

# Learning by Doing *Something Else*: Variation, Relatedness, and the Learning Curve

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Many organizational learning studies have an implicit assumption that the learning rate is maximized through specialization: the more an individual or organization focuses on a particular task, the faster it will improve. However, through contrasting the various learning process theories described in the research on organizational, group, and individual learning, we develop a set of competing hypotheses that suggest some degree of variation might improve the learning rate. Furthermore, such comparison yields competing arguments about how related or unrelated such task variation should be to improve the learning rate. This research uses an experimental study to answer the following research questions: Is the learning rate maximized through specialization? Or does variation, related or unrelated, enhance the learning process? We find that the learning rate under conditions of related variation is significantly greater than under conditions of specialization or unrelated variation, indicating the possibility of synergy between related learning efforts consistent with an implicit learning or insight effect. We find no significant differences in the rates of learning under the conditions of specialization and unrelated variation. These results yield important implications for how work should be organized, and for future research into the learning process.

*(Learning Curve; Group Learning; Organizational Learning; Insight; Transfer of Learning; Absorptive Capacity; Specialization; Variation; Implicit Learning)*

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Although management scholars and economists have vigorously scrutinized organizational learning curves since the 1930s (e.g., Wright 1936), and the field of organizational learning is attracting an increasing amount of attention, there are still many fundamental questions for which we do not have answers. Two of those questions are the focus of this study: (1) Is organizational learning maximized through specialization, or does some amount of variation improve the learning rate? (2) If some degree of task variation enhances the learning rate, must those tasks be related?

Specialization is the degree to which an individual, group, or organization performs a narrow range of activities. Within the firm, specialization refers to the extent that individuals or groups are assigned to a narrow or wide range of tasks, and is often referred to as the division of labor. At the organization level, specialization can refer to the range of the firm's product line, geographic scope, functional activities, etc. Specialization is considered a primary structural dimension of organization design (Daft 1995, Pugh et al. 1968). Despite the importance of specialization

as an organizational dimension, its impact on group or organizational learning curves has received scant theoretical or empirical attention. One possible reason for this lack of attention may be due to methodological challenges. Organizational learning curve studies most commonly utilize data from field sites to test their hypotheses. Typically, cost per unit or labor hours are regressed on cumulative output over time to obtain a learning rate, with an emphasis on specifying the functional form or comparing rates for different industries.<sup>1</sup> However, it is difficult to use a field site to examine the impact of specialization or task variation on the learning curve, because such a study requires identifying a set of production facilities that utilizes different amounts of task variation, yet is basically identical in every other way to avoid confounding the results with other sources of variance.

A second possible reason for this lack of attention may be an implicit assumption that there is no question to be resolved. The productivity benefits of specialization have been exhorted since Adam Smith's (1776) treatment of the subject, indicating that an individual's learning should be fastest when he or she is narrowly specialized. Even the standard formulations of the learning curve wherein learning is modeled as a function of the cumulative experience with a particular task (rather than a range of tasks) seems to presuppose that the learning rate is maximized through dedication to a single activity. Such a conclusion, however, may be premature. Exciting new psychology research on learning at the individual level has yielded both theory and evidence suggesting that task variation can increase individual learning-curve rates. For example, an individual who applies his or her efforts to different, but related, problem domains may be able to more rapidly develop a deeper cognitive understanding (or "schema") of both, that may enhance the learning rate (Graydon and Griffin 1996, Loewenstein et al. 1999, Schmidt 1975). Further, by combining the ideas of negative transfer (e.g., Ellis 1965) and distributed practice (e.g., Mumford et al. 1994), it is even possible to derive a hypothesis that the learning rate will be maximized when learners

engage in multiple activities that appear unrelated in any obvious way. If group and organizational learning curves rely on some of the same processes driving individual learning curves (Argote 1999, Larson and Christensen 1993), there may be reason to suspect that some degree of task variation may also improve group and organizational learning rates.

A few studies have begun to brush against these questions. For example, Fisher and Ittner (1999) examine the impact of product variety on productivity and costs at an automobile plant, and conclude that product variety increases overhead hours, rework, inventory, and the excess labor capacity required to buffer against variability. However, this study was not a learning-curve study and draws no conclusions about the impact of product variety on organizational learning. Darr et al. (1995) also indirectly broach this topic in their study of productivity in pizza franchises. They include a variable for the product mix at each store in their models, which can be interpreted as a measure of related task variation. They found no significant results for this variable in any of their models, although it is important to note that the impact of product variety was not a focus of their study, and the data in the article do not indicate whether there was significant variance in the product mix across stores. In sum, although specialization and task variety are of obvious relevance to organizational productivity, we found no explicit theoretical arguments about (nor empirical evidence of) the impact of specialization and task variety on the organizational learning-curve rate in the existing literature.

To address these research questions while surmounting the methodological challenges, we used an experimental design wherein groups of individuals solved a series of strategic problems within an artificial organizational setting. By using small groups that learn through collective action and interaction, we hoped to more closely approximate organizational rather than individual learning. Because groups are the "building blocks" of larger organizations (Argote 1999, p. 99) and because the learning within groups is shaped by the same social processes that influence learning at the organization level (e.g., communication, coordination, conflict), group learning provides

<sup>1</sup> For an excellent review of early learning curve work, see Yelle (1979).

us with a smaller scale analog to organizational learning (Argote 1999).

The first section of this paper reviews the existing research on learning curves at the organizational, group, and individual levels, and then discusses the relationships between levels—including why theories of individual learning should inform our theories of group and organizational learning. The next section draws on theory and evidence at multiple levels to build a competing set of hypotheses about the impact of specialization, related variation, and unrelated variation on the learning rate. In the second and third sections, we describe the methods of our study and the results obtained. The fourth and fifth sections discuss the meaning of our results, their limitations, and their implications for future research.

## **Organizational, Group, and Individual Learning Curves**

The learning curve is an aggregate model that may be used to represent both individual learning and group or organizational learning (Anzai and Simon 1979, Argote 1999, Yelle 1979). It has been widely applied at the individual level by psychologists (e.g., Anzai and Simon 1979, Ellis 1965, Harlow 1949, Thorndike 1898), and at the organizational level by economists and management scholars (e.g., Argote 1993, 1999, Baloff 1971, Dutton and Thomas 1984, Hatch and Mowery 1998, Levy 1965, Mukherjee et al. 1998, Yelle 1979). It has been less often applied at the group level, although research is beginning to emerge in this area (e.g., Argote et al. 1995).

