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THE EFFECTS OF INDIVIDUAL DIFFERENCES, DISCOVERY LEARNING,
AND METACOGNITION ON LEARNING AND ADAPTIVE TRANSFER

By

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ABSTRACT

THE EFFECTS OF INDIVIDUAL DIFFERENCES, DISCOVERY LEARNING, AND METACOGNITION ON LEARNING AND ADAPTIVE TRANSFER

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I/O psychologists have asserted that training research should incorporate concepts and principles from cognitive psychology into the design of training environments to facilitate transfer of training (Baldwin & Ford, 1988; Howell & Cooke, 1989; Tannenbaum & Yukl, 1992). This study focused on a particular type of transfer, adaptive transfer, defined as the extent to which individuals can adjust the knowledge and skills learned in training to novel task demands. Two training interventions, derived from cognitive and instructional research, were hypothesized to lead to greater flexibility and adaptability of trained skills -- providing opportunities for discovery learning; and metacognitive instruction. Tolerance for ambiguity and mastery orientation were identified as individual differences that would influence learning and transfer. Multiple learning outcomes were examined as intervening mechanisms in the relationships between training interventions, individual differences, and adaptive transfer.

One hundred sixty-one undergraduate students participated in the study, learning how to perform a complex, computer simulation of a radar tracking task. Results from a series of hierarchical regression analyses provided support for limited portions of the conceptual model. The discovery learning manipulation and metacognitive instruction interacted to influence verbal knowledge and adaptive transfer. The guided discovery manipulation and a mastery orientation to learning led to greater hypothesis-testing and self-regulation during training. Mastery orientation and tolerance for ambiguity were related to self-efficacy at the end of training. Limitations and directions for future research are discussed.

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INTRODUCTION

The success of any training program depends on the extent to which knowledge and skills are transferred back to the job (Baldwin & Ford, 1988; Goldstein, 1993; Wexley & Latham, 1981). Baldwin and Ford (1988) reviewed research on transfer of training and identified three factors that affect the extent to which transfer will occur: trainee characteristics; training design; and the work environment. With regard to the work environment, transfer is more likely to occur if organizational members are supportive of the training and individual's attempts to transfer, and if there are sufficient opportunities to use knowledge and skills back on the job. Recent studies have examined the role of work environment factors such as the climate for transfer (Rouillier & Goldstein, 1990) and the opportunity to perform trained skills (Ford, Quinones, Sego, & Sorra, 1992).

In contrast, current research on transfer of training has paid less attention to the learning principles incorporated into training programs to facilitate transfer back to the job. Baldwin and Ford (1988) argued that learning principles to facilitate transfer have come from a behavioral perspective on learning. Training design research has emphasized observable behavior and its relation to environmental stimuli and reinforcements (Howell & Cooke, 1989). Training principles derived from a behaviorist tradition are relevant when individuals learn highly structured tasks that

require routine and stable responses. However, the tasks that people will be trained for today and in the future impose greater cognitive demands in terms of inference, diagnosis, and decision-making (Goldstein & Gilliam, 1990; Howell & Cooke, 1989). Transfer of training requires not only the mimicking of trained skills on the job, but also the adaptation of trained skills to different situations (Baldwin & Ford, 1988).

Research from the instructional and educational literatures identify types of training transfer that differ in the extent to which adaptation of knowledge and skills is required (Royer, 1979). Research has also suggested different design principles to achieve each type of transfer (Clark & Voogel, 1985; Salomon & Perkins, 1989). In the present study, *adaptive transfer* is identified as a critical type of transfer for organizational training. Trainees should not only transfer skills to problems practiced during training, they should also be able to adapt the knowledge and skills learned to novel problems they may face on the job. The instructional and educational psychology literatures suggest training methods that will facilitate the adaptive transfer of skills. First, research suggests that allowing for *discovery learning* during instruction will facilitate an individual's capability to adapt skills to a novel transfer task (McDaniel & Schlager, 1990). Second, researchers have noted that metacognitive skills are important for the capability to adapt to novel tasks (Salomon & Perkins, 1989). *Metacognitive instruction* that provides individuals with skills in self-monitoring and self-evaluating is suggested as a method to increase adaptive transfer. Research that draws on these perspectives to training design will answer, in part, calls to introduce a cognitive perspective into the training domain (Ford & Kraiger, 1995; Howell & Cooke, 1989).

Baldwin and Ford (1988) noted a second limitation of training design research in that it has failed to consider the effects of both trainee characteristics and the type of training method used. Educational psychologists have long considered the role of individual differences in learning and transfer (Cronbach & Snow, 1977). I/O training research must also consider whether there are individual factors that influence learning and transfer. Two factors relevant for learning and adaptive transfer identified in this study are *tolerance for ambiguity* (Budner, 1962) and the *goal orientation* of the learner (Dweck, 1986).

The focus of the present study is to advance research on training design by considering design principles from a cognitive perspective on learning and transfer. In addition, a specific type of transfer is examined in this study. Adaptive transfer is identified as having particular relevance in present organizational contexts. Several researchers have noted that technology has increased dramatically and thus requires individuals to become flexible learners who are willing to update their skills (Hesketh & Bochner, 1994; Howell & Cooke, 1989). Finally, this study examines individual differences in learners that may also influence what they will learn and transfer.

First, theoretical perspectives on transfer of training will be reviewed, highlighting the contributions of cognitive psychology and the differentiation of types of transfer. Second, adaptive transfer will be defined, and design principles to facilitate adaptive transfer will be identified. Third, research on learning and individual differences will be discussed, and individual factors important for adaptive transfer will be discussed. Finally, a conceptual model will be presented that integrates and extends research on how to train for adaptive transfer.

TRANSFER OF TRAINING

Transfer of training is defined as the extent to which individuals apply the knowledge, skills, and abilities developed in training to the job (Baldwin & Ford, 1988; Goldstein, 1993). Initial conceptualizations of transfer can be traced to the doctrine of "formal discipline" that was favored in the nineteenth century (Patrick, 1992). It was believed that there were general mental faculties such as reasoning and memory skills that could be exercised through training in certain curricula such as math and Latin. These mental faculties could transfer to a wide variety of tasks that used these types of skills.

Thorndike and Woodworth (1901) reacted against this theory and instead proposed a theory of identical elements to explain transfer. According to this theory, the greater the amount of identical elements shared between two tasks, the greater the transfer. Thorndike and Woodworth (1901) were not very clear in defining what these identical elements were, and behaviorists interpreted these identical elements to be stimuli and responses (Butterfield & Nelson, 1989; Patrick, 1992). In order for transfer (i.e., the same response) to occur, the training and transfer environments had to share identical stimulus elements. Behaviorists identified training principles that were focused on how to shape the behavior of individuals during learning. These principles concerned how to structure the learning environment through methods such

as reinforcement schedules, practice schedules, overlearning, stimulus variability, and feedback. Through practice of the correct response and reinforcement of the response, stimulus control of the response was said to occur (Salisbury, Richards, & Klein, 1985). The major educational approach used in current training programs is based on these behaviorist principles (Howell & Cooke, 1989). In addition, most research in I/O psychology on the impact of the learning environment on transfer of training has focused on these behaviorist learning principles (Baldwin & Ford, 1988; Weiss, 1990).

A second theory of transfer has been referred to as transfer through principles (Goldstein, 1993; Patrick, 1992). Experiments by Judd (1908) and Hendrickson and Schroeder (1941) demonstrated that teaching individuals theoretical principles underlying skills facilitated transfer to a task that differed in stimulus features. According to the theory of transfer through principles, instruction on theoretical principles allows individuals to understand the rules underlying behavior and how to apply the behavior to a transfer task that has different requirements. These studies expanded research on transfer in two ways. First, these studies demonstrated that an individual's cognitive understanding of a skill, not just its behavioral execution and reinforcement, is important for transfer. Second, these studies showed that transfer of training can occur to tasks that are not identical to the training task.

A similar perspective developed with the rise of cognitive psychology in the 1960's. New assumptions were made about the role of the learner during the process of learning. The main assumptions of cognitive psychology are that mental processes exist and humans are active information processors (Ashcraft, 1989). Information processing theories began to identify how individuals attend to, encode, store, and

retrieve information. As researchers began studying these mental processes, cognitive explanations for the theory of identical elements began to emerge. For Anderson (1993), the common elements shared between training and transfer environments are production rules. Production rules are If-Then statements specifying the conditions for which an action is appropriate. Positive transfer between two tasks will occur to the extent that the two tasks involve the same production rules. Cormier (1987) described the encoding specificity principle as important to transfer. Stimulus cues in the transfer environment must have been encoded with information learned during training in order for the cues to aid later retrieval of that information during transfer.

