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ROLE OF COGNITIVE FACTORS IN THE ACQUISITION OF COGNITIVE SKILL

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13. ABSTRACT (Maximum 200 words)
This paper reviews recent studies and provides a theoretical framework for examining the relationships between individual differences in basic cognitive abilities and performance on tasks involving the acquisition of cognitive skill. A claim made is that much of cognitive skill can be characterized as (a) knowledge of how operators (symbols denoting an operation to be performed) in a skill domain actually work, and (b) knowledge of when to apply operators to achieve problem-solving goals. Studies of declarative learning, assumed to be the initial stage in skill acquisition, show that background knowledge and working memory capacity are primary determinants of success. Studies of cognitive skill learning per se make use of a distinction between attention capacity, which refers to how much information can be held in working memory at one time, and activation capacity, which refers to how long activation can be maintained. The success of learning by proceduralization is shown to depend on attention capacity, whereas the success of learning by composition is shown to depend additionally on activation capacity. Future research and the benefits of an individual differences approach to analyzing cognitive skill acquisition are discussed.

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SUMMARY

This paper reviews research on what factors determine who will acquire cognitive skills most readily. Research reviewed in this paper was conducted as part of the Air Force's Learning Abilities Measurement Program (LAMP), a basic research project designed to explore the implications of cognitive psychology for new ways of assessing individuals' competence, with the long-term goal of improving the current personnel selection and classification system. The research suggests that there are four categories of fundamental individual differences: background knowledge, background skills, processing speed, and processing capacity. The research also suggests that there are three phases of cognitive skill development: an initial declarative stage (memorizing the rules), a procedural stage (memorizing the procedures and memorizing chains of procedures), and an automatic stage. Over a number of studies, it has been shown that the main factors determining success in the declarative stage are background knowledge and processing capacity. The main factor determining success in the procedural stage is processing capacity.

PREFACE

Development of this paper was supported by the Air Force Learning Abilities Measurement Program (LAMP), a multi-year program of basic research conducted at the Air Force Human Resources Laboratory (AFHRL) and sponsored by the Air Force Office of Scientific Research. The goals of the program are to specify the basic parameters of learning ability, to develop techniques for the assessment of individuals' knowledge and skill levels, and to explore the feasibility of a model-based system of psychological assessment. Support was provided by AFHRL and the Air Force Office of Scientific Research, through Universal Energy Systems, under Contract No. F41689-84-D-0002/58420360, Subcontract No. S-744-049-001. The present work was initiated while Dr. Kyllonen was at the Institute of Behavioral Research, University of Georgia, and completed by Drs. Kyllonen and Woltz as part of their official duties at AFHRL. Both authors wish to thank Raymond Christal of Universal Energy Systems and William Alley of AFHRL for their comments on this paper.

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I. INTRODUCTION

Facility in acquiring cognitive skills, such as those associated with programming computers or troubleshooting electronic equipment, is popularly regarded as an indication of general intellectual proficiency. At least part of the reason for this is that learning new skills is intellectually demanding and thereby discriminating. We generally avoid learning new skills when the old ones are adequate, even "barely adequate," because skill learning is such an intellectually excruciating process. And mathematics, physics, and computer science classes, which can be characterized as emphasizing the acquisition of novel cognitive skills, as opposed to the accumulation of domain facts, are generally regarded as the most difficult subjects in the college curriculum.

In recent years, research in cognitive psychology has begun to consider the processes by which students come to acquire new cognitive skills. It is appropriate, we think, to view this research as having the goal of identifying the underlying mechanisms and capacities which enable and mediate skill acquisition and development. The primary focus of this work has been on cataloging the kinds of errors students make when learning new skills (e.g., Anderson, Greeno, Kline, & Neves, 1981; Brown & Burton, 1978) and on developing sophisticated formal models, primarily computer simulations, of the skill acquisition process (Klahr, Langley, & Neches, 1987). These models provide computationally plausible explanations for how skill can develop in light of the kinds of errors students typically make. But, interestingly, a potentially powerful methodology for the analysis of skill acquisition--that of comparing those who acquire skill easily with those who do not, in terms of other differentiating cognitive factors--has only infrequently been employed. Although there have been some studies comparing domain experts with novices (Chi, Feltovich, & Glaser, 1981), systematic individual differences analyses of cognitive-skill acquisition per se have only recently begun to appear in the literature (Kanfer & Ackerman, in press), and have not enjoyed anything like the popularity of individual differences analyses of performance on intelligence tests, as exemplified in the work of Sternberg (1977) or Hunt (1978). This is especially surprising given the historical association of intelligence and learning in the individual differences literature.

In this paper we review a number of our recently completed and in-progress studies that have employed an individual differences approach to the analysis of cognitive-skill acquisition. Much of the earlier research on individual differences in skill acquisition focused on the development of perceptual-motor skills (e.g., Fleishman, 1972). Our focus is on the development of cognitive skills in which procedures for transforming information are more critical than perceptual and motor operations. In studying cognitive skills, our primary interest is in the role of working memory capacity. But this reflects as much an anticipation of conclusions as it does an initial intention. Over many studies, we simply have not found any other cognitive factor that plays as critical a role in governing success in cognitive-skill acquisition as that played by working memory capacity.

II. DEFINITION OF COGNITIVE SKILL

Our work has been guided by the notion that much of cognitive skill can be characterized as the possession of two kinds of knowledge:

1. Knowledge of how domain operators work; that is, knowledge of what output is produced by an operator as a function of input.

2. Knowledge of when to select particular operators to achieve particular problem-solving goals.

For example, in learning a programming language such as LISP, the operators initially learned are the predefined functions, such as CAR, CDR, CONS, LIST, APPEND, etc., which operate on the data structures of the language, atoms and lists in order to build new atoms and lists. In geometry, the operators are the postulates and theorems which transform a statement into a new conjecture. In learning logic gates, the operators are the gates--AND, OR, INVERT, NAND, NOR, XOR, etc.--which transform incoming signals to an outgoing signal.

In all these domains, the successful student must first learn how the operators work; that is, learn how statements, signals, or other kinds of data are transformed by the domain operators. Next, usually through experience, the student must learn when, and in what order, to apply the various operators. In some contexts, knowing when to apply operators is a creative process: Consider the task of writing computer programs, solving geometry proofs, or designing circuits. In some contexts, learning when to apply operators is a matter of learning a sequence of steps to follow; for example, knowing emergency procedures for dealing with system failures. In any event, true cognitive skill is achieved when the student knows the domain operators and knows when to use them.

Our claim is not that this is all there is to acquiring cognitive skill. For one thing, these forms of knowledge do not seem to capture the essence of creativity or insight-based problem solving. Certainly, an important cognitive skill involves not merely the memorization of how given operators work, but the development of new operators that perform "interesting new actions" (Neches, Langley, & Klahr, 1987). We also are not claiming that these two kinds of knowledge are necessarily explicit. There is evidence that people can learn to employ an operator successfully without explicitly knowing how it works (Berry & Broadbent, 1988; Lewicki, Czyzewska, & Hoffman, 1987; Nissen & Bullemer, 1987). Rather, our claim is that much of cognitive skill consists of knowing how operators work and when to use them, and that an analysis of how students come to acquire this kind of knowledge can be an important first step in understanding how students acquire more complex cognitive skills.

Cognitive skill characterized as simply knowledge of operators and when to use them suggests that skill learning is merely a special case of fact learning. But in keeping with contemporary views on the matter, we believe it is useful to distinguish declarative (factual) knowledge from procedural skill. A current learning theory that employs the declarative-procedural distinction is Anderson's (1987) ACT* theory. This theory also serves as the foundation for much of our thinking about the role of cognitive factors in acquiring cognitive skill; thus, we shall briefly review that theory here. Following Fitts (1963), Anderson has proposed that acquiring cognitive skill involves three distinct learning phases. We illustrate these in Figure 1, along with an example drawn from learning logic gates.

Knowledge Acquisition Phase

The learner first commits to memory a declarative representation (propositions and relations) of the rules regarding how domain operators work. In learning logic gates from text, for example, the learner encodes the relation between the spatial description and the name of the AND gate (i.e., "the AND gate looks like D"). The learner also encodes the assertion, found perhaps in an instructional text, that "the AND gate outputs a high signal if all inputs are high, but it outputs a low signal otherwise." Although this is a single sentence, it is a fairly complex single sentence in terms of what the learner has to encode. For example, we informally broke this sentence down into the following propositions:

P1: AND (gate)
P2: high (signal)

