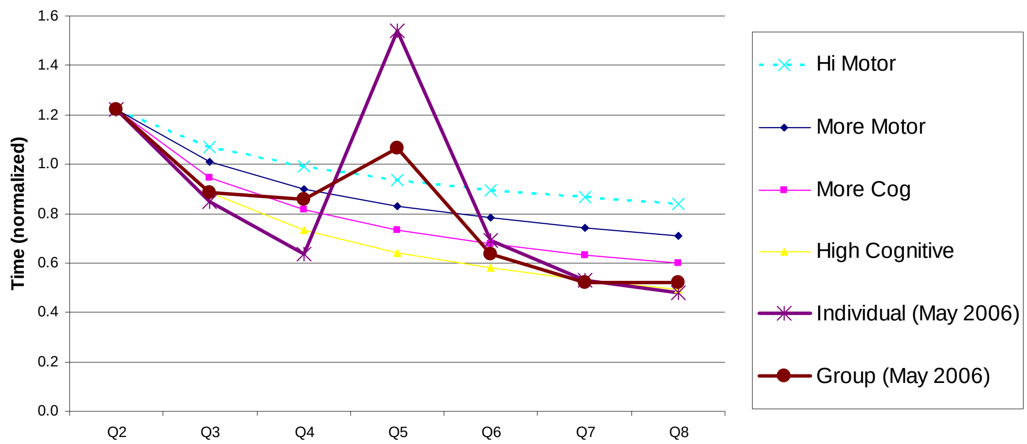

Figure 4.2: Dar-El et al. Learning Curves with Individual and Group Learning Rates Aggregated Over Time. The data shows the replication of high-cognitive learning (and forgetting) plus the reacquisition of the curve following a production break after Q4.

We observe that our data plots along the cognitive curve for both the individual and the group data for the second and third quarters. We also note that the group data decrease very little between Q3 and Q4. This anomaly is not explained by our interventions. Q5 shows a significantly increased time requirement for both individuals and groups, with the amount of time for individuals increased more than the group time. This forgetting is due to an imposed production break between simulation runs and potentially also due to the exchange of roles within the groups.

We also observe that both the individuals and the group times return quickly to near their original trend - and again along the cognitive curve. In replicating the theoretic findings of Dar-El et al., we provide compelling evidence that predictions of individual knowledge can be validated and perhaps calibrated for use in predictive organizational models for cognitive skill.

We observe that although group learning follows qualitatively the same pattern as individual learning, groups tend to learn and forget more slowly than individuals within the same knowledge environment. This qualitative finding supports the notion that groups, rather than individuals, might provide a preferred echelon of learning because of the retained knowledge revealed through reduced levels of forgetting.

Research Questions

This chapter follows the same line of inquiry as before, yet takes the next step of exploring the observable learning differences that occur as a result of formal training and mentoring. This leads us to consider the following questions:

1. How are project organizations affected by the sum of the skill growth and decay of individual participants?
2. How are individual and group learning affected by formal training and mentoring?

3. Will a group of individuals subject to formal training and mentoring, exhibit the same sort of behavior as those who learn through OJT, and will their learning be reflected in the macro-performance of their organization?

Experimentation

We designed and implemented experiments in a business case simulation, entitled *AROUSAL* (Lansley, 1982) where participants were asked to develop and integrate quarterly functional plans (Marketing/Sales; Human Resources; Operations and Finance) for a simulated construction business. Observations of team members engaging in the AROUSAL exercise provide measures of individual knowledge level though individuals' time to perform a repeated, complex skill — developing a functional plan for the next quarter; of group learning by the time required to integrate team member plans each quarter; as well as a group measure of task quality through the profit earned by the team and the grade given to the team by the instructor (who did not participate directly in the experiment).

A class of 41 Master of Science students was asked to participate in a business case simulation where they manage a simulated construction company. Each participant was randomly placed in a group and given a role to perform. These roles consisted of either: marketing-sales, operations, human resources or finance. There were four participants per group and the groups decided who would take each role. One group consisted of five participants. Each participant was directed to develop his/her individual quarterly business plan. Each group was then directed to convene to integrate these plans. Integration was not trivial because each individual competed for limited group resources. For instance, the budget of each group had to be allocated among initiatives related to marketing, hiring new people to support the work of each role, and writing proposals (bids) for new construction jobs.

The simulation ran for eight quarters. Each iteration, or simulated business quarter, required approximately 90 minutes. Four quarters of AROUSAL exercise therefore required approximately six hours to complete. After 4 quarters, the groups were asked to interrupt the exercise and resume at a mutually agreeable time. The average production break was approximately three days. All of the groups were also asked to exchange roles during the production break portion, and for the remaining four quarters, to test for the effects of OJT, formal training and mentoring, whose implementation is discussed below. This provided all the groups with approximately equal levels of *trans-specialist* knowledge (Postrel, 2002).

We asked each participant to voluntarily sign a release form under appropriate protocol, notifying them of the anonymous nature of the recorded data as well as their voluntary participation in this study. They were then asked to self-report their background or Knowledge Inventory (KI). They were also asked to self-report duration data about the exercise. The first quarter's inputs were predetermined and provided to each group to familiarize them with the software.

Measurements

We measured how long it took for participants to accomplish a recurring skill (i.e. a specific functional portion of a quarterly business plan), and then measured how long each group required to integrate these plans. We also measured their *company's* net worth at the end of each iteration. We measured this for eight iterations.

We measured this to understand the rate at which individuals and groups learn so that we might embed these learning and forgetting rates into an agent-based, project organizational simulation to allow it to reliably simulate learning in other organizational contexts.