Gick and Holyoak (1987) emphasized that it is the perceived similarity between the training and transfer environments, not necessarily the actual similarity, that will determine the amount of transfer. They also identified four determinants of transfer: the structure of the task; encoding factors; retrieval of knowledge; and the learner's background knowledge. Viewing the learner as an active information processor has led to learning principles focused on enhancing the organization, depth, and richness of knowledge stored in memory. Cognitive psychologists have used the constructs of schema, mental models, and knowledge structures to explain how information is stored in memory. Training methods that link the learner's existing knowledge to the to-be-learned material should enhance transfer (Gick & Holyoak, 1987).

Several I/O psychologists have recommended that training research incorporate principles from cognitive psychology when examining learning and transfer (Ford & Kraiger, 1995; Goldstein, 1993; Howell & Cooke, 1989). For example, Kraiger, Ford, and Salas (1993) emphasized that training research and practice must consider

evaluation criteria beyond traditional behavioral measures and simple knowledge tests. They identified additional cognitive and affective outcomes that may be used to evaluate the effectiveness of a training intervention. In addition, Ford and Kraiger (1995) argued that research and practice must redirect attention to understanding the learning process and the role of the learner during learning and transfer.

Researchers have begun to take a multidimensional perspective to learning by developing more integrated models of complex skill acquisition. For example, Kanfer and Ackerman (1989) developed and tested a theory of skill acquisition incorporating individual differences in cognitive ability, motivation, and information-processing demands. Kozlowski, Gully, Smith, Nason, and Brown (1995) developed and tested a model of learning for complex tasks. They examined how individual difference factors and training design interventions impacted outcomes such as declarative knowledge, knowledge structure, training performance, and self-efficacy. In addition, they examined how these learning outcomes affected generalization to a more complex version of the trained task. Smith, Ford, Weissbein, and Gully (1995) examined how individual differences and learning activities affected multiple learning outcomes and training transfer. In addition, they examined a learning environment where individuals were responsible for choosing the exercises they would practice during training. Thus, training research has begun to draw upon cognitive and instructional research to develop more integrated models that examine how the learner plays an active role in the learning process.

However, I/O training research has tended to treat transfer of training as a unidimensional construct. Instructional psychologists have made distinctions between

different types of transfer. Instructional research has also identified individual and instructional factors that lead to these different types of transfer. The I/O training literature can benefit from instructional research by identifying more precisely the type of transfer to be gained from training. Then appropriate instructional factors can be designed into training to promote that type of transfer. The following section describes various conceptualizations of transfer that have been developed in the educational and instructional literatures.

Types of Transfer

Royer (1979) has identified several distinctions that have been made in the instructional literature regarding transfer. For example, Gagne (1965) differentiates vertical and lateral transfer. Vertical transfer takes place when knowledge or skill facilitates the acquisition of superordinate knowledge or skill. Lateral transfer is defined as the generalization of knowledge or skill across a broad set of situations at a similar level of complexity. The literature also distinguishes between specific and nonspecific transfer. Specific transfer occurs when there is a clear similarity between stimulus elements in the training and transfer tasks. Nonspecific transfer occurs when there are no obvious shared stimulus elements in the training and transfer tasks, and is demonstrated by learning to learn and warm-up effects in laboratory experiments. A third distinction in the literature is made between literal and figural transfer. Literal transfer occurs when knowledge or skill is transferred to a new learning task. Figural transfer occurs when an individual uses a portion of their knowledge for thinking or learning about a specific problem. An example of figural transfer is the use of a metaphor or analogy to understand a current problem.

A distinction that has the greatest relevance for transfer of training to the job is that of near v. far transfer. Near transfer occurs when the stimulus complex for the transfer event is very similar to the stimulus complex for the learning event. In contrast, far transfer occurs when the stimulus complex for the transfer event is different from that for the original learning event. In an educational application, for example, far transfer would involve the transfer of learning in school to real-world problems or learning situations (Royer, 1979). However, in organizational settings, one is usually interested in transfer of knowledge and skills back to the job; transfer to another setting such as to life at home or in a social context is not usually necessary. Therefore, the focus of the present study will be on a more specific form of far transfer, which has been labelled **adaptive transfer**.

Royer (1979) noted that the previous distinctions between types of transfer are not mutually exclusive. For example, he suggested that there is considerable overlap between vertical v. lateral transfer and specific v. nonspecific transfer. In the present study, the notion of adaptive transfer overlaps to some degree with the notion of nonspecific transfer as well as the notion of far transfer. A description of adaptive transfer and its distinction from near transfer is presented next.

Near and Adaptive Transfer

Researchers have noted that the distinction between near and far transfer requires the concept of similarity, or in opposite terms, distance from the training task (Butterfield & Nelson, 1989; Salomon & Perkins, 1989). Researchers have also described far transfer as transfer of training to a novel situation (McDaniel & Schlager, 1990). However, they have noted that it has been difficult to define similarity,

distance, or novelty precisely or quantitatively (Butterfield & Nelson, 1989). Gick and Holyoak (1987) have identified two features of tasks that can be used to define and understand the difference between near and far transfer. Training and transfer tasks can differ on two dimensions -- surface components and structural components.

Surface components are features of a task or situation that are not related to outcomes or goal attainment. Structural components are features of a task or situation that are causally or functionally related to outcomes or goal attainment (Gick & Holyoak, 1987). Near transfer can be defined as transfer between two tasks that share structural components, but that differ in minor ways in terms of surface components. For example, students learning to apply the same mathematical formula across word problems with different surface components (e.g., two trains converging v. two cars converging) would be an example of near transfer. Training that exposes individuals to the variety of instances for which the knowledge or skill is applicable would lead to easy retrieval and application of the knowledge or skill to a familiar instance.

Researchers have described far transfer in terms of differences in both surface features and structural features. When the surface features of two tasks are very different, individuals have difficulty spontaneously transferring what was learned from one task to the second task. For example, Gick & Holyoak (1980) found that training on one example where a certain strategy was applicable led to very little transfer to a second example where the surface features were different. In a subsequent study, individuals were exposed to two examples where the strategy applied, and then had to compare the two examples and write a description of their similarity. Gick and

Holyoak (1983) found that the quality of the description predicted transfer to a third example that also varied on surface features.

The conceptualization of far transfer in terms of surface features conforms to what Patrick (1992) defined as the weakest form of novelty between a training and transfer task. The weakest form of novelty involves a task that requires the same method learned in training applied to a new exemplar. This can only be defined as far transfer if training failed to identify and train for all possible exemplars. However, if the correct method or strategy is identified by the trainer, and the range of possible exemplars is also identified and trained, then generalization of the method outside of training becomes a near transfer situation. Individuals exposed to a sufficient variety of exemplars can quickly recognize that a situation falls within the range of those that were trained. They will then retrieve and apply the appropriate method.

In contrast, far transfer can also be defined in terms of differences in the structural features of the training and transfer tasks. Patrick (1992) has identified two additional forms of novelty that are examples of changes in structural components. A stronger form of novelty requires the same methods learned in training but the methods must be reconfigured to handle the novel task. For successful transfer to this type of task to occur, trainees must learn a variety of methods, as well as learn how to select and combine them in order to perform the novel task. Finally, the strongest type of novel task requires different methods to those learned in training. In this case, trainees must learn to identify when an existing strategy is not sufficient, as well as how to create a new and more appropriate one.

From this perspective, **adaptive transfer** can be defined as the capability to adjust knowledge, skills, or methods to successfully handle changes in the structural features of a task. In this sense, adaptive transfer requires additional learning or conscious processing on the part of the learner to adjust what is known from training to what is required in the transfer environment. Adaptive transfer can take several forms. For example, knowledge or skills learned in training must be combined in a different way from the method learned in training. Butterfield and Nelson (1991) provided an example of this, which they labelled inventive transfer. Individuals learned to combine two pieces of information through addition in the training task, but the transfer task required them to combine the information multiplicatively. A second form of adaptive transfer occurs when new knowledge or information is available in the transfer setting that qualifies what was learned in training. Adaptive transfer occurs when individuals are successful in integrating this new knowledge into their existing method or strategy. A third example of adaptive transfer occurs when knowledge or skills learned in training are not appropriate for the transfer task, and a new method for performing the task must be learned.

Several researchers have made similar distinctions between near and adaptive transfer. For example, Hatano and Inagaki (1986) have identified two types of expertise, routine and adaptive expertise. Routine expertise involves the development of procedural knowledge that allows individuals to function effectively in familiar environments. In contrast, adaptive expertise requires the development of conceptual knowledge in addition to procedural knowledge. Individuals who become adaptive experts try to understand more deeply the procedural skills they have developed. This

conceptual knowledge may allow individuals to develop new procedures and make new predictions. Individuals who are adaptive experts are flexible and able to adjust their skills to new problems or situations (Hatano & Inagaki, 1986).