### **Organizational Learning Curves**

As articulated by Levitt and March (1988, p. 320) organizations learn “by encoding inferences from history into routines that guide behavior,” and one of the purest examples of organizational learning is manifested in the effects of cumulative production on cost and productivity—otherwise known as “learning by doing” (Arrow 1962). Organizations experience productivity improvements as a “consequence of their growing stock of knowledge” (Dutton and Thomas 1984, p. 235), and the application of this knowledge

to increase the effectiveness and efficiency of production technologies (Amit 1986, Hall and Howel 1985). Organizational learning scholars typically model the learning curve as a function of cumulative output: performance increases or cost decreases, with the number of units of production, usually at a decreasing rate. This pattern has been found to be consistent with production data on a wide range of products and services (Argote 1993, Baloff 1971, Hatch and Mowery 1998, Yelle 1979), and for a variety of dependent variables, including total costs per unit (Darr et al. 1995), accidents per unit (Greenberg 1971), and waste per unit (Mukherjee et al. 1998).

One significant finding is that although learning curves are found in a wide range of organizational processes, there are substantial differences in the rates at which organizations learn (Argote 1999). Understandably, both managers and scholars are interested in understanding why one firm reaps great improvement in a process whereas another exhibits almost no learning. Many studies have examined various reasons for this variability in learning rates, including looking at how the firm’s learning rate is influenced by process-improvement projects, intentional innovation, or contact with customers and suppliers (Dutton and Thomas 1984, Levy 1965, Mukherjee et al. 1998). Our study contributes directly to this area of inquiry by examining how specialization, variation, and the relatedness of variation in the learning task influence the learning rate.

### **Group Learning Curves**

Although there is a considerable body of research on learning and productivity in groups (see Bettenhausen 1991, Williams and O’Reilly, 1998 for reviews), few group studies explicitly consider the nature of the task as a variable (e.g., Argote et al. 1995, Lord and Rowzee 1979), and even fewer utilize a learning-curve framework. There is, however, evidence that group learning demonstrates a learning-curve pattern similar to that found in studies of individual and organizational learning (e.g., Argote et al. 1995, Guetzkow and Simon 1955, Leavitt 1951, Shure et al. 1962). For example, Argote et al. (1995) use a learning-curve framework to examine the impact of turnover and task complexity on group performance during

six experimental periods. They found that group performance conformed to learning-curve patterns that have been demonstrated at the organizational levels, and that performance was negatively affected by group turnover and task complexity. Compared to the literature on organizational and individual learning curves, the research on group learning curves is limited, making this an area ripe for exploration.

### **Individual Learning Curves**

Psychologists discovered learning curves in their study of individual learning processes in both humans and other species, and demonstrated the persistence of the learning curve across many different types of tasks (e.g., Harlow 1949, Thorndike 1898). Ellis (1965) explains the individual learning curve as a type of learning transfer: If one deconstructs learning curves into the individual units of output, one can define the overall performance at any unit as some amount of performance that is derived from learning in the previous units that is transferred to the current unit, plus some incremental increase in performance due to new learning. The learning that is transferred can be further deconstructed into knowledge content transfer (knowledge gained about the previous unit transfers to the current unit) and learning process transfer ("learning to learn"). The latter process indicates that individuals become better at learning over time because they transfer their previous learning about *how to assimilate or process* particular kinds of information to the new problem set. For example, they may learn general approaches to problem solving or "modes of attack" (Ellis 1965, p. 33).

### **Relationships Across Levels**

Our study was motivated by a desire to understand organizational learning curves and, thus, in the tradition of the research on organizational learning, we have drawn from the organizational learning literature and we have employed a study design and data analysis methods that are consistent with the research on organizational learning curves. However, we also draw from the research on group learning because (1) organizations are defined as "a group of persons organized for a particular purpose" (Webster's dictionary), (2) organizations are typically a hierarchically-nested system of other smaller groups (Simon 1962),

(3) much of the learning that takes place in the organization does so at the small group level (Argote 1999, Brown and Duguid 1991), and (4) our data is collected at the small group level.

We further draw from the research on individual learning, because organization and group learning is, to some degree, a function of individual learning. For example, Crossan et al. (1999) eloquently relate all three levels by arguing that all intuition, insight, and innovative ideas occur at the individual level (Simon 1991), but that these ideas are then shared and interpreted within the group, wherein common meaning is developed (Argyris and Schon 1996, Daft and Weick 1984, Huber 1991). This shared understanding may subsequently become institutionalized in organizational routines or artifacts (Hedberg 1981, Shrivastava 1983). It is also argued that the development of organizational routines that embody experiential learning is a highly parallel process to that employed by individuals when developing procedural knowledge (Anderson 1983, Argote 1993), and thus might be shaped by similar forces.

The relationship between individual and group learning has received more attention than the relationship between organizational learning and either of the other two levels. For example, there is a considerable body of research that postulates that groups may form interactive information systems that (1) utilize the memory and learning of individual members (e.g., see the work on transactive memory, Moreland 1999, Rulke and Rau 2000, Wegner 1987), (2) foster the development of a shared mental model that is more than (or at least different from) the sum of the properties of its individual members (Klimoski and Mohammed 1994, Mathieu et al. 2000, Sandelands and Stablein 1987), and might be able to outperform individuals on cognitive tasks (e.g., Collins and Guetzkow 1964, Hinsz 1990, Lorge and Solomon 1959, Shaw 1932).

Although Argote (1993) describes a considerable amount of research suggesting that individual experience does not contribute to group performance (e.g., Katz 1982, Laughlin and Sweeney 1977, Tuckman and Lorge 1962), she also points out that this finding is likely to depend on the degree to which the task requires extensive coordination, whether the group

or organization is highly structured (through standardization, formalization, and centralization), and the skill level of the individual(s). She concludes that group and organizational learning curves have an individual learning component, a system component (i.e., the ways in which work is organized and coordinated, and the organization's technology), and an environmental component (i.e., learning that is obtained from suppliers, from competitors, etc.).