In this round of experimentation we add formal training and mentoring for some of the groups. Formal training was completed by the Professor who taught the course and was given only to those assigned the role of finance in selected groups. This training included concise methods to estimate company overhead in future periods, allowing for improved competitive advantage in bidding for construction jobs. Note: All of the information conveyed in the training could have been found by all participants from the AROUSAL documentation provided to them. This training served only to focus and explain information already available to all participants and was conducted before the commencement of the entire exercise.

Mentoring took place after the production break and the role exchange. Participants who had held the role of finance were asked to explain what they had learned to the new person taking on the finance role, and to continue to answer their questions and provide guidance for the four remaining quarters. Our experimental design was structured using the following table for the ten groups.

Table 4.1. AROUSAL Experimental Design The first three groups each received both formal training and mentoring. The second three groups received no formal training and were allowed to mentor each other. The third three groups each received formal training and were asked not to mentor each other. This provided a full factorial 2x2 design. The final group was not given formal training and asked not to mentor.

	Q1-Q4	Production Break	Q5-Q8
Group	Formal Training		Mentoring
1	1	1	1
2	1	1	1
3	1	1	1
4	0	1	1
5	0	1	1
6	0	1	1
7	1	1	0
8	1	1	0
9	1	1	0
10*	0	1	0

* control group

Our Hypotheses

We considered how the rate of learning (measured by decreases in task duration) might change as a result of formal training and mentoring. We also considered how formal training and mentoring might affect the groups' decision making ability. Hypotheses 1, 2, and 3 are stated and illustrated below

Hypothesis 1: Participants who received formal training will afterward demonstrate a faster learning rate.

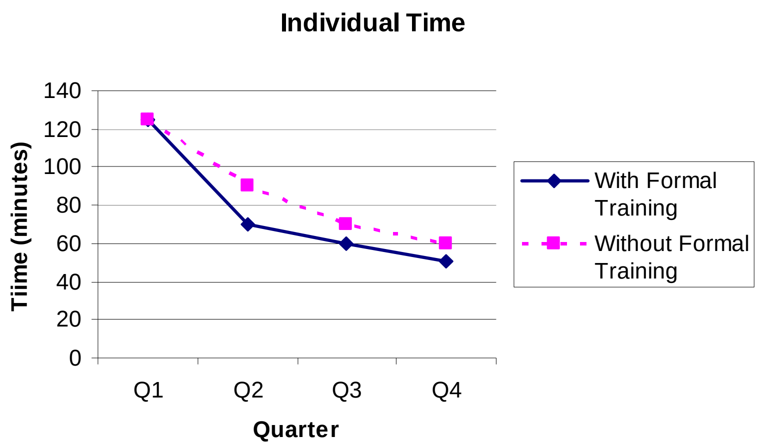

Figure 4.3: Hypothesized Time Spent after Formal Training showing the hypothesized average time each student spends in preparing their portion of the business case having received formal training (solid) compared to those who have not (dashed line).

Hypothesis 2: Participants who received mentoring will demonstrate a faster learning rate as they were being mentored.

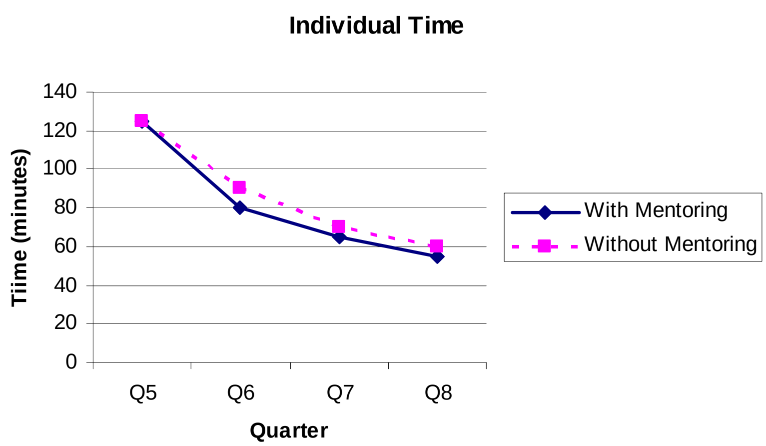

Figure 4.4: Hypothesized Time Spent after Mentoring showing the hypothesized average time each student spends in preparing their portion of the business case having received mentoring (solid) compared to those who have not (dashed line).

Hypothesis 3a: Participants who received formal training will demonstrate improved decision making that will be observable through improved company net worth over time.

3b: Groups who conduct mentoring will perform better than those who do not conduct mentoring in terms of net worth, but not as well as those who receive formal training.

3c: Groups who are both formally trained and mentored will perform better than all other groups in terms of net worth.

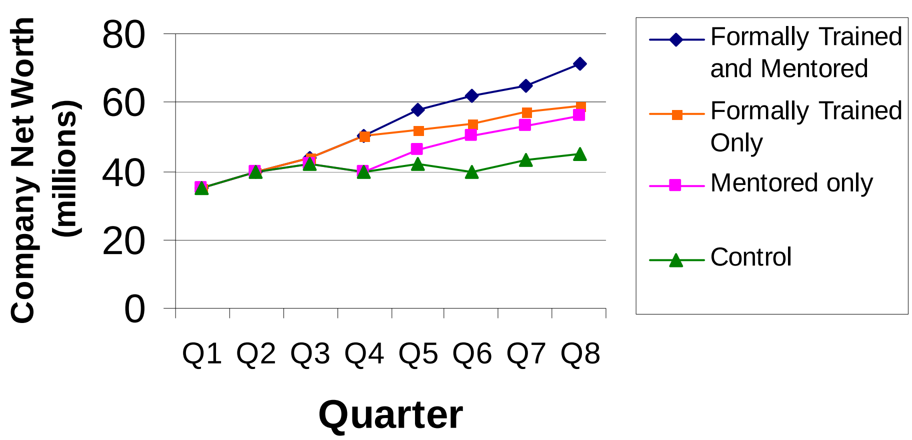

Figure 4.5: Hypothesized Decision Making Quality showing the average *company* net worth among groups who had formal training with and without mentoring compared to those whom did not.