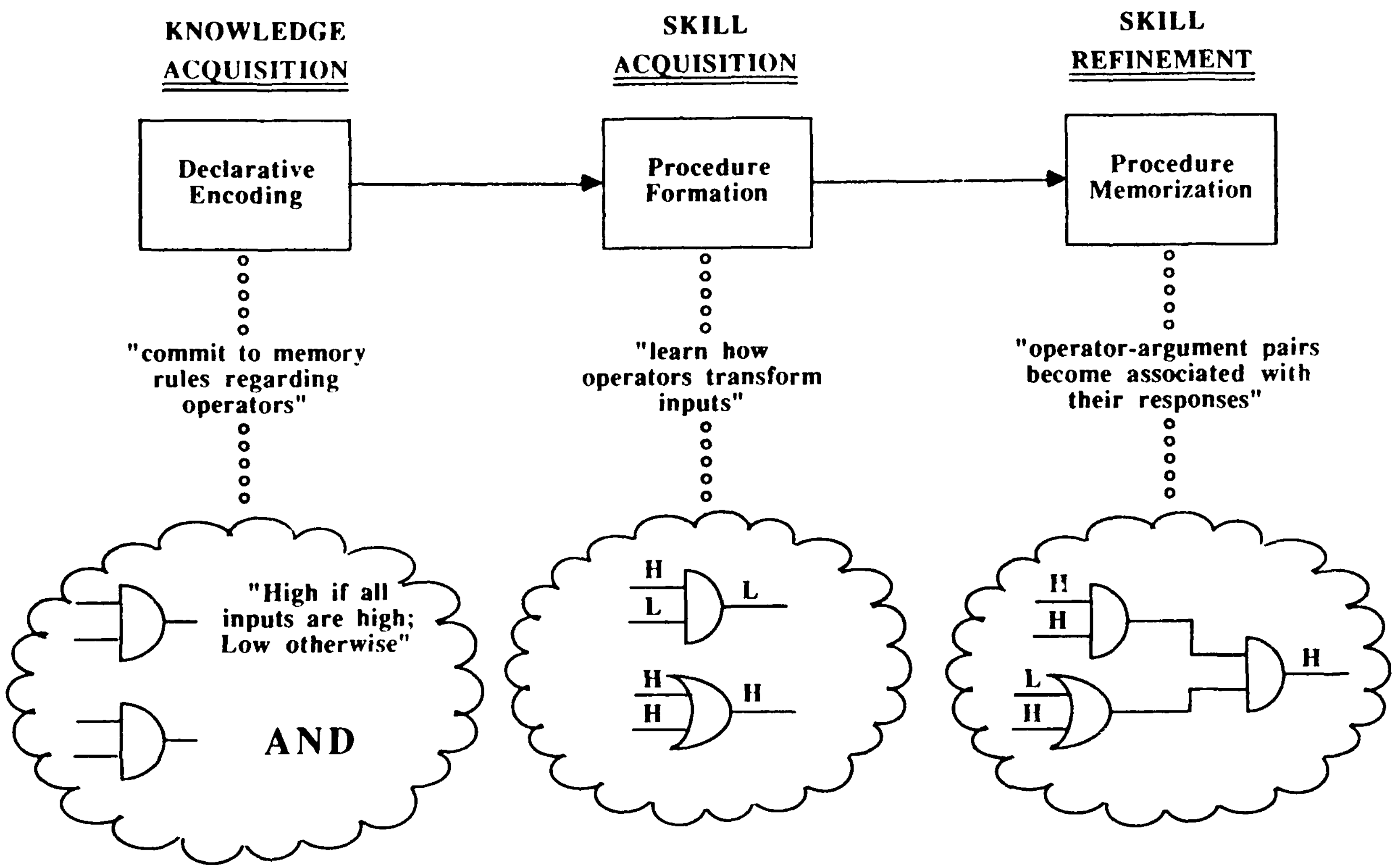


Figure 1. **Model of the Development of Cognitive Skill.**

P3: outputs (P1, P2)
P4: all (inputs)
P5: high (P4)
P6: if-then (P5, P3)
P7: low (signal)
P8: outputs (P1, P7)
P9: not (P5)
P10: if-then (P9, P7)

After reading the gate definition, and encoding these 10 propositions, the learner could be said to possess declarative but not procedural knowledge regarding the AND gate. (There is some controversy on this point. Kieras and Bovair [1987] suggest that learners can encode if-then rules directly as procedures.)Applying this declarative knowledge in problem solving, to predict the output of an AND gate given the input "High, Low," for example, would be slow and error-prone. The learner would have to keep active in working memory the 10 propositions encoding the AND description (a considerable memory load), while simultaneously having to evaluate the actual gate presented in the problem, determine its state, and determine whether P5 or P9 was true in this particular problem. Encoding the problem itself would involve encoding at least the following three propositions:

P11: gate-type-is (AND-gate)
P12: high (line-1)
P13: low (line-2)

along with a proposition representing the goal of problem solving:

P14: goal (determine-output-value).

Knowledge in this form is not sufficient for solving problems. Rather, the learner has to have general problem-solving knowledge that guides the process of applying this propositional knowledge to the task of determining the answer to the presented problem. For example, the learner has to know that if the goal is to determine an output value, and the output is dependent on input values, then he or she ought to look at what those input values are. The reason problem solving at this point is so difficult is that there is a considerable memory load and there is a need to make a sequence of decisions involving the propositional information. Mistakes made anywhere along the way may result in errors in the subject's decision about whether a high or low signal will be output.

Skill Acquisition Phase

Following declarative encoding, the learner advances toward bona fide cognitive skill in a couple of different ways. First, by a process of proceduralization, the learner, as a result of solving problems, begins to develop a procedural understanding of how the various operators work. The following example shows the kind of procedure (i.e., if-then or production rule) acquired in learning logic gates:

IF (a) there is an AND gate, and
(b) line-1 (one of the inputs) is HIGH, and
(c) line-2 (the other input) is LOW,

THEN the output is LOW.

Having this and similar production rules reduces working memory burden, as follows. When a problem involving the AND gate is presented, it is now no longer necessary to activate all 10 propositions that encode the AND rule, because the knowledge of how AND works is stored in long-term memory in the form of these production rules. Rather, only three propositions have to be active; specifically, those that encode the state of the illustrated logic gate (i.e., what kind of gate it is, what the value of one incoming line is, and what the value of the other incoming line is; see P11, P12, and P13) and the goal (see P14). In other words, having proceduralized knowledge of the AND gate amounts to having a production rule, or set of production rules, that encodes that knowledge. Because these production rules are assumed to be stored permanently in long-term memory, having these rules results in a reduction of the load on working memory, and leads to speedier and more accurate problem solving.

Intuitively, this idea of a declarative-to-procedural transition seems right: It is possible to know a skill on a declarative-factual level yet not be capable of procedural execution of that skill. For example, we might be able to dictate the steps necessary to land an aircraft on a runway, yet not be able to actually do it. A demonstration in a more purely cognitive realm comes from a dissertation by Schmalhofer (1982). He had computer science and psychology students read a chapter from a programming textbook teaching the language LISP, with which neither group had any prior familiarity. An immediately following posttest demonstrated that both groups developed an adequate declarative knowledge base of the material presented in the chapter. The psychology students remembered as much of the propositional content as did the computer science students. However, for the psychology students, this knowledge was strictly declarative. They were unable to apply this knowledge to problem solving (verifying and debugging LISP programs). In contrast, the computer science students apparently went beyond a strictly declarative understanding, and were able to proceduralize some of the knowledge taught in the text, as indicated by their ability to verify and debug LISP programs. This study nicely demonstrates that prior knowledge may determine the degree to which new incoming knowledge about a skill will become proceduralized.

Another way in which learners attain cognitive skill is composition. By this method, long chains or sequences of production rules (which can be thought of in this context as mental steps) are collapsed into single production rules. Composition thus represents one way in which the learner comes to know when to apply particular operators. An example, from logic gates, is a problem consisting of a series of logic gates linked together in a circuit, where the output of one gate serves as the input to another. The novice problem-solver undoubtedly solves circuit problems sequentially, one gate at a time. In contrast, there may be experts who have composed sequences of single-gate problems, and who can evaluate entire multiple-gate circuits in a single step, simultaneously.

Skill Refinement Phase

Once knowledge is proceduralized and composed, it continues to undergo further refinement. In a third and final learning stage, cognitive skill is tuned or automatized as the learner develops increasingly specialized production rules to handle any of the possible problem types likely to be faced. That is, the learner essentially comes to memorize correct responses to particular stimulus configurations. These more specialized production rules can be seen as stimulus-response pairs, where the stimuli are the operator and the arguments (e.g., AND gate; high and low incoming signals). With practice, these more specialized rules grow in strength to the point where they ultimately require minimal conscious attention for their application. Problem solving becomes rapid and relatively error-free, and can even be accomplished while the solver is engaged in other cognitive activity. This might characterize experts who can trace signals through logic gates while simultaneously conversing with fellow troubleshooters, for example.

It is useful to consider how the Anderson-Fitts three-phase model intersects with our ideas about the two kinds of knowledge (how domain operators work, and when to apply them). One way of thinking about the relationships is that phase and knowledge type are independent dimensions. Operator knowledge of either type (how or when) can be in declarative, procedural, or automatic form. In the normal course of cognitive-skill development (though, as we pointed out above, not necessarily in all cases), operator knowledge originates in declarative how-it-works form, as the result of lecture or textbook instruction. Then, with problem-solving experience, the learner becomes increasingly proficient in two ways. First, the knowledge of how operators work becomes increasingly proceduralized and automatized, along the lines of the Anderson-Fitts model. *Second, knowledge of when to apply the operators is acquired, usually tacitly.* Conventional instruction typically fails to explicate the conditions under which operators should be used, leaving it up to the student to infer when those operators are relevant (Lewis & Anderson, 1985). Presumably, this type of knowledge, of when operators should be applied, also undergoes proceduralization and automatization with experience.

III. DETERMINANTS OF SUCCESS IN ACQUIRING COGNITIVE SKILL: THE FOUR-SOURCE FRAMEWORK

Given this model of cognitive-skill acquisition, it is useful to consider what determines success at each stage. For example, we might expect that prior knowledge will facilitate the declarative-to-procedural transition of new material, as Schmalhofer (1982) demonstrated. As another example, we might expect that working memory capacity will play an important role in early stages of skill development, when working memory demands are high; but other cognitive factors, such as the speed with which items can be retrieved from long-term memory, will play an important role relatively late in the process, after the rules are well-practiced. There is support for this prediction as well. A number of studies (Ackerman, 1987; Fleishman, 1972) have shown that measures of general cognitive ability, which presumably stress working memory capacity (a point we return to in a later section), are especially highly correlated with performance on initial trials of various learning tasks. Conversely, more specifically speeded tests become better predictors of performance on later trials, after the subject becomes familiar with the task. Interestingly, if subjects somehow can be prevented from proceduralizing their task knowledge, then working memory demands will be kept high, and working memory capacity (or general cognitive ability), therefore, will remain a strong determinant of task success regardless of how much practice subjects have (Ackerman, 1986).