Larson and Christensen (1993) also address this issue in their cogent description of how groups use social cognition to solve problems. They define social cognition as "those social processes... that relate to the acquisition, storage, transmission, manipulation, and use of information for the purpose of creating a group-level intellectual product" (1993, p. 6). They point out that some stages of problem solving (e.g., manipulating and using information) may rely primarily on cognitive processes that take place *within* individuals. Other stages of problem solving (e.g., storing information) may rely on processes that are group level, but operate in a way that is highly analogous to processes that occur at the individual level. For instance, it has been argued that information in the individual memory is organized as nodes corresponding to particular concepts, connected in a network, with the number and directness of connections affecting the likelihood (and effectiveness) of retrieval. Similarly, at the group level, information may be distributed across individuals, and those individuals may be thought of as nodes that collectively form a network. Retrieval of information from this network also relies on the pattern of connections or communication between the individuals. Thus, theories of individual cognition should inform theories of group cognition both because (1) some processes of group cognition may actually take place at the individual level, and (2) some processes of group cognition may behave analogously to individual cognition.

## Specialization, Variation, and Relatedness

Although examination of the various bodies of research on learning indicates a number of implicit and explicit references to how the organizational

learning rate might be affected by task specialization, related variation, or unrelated variation (e.g., Darr et al. 1995, Fisher and Ittner 1999), there is little empirical evidence or consensus about whether specialization or some degree of variation maximizes the organizational learning rate. In the sections that follow, we draw from multiple bodies of research to develop competing hypotheses about the impact of task specialization, related variation, and unrelated variation on the organizational learning rate.

### Specialization

There is research at both the organizational and individual levels that supports the proposition that specialization will enhance the learning rate. For example, Smith's (1776) early arguments about the benefits of division of labor suggest that specialization enables performance gains at both the individual and organizational levels. Both the learning curves used by psychologists to capture individual learning and those used by management scholars to measure organizational learning have also reinforced the inference that learning is maximized through specialization by modeling performance as a function of the cumulative output at a particular activity. In a condition of pure specialization, individuals or organizations can focus all of their time and energy toward one task. Specialization allows them to complete the most repetitions of a particular kind of problem within a finite time period, and to gain an in-depth understanding of the problem domain. An individual or organization switching between multiple kinds of tasks, even if they were related, would be taking time away from learning the core task, and might become distracted from learning concepts that apply only to the core task. The learning transfer explanation for learning curves put forth by Ellis (1965) also suggests support for specialization benefits: If (1) overall performance improves with the number of units, because for each unit performance is equivalent to learning that is transferred from the previous unit, plus an incremental increase in learning for the current unit, and (2) if the amount of learning that transfers from unit to unit is positively related to the similarity of the units, then (3) in absence of any explanation for a difference in incremental learning for the current unit,

the learning rate should be positively related to the degree of similarity of the units.

At the individual level, some psychologists have noted that an individual is unlikely to make a significant contribution to an area until they have at least a decade of intense study in a particular domain of knowledge (Hayes 1989). Simon and Chase (1973) quantified this expertise by studying chess grand masters and other experts, concluding that individuals need approximately 50,000 "chunks" of information related to a narrowly defined problem domain prior to making a fruitful discovery.

At the organizational level, Von Hippel (1998) has argued that a firm that solves more of the *same kinds of problems* should get better at it, leading to the conclusion that groups or organizations that are more specialized should have steeper learning curves. Furthermore, some of the early empirical studies on organizational learning curves suggest that specialization yields efficiency gains, though also often noting the risk of loss of flexibility (e.g., Abernathy and Wayne 1974). We begin, then, with the following hypothesis.

**HYPOTHESIS 1.** *The learning rate will be greatest under conditions of pure specialization.*

### **Variation**

Both the individual and organization learning literatures can yield arguments for the beneficial role of variation in the learning process, but it is predominantly research at the individual level that enables arguments to be separately drawn for related versus unrelated variation. First, we examine research supporting variation in general, and then turn to the arguments in favor of related and unrelated variation in turn.

Although the efficiency advantages of specialization are commonly acknowledged, more recent work on organizational learning has begun to examine the role of product or process variety (e.g., Fisher and Iltner 1999). Although Fisher and Iltner conclude that variation negatively affected productivity, many authors have argued that in the long run, variation is critical for the firm to develop new capabilities, increase its absorptive capacity, and maintain long-term productivity. For instance, as Leonard-Barton

(1992) has pointed out, firms that do not develop new competencies risk becoming trapped in "core rigidities." Levinthal and March (1993) have argued that firms have a tendency to overinvest in the exploitation of the organization's existing competencies to the detriment of exploring new problem domains. Moreover, several authors have noted, that in contrast to the image one may have of highly specialized research divisions producing important innovations, invention is more often the result of borrowing among disparate fields than through intensive focus on a single field (e.g., March and Simon 1958, Usher 1929).

The absorptive capacity construct mentioned above (a direct application of Ellis' (1965) learning-curve arguments to the organizational level) can be interpreted to suggest that varied prior learning might enhance the future learning rate—or at least, not negatively impact it. As articulated by Cohen and Levinthal (1990 p. 128), "...the ability to evaluate and utilize outside knowledge is largely a function of the level of prior-related knowledge. At the most elemental level, this prior knowledge includes basic skills or even a shared language but may also include knowledge of the most recent scientific or technological developments in a given field. Thus, prior knowledge confers an ability to recognize the value of new information, assimilate it, and apply it to commercial ends." Like Ellis' (1965) explanation of learning curves, the absorptive capacity construct has both content and process components. The argument that the more information we have, the more likely some of it will apply to the new problem, is the transfer of knowledge content from one problem to another. The other part of the absorptive capacity argument—that individuals (and organizations) learn about the learning process itself, is what Ellis calls "learning to learn" (Ellis 1965, p. 32). The process of learning to learn implies that absorptive capacity may be improved even if the knowledge base possessed is not directly related to the knowledge base being acquired. Learning skills may be transferred across fields of knowledge that are organized or described in similar ways, even if the content of the knowledge is substantively different. In essence, this research extends the notion of "learning by doing" to "learning by doing *something else*." Although an organization working on different but related tasks may find that not all of the

knowledge content transfers from one unit to the next, the learning process knowledge may readily transfer.

Research on individual learning has also supported the role of variation. Although Simon and Chase's (1973) findings suggest benefits of specialization, Simon (1985) later argued that possessing a diverse knowledge base may elicit greater learning or problem-solving skills. Some researchers have explained this process by arguing that when a person gains experience and knowledge in an area, he or she creates new cognitive nodes of knowledge, and strengthens the connections between those nodes. The more knowledge nodes that are developed, and the more links developed between them, the larger and more dense the scaffolding within which to build new knowledge structures. This knowledge network may enable faster assimilation of new information because of increased speed and efficiency through these network links (Leonard and Sensiper 1998, Martindale 1995).