Results

Considering learning by repetition and forgetting due to production breaks, our results illustrate that we were able to replicate the Dar-El et al., (1995) learning curves twice (May 2006 and. May 2007). They also illustrate the difference between learning among individuals and groups as shown below.

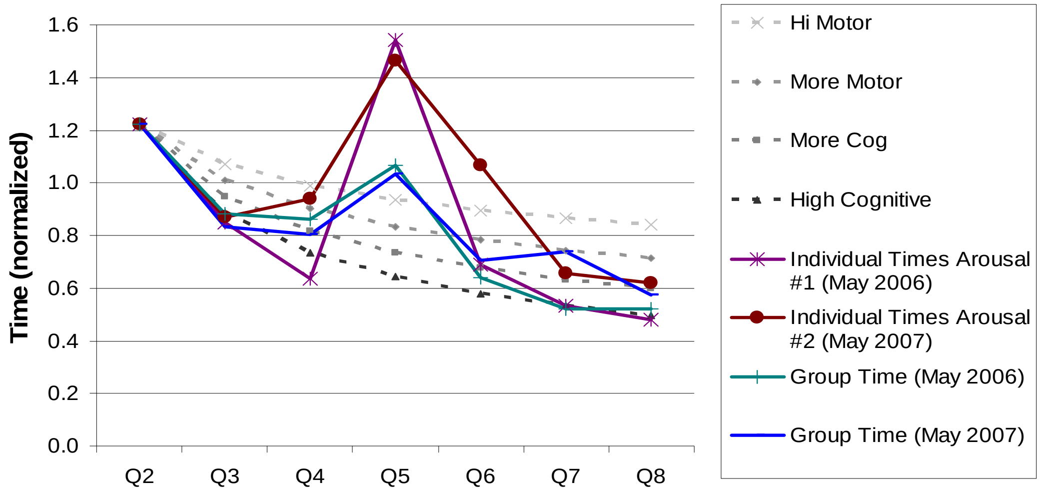

Figure 4.6: Normalized Empirical Findings of Learning vs. Dar-El Learning Curves. These graphs **c**ompare the average time spent by all individuals and groups conducting seven trials of two separate AROUSAL exercises (May 2006 and May 2007) with a production break imposed after period Q4 to the Dar-El et al. (1995) learning curves.

In this graph we note that all curves tend to follow the high cognitive curve at first and that the group learning curve remains close to the group learning curve of 2006. We observe that the time required for Q5 in the May 2007 exercise is again greater than when the exercise began. Perhaps the expected effect of the 3-4 day production break in causing forgetting is exacerbated by the role exchange that takes place by all participants during the production break between Q4 and Q5.

We also observe that the individual learning curve in 2007 remains above the individual learning curve of 2006. This seems to occur as a result of our introducing formal training prior to the start of the experiment. The POW-ER 3.2 model forecast for individual time remains a close approximation among these two experiments (see figure 3.12).

We now consider only the May 2007 AROUSAL exercise, in which we introduced the additional interventions of formal training and mentoring for some groups. Our goal is to analyze the effects of formal training and mentoring on learning rates and decision quality of participants in greater detail.

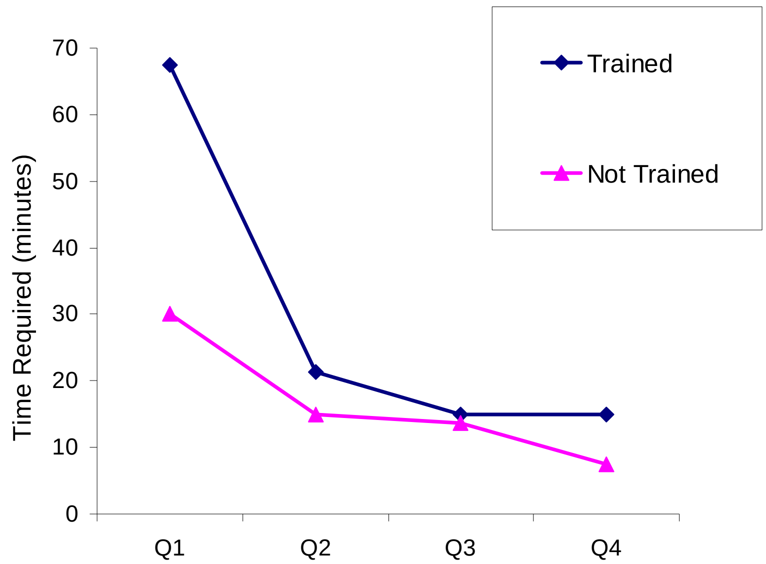

Figure 4.7: Individual Times of Formally Trained Participants showing the average time spent by those who received and those who did not receive formal training.

The graph above steps away from the Dar-El et al. (1995) depiction of normalized data and depicts the time required over the first four quarters of the AROUSAL exercise. The graph demonstrates the difference between groups who received formal training vs. those who did not. The p-values for Q1 through Q4 are: .093, .230, .444, and .044 respectively. Only Q4 is statistically different. There are mixed statistical differences between the two curves at each AROUSAL business quarter; however, there is a qualitative difference between the two curves: In every quarter, the groups who were formally trained required, on average, more time to complete the development of their individual plans. We observe that the time required among individual participants in the first quarter is more than double the length of time required by the other participants – even though the first quarter input data is provided to all the participants as a training trial. This was an unexpected result!