In our own work, we have been guided by what we have called the four-source framework (Kyllonen & Christal, 1989). According to this general proposal, illustrated in Figure 2, performance in each of the three learning phases (knowledge acquisition, skill acquisition, and skill refinement) is presumed to be determined by (a) prior learning factors representing the degree of completeness of the prior learning phase, and (b) four categories of general cognitive factors:

1. Knowledge--general and domain-specific;

2. Skills--general and domain-specific;

3. Processing Capacity (i.e., working memory capacity); and

4. Processing Speed (e.g., retrieval speed, decision speed)

As an illustration of how this framework can be applied, consider a model for predicting the acquisition of procedural skill in some domain, say logic gates. Suppose that an individual had already been given declarative instruction on the rules governing the workings of logic

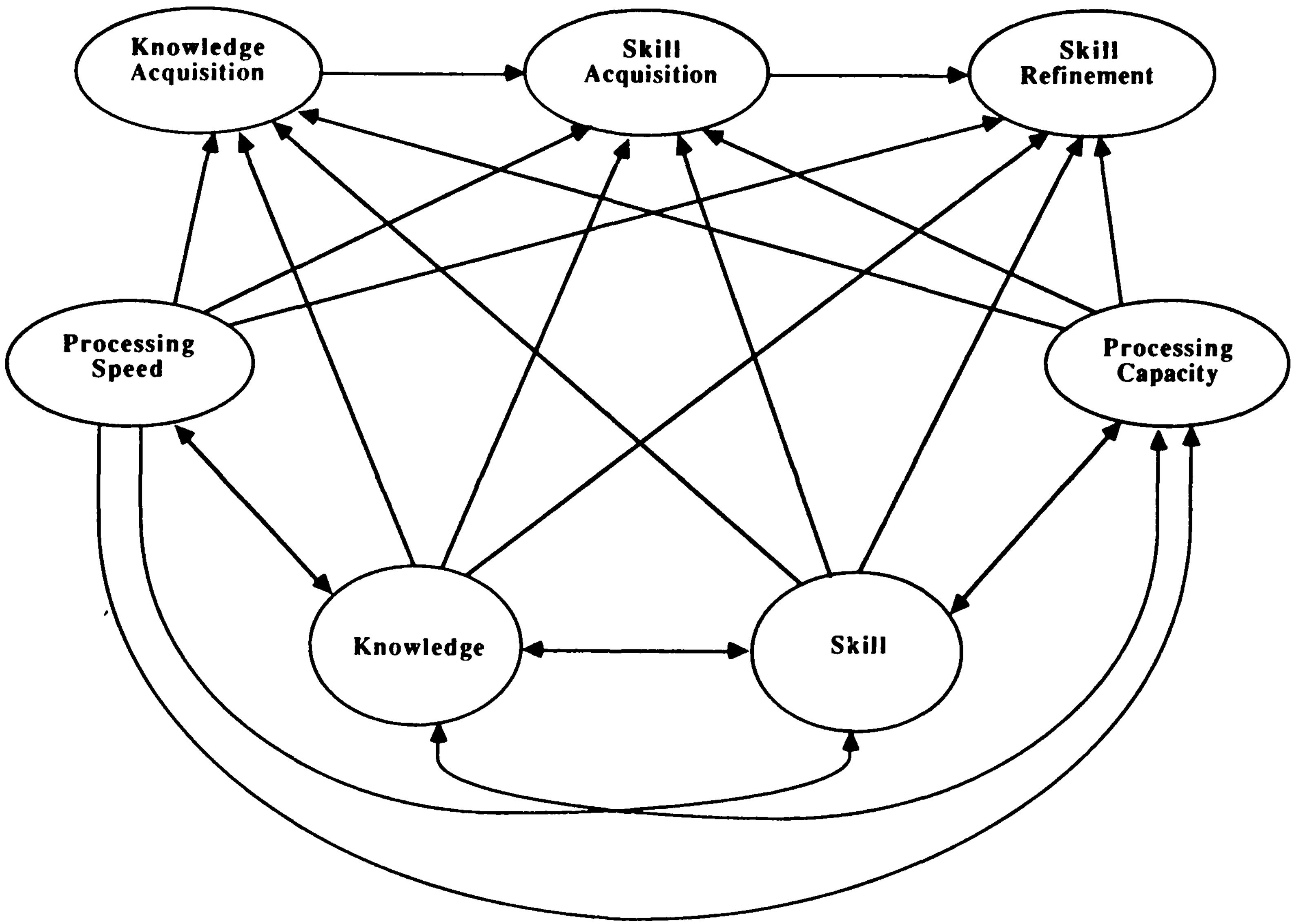


Figure 2. **Four-Sources Framework.**

success at this phase of skill acquisition would be presumed to be predictable from (a) the level of general world knowledge possessed by the individual (e.g., as indicated by performance on a general knowledge survey); (b) the level of domain-specific knowledge (e.g., the degree of prior declarative knowledge of logic gates); (c) the amount of general skill or strategic knowledge available (e.g., the degree of knowledge of good problem-solving strategies, such as those found in Hayes [1981] or Wickelgren [1974]); (d) the amount of specific procedural skill (e.g., experience with logic gates or logical operators in other contexts, such as a formal logic course); (e) working memory capacity (e.g., as indicated by performance on something like the Daneman-Carpenter [1980] reading span test); (f) processing speed (as indicated by performance on retrieval speed tests, such as physical-, name-, and semantic-matching [Jackson and McClelland, 1979]); and (g) degree of prior learning (i.e., the degree of success experienced during the declarative portion of the task, or more abstractly, the strength of the declarative knowledge that serves as the foundation for procedural skill development).

We cannot claim that these factors are sufficient for determining learning success, but we now have evidence over a number of studies on declarative learning that these factors are necessary for determining learning success, insofar as each can be shown to predict declarative learning uniquely. We now briefly consider that evidence before launching into studies of the relationship between cognitive factors and cognitive-skill learning.

IV. ROLE OF THE FOUR SOURCES IN DECLARATIVE LEARNING

Knowledge

When we speak of the role of existing knowledge in acquiring new knowledge, potentially we are referring to the depth, breadth, accessibility, and organization of the knowledge possessed by an individual. In Kyllonen and Christal (1989), we provided a detailed rationale for how each of these attributes of general knowledge could be considered important in learning. However in actual empirical research to date, we have investigated only the breadth attribute.

In a series of experiments (Kyllonen & Tirre, 1989; Kyllonen, Tirre, & Christal, 1989) with over 2,500 subjects, we have repeatedly found that breadth of knowledge is an important predictor (with correlations ranging from .23 to .54) of the success an individual experiences in acquiring new arbitrary "facts." We have measured breadth of knowledge in a variety of ways--by performance on (a) vocabulary tests, (b) general world knowledge surveys (example item: "Ostrich is the name of the bird that cannot fly and is the largest bird on earth, true or false?"), and (c) general science knowledge surveys (example item: "Water is an example of a gas, solid, liquid, or crystal?"). Scores on these kinds of tests are typically highly intercorrelated and thus define a general knowledge factor. The learning criterion is typically some indicator of learning speed on a paired-associates or free-recall learning task.

This finding of a relationship between knowledge and learning speed seems to be particularly robust. It seems not to depend on study time (Kyllonen et al., 1989), on whether the learning task consists of arbitrary pairs or whole sentences, or on whether the test is of a recognition, multiple-choice, or recall nature (Kyllonen et al., 1989; Kyllonen & Tirre, 1989). However, the finding thus far is limited to learning verbal (or at least pronounceable alphanumeric) stimuli.

There are a variety of ways to think about why general knowledge should predict success in acquiring new declarative facts. One is that learning paired-associates involves establishing relations between pair terms through a process of elaboration (Kyllonen et al., 1989). The success of the relation establishment process depends on the amount of material, especially distinct material, available for forming elaborations. High-knowledge individuals, by definition, have more material and more distinct material available; that is, a richer network of facts and associations into which new facts and associations might be interwoven. This seems rather obvious, and might even be dismissed as trivial except for the fact that others (e.g., Underwood, Boruch, & Malmi, 1978) have failed to find a relationship between general semantic knowledge and episodic learning success.

Skills

Skills refer to the general and domain-specific problem-solving skills, strategies, and "meta-cognitive" approaches students bring to the learning situation. In procedural learning, these may be general heuristics (e.g., if the first method fails, try a new one) and general problem-solving strategies (e.g., means-ends analysis, working backward, hill-climbing, depth- and breadth-first search through the problem space). Or they may be specific skills (strategies and heuristics) for solving specific problems such as how to trace a complex circuit. In declarative learning, problem-solving skill is primarily knowledge of how to learn, such as mnemonic strategies.

We have not conducted an extensive investigation of the role of general skills, partly because it is not entirely obvious how to measure them directly in a context-free way. In most cases, we can only infer the possession of an extensive repository of general problem-solving procedures in an individual indirectly--by his or her performance on a novel task that requires the invocation of such procedures. But tasks with these characteristics, such as progressive matrices (Raven, 1960) or letter series, inevitably are considered primarily to reflect general intelligence. Then there is an interpretation problem: Should we attribute performance on these tasks to procedural skill proficiency or to general intelligence?