Similarly, Salomon and Perkins (1989) have differentiated between low-road transfer and high-road transfer. Low-road transfer occurs when automatic, well-learned behavior is triggered in a new context. This is consistent with the concepts of routine expertise and near transfer. In contrast, high-road transfer occurs when an individual purposefully and mindfully abstracts knowledge or skills from one context and applies it to another. This is similar to the notion of adaptive transfer or expertise. In fact, research in cognitive and instructional psychology has begun to identify training methods that may lead to greater adaptive transfer. These methods are somewhat different than prescriptions for training for near transfer.

Training for Near and Adaptive Transfer

Cognitive research on the nature of expert performance has helped to identify some of the mechanisms for achieving near and adaptive transfer. Holyoak (1991) has distinguished three generations of theories on expertise. The first generation of theories on expertise are best captured by the work of Newell and Simon (1972). They were interested in problem-solving as heuristic search strategies that could be applied across a variety of domains. Thus, they considered skill at general heuristic search to be the definition of expertise. However, examination of experts in knowledge-rich domains such as chess and physics called this definition into question (Holyoak, 1991). In addition, research provided little evidence that training in general problem-solving skills transferred across content domains.

Research comparing the performance of experts and novices in particular domains found that expertise was dependent on detailed domain knowledge (Holyoak, 1991) and the ability to represent and understand problems in terms of deeper, structural features (Chi, Feltovich, & Glaser, 1981). In contrast to experts, novices relied on the surface features of problems, and engaged in heuristic search strategies. In addition, research indicated that expertise involved extensive time invested in domain learning. Finally, experts were found to store more information, that was better organized, in long-term memory (Anderson, 1993).

This research led to what Holyoak (1991) termed the second generation of expertise theories. He cited Anderson's ACT* theory as a clear example of the second generation theories. Because expertise was defined as knowing how to do something well, these theories focused on studying procedural learning in addition to declarative knowledge (Holyoak, 1991). According to ACT* theory, practice at a task leads to compilation of declarative knowledge into procedural, condition-action rules. Compilation also leads to larger, integrated chunks of procedural knowledge. With continued practice, declarative knowledge becomes less accessible. Instead, speeded-up "rule-firing" leads to automatic and efficient performance (Anderson, 1993; Holyoak, 1991). Interestingly, this cognitive theory of skill acquisition relies on the law of exercise that began with Thorndike (Anderson, 1993). Thus, what this theory provides is a cognitive explanation for the long-standing finding in behaviorist research that learning improves with practice. Holyoak (1991) likened this second generation of expertise to the concept of routine expertise (Hatano & Inagaki, 1986).

In a similar vein, Clark and Voogel (1985) argued that the principles for achieving near transfer come from behaviorist models of training. In general, design principles from the behaviorist tradition tend to lead to near transfer, but are not effective for achieving adaptive transfer. For example, behavioral models assume that instruction is controlled by the instructional design. Methods for instruction typically include behavioral objectives that guide instruction and evaluation, explicit directing and monitoring of the learner's progress, and shorter instructional sessions. In these instructional sessions, language is standardized and simple, practice to criterion is encouraged, feedback and reinforcement are provided, and tests immediately follow instruction (Clark & Voogel, 1985).

Hatano and Inagaki (1986) and Salomon and Perkins (1989) also argue that there are different mechanisms for achieving near and adaptive transfer. For near transfer to occur, repeated practice is a critical requirement. Through repeated experience, individuals learn to perform a skill more quickly and accurately, and eventually automatically (Hatano & Inagaki, 1986). In addition, this extensive practice must include sufficient variability in surface features to allow for generalization of skills to the range of contexts for which they are applicable (Salomon & Perkins, 1989).

Holyoak (1991) described this second generation of theories as a simple picture of the development of expertise. He noted that theories of expertise must account for the ability of experts to induce, retrieve, and instantiate schematic knowledge structures. Serial production systems comprising specific condition-action rules (e.g.,

ACT*) cannot account for the ability of experts to simultaneously integrate multiple sources of knowledge (Holyoak, 1991).

Holyoak (1991) introduced the notion of a third generation of expert theories that corresponds to the notion of adaptive expertise (Hatano & Inagaki, 1986).

Although routine experts can solve familiar categories of problems quickly and accurately, they have difficulty with novel problems. In contrast, adaptive experts can invent new procedures based on their knowledge. The key to their ability to adapt to novel problems is a deeper conceptual understanding of the target domain.

This means that individuals must not only learn procedural knowledge of what to do, but also understand why procedures are appropriate for certain conditions.

Clark and Voogel (1985) argued that a cognitive model for instruction tends to lead to greater adaptive transfer. Using a cognitive approach to design, training methods will include encouragement of discovery strategies for learning, and will facilitate the linking of previously acquired, abstract skills through the use of analogies, paraphrasing, and advance organizers. For example, learners might be encouraged to create their own organization for material to be learned (Clark & Voogel, 1985).

Similarly, Salomon and Perkins (1989) asserted that adaptive transfer depends on the process of mindful abstraction -- the intentional, metacognitively guided decontextualization of knowledge, principles, strategies, or procedures that then can be transferred to a new setting. They also suggested that the processes for near and adaptive transfer can occur at the same time; by both practicing skills and reflecting on their execution, individuals not only improve their performance, but are also able to apply their skills to new situations. Hatano and Inagaki (1986) suggested that the

deeper understanding required for adaptive expertise is more likely to occur when learning involves tasks that are variable and somewhat unpredictable, and learners are given opportunities to explore the task without explicit external rewards. Salomon and Perkins (1989) suggested that the processes called upon during active or exploratory learning are more learner- than stimulus-controlled, and therefore engage the learner's previous knowledge structures in the understanding of the new material. For adaptive transfer to occur, the abstractions that are learned must be understood at a deeper level, not just learned as a formula. Active or exploratory learning settings allow individuals to achieve abstractions through their own efforts, and this should lead to greater adaptive transfer compared to learning settings where individuals learn abstractions by rote (Salomon & Perkins, 1989).

In summary, training for adaptive transfer rests on several key learning mechanisms. First, the learning environment must be one in which the learner is required to engage in more active and exploratory learning processes (Clark & Voogel, 1985; Hatano & Inagaki, 1986). Providing opportunities to discover task strategies will promote adaptive transfer for two main reasons. Discovery learning should lead to a deeper conceptual understanding of the task because a variety of task strategies may be attempted in trying to develop the appropriate task strategy. The learning processes involved in more exploratory learning, namely hypothesis-testing and problem-solving, are capabilities that are in themselves necessary in an adaptive transfer environment. For example, individuals attempting to transfer trained skills back to the job are likely to find little guidance or assistance in these efforts. In addition, problems faced on the job may be more ambiguous or ill-structured compared

to the examples practiced in training. The development of a deeper understanding of the task, as well as practice at discovering task strategies should assist individuals when faced with performing a novel task.

A second factor important for adaptive transfer is the capability to monitor and regulate one's comprehension (Holyoak, 1991; Salomon & Perkins, 1989). Salomon and Perkins (1989) argued that the learning of knowledge and skills must be metacognitively guided so that these knowledge and skills become abstracted and decontextualized. This mindful reflection and evaluation during learning should lead to a more complete understanding of the task being learned. This deeper conceptual knowledge will improve one's capability to adapt to novel tasks.

Two areas of research conducted in the cognitive, instructional, and educational literatures provide suggestions for how to incorporate training design factors that promote adaptive transfer. First, research on the discovery method of instruction has focused on the benefits of an exploratory approach to learning. Second, research on metacognition suggests ways to guide learning activities so that individuals are mindfully monitoring and evaluating the information they are learning. The literatures on these constructs are reviewed with regard to their implications for adaptive transfer.

Discovery Learning

Hatano and Inagaki (1986) argued that the opportunity to explore a task is important for adaptive transfer. In fact, research in educational and instructional psychology has focused on a method for promoting experimentation, discovery learning. In discovery learning, individuals must explore and experiment with the task to infer and learn the rules, principles, and strategies for effective performance. This

has often been described and operationalized as an inductive instructional method. In contrast, explicit training on concepts, principles, or strategies that the individual then applies to task performance is a deductive instructional approach.

Researchers have described several theoretical reasons for the benefits of discovery learning. First, individuals in a discovery learning setting are more motivated because they are responsible for learning, and they are engaging in an active learning process (Singer & Pease, 1976). In traditional instructional approaches, individuals are explicitly taught the correct task procedures, and then they practice the application of these procedures. In contrast, individuals in a discovery learning setting must explore the task and generate correct task strategies on their own. Discovery learning settings promote the use hypothesis-testing and problem-solving learning strategies (McDaniel & Schlager, 1990; Veenman, Elshout, & Busato, 1994). Individuals who use hypothesis-testing approaches during training will have these strategies available to them when they face a novel transfer situation and must search for a new response (McDaniel & Schlager, 1990). Thus, the specific learning strategies used in a discovery learning setting may lead individuals to use similar strategies when adapting to a novel transfer task (Singer & Pease, 1976).