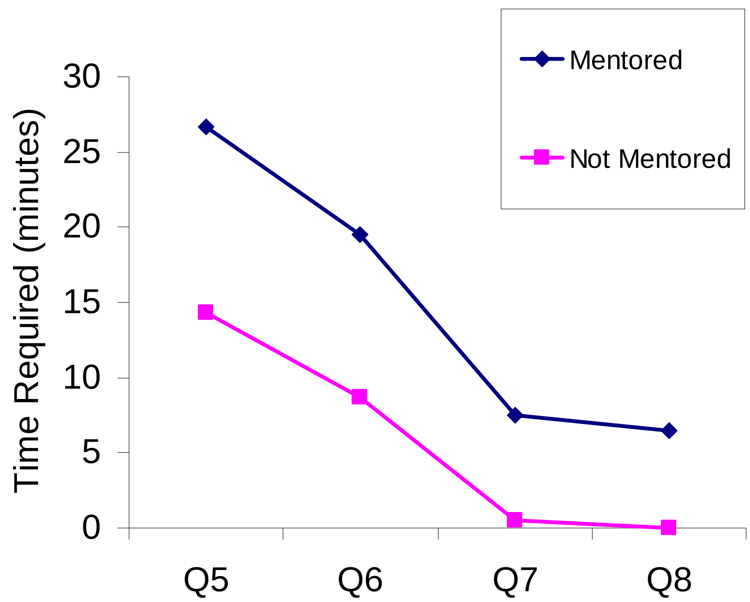

Figure 4.8: Individual Times of Mentored Participants comparing the average time spent by those who received mentoring with those who did not.

Figure 4.8 shows a second surprising result: those individuals who were mentored tended to require more time than their counterparts who were not! The analysis indicates that the p-values for Q5 through Q8 are: .231, .222, .017, and .007 respectively. Q7 and Q8 are statistically different. Again we note that although there are mixed statistical differences between the two curves at each AROUSAL business quarter, there is a consistent qualitative difference between the two curves and, in every quarter, the groups who were mentored required more time, on average, to complete the development of their individual plans.

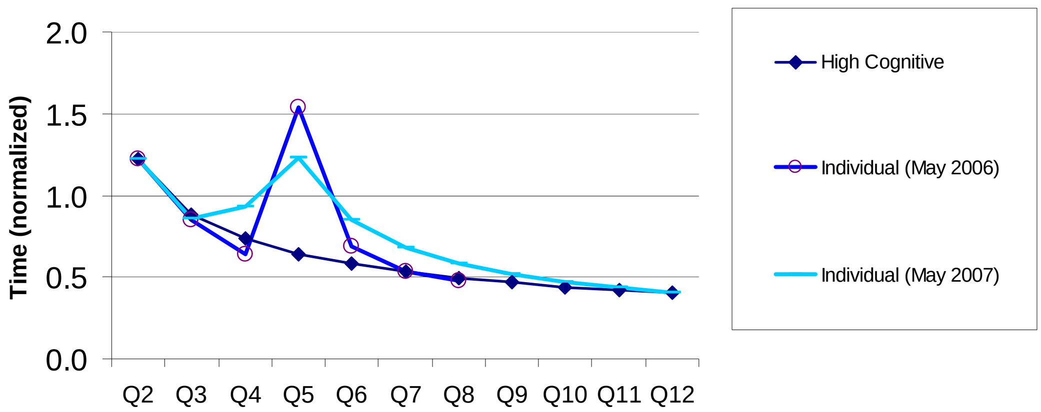

Figure 4.9: Normalized Individual Times of Formally Trained vs. Untrained Participants, extrapolated out for four more trials, comparing the average time on each trial for those who received mentoring vs. those who did not.

The graph above was developed because of the increased downward slope of the learning curve observed after formal training and mentoring had both been conducted. We noted that neither the learning curve of the "untrained, trained and mentored" individuals from 2007 AROUSAL case nor the "untrained" individual learning curve from 2006 had, by the end of the AROUSAL exercise decreased durations as much as we hypothesized. We were curious to determine when the recently observed curve, and the individual learning it represents, would achieve the speed of processing predicted by the Dar-El high cognitive curve. Our extrapolated curve indicates that if allowed to continue working, the individual curve would achieve the same time performance at approximately Q12. This suggests that there is benefit from providing formal training and mentoring. It seems that in the short term, speed of processing is sacrificed for current improved knowledge, yet over time the processing speed deficit seemingly caused by formal training and mentoring is eventually overcome and perhaps exceeded.

We next analyze the net worth of each group after each successive AROUSAL business quarter and examine how formal training and mentoring affected the "quality" of decision making by groups.

Net Worth

Groups were judged by how well their individual company performed in terms of final net worth, among other deliverables. In the graphs below we compare dynamic net worth (= starting net worth plus net profit (or minus net loss) earned in the prior quarter) as observed during each trial of the AROUSAL exercise. We examine this in terms of the different experimental groups to understand how formal training and mentoring may have affected the performance of each group in terms of final net worth. The graph below depicts how each of the experimental groups performed as indicated by net worth at the end of each AROUSAL exercise quarter.

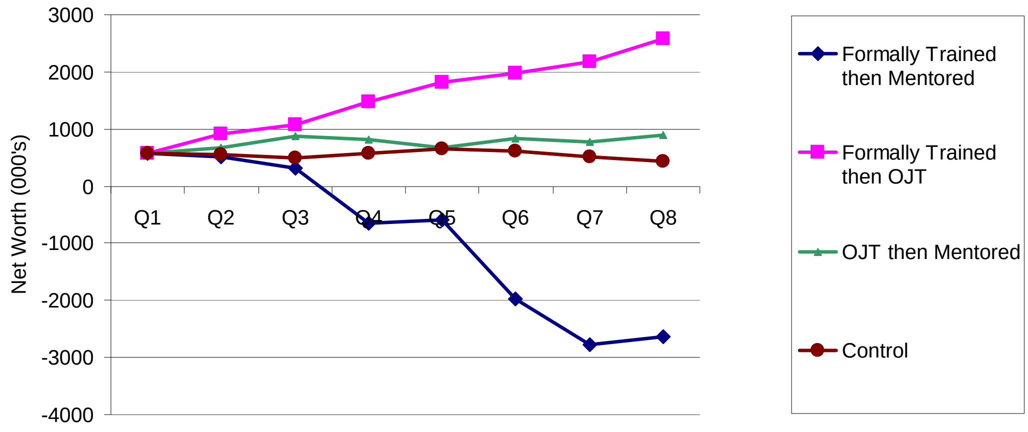

Figure 4.10: Dynamic Net Worth for each Group showing how each experimental group performed on average in terms of net worth.