We do have evidence that some kinds of general skills are important in declarative learning. In a series of studies (Kyllonen et al., 1989; Tirre, 1989), we demonstrated the importance of a form of strategic knowledge (or procedural skill)--knowledge of mnemonics--by showing that a 5-minute lesson on elaboration boosted paired-associates learning scores by roughly 20% (N = 500). However, the most interesting feature of these studies was that such strategy provision actually served to increase the relationship between general knowledge and learning performance (from r = .28 to r = .49). That is, it seems that in declarative learning at least, knowledge of mnemonics is primarily a noise factor: If everyone is given the same strategic knowledge, learning proficiency depends more on general declarative knowledge (Hughes [1983] found a similar result). It is interesting that Anderson and Bower (1972) suggested that strategic knowledge might have been an important determinant of individual differences in associative learning. Wang (1983) apparently found evidence for the Anderson-Bower view, in that fast learners were demonstrated to naturally use more sophisticated mnemonics than those of slow learners. Our research suggests that although individual differences in mnemonics knowledge are important in one sense (they affect performance), they are unimportant in another; namely, they are relatively unstable and can easily be changed with a short instructional intervention. It is obviously much more difficult to change an individual's breadth of general knowledge.

Processing Speed

A considerable body of literature has formed around identifying processing speed relationships with learning, particularly learning through reading text. This line of research began with Hunt and colleagues' (Hunt, Lunneborg, & Lewis, 1975) somewhat surprising finding of a correlation between lexical access time and scores on standard tests of verbal ability, such as vocabulary and paragraph comprehension. This relationship has been demonstrated in declarative learning by Jackson and McClelland (1979), who showed that reading speed (a composite of reading time and comprehension accuracy) could be almost completely accounted for by two factors:

general comprehension ability and lexical access. In this and myriad replications, lexical access time is typically estimated by subjects' reaction time to recognize opposite-case letters (A a) or words (CAT cat) as matches, minus their time to recognize same-case, "physical-identical" letters (A A) or words (CAT CAT) as matches. According to the popular interpretation, only on the opposite-case task is it necessary for subjects to access long-term memory; in the physically identical case, perceptual information is sufficient for reaching a matching judgment. Thus, a subject's difference in reaction time between the name-identical and physical-identical conditions can be taken as an uncontaminated measure of long-term memory retrieval time. Because long-term memory accesses are repeatedly executed during reading, those who spend less time accessing long-term memory have a major advantage over those who linger, not only in terms of how long it takes to get through the text but also in terms of the amount of attentional resources available for higher-level comprehension processes (Perfetti & Lesgold, 1979).

Based on our own more recent research, it seems that the role of processing speed in learning needs to be qualified somewhat. In one extensive study (N = 240), Tirre and Rancourt (1986) separated out the reading speed and comprehension factors that Jackson and McClelland combined, and found that semantic access time (time to judge two words to be synonyms) predicted reading speed but did not uniquely contribute to reading comprehension. In Kyllonen et al. (1989), we found that semantic access time was a significant predictor of the probability of remembering a pair of words, but only when study time was short (.5 s to 2 s per pair). Further, we were unable to replicate the finding with lexical access time. Over a number of studies, we have found that lexical access time does not uniquely contribute to a learning criterion when a semantic access time score is also included in the model (Kyllonen et al., 1989). Thus, processing speed is an important determinant of declarative learning, but subject to at least two qualifications. First, the processing speed measure must reflect time to search long-term memory for semantic as opposed to lexical information. Second, the declarative learning criterion must be *speeded* (limited study time) or the measure must reflect processing time rather than simply accuracy.

Processing Capacity

Our use of the construct of processing capacity primarily follows Baddeley (1986), who defines working memory as "the temporary storage of information that is being processed in any range of cognitive tasks" (p. 34). The key feature of this definition, as opposed to the classic definition of short-term store, has to do with the implication that performance on any of a range of tasks involving "different processing codes and different input modalities," even those without a short-term memory component (e.g., retrieval from long-term memory), will deteriorate if the limited working memory capacity is used by a supplementary task. The implication is that we can measure working memory capacity by requiring a subject to simultaneously process and store new information.

For example, in the reading span test (Daneman & Carpenter, 1980), subjects read (i.e., process) a series of sentences and simultaneously attempt to remember (i.e., store) the last word in each one. The subject's score is the number of successive sentences that can be read (and comprehended) before the subject is no longer able to recall all the final words (typically this is three to five sentences). Engle (1988) has generalized this method so that the primary task can be arithmetic operations, rather than reading sentences, and the secondary task can be remembering digits or words presented separately after the end of each sentence or arithmetic expression, rather than being words included in the primary sentence as in the Daneman-Carpenter version. Engle's variants are all highly intercorrelated, suggesting the existence of a general working memory factor.

The importance of this factor in declarative learning is demonstrated in studies that show that high-scoring subjects (i.e., those with high working memory capacity) tend to comprehend text better (Daneman & Carpenter, 1980; Engle, 1988; Tirre & Rancourt, 1986), resolve ambiguous words and inconsistencies in prose passages more accurately (Daneman & Carpenter, 1983), and learn novel words set in a paragraph context more reliably (Daneman & Green, 1986). In contrast, simple memory span scores typically correlate only modestly with indicators of declarative learning success, such as reading comprehension scores.[1]

A noteworthy discovery we have made about the working memory construct over the last year or so is that it seems to be closely related to the construct of general reasoning ability. Kyllonen and Christal (in press) prepared a series of working memory tasks that conformed to Baddeley's definition in that the tasks required working memory resources to be split between concurrent processing and storage of information. They also constructed a set of tasks, such as letter series, letter sets, and other measures adapted from the Educational Testing Service Kit of Reference Tests for Cognitive Factors (French, Ekstrom, & Price, 1963) that have historically been treated in the differential literature as measures of general reasoning ability. Over four independent studies, using different subjects and different measures of working memory capacity and reasoning factors, a consistent finding was that working memory capacity correlated around .90 with reasoning ability.

There are numerous studies in the literature reporting a relationship between reasoning ability and declarative learning (e.g., Allison, 1960; Kyllonen & Tirre, 1988; Snow, Kyllonen, & Marshalek, 1984; Stake, 1961; Thurstone, 1938). The Kyllonen-Christal result, equating reasoning ability with working memory capacity, suggests that working memory capacity governs the efficiency of declarative learning.

V. ROLE OF THE FOUR SOURCES IN COGNITIVE-SKILL LEARNING

We have presented evidence concerning the role of the four sources--declarative knowledge, procedural skills, processing speed, and processing capacity--in declarative learning. We now consider in somewhat more detail some recently completed work on the role of the four sources in cognitive-skill learning. Insofar as the first phase of skill learning is essentially declarative learning, according to the model shown in Figure 1, we should expect to replicate the findings reported above concerning the role of each of the four sources. But we are mainly concerned in this section with how each of the four sources predicts the subject's ability to transform declarative knowledge into effective procedural skills that can be used in problem solving. Thus, in both of the investigations to be reported, we observe a subject in extended learning--usually from 30 to 90 minutes. We begin by teaching domain facts, such as the rules guiding the operators in the domain, then we have the subject solve problems with these rules.

Study 1: Distinguishing Attention-Capacity from Activation-Capacity

The first investigation in this series was concerned primarily with the role of working memory at different stages in cognitive-skill acquisition. In the discussion of declarative learning above, we defined the working memory construct in the sense used by Baddeley (1986). Specifically, working memory was assumed to be severely limited (3 to 7 chunks), and responsible for performance deterioration when a subject is required to simultaneously store and actively process

[1] However, Engle's (1988) research has shown that simple word span predicts comprehension almost as highly as does reading span, as long as subjects are required to recall words in serial order.

information. Woltz (1988a) refers to this as "the controlled attention capacity" conceptualization of working memory due to the fact that both the storage and processing require controlled attention operations. Woltz pointed out that there is a second definition of working memory in the psychological literature which pertains to the limitations of automatic spreading activation and decay of that activation over time. As conceptualized in this manner, working memory is assumed to be larger (20 chunks may be activated simultaneously, at least to some degree), and is limited by automatic rather than controlled cognitive operations.

To test the degree to which these two theoretical definitions match-up empirically, Woltz (1988a) estimated attention capacity and activation capacity in subjects by the subjects' performance on various tasks, and then correlated the two sets of measures. Two attention capacity measures were administered. In one, which he called "Digit Order," subjects were required to remember either three (e.g., 2 8 5) or six (e.g., 9 4 8 2 1 3) digits, then verify sentences concerning the order of the digits (e.g., "8 does not come before 2, true or false?"), and then recall the digits by pressing number keys on a keyboard. Consistent with findings on similar tasks by Baddeley and Hitch (1975), Woltz found that substantial performance deterioration on the sentence verification task occurred in the 6-digit load condition, indicating consistency between the original Baddeley-Hitch definition of working memory and Woltz's operationalization of the construct. In a second test, "ABCD Order," subjects were required to construct an ordering of the letters A, B, C, and D, consistent with three statements constraining their order. A typical item would begin with the assertion "B follows A," followed by the statement that "Set 1 (i.e., the letters A and B) precedes Set 2 (i.e., the letters C and D)," followed by the statement that "D precedes C." The subject then would be expected to recognize the order of the four letters as "ABDC." Woltz found that performance results for these two tests were highly correlated (r = .63).

Woltz estimated subjects' activation capacity by observing latency savings on repeated trials (i.e., time on Trial 1 minus time on Trial 2, where Trial 2 occurs 1 to 8 trials after Trial 1) of a semantic identity task requiring subjects to determine whether two words (e.g., big, large) were synonyms. The rationale was that latency savings reflect the degree to which activation of semantic elements is maintained over time. Consistent with this general rationale, subjects did respond faster to repeated trials, and the amount of savings decreased with the number of intervening trials. Savings scores were thus considered measures of an individual's capacity to maintain activation over time. Correlations of this measure with the attention working memory measure described in the previous paragraph were zero, suggesting that activation and attention capacities represent independent working memory limitations.