In addition, because individuals must generate optimal methods on their own, the knowledge they acquire becomes better integrated into their existing knowledge (Egan & Greeno, 1973; Frese, Albrecht, Altmann, Lang, Papstein, Peyerl, Prumper, Schulte-Gocking, Wankmuller, & Wendel, 1988). This knowledge is also more flexible because the active processing during learning leads to acquisition of knowledge at a higher level of regulation (Frese & Zapf, 1994). Students who are

first presented with ambiguous material are given the opportunity to organize it in terms of concepts developed through their own constructive abilities (Bruner, 1961).

A final benefit claimed for discovery learning is related to the type of knowledge acquired during training. Researchers have argued that discovery learning allows individuals to make errors and learn from them (Frese et al., 1988; Ivancic & Hesketh, 1995/1996; Singer & Pease, 1976). While traditional behavioral approaches have sought to minimize errors or incorrect responses (e.g., Skinner, 1987), some researchers taking a cognitive perspective to learning have argued that error-making is beneficial to learning. Individuals learn not only from performing a task correctly but also from making mistakes. Making mistakes leads to the development of a better operative mental model of the task (Frese et al., 1988). In addition, the exploration of dead ends and mistakes may provide individuals with a greater repertoire of strategies to try out when faced with an adaptive transfer task (McDaniel & Schlager, 1990).

An early review of discovery learning studies indicated that, in general, discovery learning (inductive learning) leads to greater transfer than rule-example methods of instruction (deductive approach) (Hermann, 1969). In addition, there was a slight tendency for discovery learning to be more effective for transfer over longer time periods, and for transfer tasks that were more complex or novel. The rule-example method led to greater retention than discovery instruction. However, there were nonsignificant results in a number of studies comparing these two instructional methods. Hermann (1969) noted a number of limitations of the existing literature. For example, experimental groups had differed on additional factors such as the amount of time spent learning, the number of examples presented, the meaningfulness

of the material, and the amount of activity during learning. An additional limitation from an I/O training perspective is that this early literature on discovery learning had focused on either relatively simple tasks such as coding or understanding word relationships, or on academic tasks such as mathematics and other subjects. It is not clear from this early literature whether or not a discovery learning method is effective for more complex cognitive and/or motor skills.

Hermann (1969) noted that one of the key factors in the effectiveness of discovery learning methods is the amount and type of guidance provided to learners during instruction. In general, research suggests that a reasonable degree of guidance is more effective than little guidance during discovery learning. Guidance can include the following types: providing answers to problems; providing leading questions or hints to learners either based on individual progress or constant across learners; varying the size of steps in instruction; and providing prompts without giving solutions (Hermann, 1969; Kamouri, Kamouri, & Smith, 1986). However, Hermann (1969) noted that type of guidance had not been systematically examined in the literature.

Current research. Some contemporary research on discovery learning has examined the theoretical mechanisms underlying the effectiveness of discovery learning over procedural instruction for transfer of training. For example, Kamouri, et al. (1986) compared an exploration-based (discovery) condition, in which individuals experimented with three analogical training devices, to an instruction condition, in which individuals were presented with specific procedures (i.e., rules) to practice on the devices. The exploration-based discovery condition led to greater transfer to an analogous, novel transfer device two days later, compared to transfer to a disanalogous

device. This benefit was not found for the instruction condition. In addition, the discovery learning group reported greater similarity between the training devices and analogous transfer device compared to the instruction group. Results suggested that the exploration-based training promoted the use of analogical reasoning and facilitated the induction of abstract device schema (Kamouri et al., 1986).

Other researchers have examined the role of errors during training. For example, Prather (1971) compared trial-and-error training v. errorless training on a range estimation task. In the trial-and-error learning condition, individuals had to press the trigger when they estimated that a simulated target was at the correct open-fire range. In contrast, the errorless learning condition required individuals to press the trigger when a green light came on. This light came on at precisely the correct open-fire range. Results indicated that trial-and-error learning led to greater transfer of training to a photograph of a MIG-21 at various ranges.

Frese, Brodbeck, Heinbokel, Mooser, Schleiffenbaum, and Thiemann (1991) examined error-free v. error-training conditions for learning word processing software. The error-free group received written instructions on each step for the commands used for solving each word processing task. In contrast, the error-training group did not receive detailed instructions for each task. Instead, individuals in this group had to discover which were the appropriate steps and commands to solve the tasks. Error-training participants were provided a leaflet with all the necessary commands, and were presented with heuristics on an overhead screen to counter the frustrating effects of making errors (e.g., "I have made an error. Great!" and "There is a way to leave the error situation").

Results indicated that the error-training group recalled significantly more commands than the error-free group. While the two groups were equally competent at easy and medium difficulty tasks, the error-training group was significantly more competent at handling difficult tasks. Surprisingly, the two groups did not differ on a transfer task requiring them to solve three tasks not taught during training. Finally, the correlation between the number of keystrokes and the performance rating on the transfer task was higher in the error-training group than the error-avoidant group. The authors suggest that the error-training group learned to explore the task (i.e., more keystrokes), and those who explored the task also performed better (Frese et al., 1991).

Other research has been focused on the notion of guided discovery learning, and various conceptualizations of guided discovery have been compared to pure discovery and procedural instruction conditions. Guidance has been operationalized in some studies as the degree of cues or prompting that are given to individuals in terms of the correct task procedure. For example, in teaching a serial manipulation task, Singer and Pease (1976) included a combination condition of prompted instruction and discovery learning. In the first four practice trials, cues appeared on a screen to indicate each correct move in the sequence. Then for the remaining sixteen trials, the learners had no cues available and had to practice the correct sequence without prompts. This combination condition was compared to a pure discovery condition, in which participants had to discover the correct move sequence, and a prompted instructional condition, in which participants were cued on the correct moves for all training trials. Dependent variables were measured as the time to achieve the correct task procedure. Participants in the prompted instruction and combination instruction

conditions outperformed the discovery condition during the learning of the task. However, the discovery and combination conditions performed better than the prompted group on a retention test, and initial trials of a novel transfer task on the following day (Singer & Pease, 1976).

Guidance has also been operationalized in terms of reducing the total variability of possible responses. For instruction on a mirror tossing task, Greenockle and Lee (1991) compared single guidance, variable guidance, and discovery conditions. The single guidance condition allowed participants to practice throwing a volleyball to rebound off a circle marked on a wall in order to hit a target on the floor hidden by a partition. This circle was in the correct position for the ball to hit the floor target. The variable guidance condition allowed participants to practice throwing the volleyball at three circles at different locations on the wall. The discovery group had no targets marked on the wall and they had to find the correct area on the wall in order to hit the floor target accurately.

During acquisition, participants in the single-guidance group performed significantly better than the discovery group, with the variable-guidance group falling in between the other two. Participants were tested on a transfer task that required them to throw the volleyball at the same target but from a greater distance. No significant difference for groups or for the groups X trial interaction was found on the transfer task, but follow-up comparisons indicated that the variable-guidance group outperformed the discovery group on initial transfer trials (Greenockle & Lee, 1991).

Researchers have also examined discovery learning of problem-solving tasks. In these tasks, researchers have operationalized a guided discovery learning condition

as one in which the general strategy for accomplishing the task is known, but where the specific moves or routines for accomplishing the strategy must be discovered (Carlson, Lundy, & Schneider, 1992; McDaniel & Schlager, 1990). For example, McDaniel and Schlager (1990) conducted an experiment to teach individuals how to solve water-jar problems. These are transformation problems where individuals must learn how to obtain a specific amount of water using a number of jars of different sizes. The complete discovery condition required individuals to figure out both the general strategy and the specific move sequence. The guided discovery condition provided individuals with the general strategy and they had to discover the specific move sequence. An example of a general strategy is $1 - 2 + 1$, which indicates that one jar must be filled with water, and then two of another jar subtracted and one of a third jar added. For far transfer to a task requiring a different general strategy than those learned in training, the pure discovery condition led to greater transfer (measured by time to solution) than the guided discovery condition.

Carlson, Lundy, & Schneider (1992) examined four instructional conditions for learning how to troubleshoot a simulated information network. They examined the impact of these conditions on transfer to problems containing more complex information networks. A discovery condition provided no guidance to learners. A variable template condition allowed individuals to choose from a number of possibly correct moves at each step. A fixed template condition only allowed individuals to choose the one correct move to make at each step. Finally, a procedural instruction condition provided learners with instruction on the algorithm they should use to troubleshoot the network. In addition, Carlson et al. (1992) examined whether

guidance in the form of memory aiding (i.e., leaving the status of all tested components on the screen) would lead to greater transfer compared to no memory aiding. The procedural instruction group with memory aiding performed most effectively on the transfer task. This procedural group was followed by the discovery groups, the variable template group with memory aiding, and the procedural instruction group without memory aiding which did not differ significantly from one another. Both fixed template groups and the variable template group without memory aiding performed significantly worse than the discovery groups.