The study of cognitive insight also yields similar arguments. Some researchers have posited that insight is the direct result of the transfer of knowledge among different types of learning activities (Mayer 1996). Individuals appear to spontaneously develop a new understanding of a problem because they transfer knowledge from one domain to another: what was well understood in one problem domain, suddenly provides an analogous solution to a new problem domain.<sup>2</sup> Such transfer of knowledge may even occur across domains that appear to have little in common; in fact, Simonton (1999) notes that the most fruitful of insights are likely to be between those areas that had previously seemed unrelated.

**Related Variation.** Psychology studies of individual learning have demonstrated that related task variation (varying the content or context of the task) may enhance the learning process through facilitating the development of more abstract principles (or "schema") related to a general class of tasks (Graydon and Griffin 1996, Paas and Van Merrenboer 1994, Schmidt 1975). Such schemas promote the

rapid acquisition of related skills or knowledge sets. For instance, Loewenstein et al. (1999) demonstrate that students who compare two different but similarly structured decision scenarios were more likely to derive an abstraction based on their commonalities ("analogical encoding"). The abstraction then enabled those students to transfer knowledge gained from those previous examples to a new decision scenario more effectively than students who received only a single initial scenario.

In a related vein of research, it has been shown that varying the context of a task may also enhance the development of implicit learning (Wulf and Schmidt 1997). Implicit learning is a passive form of learning whereby the learner picks up "critical covariations in the environment" (Reber 1989, p. 233) without even being aware of it. It is an unconscious process that yields abstract knowledge that may be complex and difficult to articulate. If a concept is presented in varied contexts, it gives the learner more possible associations for the concept, thereby improving understanding and recall (Maskarinec and Thompson 1976). Tyre and Von Hippel (1997) note a similar phenomenon within organizations when they find that engineers often need to explore a problem in multiple settings (e.g., plant and lab) before they are able to understand and resolve the problem. "Schema" and implicit learning are both ways in which learning is transferred between related problem domains through the development of a deeper cognitive structure that applies to both, which brings us to our second hypothesis.

*HYPOTHESIS 2. The learning rate will be greatest under conditions of related variation.*

**Unrelated Variation.** Although, perhaps, less intuitively obvious, there is nonetheless sound evidence upon which to base an argument that the learning rate may be improved through unrelated variation. One of the major areas of research on individual learning processes is the subject of "massed" versus "distributed practice." Under massed practice conditions, the learner repeats a task without interruption for the entire learning period. Under distributed practice conditions, trials of performing the task are interspersed with break periods during

<sup>2</sup> There are various competing views of the mechanisms underlying insight. For a comprehensive survey, see Sternberg and Davidson (1995).

which the learner rests or engages in some other task. There is abundant research indicating that distributed practice results in improved learning rates over massed practice, presumably because it gives the learner time to do the deep, elaborative processing necessary for the development of the knowledge structures and general principles underlying a task (Mumford et al. 1994). Several research studies found distributed practice resulted in better performance on cognitive tasks, including multiplication problems (Cornelius and Modigliani 1985), French vocabulary (Bloom and Shuell 1981), and statistical operations (Mumford et al. 1994, Smith and Rothkopf 1984).

Because unrelated variation offers the learner time away from the core task, it may offer a form of distributed practice, and thereby improve the learning rate. By contrast, if learners alternate between two related tasks, they may engage in constant cognitive processing of the knowledge structures common to both tasks, and thus not have the "rest period" accommodated by distributed practice. To the degree that group and organizational learning is a function of individual learning, these arguments may also be true for groups and organizations, bringing us to our third competing hypothesis.

**HYPOTHESIS 3.** *The learning rate will be greatest under conditions of unrelated variation.*

## Method

To test the preceding hypotheses, 90 subjects (primarily college students) were solicited to participate in an experimental design utilizing an artificial organizational setting. The 90 subjects were divided into 30 teams of 3 subjects each. Because the learning within groups is shaped by the same social processes that influence learning at the organization level, group learning provides us with a smaller scale analog to organizational learning, and enables us to implement an experimental design that would otherwise be unfeasible. Laboratory studies can allow knowledge or performance to be more directly measured, and can enable better control over other potential sources of variance in the group, task, or learning environment (Argote 1993). Our design allows us to compare multiple learning curves in a controlled setting,

whereby the primary sources of systematic variation across conditions are our experimental manipulations.

### The Problem-Solving Task

The first challenge of constructing the experimental design was to identify problem-solving tasks that would enable (1) repetition without one ideal solution, (2) extended learning over time, (3) controlling for difficulty, and (4) accurate performance appraisal. After consideration of many alternatives, we decided to have the groups play games against a computer. We evaluated more than 300 game possibilities and narrowed the list down by consulting several game review sources, including (1) *A History of Traditional Games* (Masters 1999), (2) *A History of Card Games* (Parlett 1990), (3) *The Oxford History of Board Games* (Parlett 1999), and (4) an extensive index of card games by type, developed by McLeod (1998). We finally chose the game of *Go* for our core game.<sup>3</sup> We chose the alternate games of *Reversi* (related game) and *Cribbage* (unrelated game).

**Go.** *Go* is an ancient strategic board game that is widely played in Asia. In addition to meeting our above criteria, the game of *Go* also provided the following additional benefits: (1) it was unfamiliar to most of the subjects who responded to the solicitation (more information on screening is provided below); (2) it is a strategic game that is simple to learn, yet difficult to master; (3) a game can be completed in 10 minutes or less (using a 13 × 13 board grid); and (d) it is one of the oldest board games in existence, thus demonstrating its robustness, and its ability to capture and hold the attention of participants for an extended period of time (Parlett 1999).<sup>4</sup>

**Reversi.** We chose *Reversi* as the related alternate game because it met the above criteria, and is considered to be highly related to *Go* in appearance,

<sup>3</sup> In each condition, the learning curves are estimated for the game of *Go* only (not alternate games) to ensure comparability.

<sup>4</sup> According to legend, *Go* (also known as *Wei-Qi*) was invented by Emperor Yao of China (2357–2256 BC) for the purpose of developing the mind of his son, Tan Chu. The game was commonly used by military leaders of China, Korea, and Japan for the development of strategic skills, and by Buddhist monks as a route to enlightenment (Parlett 1999). It continues to be one of the most highly revered of Asian board games.



objectives, and ancestry (Parlett 1999). Both games are played on an unchequered grid with stones. Both games emphasize spatial strategy, and the objective of both games is to control territory. Furthermore, both games employ only placement of stones rather than movement, award points based on the amount of territory controlled, and permit capturing of an opponent's pieces by surrounding those pieces.