Capacity Limits in Learning Sequenced Cognitive Procedures

Given two kinds of working memory capacity, an obvious question is, "Which one is predictive of cognitive-skill acquisition?" A follow-up study (Woltz, 1988b) addressed this question. The idea was to develop a task that resembled a typical operator's task in which actions are based on a series of condition evaluations. For example, the operator of a complex system, such as a power plant, has to evaluate many conditions prior to taking an action. In Woltz's version of the generic operator's task, subjects (N = 701) made a sequence of judgments about a number presented on a computer screen. Subjects had to determine whether the number was big (11--20) or little (1--10), even or odd, and alphabetic or numeric, and whether it appeared at the top or the bottom of the screen, and then respond according to rules such as those listed in Figure 3a. Figure 3b illustrates a typical trial.

With respect to our model of skill learning, this task requires that subjects learn how the operators big-little, odd-even, alphabetic-numeric, top-bottom worked, in the sense of (a) learning how to determine whether a number is big, even, etc., and (b) learning which judgment to make about a number next, given that a judgment regarding one of its properties has just been made. We assume that subjects come to the experimental session with at least a declarative understanding of the operators; that is, they know what it means for a number to be even or big or written in alphabetic or numeric form. Proceduralizing this knowledge is probably fairly trivial, amounting to simply a slight modification of already well-known concepts to suit the demands of this experiment (e.g., to proceduralize the fact that in this experiment "big" means greater than 10). We assume that much of this proceduralization takes place during the early learning trials.

Perhaps the more important learning skill tapped by this task, and one that becomes particularly important on the later trials, is composition. Subjects learn in which order operators are applied, and then compose these sequences into larger production rules. Subjects learn to apply the evenness operator, followed by the alpha operator and the bigness operator, for example. Composition efficiency is thus what will primarily be reflected in various measures of performance over trials, particularly later trials after proceduralization is more or less complete.

Cognitive Proficiency Measures

Subjects were also administered four sets of tasks designed to tap different cognitive proficiencies. Verbal knowledge was indicated by performance on a standard vocabulary test. Attention capacity was measured with two tasks: (a) the ABCD Order task used in the previous study, and (b) an Alphabet Recoding task, which required subjects to memorize a three-letter string (e.g., 'M F Q') and then transform the string by adding or subtracting a value to or from each letter's alphabetical ordinal value to obtain a new set of letters (e.g., M F Q + 3 = P I T). Activation capacity was measured as latency savings on repeated trials of semantic-identity (big-little, odd-even, etc.) judgments, as in the previous study. A fourth construct, component efficiency, was indicated by response time to one-operator judgments about numbers (e.g. Big - 12, true or false?; Even - 10, true or false?).

Results and Discussion

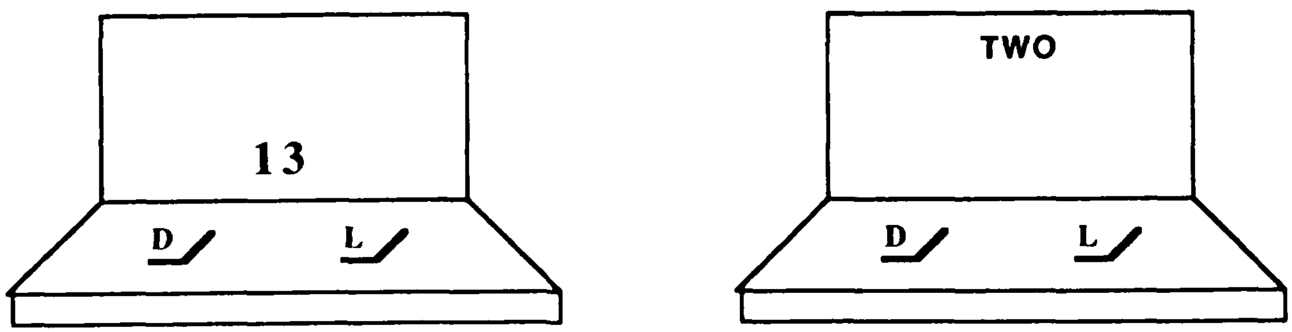
Over the 11 trial blocks (64 trials each), subjects made the number judgments with increasing speed and accuracy, and both log latency and log errors were linearly related to log trial number, consistent with the power law of practice (Newell & Rosenbloom, 1981). This was an important finding in that production composition is assumed to be responsible for power law improvement (Lewis, 1978). Thus, it can be claimed that the data from this task were consistent with what would be expected if composition were taking place. (See Woltz [1988b] for a detailed explanation of the likely nature of composition on the number judgment task.)

More important, for the present discussion, was the pattern of changing relationships between the cognitive proficiency measures and performance on the successive trial blocks, which are shown in Table 1 for the condition in which subjects become most proficient in the skill (N = 330). Consider first the results for the accuracy measure. Accuracy in early trials was determined jointly by verbal knowledge (r = .25) and attention capacity (r = .44), but the dependency of performance on these two factors diminished with experience on the task (to r = .10 and r = .22, respectively). Neither component efficiency nor activation capacity predicted task accuracy at any point in learning. Results for latency provided a different picture. The dependency of task latency on component efficiency and on activation capacity steadily increased from the early trial blocks (r = .23 for component efficiency; r = .05 for activation capacity) to the later ones (r = .55, r = .27, respectively). Attention capacity and verbal knowledge, however, played their most important role during the middle blocks.

(a)

If a new number is presented, determine if it is odd or even.
  If the number is a odd, determine if it is big or small.
    If the number is big, determine if it is at the bottom.
      If the number is at the bottom, press L, else press D
If the number is small, determine if it is at the top.
  If the number is at the top, press L, else press D.
If the number is even, determine if it is a digit or word.
  If the number is a digit, determine if it is at the bottom.
    If the number is at the bottom, press L, else press D.
If the number is a word, determine if it is at the top.
  If the number is at the top, press L, else press D.

(b)



11 blocks @ 64 trials per block

Figure 3. Woltz' Procedural Sequence Task.

Table 1. **Woltz (1988b) Study: Aptitude-Learning Correlations by Trial Block (N = 330)**

Aptitude	**Trial block** 1	2	3	4	5	6	7	8	9	10	11
					Learning Task Accuracy						
Verbal Knowledge	25	21	15	18	21	19	15	12	15	17	10
Component Efficiency	-09	-14	-10	-09	-06	-04	-03	00	-03	-03	01
Attention Capacity	44	41	37	39	37	36	34	29	29	29	22
Activation Capacity	-03	-09	-03	-05	01	04	-03	-03	-03	01	-02
					Learning Task Latency						
Verbal Knowledge	04	-18	-18	-15	-14	-14	-13	-13	-11	-10	-11
Component Efficiency	23	22	36	39	40	46	48	46	50	47	55
Attention Capacity	-01	-14	-19	-21	-26	-25	-21	-22	-23	-24	-18
Activation Capacity	05	08	15	19	17	15	17	19	21	21	27

Note. Correlations were significant at r > .13 (p < .05, 2-tailed).

These findings are consistent with the idea that attention capacity and verbal knowledge are what govern the rate at which initial declarative rule acquisition and proceduralization occur. During these initial stages of learning, performance requires active maintenance and processing of declarative knowledge of the sequential steps. Later performance, dominated by production composition, depends more on component procedure efficiency and activation capacity. Here performance no longer requires the interpretation of declarative knowledge; rather, it depends on the availability or activation of many large, composed productions.

This differential pattern points up the importance of the distinction between attention capacity and activation capacity, which are separable working memory capacity limits. The attention capacity limit pertains to the amount of information that can be simultaneously processed and attended to. This limit apparently governs success in proceduralizing new knowledge. The second limit, activation capacity, corresponds to the temporal nature of the process of automatic spread and decay of activation. Individual differences in this limit, which are reflected in how long one can keep material active in working memory without rehearsal, determine relative success in composing and strengthening new rules.[2]

At one level, Woltz's (1988b) findings are consistent with those of Ackerman (1987) and Fleishman and Hempel (1954), who found that general cognitive abilities are most important in

[2] An alternative explanation is that Woltz's activation capacity measure is a measure of strength accrued by a memory trace from a single retrieval. Woltz and Shute (in preparation) have evidence that this may be correct

early skill acquisition. Ackerman (1987, 1988) interpreted these patterns in terms of a learning model that suggests that early learning depends on general abilities, and that later learning is less dependent on general abilities and more dependent on perceptual and motor skills. But Woltz's results diverge from those of these other investigators in that his results showed that activation capacity (which should be seen as a general cognitive ability in that it affects performance on a wide range of tasks) had increasing relations to performance as practice continued.

Study 2: Acquisition of Skill: Logic Gates

The Woltz (1988b) study was intriguing in showing an apparent dissociation between attention and activation capacity in predicting early versus later success in acquiring a cognitive skill. Our goals for the second investigation (Kyllonen & Stephens, in press) were twofold. First, we wished to investigate skill acquisition on a learning task where proceduralization is an important learning process; that is, one in which subjects are taught rules for operators they have not been exposed to prior to the experiment. This provides somewhat of a contrast to Woltz's learning task in which proceduralization was mostly complete after some initial trials, and in which composition was probably, therefore, the main learning skill being called upon. Second, we wished to include additional measures of cognitive proficiency drawn from the four-source framework, so that we could more precisely evaluate the importance of working memory (activation capacity and attention capacity), as opposed to other cognitive factors, in determining skill acquisition success.

Fortunately, a study recently conducted by Gitomer (1984) suggested an ideal learning task for our purposes: the logic gates task. In Gitomer's paper-and-pencil version of this task, subjects determne how various logic gates (such as AND, OR, etc.) transform incoming signals (e.g., High and Low) to an outgoing value (High or Low). Gitomer administered this task, along with a battery of other tests designed to probe other facets of troubleshooting skill such as tests of electronic component knowledge and retrieval efficiency, to a group of experienced Air Force electronic equipment troubleshooters. Although the study was rather small in scale ($\underline{N}$ = 13), performance on the logic gates task was shown to be significantly related to troubleshooting proficiency as indicated by supervisor ratings. Further, no other task administered by Gitomer was as discriminating in its relationship to rated expertise. This encouraged us to believe that logic gates was an ecologically valid performance task, and that an analysis of the determinants of success in learning logic gates might yield insights into an important class of learning.