Andrews (1984) compared discovery learning and expository methods for teaching students about a chemical concept. The discovery learning method differed from traditional instruction in the order in which practice and concept introduction are presented. In the discovery learning method, instruction begins with an exploration phase which allows learners to work with the materials and experiment with different ways to understand the material. Once the learners have been given the chance to explore the material, clarifying and explanatory concepts are introduced. Thus, the second step builds on what the learner has already discovered inductively, and adds any additional concepts not discovered. This can be considered a form of guided discovery, in that individuals are eventually taught the correct concepts after having a chance to explore the materials. In contrast, the expository format begins with concept introduction and explanation, followed by a phase of working with the materials. This is a deductive approach where the practice becomes an application exercise. Andrews (1984) found that the discovery learning format led to superior performance on an immediate posttest.

Summary and limitations. Current research on discovery learning has made several advances since Hermann's (1969) review of the literature. First, some research has examined the processes theorized to account for the benefits of discovery learning on transfer of training. When using a discovery learning approach to learn how to use several analogous devices, an analogical reasoning process assists individuals to transfer this knowledge to another analogous device. Several studies have also shown the positive function of errors during instruction. A second advance of the discovery learning literature is that it has expanded its domain of tasks to include perceptual-motor skills, problem-solving skills, and job-relevant tasks such as range estimation for pilots and word-processing skills. Third, this literature has focused attention on operationalizing guidance in a discovery learning environment.

However, results of this current research are not conclusive for the benefits of pure discovery and guided discovery learning. Some research has found that discovery learning (Frese et al., 1991), guided discovery learning (Andrews, 1984), or both methods (Singer & Pease, 1976) led to better performance on learning and retention measures compared to more traditional, structured approaches. However, others have found opposite results (Greenockle & Lee, 1991). Similarly, some research has found that discovery learning leads to greater transfer of training to novel transfer tasks (Kamouri et al., 1986) compared to procedural instruction. Other research has found that procedural instruction with memory aiding leads to greater transfer than discovery learning (Carlson et al., 1992). Finally, research has found that pure discovery is better than guided discovery for far transfer (McDaniel & Schlager, 1990), while other

research has shown the two methods to have similar results (Singer & Pease, 1976), or that guided discovery is more effective than pure discovery (Greenockle & Lee, 1991).

Reasons for these inconsistent results may be the different types of tasks used, the different operationalizations of transfer, and the different operationalizations of discovery, guided discovery, and traditional (i.e., procedural or expository) instruction. In fact, the conceptualization and operationalization of guided discovery has been limited in the literature. The guided discovery conditions have mainly focused on ways to limit the range of responses a subject may attempt in learning the task, or providing some information that limits the range of errors that could be made. One of the major theoretical mechanisms for the effectiveness of discovery learning is the opportunity for individuals to engage in active hypothesis-testing and problem-solving; however, instructional research has not based operationalizations of guided discovery on this theoretical foundation. It would seem that providing guidance to learners to focus their attention on forming hypotheses about the learning material and testing these ideas out would be an effective way to provide more structure to a discovery learning environment. No research in the instructional literature was found that examined how to guide individuals in hypothesis-testing and problem-solving during discovery learning.

In fact, only one study was found that actually examined an instructional condition employing a hypothesis-testing approach. Specifically, Frese et al. (1988) were interested in comparing three instructional methods for teaching computer software skills. The instructional conditions varied on two dimensions: sequential v. integrated training; and passive v. active development of a mental model. One

condition was labelled the sequential group (sequential training, passive mental model). The instruction for this group focused on the step by step keystrokes for commands that individuals would use in word processing software. The chances to make errors were minimized, and no explanations were given for why certain commands had to be used. A second instructional condition was a hierarchical group (integrated training process and a passive development of a mental model). In this group, individuals were provided with a manual plus a hierarchical diagram presenting all the commands to be learned. The materials also gave explanations and mnemonic aids. The third group was called the hypotheses group (active training process plus an integrated mental model). Individuals did not receive any written material because they were to develop their own mental model of the system. Individuals were asked to develop hypotheses about commands to use to correct a flawed text, and were encouraged to try out solutions they developed.

Results indicated a marginally significant difference in recall across the groups on the second day of instruction, which disappeared on the third day of training. On the third day of training, participants had to type a copy of a text under speeded conditions. Results indicated that the sequential group took longer than the hierarchical group to correct errors made (marginally significant). The sequential group also took significantly longer than the hypotheses group to correct errors made in typing the text. Participants were also tested on a non-speeded performance test where they had to correct errors in a text. A marginally significant difference was found between groups in the number of keystrokes used to make difficult corrections. Transfer to a relatively easy command not taught in training was significantly different

for the sequential and hypotheses groups. The hypotheses group learned the new command in significantly less time than the sequential group (Frese et al., 1988).

The results of this study are suggestive of the beneficial effects of guiding individuals in a hypothesis-testing approach to learning. However, the very small sample size (five participants per group) led to a number of effects reaching only marginal levels of significance. In addition, the study did not find significant differences between the hypotheses group and the hierarchical group. One could argue that the hierarchical group is in fact more representative of current training prescriptions and practice compared to the sequential group. Therefore, it is not clear from this study that the hypotheses instruction is better than current training practices.

From a theoretical standpoint, one would also need to assess whether providing guidance in hypothesis-testing leads to greater learning and transfer than just providing an environment of pure discovery. Finally, the transfer task used in the study was limited from the standpoint of the notion of adaptive transfer. During training, participants were focused on learning an interrelated set of commands for performing the task of editing a flawed text. However, the transfer task used in this study was the amount of time necessary to learn one new command. These two tasks are not comparable in their levels of complexity (Wood, 1986). A research question to be answered is whether or not guidance in hypothesis-testing leads to greater adaptive transfer to a task at the same or higher level of complexity and task demands compared to the training task.

Thus, the Frese et al. (1988) study was a positive step in conceptualizing and operationalizing guidance consistent with the theoretical basis for discovery learning.

Research questions remain concerning its real benefit compared to traditional instruction and pure discovery learning, as well as its effect on adaptive transfer tasks.

A final limitation with current research on discovery learning is that no attempt has been made to assess the influence of this instruction on the structure of the learner's knowledge. Several researchers have suggested that guided discovery and pure discovery learning will lead to better integration of new knowledge into the learner's existing cognitive structure. In addition, this knowledge has been hypothesized to be more complete due to the understanding of errors and incorrect task strategies. However, research has not examined learning outcomes that assess aspects of the structure of the learner's knowledge.

Allowing for exploration during learning was one condition identified as important for adaptive transfer. Several researchers have noted that metacognitive skills are critical for individuals to benefit from opportunities to explore the task (Leutner, 1993; Veenman, et al. 1994). An implicit assumption made in discovery learning research is that the learners are actively engaged in planning, monitoring, and correcting errors. However, individuals differ with respect to their metacognitive skills. Some individuals may not know how to take advantage of the opportunities of a discovery learning environment; individuals with insufficient metacognitive skills may not engage in systematic learning activities (Veenman et al., 1994). Novices in particular may lack the skills for planning, monitoring, and revising task behavior (Dorner & Scholkopf, 1991; Etelapelto, 1993). With a limited exception (Veenman et al., 1994), research on discovery learning has not examined the benefits of providing

metacognitive instruction. The next section reviews literature on metacognition to identify ways to promote mindful learning.

Metacognition

An individual factor that has been identified as important for adaptive transfer is metacognition (Salomon & Perkins, 1989). Metacognition is defined as one's knowledge of and control over one's cognitions (Flavell, 1979). It includes planning, monitoring, evaluating, and revising goal-directed behavior (Karoly, 1993). Metacognition is hypothesized to facilitate learning because individuals with greater metacognitive skills can monitor their progress, determine when they are having problems, and then adjust their learning or performance strategies accordingly. In addition, the knowledge acquired through metacognitively guided learning is hypothesized to be more abstract and decontextualized; therefore, it is more likely that individuals will apply this knowledge to a novel task (Salomon & Perkins, 1989).

Nelson and Narens (1990) described two major components of metacognition: monitoring and control. Cognitive processes are split into at least two interrelated levels: the meta-level and the object-level. The object-level performs some process in relation to a goal state defined by the meta-level. Metacognitive control consists of the modification of the object level by the meta-level. Metacognitive monitoring involves information from the object-level apprising the meta-level of the current state or situation.