**Cribbage.** A computer version of *Cribbage* was chosen as the unrelated alternate game, because while it met the above criteria, it is vastly different from *Go* or *Reversi*. *Cribbage* is a card game, that is played in multiple hands, with the cumulative adding of points. Sophisticated *Cribbage* players can be strategic in playing or withholding cards to maximize their point scores while minimizing those of their opponents. Unlike *Go* and *Reversi*, which rely predominantly on spatial skills, *Cribbage* relies more on math skills, with a particular emphasis on probabilities. We used a version of *Cribbage* that played to 61 points (rather than the traditional 121) to ensure that games could be played in 10 minutes or less.

### Solicitation and Screening

The participants were solicited with flyers that specified that subjects would perform basic problem-solving tasks. The flyers did not indicate that the experiment would entail playing games (to avoid creating a response bias). The flyers also offered a \$100 payment to subjects upon completion of the experiment period, with a stipulation that no partial participation would be compensated, and that no subject would be permitted to participate in more than one period.

To ensure that the teams all began at the beginning of the learning curve, respondents to the flyer were screened to avoid inclusion of any participant with experience playing the games used in the experiment. The respondents were asked a series of questions, including those asking for demographic information (e.g., age, gender, occupation), and about a variety of activities in which they engage (e.g., reading the newspaper, tennis, golf, etc.). Although participants were only screened based on their experience with the games used in the study (no participant was included

if they had played *Go*, *Reversi*, or *Cribbage* within the last 5 years, or more than 5 times in their life), a wide variety of questions were asked to avoid signaling the respondents about the particular activities of interest.

### Conditions

Respondents were randomly assigned to teams and experimental condition (3 subjects per team, 10 teams per condition). In each condition, the teams repeatedly played the games for 5 hours a day for 2 consecutive days. In the specialization condition, the teams played only *Go*. In the conditions involving variation, the teams played alternating blocks of 4 games of *Go* (the core game), and 4 games of their alternate game (either *Reversi* or *Cribbage*). The games were sequenced in blocks in the variation conditions, because research has indicated that if tasks are varied too quickly, it may become confusing to the learners, which would prevent both learning in the core task and transfer of learning from the alternate task (Graydon and Griffin 1996).

Other than the variation in tasks, all teams were subjected to identical experimental conditions. Prior to commencing play of the games, all individuals were asked to complete an entrance survey (which collected basic demographic information, personality assessment information, and prior game experience), and were given instruction sheets for playing the games. Teams were told that the experiment was a learning study, and that their objective was to work together to get as good at the game(s) as possible. Teams were also instructed that each game was to be a group endeavor (i.e., delegation of game playing among the team members was not allowed), however, they were also instructed not to speak to any members of any *other* team, to prevent information leaks between teams.

Teams were permitted to play at their own speed. The teams were given detailed score sheets to track the time at which they began and ended each game, their score on each game played, and the computer's score. The score sheets were coded with the team's identification code, and the name of the games they played listed in the appropriate order. The teams that played alternating blocks of different games recorded

time and score data for both games—there was nothing to indicate to the teams that one game was more important than the other. Three monitors observed the teams in each condition (i.e., 3 monitors for 10 teams) at all times to ensure that teams adhered to the rules of the experiment and to note any unusual activity. After completion of the 10 hours, the individuals were asked to complete an exit survey about how the team interacted during the experiment.

### Dependent Variable

The dependent variable in all 3 conditions is the score for the games of *Go* only to ensure comparability. These scores range from 0–149, with many instances of 0 scores, and no instance of a perfect (169) score. It is important to note that in production studies, it is unusual for firms to experience significant decreases (lapses in their performance) in their production, therefore, their learning curves tend to demonstrate fairly consistent improvement. However, in robust computer versions of the game of *Go*, the computer is a skilled player, and even teams that have acquired good *Go*-playing skills (and demonstrate increasing average scores) will occasionally earn poor scores. Low scores are particularly likely to occur when teams experiment with new strategies. Thus, there is more variability in the learning curves for the game of *Go* than one would expect in production learning curves.

### Overview of Analyses

The standard form of the learning curve is formulated as

$$y = ax^{-b},$$

where  $y$  is the number of direct labor hours required to produce the  $x$ th unit,  $a$  is the number of labor hours required to produce the first unit,  $x$  is the cumulative number of units produced, and  $b$  is the learning rate. By rewriting the formula in logarithmic form, we obtain the following formula, enabling the learning coefficient to be obtained through linear regression:

$$\log y = \log a - b \log x.$$

Our specification uses this standard formulation but with one exception; rather than modeling the outcome as a decrease in labor hours, we model the outcome as an increase in scores, resulting in a negatively

accelerated increasing curve. Our learning curve form is as follows:

$$y = ax^b \quad \text{or} \quad \log y = \log a + b \log x.$$

In learning rate studies, the dependent measure is typically regressed on the number of learning trials. In this study, this translates into regressing the game score on the number of games played. Though total play time was carefully controlled in our study, there is variability in the number of games played because teams were allowed to play at their own speed. Some teams played quickly, in a trial-and-error fashion, whereas others played more deliberately, discussing each move in advance. There was also variability in speed of play over time for individual teams (i.e., a team might play quickly for awhile, and then take a more measured approach).

To standardize the number of observations across teams and permit comparison across the multiple learning curves, we employ an analytical approach similar to that used by Darr et al. (1995). They examined learning curves of individual pizza stores and the effect of belonging to a particular franchise by gathering weekly data on the pizzas made and average cost per unit. By aggregating the number of pizzas per week for each store, franchise, and across all franchises, they were able to analyze the degree to which learning occurred with experience at the store, franchise, and interfranchise level despite variation in the number of pizzas produced.