Learning Task

Figure 4 illustrates the sequence of events undergone by the subjects participating in the Kyllonen and Stephens (in press) study, along with descriptive statistics for each event.[3] First, subjects were given a paired-associates learning task (the associative pretest) in which they learned to associate gate names (e.g., AND, OR, XOR, INVERT) with pictures of the gates. After achieving a criterion of three successive successful responses, subjects were given 10 to 15 minutes of instruction on how the logic gates worked; i.e., the rules by which incoming signals were transformed to an outgoing signal. Figure 5 presents a synopsis of the instructions

[3]In this paper we are reviewing data from only one of the studies reported in Kyllonen and Stephens (in press), due to space limitations. Also, the present analysis is slightly different from theirs.

we provided in the form of a "cheat sheet" which subjects were allowed to use during the instruction period.

After receiving their instructions, subjects were given a declarative matching test in which they were shown either a name-symbol, name-function, or symbol-function pair (exactly as shown on the cheat sheet), and were required to indicate whether the two paired entities referred to the same logic gate. Following this declarative test, subjects were given a single-gate procedural test in which they were shown signals coming into logic gates (e.g., a High and Low signal coming into an AND gate) and were required to indicate the value (either High or Low) of the resulting outgoing signal. After this, subjects were given a whole-circuit or linked-gates test which required them to evaluate a sequence of linked gates. Then subjects were administered a symbol-name matching test. We assumed that by this point, given all the practice they had received, subjects would have known the symbol-name relationships quite well, and thus response time would reflect the degree to which memory strength for these pairs had accrued automatically as a function of practice.

Cognitive Proficiency Measures

We administered five sets of tests to measure five cognitive factors: general knowledge, processing speed, working memory attention capacity, activation capacity, and proceduralization efficiency. General knowledge measures were as follows: a standard vocabulary test, a survey of general science facts (e.g., "The chief nutrient in lean meat is [a] fat, [b] starch, [c] protein, or [d] carbohydrates?") taken from the Armed Services Vocational Aptitude Battery (ASVAB), and a survey of general world knowledge (e.g., "Photosynthesis is the process by which plants make food from sunlight, true or false?") adapted from Nelson and Narens (1980).

Processing speed measures were (a) a choice reaction time task; (b) a synonym matching task, in which each word used was determined in a pilot-study to be such that 95% of the sample could properly identify its synonym; and (c) a word string (e.g., triangle square circle) and picture string (e.g., pictures of triangles, squares, and circles) matching task adapted from Santa (1977).

We administered two working memory attention capacity measures. The first was a computerized adaptation of Daneman and Carpenter's (1980) reading span test. Subjects read a set of unrelated, successively presented 10- to 15-word sentences. The number of sentences in a set ranged from two to six. After completing the set, subjects typed in the first letter (so as to minimize the importance of typing ability) of the last word in each sentence. To ensure semantic processing of the sentences as they were presented, subjects were required to verify whether the sentences presented were true or not. Half the sentences were declarative versions of the Nelson-Narens general world knowledge questions, and half were falsified versions of those sentences (e.g., "Stockholm is the capital of Norway, true or false?") In fact, these sentences were the same as those used to produce a measure of general knowledge (see above). The subject's working memory score was simply the proportion of last-word first letters typed in correctly.

The second working memory capacity measure was ABC assignment, which had been found to produce reliable scores in a previous study (Christal, 1987). In this task, subjects were presented a series of frames in which either numerical values or simple equations are assigned to the letters A, B, and C. A typical item might present the following frames one-at-a-time (subjects were not allowed to move backwards): "A = B/2" "C = B + A" "B = 4" "B = ?" "A = ? C = ?" This task stresses working memory in that subjects must simultaneously remember the assignments of previous frames and process the current frame. In addition to these two working memory capacity measures, which tap the attention capacity attribute of

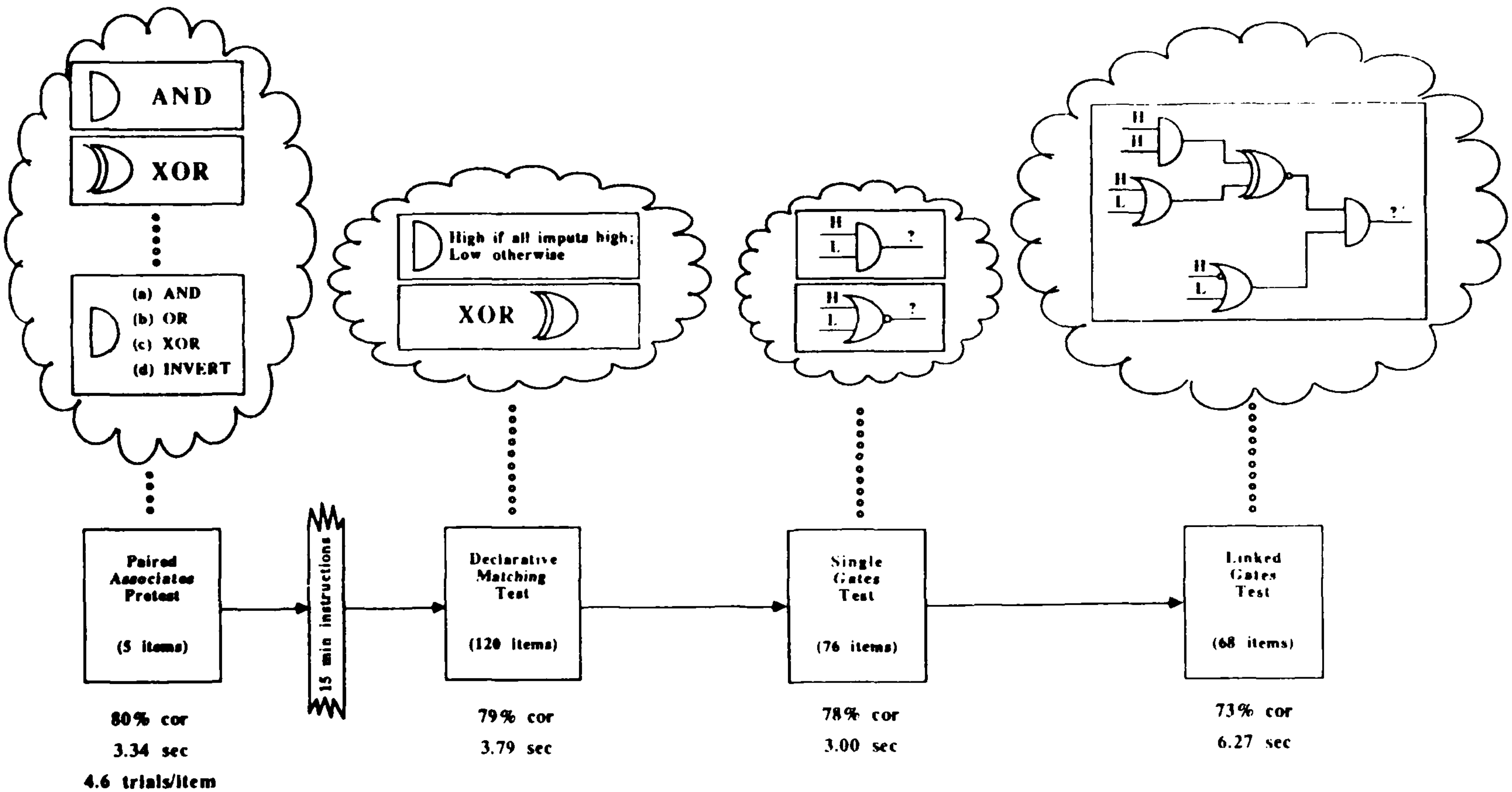


Figure 4. Order of Events for the Logic-Gates Task, along with Descriptive Statistics.

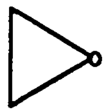
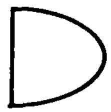
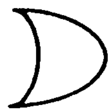
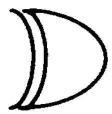
SYMBOL	NAME	FUNCTION
	INVERT	High if incoming signal is low; Low if incoming signal is high.
	AND	High if all incoming signals are high; Low otherwise.
	OR	High if at least one incoming signal is high; Low otherwise.
	XOR	High if only one incoming signal is high; Low otherwise.
	CHANGE	Changes high to low; and low to high.

Figure 5. **Logic Gates Symbols, Names, and Associated Definition (Functions).** Subjects also used this as a "cheat sheet" during initial phases of learning.

working memory, we also administered Woltz's (1988b) latency savings task to measure activation capacity.

We also administered two procedural skill tests designed to measure the efficiency with which subjects were able to transform simple declarative rules into problem-solving procedures. The first task, based on Thurstone and Thurstone's (1941) ABC task, required subjects to transform according to two rules a five-letter string consisting only of the letters A, B, and C (e.g., ABACC). The first rule was that successive same letters evaluate to the same letter (e.g., AA = A; BB = B). The second rule was that successive different letters evaluate to the third letter (e.g., AB = C; CB = A). Working from left to right, one evaluates the first pair, and then takes the result as the first letter of the second pair until a final letter is determined.