The graph illustrates that the "formally trained then OJT" groups performed substantially better than other groups. By the eighth quarter of the AROUSAL exercise, the "formally trained then OJT" group's net worth was statistically significantly better than its nearest competitor "OJT then mentored" (p=.008). Our analysis also indicates that the group that performed the worst with respect to net worth was the "formally trained then mentored" group. This experimental group contained one group, in particular, whose net worth continued to decrease as the AROUSAL exercise continued. The reason for this poor performance can be partially explained by the stochastic nature of construction bidding process in which each group must engage the software and hope to be awarded bids after having provided its set of bids. These inputs include, but are not limited to: overhead and profit margin. Market environment must also be considered to help ensure a successful bid. We omitted the data from this poorly performing outlier group from the analysis to develop the following graph.

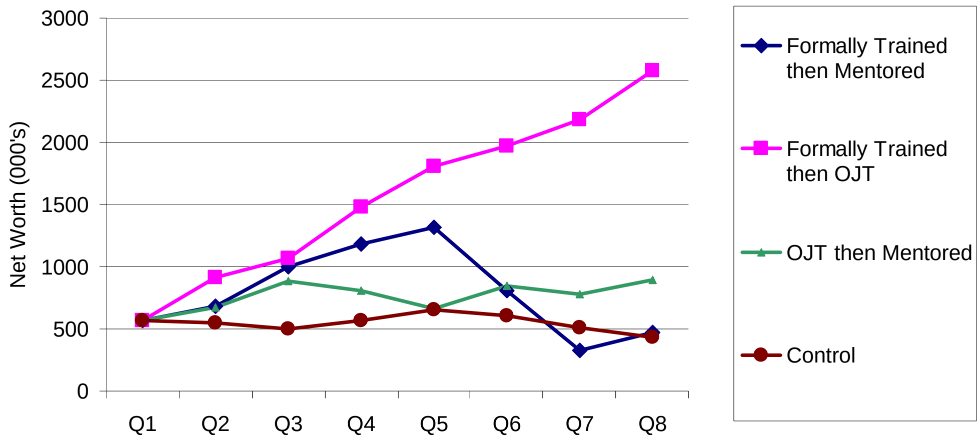

Figure 4.11: Dynamic Net Worth for each Group (outlier removed) showing how groups subject to each experimental intervention performed on average in terms of net worth.

This graph, without the poorly performing group, reveals that those groups who were formally trained then allowed to learn from OJT performed much better with respect to net worth.

We now aggregate all of the groups who received formal training and compare their net worth to those groups who did not receive formal training. The outlying group has been removed from the graph below.

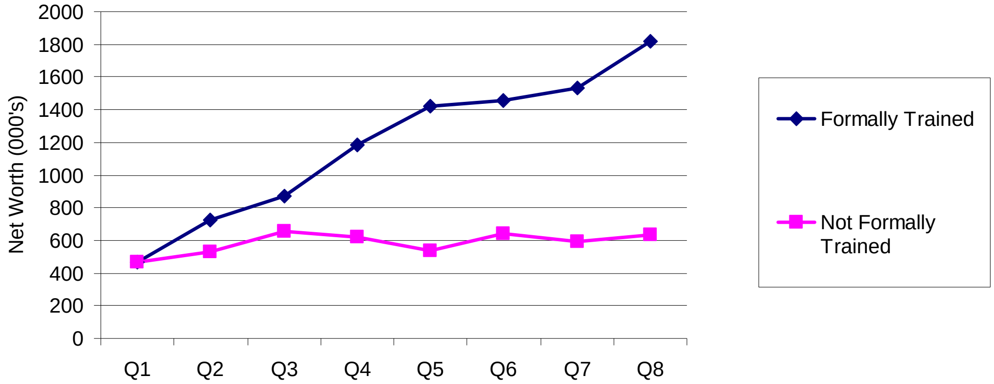

Figure 4.12: Dynamic Net Worth for Formally Trained and Untrained Groups showing how groups with each experimental learning intervention performed on average in terms of net worth. The outlier was removed.

Our analysis indicates that when the groups are combined in terms of those who received formal training vs. those who did not, we obtain the following p-values for Q2 through Q8: .064, .059, .013, .004, .011, .019, .014, respectively. We note that after Q4, there are sustained statistical differences of net worth between the groups who received formal training and those who did not. This supports Hypothesis 3a.

Approximately half of each formally trained and untrained group received mentoring. The groups who received mentoring did not significantly differ in their net worth from the other groups ($p = .077$).

We now analyze final net worth as compared to the total time required for each group in individual and group decision making. This may provide a corroborating explanation as to why the groups performed differently.

The graph below demonstrates that while the formally trained group performs well, it also spent more overall time to consider its quarterly response.