In a similar fashion, we aggregated our data to the hour level, and regressed the average score a team achieved on *Go* games in a given hour  $t$  on the cumulative number of *Go* games played by the end of the previous hour (i.e., cumulative number of *Go* games played from the beginning of the first hour to the end of the  $t - 1$  hour).<sup>5</sup> This aggregation allows us to control for both time and the number of games played by any particular team over time, while also yielding an equal number of observations (10) for each team, for a sample size of 300. As mentioned above, there was variability in the speed and deliberateness of play both across teams and over time. To control

<sup>5</sup> An alternative specification that includes all of the games played is discussed in the Results section.

for effects due to speed of play and exploratory trial-and-error strategies, we included the number of Go games played in the hour  $t$ , and the standard deviation of the scores earned on Go games in the hour  $t$  as control variables. We included dummy variables (0, 1) for each condition (specialization, related variation, and unrelated variation), and interaction terms between the cumulative number of Go games and the condition, to test whether the condition significantly influences the learning rate. The interaction terms effectively separate the learning curves into those for specialization, related variation, and unrelated variation (for another example of this approach, see Lapre et al. 2000). We also included dummy variables for each team to control for team-level effects. We used the following symbols:

$s_{it}$  = average score earned by team  $i$  in hour  $t$  on Go games.

$Q_{it-1}$  = cumulative number of Go games played by team  $i$  from the beginning of the first hour through the end of hour  $t-1$ .

$G_{it}$  = number of Go games played by team  $i$  in hour  $t$ .

$SD_{it}$  = standard deviation of scores earned on Go games by team  $i$  in hour  $t$ .

$S$  = dummy variable for the specialization condition.

$R$  = dummy variable for the related variation condition.

$U$  = dummy variable for the unrelated variation condition.

$V_i$  = dummy variables for each team.

Our most basic model estimated was

$$\ln s_{it} = b_0 + b_1 G_{it} + b_2 SD_{it} + b_3 \ln Q_{it-1} + b_i V_i + e. \quad (1)$$

If  $b_3$  is statistically significant and positive in the first model, then overall, the teams significantly improved their performance as they played games, indicating a learning-curve effect. To control for the impact of different play strategies (e.g., fast versus slow, deliberate versus exploratory) or differences in the amount of time spent on the alternate games, the model includes a control variable ( $b_1 G_{it}$ ) for the number of Go games played in the hour, and a control variable ( $b_2 SD_{it}$ ) for the variability of scores earned

on Go games in the hour. In the second model, we estimated the following function:

$$\begin{aligned} \ln s_{it} = & b_0 + b_1 G_{it} + b_2 SD_{it} + b_3 \ln Q_{it-1} \\ & + b_4 S + b_5 R + b_i V_i + e. \end{aligned} \quad (2)$$

If  $b_3$ ,  $b_4$ , and  $b_5$  in the second model are significant (and  $b_3$  is positive), then the teams demonstrate an overall learning-curve effect, and the condition significantly influences the average scores achieved. In our final model, the cumulative production variable is divided into the 3 conditions by multiplying it by the condition dummies, allowing different learning rates to be estimated for teams in each condition:

$$\begin{aligned} \ln s_{it} = & b_0 + b_1 G_{it} + b_2 SD_{it} + b_3 S \\ & + b_4 R + b_5 S \ln Q_{it-1} + b_6 R \ln Q_{it-1} \\ & + b_7 U \ln Q_{it-1} + b_i V_i + e. \end{aligned} \quad (3)$$

In this model, if the constant,  $b_3$  and  $b_4$  are significant, then the conditions significantly influence the curve intercepts (teams' initial performance at the start of play). If  $b_5$ ,  $b_6$ , and  $b_7$  are significant, and significantly different from one another, then the conditions significantly influence the learning rate and one of the three competing hypotheses should be supported.

## Results

After 10 hours, the teams had played an average of 86 games each of Go. Although teams could have attempted to delegate play to an individual member, the monitors noted that the team members vigorously interacted during the entire experimental period. Although some individuals became more involved with the game than others,<sup>6</sup> team performance appeared to be almost always a collective effort. Within the teams, members actively discussed potential moves, evaluating what appeared to be successful or unsuccessful and formulating strategies. Although the individual holding the computer

<sup>6</sup> Responses to the exit survey indicated that 62 of the subjects felt that all team members were equally involved with the game most or all of the time, whereas 28 subjects felt that some members were more involved than others most of the time.

**Table 1** Regression Results for Learning Models

Variables	Model 1 <i>B</i>	Model 2 <i>B</i>	Model 3 <i>B</i>	95% Confidence interval for <i>B</i>	
				Lower bound	Upper bound
Constant	2.98*** (0.32)	3.18*** (0.55)	3.11*** (0.54)		
Number of <i>Go</i> games played in hour <i>t</i>	−0.01 (0.01)	−0.01 (0.01)	0.00 (0.01)		
Standard deviation of scores in hour <i>t</i>	0.01** (0.00)	0.01** (0.00)	0.01*** (0.00)		
Cumulative <i>Go</i> games at time <i>t</i> − 1	0.25*** (0.03)	0.25***† (0.03)			
Specialization dummy		−0.35 (0.77)	−0.32 (0.74)		
Related variation dummy		−0.25 (0.77)	−0.36 (0.75)		
Specialization <i>X</i> cumulative games			0.14*** (0.05)	0.06	0.23
Related variation <i>X</i> cumulative games			0.40*** (0.05)	0.31	0.50
Unrelated variation <i>X</i> cumulative games			0.21*** (0.04)	0.13	0.29
<i>R</i> <sup>2</sup>	0.40	0.40	0.44		
Adjusted <i>R</i> <sup>2</sup>	0.32	0.32	0.36		
<i>F</i>	5.21***	4.88***	5.45***		
$\Delta R^2$		0.00	0.04		
<i>F</i> of the $\Delta R^2$		0.11	9.68***		

*N* = 296 (4 of the 300 team hours had unusable data).

\**p* < 0.05

\*\**p* < 0.01

\*\*\**p* < 0.005, standard errors are shown in parentheses. Team dummy variables are included in all models, although coefficients are not reported here due to space constraints.