The second task, adapted from Harvey (1984) and dubbed the HI-LO task, required subjects to match a cue letter (either X or O) with a spatial position probe (either the word HI or the word LO). The cue letter appeared on the left side of the display screen, either toward the top (High) or the bottom (Low). The probe appeared on the right side of the display screen, either toward the top or the bottom. The cue signalled the rule by which subjects were to make the cue-probe matching judgment. If the cue letter were X, then subjects were to "match by position." That is, an X in the top position, flanked by either probe in the top position, was considered a match; but an X in the top position flanked by either probe in the bottom position was considered a mismatch. An X in the bottom position was considered to match either probe appearing in the bottom position. The cue letter O, on the other hand, signalled subjects to "match by meaning." That is, an O in the top position matched the word HI regardless of whether it appeared in the top or bottom position. An O in the bottom position matched the word LO regardless of whether it appeared in the top or bottom position. (The letter-rule mappings were reversed for half the subjects.) Although Harvey was able to train subjects to the point where they made few errors, we found in our preliminary investigations that considerable variance in accuracy occurred over the 100 trials administered.

Results

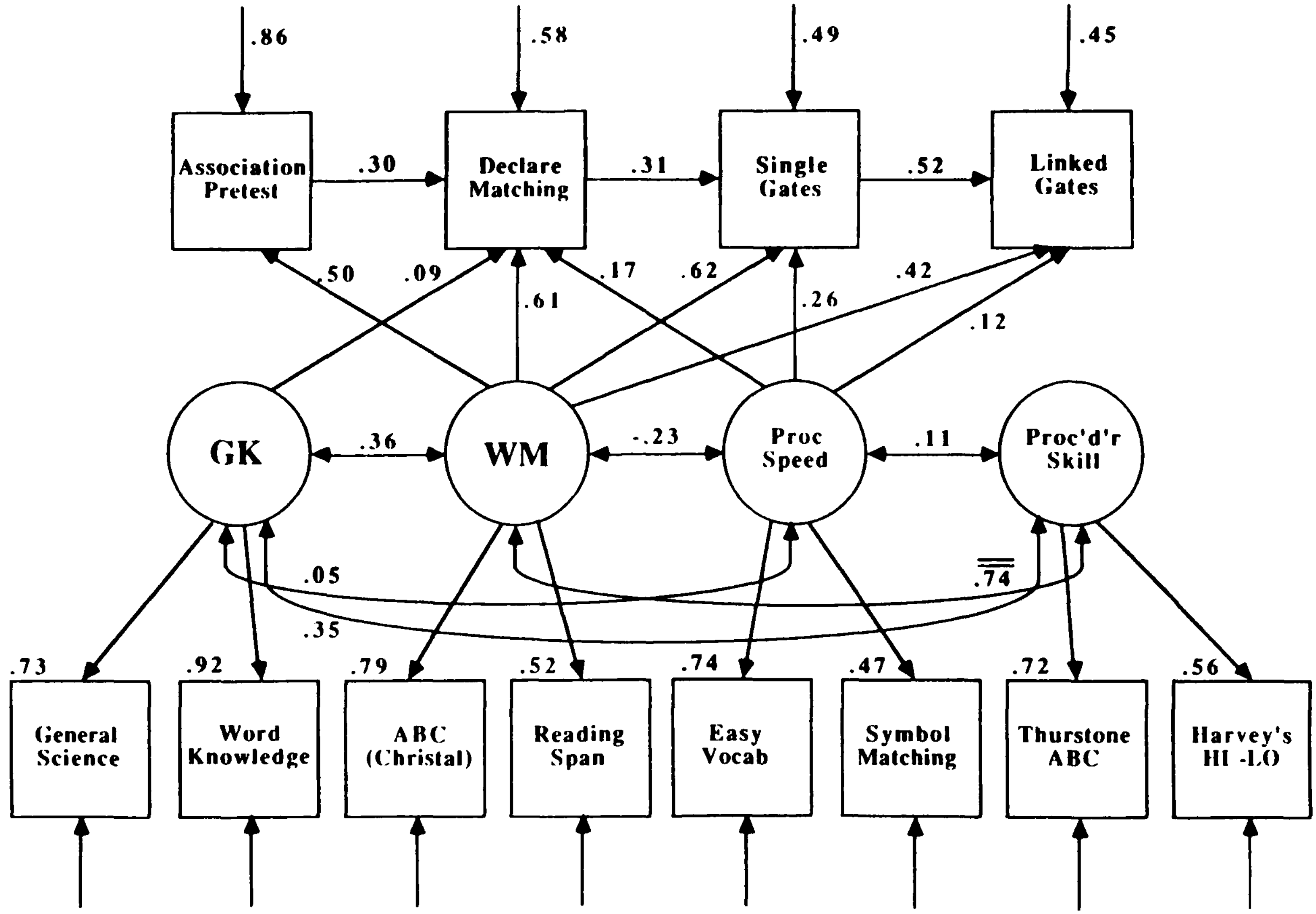
We constructed a number of latent variable path models representing various hypotheses regarding the relationships among the variables and the hypothetical factors measured in this study. In all the models, dependent variables were accuracy measures from the various phases of the learning task: (a) the associative pretest, (b) the declarative matching test, (c) the single gates test, and (d) the whole-circuit test. Independent variables were both (a) factors reflecting performance on the cognitive proficiency measures, and (b) accuracy scores from the previously completed learning phase(s). Models were tested against the variance-covariance matrix of all learning and cognitive task scores (from a reduced sample, N = 144, which had scores on all measures) using Bentler's (1985) EQS computer program. This program fits latent variable path models using full information maximum likelihood procedures to estimate model parameters.

Three issues deserve brief mention before considering results. First, accuracy measures on both learning and cognitive proficiency tasks were typically d' (either computed as z [Hit] - z [False Alarm] or by the Hacker-Ratcliff [1981] forced-choice conversion tables). Although in Kyllonen and Stephens (in press) we provided a theoretical rationale for why d' is the preferred measure, for present purposes it is useful simply to point out that for many of our tasks, d' is often normally distributed (even on the choice-reaction time task which averages 95% accuracy) whereas percent correct usually is not. Second, log latency was typically the latency measure we used. This simply represents a transformation of convenience (log latency is more normally distributed than latency, almost always), without a theoretical rationale. Finally, a reparameterization of accuracy and latency scores from the information processing speed tasks was accomplished as an attempt to deal with speed-accuracy tradeoff problems. (In none of these tasks did accuracy correlate significantly with speed over subjects.) A processing efficiency score was the difference between standardized (0, 1) d' and standardized log latency for each task. A processing carefulness score was the sum of the standardized d' and standardized log latency. This reparameterization was shown in a factor analysis to result in more interpretable processing speed factors.Third, percent correct was chosen as the learning measure on the paired-associates pretest because it is known to be a good estimator of memory strength as indicated by probability of passing on a hypothetical next trial (Underwood, 1964).

Figure 6 shows the best-fitting model and its associated parameter estimates. In this model, the four learning phase scores (from the associative pretest through the whole-circuit test) are ordered as a simplex, reflecting their temporal relationship, and reflecting the hypothesis that performance in each learning phase serves as a determinant of subsequent learning success. In the model, these four learning scores are treated as observed, dependent (i.e., endogenous) variables. (EQS allows free mixing of observed and latent variables in models.) The four scores, in turn, are each regressed on the preceding learning event (except for the associative pretest, which was the first learning event), and four cognitive factors--general knowledge, working memory attention capacity, processing speed, and proceduralization skill. The activation capacity factor is not shown in the figure because it was found to be uncorrelated with any of the learning variables and, therefore, including it in the model resulted in poorer model fits.

Considering first results from the paired-associates pretest, the cognitive proficiency factors accounted for 26% of the variance on this measure, which is roughly consistent with results we have obtained with other paired-associates tasks (Kyllonen & Tirre, 1988; Kyllonen et al., 1989). The fact that working memory capacity was the factor predicting associative learning success is consistent with previous work, and is consistent with our claim earlier, in the context of Woltz's study, that the initial declarative phase of cognitive-skill learning is dependent on attention capacity. However, contrary to past research, no other cognitive measure contributed to the prediction of associative learning success. In previous work (Kyllonen & Tirre, 1988; Kyllonen et al., 1989), breadth of general knowledge added to the working memory factor in predicting declarative learning. It is informative to consider the difference between that previous work and the current study. In this study, the items paired were a name and a symbol. This pairing may have tapped non-semantic spatial encoding mechanisms and thereby reduced the dependence on semantic knowledge. Had we administered a test of spatial declarative knowledge (if such a factor could be defined), we might have expected such a factor to predict success in the kind of associative learning task we administered in this study.

The declarative matching task was designed to reflect the strength (d' accuracy) of subjects' declarative knowledge following study. Subjects performed considerably less than perfectly on this task ($\underline{M}$ = 21% errors), reflecting the fact that subjects exited text instruction with only partial declarative knowledge of the gates. Figure 6 shows that 66% of the individual differences variance in that knowledge ($1 - .58^2$) was accounted for by all factors combined, with accuracy on the immediately preceding paired-associates task accounting uniquely for 9% of the variance. This latter correlation reflects the role of domain-specific knowledge gained as a result of the initial exposure to the symbol-name relationships. Controlling for that domain-specific knowledge, other general cognitive factors contributed to the prediction of how well subjects learned from instruction after they had received initial exposure to the pairs. Specifically, general knowledge ($\underline{r}$ = .09), working memory capacity ($\underline{r}$ = .61), and processing speed ($\underline{r}$ = .17) each uniquely contributed to the prediction of accuracy in declarative matching. Thus, each of these cognitive factors is a partial determinant of the declarative knowledge a subject acquires as a result of studying a short lesson in a text. It is probably theoretically significant that more cognitive factors are relevant in determining learning of actual text than in determining learning of arbitrary associated pairs. It is also noteworthy that of all the factors, working memory capacity again played the most important role in determining learning.