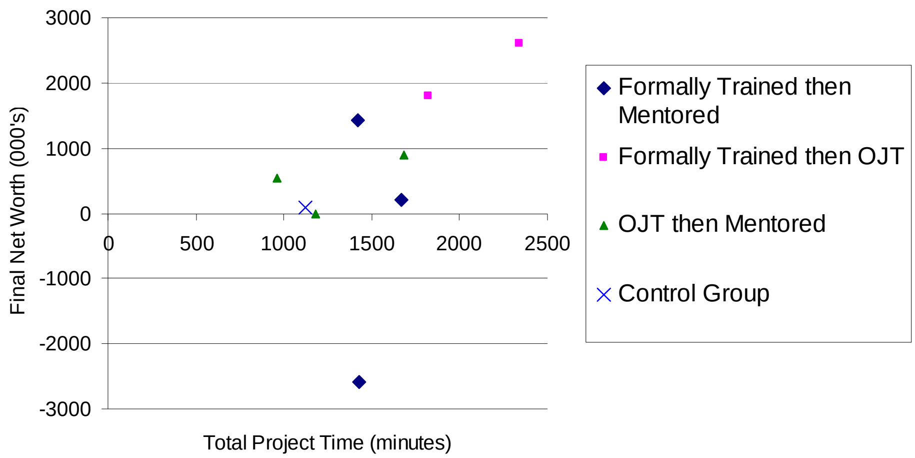

Figure 4.13: Net Worth vs. Total Project Time for formally trained, mentored, versus untrained and unmentored groups.

We observe that the "formally trained then OJT" groups tended to perform the best, while we observe mixed results for the "formally trained then mentored" groups. The "OJT then mentored" group tended to perform near the control group. It seems that mentoring provided little help in terms of final net worth. We note that the mentoring provided was performed by participants who had recently learned the requirements for the position. Their knowledge levels might have been weak as compared to an expert. Regression analysis indicates that a least squares, linear fit, trend line has the equation of

$$y = 1.8651x - 2268.4,$$

$r^2 = 0.2883$, and $p = .136$ (slope is not statistically different than 0)

For our initial exploratory purposes, we included the apparent outlier —the group that performed exceptionally poorly in all dimensions. Perhaps this was due to a poor understanding of the exercise or perhaps due to the stochastic nature of being awarded construction jobs within the AROUSAL exercise – a key component to improving net worth. We therefore removed this outlier to illustrate how the data trend is altered. The next graph shows the same data with the outlier omitted.

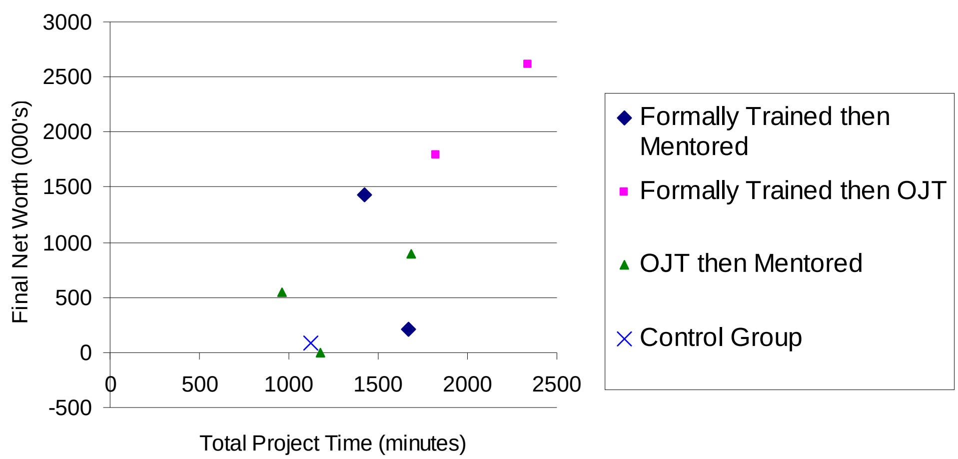

Figure 4.14: Net Worth vs. Total Project Time (outlier removed) for formally trained, mentored, versus untrained and unmentored groups.

Our graph now indicates that there is a statistically significant correlation between overall time spent on the project and the net worth earned – and that the groups who tended to perform the best were "formally trained and then learned by OJT."

$$y = 1.6638x - 1589.5,$$

$r^2 = 0.6422$, and $p = .016$ (slope is statistically different than 0)

Conclusions

This chapter has begun the quantitative effort to understand how formal training and mentoring might effect individual speed of performance and decision making quality.

Our analysis suggests that perturbations in knowledge flow at the individual level (e.g. formal training and mentoring) will be manifested in group performance in terms of required time and perhaps in improved decision making quality. Formal training caused a statistically significantly greater time requirement, while mentoring did not. The analysis indicates that, while training and mentoring will not cause an immediate improvement in processing speed, they can improve and surpass the growth in speed of processing from pure OJT learning over a more extended time period, and can cause improvements in decision quality. The set of groups that achieved the highest net worth via the AROUSAL exercise was the set that was formally trained then allowed to learn from OJT.

Perhaps individuals who are learning a complex task should be trained, then allowed to perform the task for a some time. We note that the groups who spent more time considering their options tended to perform better, thus confirming a tension between quality and speed.

Table 4.2. Hypothesis Results Summary The three proposed hypotheses are summarized below. Statistical significance levels are provided where appropriate.

Hypothesis Summary	Results	Level of Significance
Hypothesis 1: Participants who received formal training will afterwards demonstrate a faster learning rate.	Refuted by the data. Our findings suggest that the opposite is true. Our findings indicate that after formal training, participants tended to spend more time considering more alternatives vs. individuals who did not receive training.	(p=.204) on average. Only statistically different in the fourth quarter (p=.035).
Hypothesis 2: Participants who received mentoring will demonstrate a faster learning rate.	Refuted by the data. Our findings suggest that again the opposite is true. Our findings indicate that as mentoring continued, participants tended to spend more time considering more alternatives vs. individuals who did not receive mentoring.	Not statistically significant.