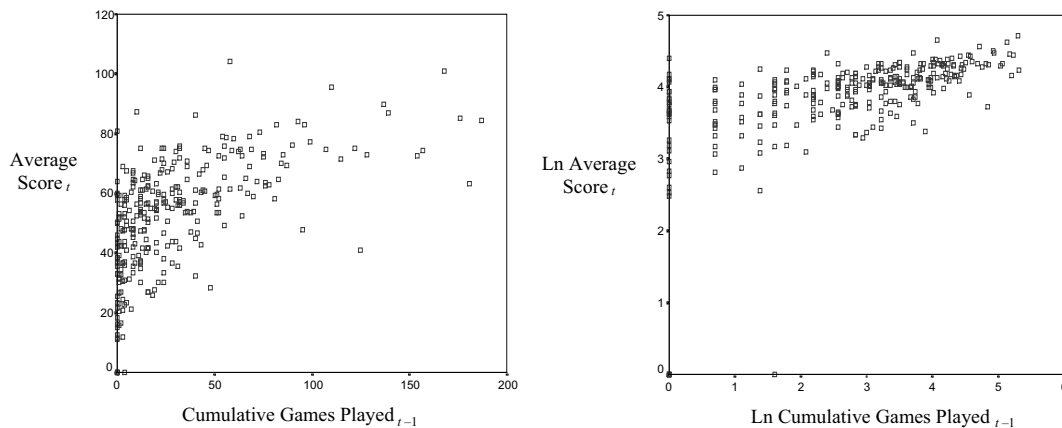
†In Model 3, the cumulative games variable is divided into three separate variables for each of the conditions; the original cumulative games variable must then be omitted to avoid overspecification (the three interaction terms add linearly to the single cumulative games variable).

mouse would execute the move, most move decisions were decided through group interaction. Many teams demonstrated a pattern whereby control of the mouse was rotated from individual to individual. Furthermore, the individual controlling the mouse was frequently not the most active proponent of the next move (that is, control over the mouse did not appear to indicate decision authority over game moves). For most teams, the emotional involvement with the game appeared to escalate over time. Discussion among team members sometimes became quite heated, with individuals occasionally voicing anger or frustration. Particularly high scores often resulted in an eruption of cheers.

For each team, the average scores for each hour, and cumulative number of *Go* games played by the end of

the previous hour were tallied. We used a natural log transformation of the average scores and cumulative games, which is consistent with a standard learning-curve power function. Ordinary least squares regression was used to estimate the models (see Table 1). We tested for first-order autocorrelation in the residuals, and found no significant autocorrelation. Scatterplots of the residuals were also examined, and they did not indicate autocorrelation or heteroscedasticity.

Model 1 shows a significant and positive coefficient for the cumulative games variable (0.25, *p* < 0.005), indicating that overall, the performance of the teams demonstrates a significant learning-curve effect (graphically depicted in Figure 1). The control variable for the games played per hour is insignificant, but the control variable for the standard deviation of

**Figure 1** Relation Between Average Score<sub>*t*</sub> and Cumulative Number of Games Played<sub>*t-1*</sub>, Raw and Natural Log Transformed

scores earned in the hour is positive and significant ( $0.01, p < 0.01$ ).<sup>7</sup>

In Model 2, the dummy variables for the conditions are added. Again, the results indicate a significant learning-curve effect overall ( $0.25, p < 0.005$ ). The control variable for number of games per hour is again insignificant, and the control variable for standard deviation of scores is again positive and significant ( $0.01, p < 0.01$ ). Neither of the condition dummy variables is significant.

In Model 3, interaction terms of condition  $\times$  cumulative number of games have been entered, essentially splitting the data into 3 samples: (1) the learning rate over cumulative number of *Go* games for teams in the specialization condition, (2) the related variation condition and (3) the unrelated variation condition. The inclusion of these interaction terms results in a significant increase in the *R*-squared ( $p < 0.005$ ), indicating that the inclusion of the interaction terms significantly improves the model. Furthermore, all 3 interaction terms are significant ( $p < 0.005$ ) and positive (0.14 for specialization, 0.40 for related variation, and 0.21 for unrelated variation), indicating significant learning curves in all 3 conditions. However, the learning rate for the related variation condition is much larger than those for the specialization condition and unrelated variation condition. The 95% confidence interval for the learning rate for the related

variation condition does not overlap with those for the other conditions, indicating that the learning rate for teams in the related variation condition was significantly greater ( $p < 0.05$ ) than the learning rates for teams in the other conditions. This finding supports Hypothesis 2 and provides evidence against Hypotheses 1 and 3, and against the null hypothesis that condition has no significant impact on learning rate. The confidence intervals do not indicate a significant difference between the learning rates for the specialization and unrelated variation conditions. An alternative specification wherein every game (*Go* games and alternate games) was included in the cumulative games and games-per-hour variables yielded the same results. The coefficients obtained for the learning rates were lower for all 3 conditions, but their relative sizes were unchanged (specialization = 0.003,  $p < 0.05$ ; related variation = 0.01,  $p < 0.01$ ; unrelated variation = 0.003,  $p < 0.05$ ).<sup>8</sup>

Adding the interaction terms also parses the impact of condition into two effects: (1) the impact on the intercept (captured by the condition dummies and

<sup>7</sup> The coefficients for the team dummy variables are not of particular interest, so are not reported here. None of the coefficients for the team dummy variables were significant.

<sup>8</sup> An anonymous reviewer pointed out the possibility that teams in the specialization condition might have had decreases in performance toward the end of the experimental period due to boredom. To explore this possibility, we examined scatterplots of the specialization data, and ran models that included quadratic terms for each of the conditions. Neither scatterplots nor the models with quadratic terms indicated that teams in the specialization condition had more negatively accelerated learning curves than teams in the other conditions.

constant) and, (2) on the learning rate. The coefficients for the dummies for specialization and related variation capture the impact of those conditions on the intercept (the dummy variable for unrelated variation must be omitted to avoid overspecification), and neither one was significant. When the model was run using dummy variables for related and unrelated variation (omitting the specialization dummy), again neither coefficient was significant. Thus, the results indicate that the condition had no significant impact on initial performance. The control variable for number of games played per hour was also not significant, and the control variable for the standard deviation of scores for each hour had a significant and positive coefficient ( $0.01, p < 0.005$ ), suggesting that while speed of play may have had no significant impact on average score, willingness to take an exploratory approach (resulting in variability of scores) might be associated with higher overall performance.

## Discussion

The findings indicate that groups working under conditions of related variation—that is, working on different but similar types of problems over time—learned at a significantly faster rate, on average, than did teams that either worked under conditions of specialization or unrelated variation. Furthermore, teams that worked under conditions of specialization learned at a rate that was not significantly different from that of the teams that alternated between unrelated types of problem-solving tasks. Finally, though not hypothesized, the results suggest that teams with greater variability in their scores per hour performed slightly better overall. These results have interesting implications both for theory and practice.