N = 144; χ^2 (63) = 78.5, p = .09; NFI = .912
NNFI = .972

Figure 6. **Structural Equation Model for the Logic Gates Data (Study 2)**. (NFI = Normed fit index; NNFI = nonnormed fit index [See Bentler, 1985])

After declarative matching, the single-gate task was administered prior to the whole-circuit task and was the first chance subjects had to demonstrate procedural skill in tracing signals over logic gates. Mean error rate on this task was 22% (chance was 50%). As can be seen in Figure 6, 76% of the variance in accuracy on the single-gate test was predicted by the factors in the model. Of that, 10% was due to the strength of individuals' declarative knowledge going into the procedural test, and the remaining 66% was due to the general cognitive factors, holding declarative knowledge constant. Thus, there was an excellent accounting of performance on this task, and the cognitive proficiency measures alone accounted for an overwhelming share of the variance in signal-tracing performance. Further, the single factor of working memory capacity (r .62) was responsible for most of the prediction. The single-order correlations are informative. The correlation between signal-tracing accuracy and accuracy on the ABC Assignment task, for example, was .69, a remarkably high correlation between a general cognitive measure and a learning outcome measure.

Following the single-gate task, subjects were administered the whole-circuit task, which differed only in that each item required a series of responses rather than a single response (subjects were given feedback after each response so that there was no response dependency within an item). As shown in Figure 6, 80% of the variance in accuracy on the whole-circuit task was accounted for by all the cognitive factors. Of these, the most important factor was accuracy on the single-gate task, which accounted for 27% of the variance (the single-order correlation suggested an even stronger relationship between the two tasks, $r = .84$). Given this strong relationship, it is somewhat interesting that what uniqueness the whole-circuit task possessed was related to, again, working memory capacity ($r = .42$) and processing speed ($r = .12$). That is, controlling for the strength of procedural gate knowledge, as indicated by performance on the single-gate task, working memory, in particular, was still an important determinant of success in the whole-circuit task. The whole-circuit task probably places greater working memory demands on the subject than does the single-gate task, in that subjects must additionally keep track of where they are on the circuit. Thus, performance on the whole-circuit task, controlling for procedural gate knowledge, reflects the subject's ability to deal with that extra load.

Finally, it is worth inspecting the intercorrelations among the factors. For the most part, correlations are in the modest range, but there are two that stand out. One is the negative correlation between processing speed and working memory capacity (r -.22). Processing speed is the inverse of latency; so, we expected the correlation to be positive. We have administered these measures in other studies and generally do find a positive correlation between these two factors; therefore, we might dismiss this result as anomalous.

A more striking finding is the high correlation between working memory and proceduralization skill ($r = .74$). Recall that we designed the proceduralization factor to reflect the breadth of general procedural skills a subject brings to the testing or learning situation. Because we cannot measure procedural skill directly, we do so indirectly by having the subject learn new rules and apply those rules in problem solving. Put another way, the proceduralization factor reflects proceduralization skill directly (i.e., the ability to proceduralize novel declarative rules), and the breadth of procedural knowledge indirectly. That this factor correlates highly with working memory capacity can be interpreted in at least two ways. First, working memory capacity may be largely a function of the sophistication of the central executive in Baddeley's (1986) model. Subjects with a good store of general-purpose procedural skills have an advantage in monitoring and controlling working memory resources and therefore do well both on the proceduralization tests and on tests of working memory capacity. Another interpretation is that the success of the proceduralization process, which is indicated by performance on the proceduralization factor tests, depends on one's working memory capacity. This interpretation is consistent with our discussion of Woltz's (1988) finding that working memory capacity governs proceduralization success.

Summary and Discussion

The results presented above appear at first glance rather complicated; so it is useful to step back and consider the major findings. First, perhaps the most consistent and striking finding is the role played by working memory capacity (in the attention capacity sense) in determining all phases of learning success. Working memory capacity was shown to predict performance in the initial declarative stages following study of the pairs and study of the text. Next, controlling for how well subjects acquired that initially taught declarative knowledge, working memory capacity played an additional role in determining a subject's success in transforming that knowledge into effective problem-solving procedures that could be applied to the task of tracing signals over logic gates. Beyond this, working memory capacity predicted the success of the transfer of procedural knowledge from the single-gate to the whole-circuit problems.

Second, activation capacity did not exert the same kind of influence on performance as it did in the Woltz (1988b) study. In various models we tested, model fit was always improved by leaving the activation capacity factor out of the model. This suggests that the role of activation capacity might be confined to composition as we suggested earlier.

Finally, the data suggest that acquiring skill on a task like the logic gates task is not appropriately characterized as a continuous process of knowledge incrementing. If it had been, we would have found two results that did not materialize. First, we would have found that performance on one phase of the task was highly predictive of performance on the next phase. This clearly did not happen, as can be seen by comparing the magnitude of the contribution of prior test performance with the contribution of the general cognitive factors. In no instance did prior performance account for even half of the total variance accounted for, suggesting a discontinuity in learning. Second, we would not have found the changing pattern of relationships between cognitive proficiency measures and learning performance variables that we actually observed. Specifically, although working memory capacity affected learning at all phases, declarative knowledge influenced only learning of the text, and processing speed modestly affected learning during all but the initial stage of learning. Together, the pattern of changing relationships with cognitive variables over learning phases and the discontinuities in phase-to-phase performance reinforce the view that cognitive-skill learning has a multidimensional character (cf. Cronbach & Snow, 1977).

VI. CONCLUSIONS

It is useful at this point to reflect on what we have learned about the acquisition of cognitive skill. First, perhaps a rather obvious point is that cognitive-skill learning is not the same as declarative learning. Much of our work over the last several years has been concerned with identifying determinants of declarative learning as evidenced by the extensive data we cited as motivating the four-source framework. But the limitations of this focus are particularly clear when we see that despite the fact that declarative learning can be a necessary first step in establishing the foundation for learning a procedure, success in the declarative portion of a skill-learning task is not necessarily all that highly predictive of success in subsequent procedural portions of that task.

A second point is that working memory capacity, in the attention capacity sense, plays a key role in governing the success of skill acquisition at virtually all phases of skill acquisition. This was certainly true in the Kyllonen and Stephens (in press) study; but even on Woltz's (1988b) procedural task, the relationship between working memory capacity and performance, while declining over trial blocks, still was substantial toward the end of session. One may reach the point in learning where working memory capacity plays only a minimal role, but our data suggest that that point, if reached at all, occurs well into learning, after subjects stop making errors. Our individual differences analyses of the critical role of working memory capacity in cognitive-skill acquisition can be seen as validating conclusions drawn by others who have used alternative methodologies (e.g., Anderson & Jeffries, 1985).

Third, beyond the role of working memory generally, Woltz's (1988a, 1988b) proposal for two kinds of working memory limits (attention capacity and activation capacity) allows a more refined statement regarding the role of working memory in cognitive-skill acquisition. The main finding in Kyllonen and Stephens (in press) was that one of those limits, attention capacity, predicted learning success in all phases of learning. In contrast, Woltz (1988b) concluded that attention capacity was most important early in learning and that activation capacity was increasingly important with practice.

A reason for this discrepancy may be that the two studies tapped different kinds of learning. We claimed that Woltz's (1988b) sequenced cognitive-procedures task, although it required some proceduralization initially as subjects first learned the categorization rules, primarily entailed composition, especially during the later phases of learning. Composition, which combines temporally contiguous productions, is a learning process governed by the temporal flow of information through working memory. Thus, it makes sense that a variable that reflects how long items stay active in working memory (namely, Woltz's activation capacity measure) predicts the success of this process. In contrast, the logic gates task used in the Kyllonen and Stephens (in press) study was claimed to involve primarily the proceduralization of initially declarative rules. There may not have been any opportunity for composition.

To summarize, attention capacity refers to how much information can be held in working memory at one time; activation capacity refers to how long activation can be maintained. The success of learning by proceduralization therefore depends on how much information one can hold in working memory at a time; the success of learning by composition depends on how long one can maintain an item in working memory.

At the beginning of this paper, we proposed that acquiring cognitive skill involved learning how operators worked and learning when to apply them. From this standpoint, the Kyllonen and Stephens (in press) study was concerned primarily with analyzing the cognitive abilities associated with learning how operators worked. It is likely that many of the problems students have with acquiring cognitive skills begin with a failure to understand how the basic operators in the skill domain actually work; thus, we believe there is a significant payoff simply to analyze this part of the skill acquisition process. As evidence, consider that Gitomer (1984) found wide differences among electronic equipment specialists in the basic understanding of logic gates, despite the fact that these individuals had been servicing electronic equipment on the job for at least a year.

But perhaps learning how to select operators in solving problems is an even more important cognitive skill. The difficulty of selecting operators is certainly what makes tasks such as solving geometry proof problems, writing computer programs, designing electrical circuits, and solving physics problems so demanding, especially compared to the parallel tasks of recognizing a good proof, double-checking an already written program and tracing a signal through an already designed circuit. The Woltz (1988b) study can be seen as an initial attempt to understand this part of cognitive-skill acquisition. But there might be fundamental differences between learning when to apply operators (a) in the sense of learning a sequence of procedures as in the Woltz task, versus (b) in the context of these more complex operator selection tasks, such as geometry proof construction. Analysis of skill acquisition in these tasks is an obvious next step in our research programs.

Finally, it is useful to consider the merits of the four-source framework that has guided our research in cognitive task selection. The four-source framework is meant to serve as a first-cut approximation to a fundamental factor model of the cognitive ability space. That is, we believe that individuals differ fundamentally in processing speed, working memory capacity (attention and activation capacity), declarative knowledge, and procedural skills. Although fine-grained distinctions may be made within each of these categories, it is useful to see how far this approach can carry us in predicting success in a variety of learning tasks. We have demonstrated that these sources make independent contributions in determining a variety of learning outcomes and together account for much of the individual variability in learning success. The challenge now is to determine whether other sources not currently included in the framework might make important contributions to important classes of learning.

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