Hypothesis 3a: Participants who received formal training will demonstrate improved decision making through improved net worth. 3b: Those groups who conducted mentoring will perform better than those who do not perform mentoring. 3c: Those groups who were both formally trained and mentored would perform better than all the other groups in terms of net worth.	3a: Supported by the data. 3b: Qualitatively supported with some explanation. Groups whose individuals received formal training performed best while the remaining groups performed approximately equally. 3c: Not supported by the data.	3a: Groups who received formal training followed by OJT, performed better in terms of cumulative net worth . (Q8: p =.014). 3b: Groups who received mentoring did not perform better than groups who did not (p=.077). 3c: Not significant.

This analysis suggests that for participants who are initially learning a complex skill, it may be best to formally train them, then allow them to use what they have learned and continue to learn by doing. This also suggests that mentoring, although weak in this instance as it was provided by fellow participants and not an expert, may cause a performance deficit. Perhaps too much knowledge inflow caused poor performance, in this case, indicating that there may exist a tension between speed of performance and knowledge levels for cognitive tasks (Gilbert, 2007).

This improved understanding of the processing speed effects of formal training and mentoring extends cognitive theory by providing researchers and practitioners an initial quantitative framework to continue analyzing and evaluating knowledge management strategies. These significant findings continue to refine our knowledge of group level learning and forgetting within an organization.

Future Research

These promising results indicate that further research must be conducted for other skill classifications such as: high motor, more motor, and more cognitive (Dar-El et al., 1995). Findings from this research also suggest exploring alternative mixes and chronological ordering of knowledge interventions such as training with mentoring or OJT. These may be tested on larger samples to understand the contingently optimal order and mix for enhanced speed and quality of performance by individuals in a project organization for a variety of skill types.

We also note that other knowledge flow interventions such as obsolescence (Schott, 1978) and interference (Anderson, 2005) that serve to decrease individual knowledge held must also be further explored. Increased levels of obsolescence would occur in a knowledge field that undergoes rapid change or updating. An example would be any industry that directly involves the internet. The field of medicine, particularly surgery, provides another example. In these cases, individuals must constantly engage in learning to keep pace with the field, and may have to undergo refresher training if they fall out of practice. Future research along these lines may suggest best methods (OJT, training or mentoring), and the required periodicity to remain current.

Progress in this endeavor would enable improved understanding for researchers and managers to understand knowledge flow for a variety of skill types.

We continue to move closer toward our goal of "engineering" knowledge management solutions in organizations (Jin and Levitt, 1996). This effort will eventually provide managers a method to determine optimal knowledge flow interventions for a variety of task and organizational contexts.

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Chapter 5: Summary of Contributions

This dissertation is motivated by a practical problem: managers realize that their worker's performance improves as the workers perform a skill repeatedly and that their skill erodes when *production breaks* (Sikstrom and Jaber, 2002) are encountered. However there is currently no simple way for managers to quantify the effects of alternative task sequences and task assignments on rates of learning and forgetting — and hence on the speed and accuracy with which team members will perform their tasks. There is thus a need for a validated and calibrated method to forecast the performance impacts of managerial interventions that affect individual learning and forgetting on organizational outcomes.

This dissertation contributes to theory and practice by: developing a model of individual learning and forgetting of skills derived from extant literature; embedding these learning and forgetting micro-behaviors in an agent-based, computational model of project teams; and validating and calibrating the learning behaviors in a set of four empirical experiments.

Contributions to Theory

This research takes as its premise that science and engineering each consistently and successfully contribute to informing practice. Precise, explanatory mathematical flow models exist in the physical sciences such as fluid mechanics, electromagnetic wave propagation and light emissions. However, in stark contrast, organization theory and knowledge management researchers are currently hindered by the imprecise and ambiguous, natural language and textual descriptions of organizational knowledge flows (McKinlay, 2003).

This dissertation has contributed theoretically to our understanding of knowledge management, and of knowledge flow phenomena in project teams by extending the capability of computational modeling to reflect individual knowledge growth and decay in project organizations.

This dissertation specifies the key variables and variable relations necessary to apply extant skill acquisition and decay models toward understanding knowledge management for project teams. This inquiry extends organization simulation research conducted by the Virtual Design Team (VDT) research group (Jin and Levitt, 1996) via a new simulation framework, POW-ER (Project Organization Workflow model for Edge Research) (Ramsey, MacKinnon, and Levitt, 2006).

VDT agents have static knowledge levels for each skill type modeled as an ordinal variable (none, low, medium, or high) (Levitt, et al., 1999). The improved POW-ER framework provides development of a finer-grained, numerical skill metric, and simulates additions and deletions to the knowledge of agents as knowledge *inflows* and *outflows.* Some of these occur simply by task repetition or breaks in task performance; others are driven by intentional managerial interventions such as formal training or mentoring (Dierickx and Cool, 1989).

Through this extension to the POW-ER model framework, I capture the dynamics of individual knowledge gained and lost in organizations. The micro-behaviors found in the literature (e.g. Dar-El et al., 1995) are embedded in the POW-ER agent-based simulation framework and then calibrated and validated through observation of students engaged in the AROUSAL business simulation exercise (Lansley, 1982). This unique approach employs organizational simulation to implement POW-ER learning parameters. This extension of theory can provide researchers and practitioners an initial quantitative framework to begin analyzing and evaluating knowledge management strategies in a variety of project organizational contexts and designs.

This research can be contrasted with organizational learning literature that describes how aggregate performance of teams improves due to large production levels (Argote, 1999 and Wright, 1936). I examine instead, individual cognitive skill growth and decay that occurs over time among individuals (Anderson, 2005; Rickard, 2004; and Bjork, 1988) and show how this aggregates to team-level performance in emergent, non-linear ways, depending on micro-task sequences and task assignments. This bottom-up approach to organizational learning provides a more complete understanding of the aggregated "learning curve" phenomenon that can be built upon for future research.