Other metacognitive theories also suggest that cognitive processing is hierarchically organized (Carver & Scheier, 1982; Johnson-Laird, 1983). Johnson-Laird's (1983) theory of consciousness is based on three major components:

hierarchical parallel processing; recursive embedding of models; and the existence of a higher-level model that controls the parallel hierarchy. The high-level processor controls the overall goals of lower-level processors, which monitor the processors at even lower levels. Similarly, Carver & Scheier (1982) posit that individuals possess a hierarchy of control systems, including both superordinate and subordinate goals. Goals for the higher level control systems are more abstract, while goals lower in the hierarchy become increasingly concrete. In addition, the systems are linked in that the behavioral output of the higher level system provides the reference value or goal for the next lower level system (Carver & Scheier, 1982).

The notion of monitoring and control can be traced back to Miller, Galanter, and Pribram (1960). In response to the behaviorist emphasis on stimulus and response, Miller et al. (1960) argued that individuals consciously monitored and controlled their cognitive processes. They suggested the TOTE unit (Test-Operate-Test-Exit) as the element of behavior. This idea of a feedback loop is also critical to current conceptualizations of control theory (Carver & Scheier, 1982). This negative feedback loop serves to reduce sensed deviations from one's comparison value, or goal. An individual senses information from the environment, compares that information to his/her goal, and if there is a discrepancy, decides on a response to reduce the discrepancy between the information and the goal (Carver & Scheier, 1982).

Self-regulation theories are broader than a strict definition of metacognitive monitoring and control, in that self-regulation can occur at various levels of consciousness (Lord & Kernan, 1987). In contrast, metacognition is concerned with conscious, executive-level monitoring and control processes. In this study, the

processes of metacognitive monitoring and control and self-regulation are considered synonymous because the study is focused on this activity at a conscious level.

Social cognitive theories of self-regulation have identified similar processes that regulate action: self-observation; self-judgment; and self-reaction (Bandura, 1991; Schunk, 1989). In addition, social cognitive theories emphasize the role of self-efficacy during self-regulated behavior such as learning. Self-efficacy is defined as ". . . judgments of how well one can execute courses of action required to deal with prospective situations" (Bandura, 1982, p. 122). Bandura and Wood (1989) define self-efficacy as the ". . . beliefs in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands" (p. 408). Self-efficacy judgments are based on internal cues such as ability, past experiences, attributions for one's behavior, and level of anxiety, as well as external cues such as task attributes, modeling, and verbal persuasion (Gist & Mitchell, 1992). Thus, self-efficacy judgments are based on more than just assessments of one's ability; factors such as the complexity of the task, level of arousal, and attributions for success will also play a role.

Self-efficacy and self-regulatory processes are hypothesized to reciprocally influence one another during learning. For example, self-efficacy affects the personal goals that are set. It is also affected by the successful attainment of these goals. Even if individuals negatively evaluate their goal attainment, they may feel efficacious if they believe they can improve their progress through increased effort (Schunk, 1989).

In all these conceptualizations, an individual actively monitors information relevant to a goal or standard, and if there is a discrepancy between the goal and

behavior, engages in control processes to modify either thought or behavior.

Furthermore, cognitive processes are hierarchically organized, such that the highest-level processor, the metacognitive component, monitors and controls processing at lower levels. These self-regulatory theories have had the most impact on the I/O literature in the motivation domain (e.g., Lord & Hanges, 1987; Klein, 1989), but have received less attention as factors important during learning.

Research on the self-regulatory aspects of metacognition has occurred in a number of psychological disciplines. Research has been focused on the developmental and neurological aspects of metacognition, as well as the bases for metacognitive monitoring judgments and their relationship to metacognitive control. Some research has examined differences in metacognition between experts and novices in different domains. The following section describes examples of this research, with a focus on the processes of metacognitive monitoring and control.

Research on metacognition. Cognitive and developmental psychologists have examined the development of metacognition and its specific components. A majority of this research has focused on metamemory processes. Metamemory is the knowledge and regulation of one's memory (Nelson & Narens, 1990).

Developmental studies of metacognition indicate that some metacognitive knowledge and monitoring develops earlier in childhood. Bisanz, Vesonder, and Voss (1978) found that young children can accurately discriminate correct and incorrect responses. However, they found a time lag between when individuals can make these discriminations, and when they begin to use a metacognitive strategy of distributing processing effort to previously correct and incorrect items. Kreutzer, Leonard, and

Flavell (1975) found that by the third and fifth grades, children had a better understanding of the variability of memory ability over occasions and people, and showed more planning ability than younger children.

Cognitive psychologists have primarily focused on examining four types of monitoring judgments that occur during various stages of memory. The majority of research has examined Feeling-of-Knowing (FOK) judgments, which occur during or after acquisition of items on a memory task, and are predictions about whether a currently nonrecallable item is known and/or will be remembered on a subsequent retention test (Nelson & Narens, 1990). Although some research shows that FOK judgments are relatively accurate indicators of memory (Hart, 1965), their lack of perfect prediction has led to various theories regarding the mechanisms underlying these judgments (Nelson, Gerler, & Narens, 1984). Two theories that have received attention are the trace-access mechanisms perspective (Nelson et al., 1984) and the inferential mechanisms view (Costermans, Lories, & Ansay, 1992; Metcalfe, Schwartz, & Joaquim, 1993; Reder & Ritter, 1992). Metcalfe et al. (1993) provided evidence that FOK judgments are related to familiarity of cues rather than to partial information about the target in memory. Therefore, they argued that metamemory judgments are frequently inaccurate because individuals use a cue-familiarity heuristic to make these judgments rather than assessing the target itself.

Research has also examined the link between metamemory monitoring and control processes. Zacks (1969) provided some early evidence that individuals actively control and modify their learning strategies. She found that individuals engaged in self-paced paired-associate learning allocated more study time to difficult items and

less study time to easy items. Belmont and Butterfield (1971) also found that individuals allocated different amounts of study time to items in free recall tasks. Bisanz et al. (1978) found that, for college students, discrimination of correct and incorrect responses (a monitoring function) was related to acquisition performance in subsequent trials. Individuals discriminated their own correct and incorrect responses on a given trial in learning a paired-associate list, and used this information for distributing processing effort on the subsequent trial.

Pressley, Levin, and Ghatala (1984) showed that metacognitive experiences are important for understanding the relative utility of the control strategies of repetition and associative elaboration. They found that for adults, awareness of the greater utility of the elaboration strategy only occurred following practice with the two strategies along with a performance test. Pressley et al. (1984) explained their results as evidence that metacognitive experiences change people's metacognitive knowledge, which leads to modifications of their goals and actions.

Finally, Justice and Weaver-McDougall (1989) found that adults possess metacognitive knowledge about the effectiveness of potential memory strategies within and across task situations. In addition, they found that participants tended to choose the strategies they judged to be relatively effective when actually performing the different memory tasks. Interestingly, individuals' judgments of relative effectiveness of task strategies changed after performing the memory tasks. These results provide evidence that individuals use feedback from task performance to modify their metacognitive knowledge and subsequent control processes. In sum, several metacognitive monitoring judgments are related to control processes of strategy

selection and choice. In addition, research indicates that adults possess a repertoire of memory strategies that they can effectively apply and modify in various task situations.

Research on expert-novice differences in metacognition have taken a broader perspective to metacognition compared to metamemory research. First, this research indicates that experts in a domain have superior metacognitive skills compared to novices. For example, Larkin (1983) found that experts in physics would be more likely to discontinue ineffective problem-solving strategies than novices. Etelapelto (1993) found that expert computer programmers had superior metacognitive understanding of the programming task, of ideal working strategies, and a better awareness of their own performance strategies.

Dorner and Scholkopf (1991) found that experts spent more of their time at the outset setting their goals and establishing an understanding of the system. In contrast, novices began taking action earlier by making decisions. Dorner and Scholkopf (1991) characterize experts as individuals who analyze the facts of a situation, and program their actions based on self-instructions. Experts do not follow these self-instructions blindly; instead, they use self-reflection to continually check and recheck their actions. Experts pay particular attention to failures, modifying their strategies when appropriate.

In summary, research on metamemory is somewhat mixed on how accurate people are in making these metacognitive judgments. In contrast, research on experts, which examines metacognitive processes more broadly, does provide evidence that these processes improve with extensive experience. However, this research does not provide clear prescriptions for how to build this metacognitive knowledge. Research

in instructional psychology has examined methods for instruction and promotion of metacognition during learning.

Research on interventions to promote metacognition. Psychologists have suggested that metacognitive activity may facilitate adaptive transfer through its impact on the knowledge and skills acquired during training (Salomon & Perkins, 1989). Individuals who plan their learning activities, and monitor and evaluate their understanding are expected to develop more principled and abstracted knowledge about the task. In addition, theories of self-regulation also implicate motivational processes in the effectiveness of these activities (Bandura, 1991; Schunk, 1989). In particular, researchers have hypothesized that instruction on monitoring and control processes can increase beliefs in one's self-efficacy. Self-efficacy has been identified as a critical factor that provides resilience in the face of changing or difficult task demands (Bandura & Wood, 1989). Researchers in the areas of instructional psychology and education have examined how metacognitive interventions can influence knowledge as well as motivational outcomes such as self-efficacy.