First, the results are consistent with arguments suggesting that task variability enhances learning. Variation has been proposed to enhance individual learning through the development of a deeper cognitive structure (common to the research on schema, analogical encoding, and implicit learning) or through stimulating insightful synthesis between different problem domains. Task variability might prompt the learners to consider more possible associations for concepts underlying the tasks, and because the tasks

are related, the learners develop a more abstract and complex knowledge structure that pertains to both types of tasks. In essence, the variation stimulates the learners to develop a deeper understanding of the tasks than they would if they had performed only one type of task over time. Furthermore, when learners think about two different types of problems that are similar in some fundamental ways, they may be able to apply a solution or logic developed in one problem domain to the other problem domain, rapidly increasing their understanding of the second problem domain, resulting in the “Aha”! experience characteristic of insightful problem solving (Gick and Lockart 1996). In sum, consistent with recent findings on individual learning, we find that group learning rates were highest under conditions of related task variation, suggesting that groups can also reap synergies from working on different but related problems.

By contrast, there was not a significant difference between the learning rates under conditions of specialization and unrelated variation. This result is somewhat surprising and intriguing. Even if we believe in learning synergies between related learning efforts, we might still expect that specialization would outperform unrelated variation by not distracting the learner from the core task. There are at least two possible explanations here. The first is basically a null hypothesis: with the exclusion of *related* variation, the condition under which individuals or groups learn makes little difference in their learning rate. Learners are neither advantaged by specializing on a particular task nor by having variety in the context unless it is closely related. This argument posits related variation as a special condition under which the learning rate will be influenced, whereas in general condition is unimportant. However, a more likely (and interesting) interpretation of the results may be that there are learning advantages of specialization, but that there are also learning advantages achieved through distributed practice, and that in our study, the difference between these effects is inseparable. While learners may achieve focus benefits from specializing in a particular task, they may be simultaneously forfeiting the deeper cognitive processing benefits of rest from a particular task. This interpretation would also provide additional explanation for the positive impact

of related variation: Because the tasks are similar but varied, the learner reaps some focus advantages and some degree of distributed practice advantage.<sup>9</sup> The teams in the unrelated variation condition, by contrast, reap only the advantages of distributed practice and forfeit any synergy effects between the tasks. Future research should attempt to tease out these different effects, perhaps eventually reaching a point where we can predict the relative strength of the various effects and what problem-specific, learner-specific, or context-specific factors would mediate the impact of the various effects.

The results have interesting implications for the way that work is assigned within organizations. The results imply that when managers assign tasks to teams, they should consider the potential synergy effects of working on different but related problems. Rather than assigning teams to work on the same project (or a series of nearly identical projects) over time, managers might wish to introduce some degree of related variation into the teams' efforts, so that they can benefit by the potential for developing schema, implicit learning, and/or insight. Teams that are overly specialized will improve, but might be less likely to generate insightful solutions.

This implication is strengthened by considering the potential value of performance improvement in the alternate activity. In our study, we estimated the learning curves for the core task only, however, it was straightforward to observe that teams also made significant improvement in their alternate games (although we have no data to compare this improvement to what it might have been had they played only the alternate games). Because organizations typically pursue many projects simultaneously, the performance on alternate tasks would be relevant for them, thus increasing the advantage of related variation over specialization, and possibly giving unrelated variation some advantage over specialization as well.

<sup>9</sup>Note that a distributed practice effect alone is insufficient to explain the results. If distributed practice were the primary factor influencing rate of learning, then we would have expected to see both related and unrelated variation outperform specialization, and we would not have expected related variation to outperform unrelated variation.

## Limitations and Future Research

The current study utilizes a well-defined strategic problem-solving task with immediate and accurate performance feedback. Much of the early work done on implicit learning and schemas utilized motor skill learning tasks, thus it is encouraging to find similar results in a strategic problem-solving domain. The nature of the task may, however, impose some generalizability constraints. For example, many strategic problem-solving tasks that organizations face are not well defined; rather, they are open ended and "fuzzy" (Schwenk 1984). The generalizability of our results to such a domain may be limited. Future research should attempt to replicate these results utilizing different learning domains, including, perhaps, learning curves that relate to technological knowledge, production processes, market knowledge, or the social knowledge underlying effective management of human resources.

Furthermore, although we examined group-level learning to approximate organizational learning, we must exercise caution in generalizing the findings to other levels. Our groups were small, new, and had no prior training or predetermined hierarchy. Previous research has indicated that a team's training and experience can affect its development of transactive memory (Moreland 1999, Wegner 1987) and its degree of structure (Argote 1993, Devadas 1990), both of which can influence the degree to which the group is dependent on individual knowledge and cognition. Future research should attempt to replicate these findings at various levels of analysis to determine whether there are systematic differences in the ways that task variation impacts learning at the organization, group, and individual levels.

Although the current work is a first step in examining whether task variety impacts group learning rates, future studies could integrate the body of work on group process dynamics with this research, and attempt to examine the way in which task variety influences the complex group dynamics that shape the resulting learning outcomes. For instance, interesting questions might include: (1) Does task variety stimulate different types of group communication, coordination, or conflict than task specialization? (2) Do group processes mediate whether groups are

able to benefit from related variation? (3) Does team composition affect its response to task variety?

Furthermore, although the study was not designed to explore the differential impact of explorative versus exploitative strategies (Levinthal and March 1993), the unexpected finding that variability in scores was associated with higher average scores suggests interesting avenues for future research. For instance, do groups benefit by employing more exploratory learning strategies, and do such benefits depend on (1) the nature of the task, (2) the nature of the team, and/or (3) the stage of the learning curve? Clearly, there is exciting work to be done in this area.

The current study is limited in that it relies on only a few levels of variation and relatedness. Both variation and relatedness are multidimensional and continuous constructs. The research by Ellis (1965) and others points out that relatedness is a matter of both degree and kind. For example, previous knowledge might be related in its content or structure, the language with which it is conveyed, the process by which it is attained, or any number of other dimensions. In our study, the related tasks shared similarities in physical appearance, objectives, and implementation. There is also evidence that the tasks are related by origin—that is, *Reversi* is likely a descendant of *Go*. Subjectively, therefore, the tasks appear to be highly related on many dimensions. Our results thus do not enable us to determine which dimensions of relatedness enhanced learning. Because previous research has indicated that certain kinds of relatedness may actually impair learning by resulting in negative transfer (whereby stimulus similarity prompts the learner to apply a response that is actually inappropriate), the distinction between different dimensions of relatedness is an important one (Ellis 1965). Future research requires that we develop much more rigorous and multidimensional measures of relatedness and variation. Failure to do so may yield unanticipated—and undesirable—results. Ultimately, we would like to be able to answer the questions: How related must problems and solutions be to elicit positive transfer of learning? and Under what level of variation will the learning rate be maximized? We have made a step toward answering these

questions, however, much more work remains to be done.

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