Observing and experimenting with dynamic, individual knowledge has provided new theoretical insights such as the findings that:

- Group learning follows approximately the same pattern as individual learning, however, groups tend to learn more rapidly and forget more slowly than individuals within the same knowledge environment;
- The impacts of perturbations at the individual level (e.g. role changes) will be manifested at the group level, yet to a much lesser extent. Each

level will also continue to learn and forget based on frequency and length of production breaks in task performance;

- Roles changes can cause increased task duration in the short term, but can provide increased quality of decision making over time, and may provide increased flexibility for future group assignments; and
- Formal training and mentoring will not cause an immediate improvement in processing speed but can, over time, improve and surpass the growth in speed from OJT learning, and can cause improvements in decision quality.

These significant findings refine our knowledge of group level learning and forgetting within an organization.

Conceptualization and modeling of skill as dynamic over time has extended our ability to model organizational learning and forgetting. Organizational modeling experiments provide new evidence for some of the predicted performance differences found as a result of individual learning and forgetting both empirically and synthetically, and contribute toward an improved knowledge of organization knowledge flow effects (Nissen, 2006).

This research has also provided a validated and calibrated tool to develop and test individual knowledge flow impacts on novel organizational forms and can determine contingently-based costs and benefits of individual skill growth and decay interventions (such as formal training or production breaks in performing tasks) for managers of project organizations.

Contributions to Practice

This dissertation is motivated by a practical problem: managers realize that the performance of workers improves as they perform a skill with frequency and that their skill erodes if *production breaks* (Sikstrom and Jaber, 2002) are encountered. There is a subsequent need for a method to forecast the effect of individual learning and forgetting for organizational projects. This method that I developed and calibrated in this research models the dynamic nature of individual learning and forgetting and their impacts on individual and team performance and moves past the notion that an individual's skill remains static even during a single relatively short project. This dissertation addresses this problem by examining the changes in individual performance based on observed times for conducting a complex, cognitive skill while adding experimental interventions of production breaks, role exchanging, on-the-job (OJT) training, formal training, and mentoring. This initial effort lays foundations for models that will eventually allow a project manager to design a work process and organization for more optimal knowledge flow.

There are three major contributions for practitioners. The primary contribution from Chapter 2 is that it provides insight into how project organization performance might be affected through individual learning and forgetting. This analysis shows that although group learning of a skill follows approximately the same pattern as individual learning, groups tend to learn and forget more slowly than individuals within the same knowledge environment.

This finding is accompanied by the associated findings about trans-specialist knowledge (Postrel, 2002). Growing trans-specialist knowledge is shown to improve decision making quality while not affecting the speed of performance.

The primary contribution from Chapter 3 is the production of a computational organization simulation tool that implements the findings from Chapter 2. This tool, POW-ER 3.2, which is tentatively calibrated and validated for cognitive tasks, embeds the new individual learning and forgetting behaviors and thus allows practitioners to model projects. It implements the new learning and forgetting algorithm that will calculate predicted tasks, and hence, project duration, with the associated quality, cost and risk based on the skill growth or decay of individuals. It also provides additional calibration and refinement of the individual learning and forgetting micro-behaviors. It then describes a second set of experiments that further validate POW-ER 3.2 and provide for external validity by comparing model output to the ELICIT multi-player command and control exercise for two distinct organization structures.

The primary contribution of Chapter 4 is the introduction of data to begin calibrating the learning effects of formal training and mentoring. Initial findings about training and mentoring are analyzed and indicate that knowledge interventions such as formal training and mentoring may require initial investments in the time of individuals, yet can be recouped after approximately twelve iterations of a task that exercises the formally trained or mentored the skill. The analysis also suggests that formal training and mentoring contribute to improved decision making quality.

Research Limitations

We are limited in our research by a few items. We used small sample sizes that hindered more statistical significance. Both of the tasks measured (AROUSAL and ELICIT) contained no clearly defined scope or end point in terms of time limitations and correct final answer reached. The mentoring implemented in the second case of AROUSAL was not conducted by experts. Significant differences in performance and processing speed effects may be observed if experts are used. These limitations can guide future research.

Areas for Future Research

My over-arching goal is to identify for managers and researchers where deficiencies in knowledge flows exist prior to project commencement and to help them plan in advance for project success by applying principles of Computational Knowledge Management through knowledge flow "engineering". Progress toward this goal will enable managers to design progressively more optimal knowledge management strategies for a variety of organizational designs in different environmental contexts.

I envision that these efforts will enable researchers to sharpen their focus of how dynamic, individually held knowledge, demonstrated through skilled performance, can affect an organization through a myriad of contingencies. Results of organization-level experimentation can improve understanding of knowledge management and improve the probability of project success. This can also inform organizational learning, based on aggregated individual learning to improve our understanding of how changes in individuals' knowledge levels over time affect project outcomes.

I intend to continue validating and calibrating POW-ER through future experiments that involve other skills besides cognitive—i.e., motor, mostly motor, and mostly cognitive— (Dar-El et al., 1995); knowledge growth interventions such as: OJT, formal training, and mentoring and other knowledge decay interventions such as: interference, obsolescence, and employee rotation through different tasks. This will provide researchers the ability to use POW-ER to generate, model, and test novel hypotheses about knowledge flow effects in traditional and novel organizational forms—such as "Power to the Edge" organizations (Alberts and Hayes, 2003).

This work will continue to refine theories about how team performance is affected by individual knowledge interventions. This effort can eventually provide managers a method to determine optimal knowledge flow interventions for a variety of task and organizational contexts and inform managers how individual learning and forgetting rates can be used to generate increasingly reliable predictions of their effects at the organization level.

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