It should be noted that there are several problems with how metacognition has been conceptualized and operationalized by researchers interested in learning. First, the term metacognition is somewhat fuzzy in definition. In fact, it is often difficult to determine whether a phenomena of interest is metacognitive or just plain cognitive in nature (Brown, 1987). Research in the areas of reading, writing, and studying provide examples of this definitional problem. For example, Flavell (1976) pointed out that activities such as asking oneself questions about the text being read might function to improve one's knowledge (a cognitive function) or to monitor it (a metacognitive

function). Brown (1987) conceded that some of this literature is calling any strategic activity during reading as metacognitive in nature.

Nonetheless, it is possible to differentiate between the learning strategies individuals use to act upon and understand learning materials, and the executive-level processes and activities involved in monitoring and controlling cognition and behavior. In this sense, metacognition can be limited to activities of planning, monitoring, and evaluating cognition, learning strategies, and task strategies. These activities have generally been labelled self-regulatory strategies or self-regulated learning in the educational literature.

A number of studies in the educational literature have focused on teaching self-regulatory strategies to young children and, specifically, to those with learning abilities (Sawyer, Graham, & Harris, 1992). Results have generally been positive for training these groups in self-regulatory skills. For example, Sawyer et al. (1992) examined the effectiveness of teaching a multicomponent planning strategy for writing stories to students with learning problems. Specifically, they examined whether this instructional method, self-regulated strategy development (SRSD), would be more effective with the addition of explicit instruction in goal setting, self-assessment, and self-recording (full SRSD) than without this additional self-regulatory instruction (SRSD-WESR; i.e., without self-explicit regulation). A third condition removed any implicit self-regulatory instructions from the SRSD strategy and was called a direct teaching condition. One control group included students who wrote stories without instruction (practice-control). A normally-achieving group served as another control condition.

Results of the three-week training were as follows: posttest stories written by the full SRSD (with self-regulated strategy training), those in the SRSD-WESR group, and the normally achieving group received significantly higher grammar scores than the practice-control group. In addition, there were no significant differences between the SRSD, SRSD-WESR, and direct teaching methods on the posttest story grammar measure; however the direct teaching method also did not differ from the practice-control condition. No significant differences were found between the three instructional conditions on the quality of the posttest story. In contrast, students in the full SRSD condition did receive significantly greater story grammar scores on a generalization task (back in their classroom) compared to the SRSD-WESR and direct teaching conditions, which did not differ from one another. However, no impact of instructional condition was found on quality of the generalization story. Contrary to hypotheses, instructional conditions and the practice-control group did not differ on posttest self-efficacy (Sawyer et al., 1992).

Seabaugh and Schumaker (1994) examined the impact of instruction on self-regulation skills on the application of these skills to completing individual lessons. Their sample of 11 students included learning-disabled and nondisabled students enrolled in an alternative school for nonfunctional students. In this school, students were responsible for setting their own pace through individualized lessons. Descriptive results were presented on the mean number of lessons completed per day by each subject. The instruction on behavior contracting, self-recording, self-monitoring, and self-reinforcement led to increases in the rate of lesson completion after the

intervention was introduced. These increases occurred in the subject areas targeted by each student for application of the self-regulatory skills.

Bandura and Schunk (1981) examined how setting proximal goals during learning would affect the self-efficacy of children with gross deficits in mathematical tasks. Individuals in the proximal goal setting condition reported significantly greater self-efficacy than individuals in a distal goal condition or in a no goal condition. Also, individuals in the proximal goal condition performed better on a math test compared to the distal goal and no goal individuals. It should be noted that goals were focused on the quantity of material to be studied during self-directed learning.

Research has also provided some evidence that incorporating metacognitive activities into instruction will facilitate learning in older or adult samples as well (Melothe, 1990; Veenman, Elshout, and Busato, 1994). Volet (1991) found that undergraduate students who were taught metacognitive activities during an introductory computer programming course received better grades at the end of the course compared to the control group. The metacognitive treatment consisted of instruction on a planning strategy that also included monitoring and evaluation components. In addition, while a final exam revealed no difference in programming knowledge for the experimental and control groups, the experimental group was better at applying this knowledge to solving new problems (Volet, 1991).

Lundeberg (1987) identified the strategies used by experts (lawyers and law professors) in reading legal cases. She then provided guidelines based on these expert strategies to novice law students, either with or without self-control training. The self-control training consisted of training and practice in using the guidelines, feedback,

information on why the guidelines were useful, modeling of the use of guidelines, and group discussion. Lundeberg (1987) found that instruction combining guidelines and self-control training led to greater performance on a test compared to training on just the guidelines, which lead to greater performance compared to no training.

Greiner and Karoly (1976) conducted a study to teach introductory psychology students a standard study method to improve their study habits. Students were instructed on this study method alone or in combination with instruction on various components of self-regulation, as follows: (1) self-monitoring, (2) self-monitoring with self-reward, or (3) self-monitoring, self-reward and planning strategies. Results of the training indicated that training on self-monitoring or self-monitoring with self-reward did not lead to significantly different learning outcomes compared to training on the study method alone. In contrast, the group receiving instruction on self-monitoring, self-reward, and planning strategies spent significantly more time studying than the other two self-regulatory groups, and they spread their study time out more evenly over the academic quarter.

There were no significant differences between groups on the first quiz, but there were significant differences between groups on the second quiz. The planning group performed significantly better on the second quiz compared to the first, and the other groups did not change significantly. In terms of study habits, posttreatment results indicated that the planning strategy group performed significantly better than the other groups. No significant group effects were found using GPA in the introductory psychology course (Greiner & Karoly, 1976).

Zimmerman and Bandura (1994) conducted a study of self-regulatory influences on achievement in a college-level writing course. Results of a path model indicated that self-regulatory efficacy for writing was positively related to self-efficacy for academic achievement, as well as positively related to self-evaluative standards. Self-efficacy for academic achievement and self-evaluative standards were in turn positively related to grade goals. Finally, both self-efficacy for academic achievement and grade goals were positively related to final grades.

Summary and limitations. Research on instruction to teach metacognitive monitoring and control has generally shown it to be an effective intervention for increasing acquisition of knowledge and skills. Studies have shown that the combination of teaching a specific learning strategy for the task being learned and self-regulatory strategies are important for test performance (Lundeberg, 1987) and generalization of the learning strategy back to the classroom (Sawyer et al., 1992). Seabaugh and Schumaker (1994) found that instruction in self-regulatory strategies was important for increasing productivity of individuals engaged in self-initiated learning activities. Bandura and Schunk (1981) found that setting proximal goals during self-directed learning enhanced self-efficacy beliefs. Finally, there is also evidence that individuals trained in self-regulatory skills are better able to apply their knowledge to solving new problems (Volet, 1991).

Most research has examined self-regulation as a complete system; in other words, the self-regulatory instruction included all three components of planning, monitoring, and evaluating goal-directed behavior. One study that examined the effect of adding each component to instruction found the addition of the planning component

to the monitoring and evaluation components to be particularly important (Greiner & Karoly, 1976). Thus, from the research to date, instruction to improve self-regulation of learning should include guidance on the multiple components of planning, monitoring, and evaluation.

For the most part, research has examined the role of metacognitive instruction in relatively structured or traditional learning environments (Seabaugh and Schumaker, 1994 is an exception). It is likely that metacognitive skills may be even more critical when individuals are faced with unstructured learning environments such as those involved in discovery instruction. The capability to plan, monitor, and diagnose one's behavior in a discovery learning setting may enhance a more systematic and effective learning approach. One study provides a limited examination of the role of metacognitive prompting in a discovery learning environment.

Veenman et al. (1994) examined the impact of metacognitive prompting and guided discovery learning on the acquisition of electricity principles. Their task was a computer simulation of an electricity lab. They compared an unguided discovery learning condition with a condition that included two components: guidance in terms of telling individuals certain experiments to perform to learn the relationships between concepts; and metacognitive prompts for raising their working method to a more conscious level of processing. Their results indicated that individuals in the metacognitive-mediated/guided discovery condition exhibited a better working method than individuals in the unguided discovery condition. However, no differences were found between the groups on a retention test three weeks later.

One limitation of the study is that it did not test metacognitive prompting in both unguided and guided discovery conditions (i.e., it did not use a completely-crossed design). Therefore, the effects of guided discovery and metacognitive prompting cannot be separated. In addition, this study did not examine the effects of metacognitive prompting on adaptive transfer as defined in the present study. The retention test used in the study by Veenman et al. (1994) consisted of quantitative and comprehension problems similar to those given to individuals on a pretest.

In summary, discovery learning and metacognitive training are two methods to get the learner more actively involved in the learning process. These interventions are likely to lead to greater adaptive transfer of skills. First, discovery learning environments allow individuals to engage in active learning processes of hypothesis-testing and problem-solving. These strategies may prove beneficial when the individual must identify the critical aspects of an adaptive transfer task. Second, discovery learning environments allow individuals the opportunity to make errors and learn from them; this should lead to a better conceptual understanding of the task. In addition, it has been suggested that this conceptual knowledge will be better integrated into the individual's knowledge structure.

Metacognitive instruction should lead to greater adaptive transfer because it requires individuals to reflect upon their errors in understanding and develop plans to improve them. Thus, metacognitive instruction should also lead to knowledge about the task that is more principled and structured. Also, the capability to monitor and evaluate one's comprehension should be an important skill for being successful on a novel task. Learning how to engage in metacognitive activities may also impact an

individual's self-efficacy, and this self-efficacy should produce resilience and persistence in the face of an adaptive transfer task.

In addition to these design factors, one must consider how individual differences may influence the capability to learn and adapt knowledge and skills. The next section briefly reviews research in educational psychology that has examined how individual differences impact learning, and highlights individual differences that may be critical when training for adaptive transfer.

Individual Differences and Learning

Educational and instructional psychology researchers have recognized the role of individual differences in learning and transfer. People differ in what they do during learning, and in their capability to succeed in particular types of learning situations (Snow, 1989). For example, research on aptitude-treatment interactions indicates that certain instructional methods are more or less effective for different individuals.

Cronbach and Snow (1977) reviewed the literature and described several general results. First, they concluded that general cognitive ability entered into interactions more frequently than other aptitudes. In particular, ability was found to interact with the amount of structure and completeness of the instructional method. Specifically, high ability individuals learned more effectively in low structure environments, while low ability individuals learned more effectively in high structure environments. Low structure environments are those where individuals must act more independently and rely on their own efforts to structure and fill in the gaps in their understanding; inductive, discovery-oriented, and learner-controlled methods are examples of these. In contrast, high structure environments contain a high level of

external control of learning activities, pacing, feedback, and reinforcement; teacher-controlled instruction and drill and practice are examples of high structure learning settings (Snow, 1989).

A second strong ATI result was found for personality and motivational aptitudes. Specifically, anxiety and two achievement motives, achievement via independence and achievement via conformance, were found to interact with the structure of the learning environment. Anxious and conforming students learn more in high structure environments; in contrast, nonanxious or independent students learn more in low structure environments (Cronbach & Snow, 1977).

Research on individual differences and discovery learning. Several studies have examined the role of cognitive ability in discovery learning environments. Results are consistent with the conclusions of Cronbach and Snow (1977). Egan and Greeno (1973) compared learning how to solve joint probability problems through discovery or rule learning methods. They also examined the role of individual differences in conceptual, arithmetic, and permutation skills. Results indicated that participants lower in permutations and concepts abilities learned more in the rule learning than the discovery learning condition. In addition, they found a significant interaction between ability (weighted composite of arithmetic, conceptual, and permutation abilities) and instructional method on the posttest. A graph of the results indicated that low ability individuals committed more errors on the posttest when in the discovery condition compared to the rule condition. In contrast, little difference was found for moderate and high ability individuals. Shute, Glaser, and Raghavan (1989) reported on a study conducted by the first author examining the relationship between cognitive ability and

the learning of economics concepts in a computer-simulated discovery learning environment, Smithtown. Shute found that cognitive ability was significantly related to learning more concepts in the 3.5 hour training session (Shute et al., 1989).

Research has also begun to examine more dispositional factors such as cognitive styles and personality factors. Andrews (1984) examined the interaction between dependent and independent learning styles, and inductive and deductive learning sequences. Independent learners are those who prefer self-directed learning, while dependent learners rely more on external structure. Andrews (1984) found that field dependent learners outperformed field independent learners after a deductive learning sequence (i.e., exposition on key concepts, followed by application of concepts). In contrast, field independent learners outperformed field dependent learners after an inductive sequence where learners first explored the task on their own before instruction on key concepts. However, an inductive sequence led to better performance for both types of learners compared to a deductive sequence.

Frese et al. (1991) examined how a stable personality factor moderated the effectiveness of error-avoidant and error training methods. The individual difference factor they were interested in was cognitive failures, measured by the Cognitive Failure Questionnaire (CFQ; Broadbent, Cooper, Fitzgerald, & Parkes, 1982). This construct seemed to be a general tendency to commit errors, or a greater sensitivity to stress. Unfortunately, this construct was not well-defined in the study. Frese et al. (1991) correlated scores on the CFQ with learning and transfer performance in each training group. Results indicated that significant negative correlations were found between CFQ and performance variables only in the error-avoidant group. The

difference between the correlations for the two groups was significant for transfer performance. They interpreted these results to suggest that "scatty" people profit from error training, but do not profit from error-avoidant training (Frese et al., 1991).

Individual differences and I/O training research. I/O research has also examined the role of individual differences in learning and training effectiveness. For example, Ackerman (1988) found that initial skill acquisition is best predicted by general cognitive ability, intermediate skills are best predicted by perceptual speed ability, and late stages of skilled performance are best predicted by psychomotor abilities. Mathieu, Tannenbaum, and Salas (1992) found that pretraining motivation predicted greater learning and reactions to training. Gist, Schwoerer, and Rosen (1989) found that self-efficacy prior to training was positively related to performance on a test at the end of training.

Thus, training research has considered the role of ability and motivation in the learning and transfer of skills. In their review of training research, Tannenbaum and Yukl (1992) suggested that certain personality or dispositional factors may also impact learning and transfer. For example, certain "big five" personality factors may influence training effectiveness. The goal orientation of the learner has also been considered in research on training transfer (Kozlowski, et al. 1995; Smith, et al. 1995).

When the focus of training is adaptive transfer, one must identify individual differences that may be critical for the capability to be flexible in novel or complex circumstances. Tolerance for ambiguity is a personality factor that may be relevant for the capability to adapt one's skills to a novel task. Tolerance for ambiguity can be defined as a tendency to perceive ambiguous situations as desirable (Budner, 1962).

Individuals who are high on tolerance for ambiguity tend to welcome the challenge of ambiguous, complex, or novel tasks. Therefore, tolerance for ambiguity may affect how much is learned and applied to an adaptive transfer task.

In addition, Dweck (1986) has identified two goal orientations that individuals may take to a learning situation: mastery orientation and performance orientation. A mastery orientation includes the belief that effort leads to improved outcomes, and that ability is malleable. Individuals with a mastery orientation are focused on developing new skills and successfully achieving self-referenced standards for mastery (Ames, 1992; Dweck, 1986). In contrast, individuals with a performance orientation to learning believe that ability is demonstrated by surpassing normative-based standards, or by succeeding with little effort (Ames, 1992). These motivational dispositions must be considered when examining learning and transfer processes.

A conceptual model is presented next that integrates the literatures on discovery learning and metacognition. This model raises hypotheses concerning individual differences and instructional design factors that may influence adaptive transfer. In addition, this model identifies learning outcomes that serve as intervening factors between individual differences, design factors, and adaptive transfer.

TRAINING FOR ADAPTIVE TRANSFER: A CONCEPTUAL MODEL

In reviewing I/O research on transfer of training, Baldwin and Ford (1988) identified three training input factors that will affect learning and transfer: trainee characteristics; training design; and work environment. With regard to situational factors, it is acknowledged that the work environment will affect whether knowledge and skills will be adapted to novel task situations. However, the conceptual model to be presented is focused on the design of the training environment and how to structure it to facilitate adaptive transfer. In addition, the model also considers individual characteristics of the learner and how they may affect learning and transfer. Finally, this model identifies learning outcomes that mediate the relationship between individual differences, training input factors, and adaptive transfer.

Current I/O research on design principles to achieve training transfer has been limited in the types of independent variables examined, and in the definition and operationalization of transfer of training. First, training research has focused predominantly on the effects of design principles that have been developed from a behaviorist paradigm. As the review suggested, these principles lead to well-learned, and efficient procedures, but not necessarily to flexibility of skills. Second, the training literature has provided little differentiation between types of transfer and how to train for them. It is argued that adaptive transfer is of critical importance in the

rapidly changing organizational environment. Principles for instruction when jobs were relatively stable and well-defined may be insufficient in today's increasingly complex, and cognitively demanding jobs.

With advances in technology, individuals will be required to learn more complex skills, and they will need the capability to learn new skills in the future (Hesketh & Bochner, 1994). This places a greater emphasis on the flexibility and adaptability of skills learned in training to new or unforeseen contexts. Hesketh and Bochner (1994) argued that training for jobs in the future require that individuals take responsibility for their own learning.

Several programs of research at Michigan State University are focused on how to engage the learner more actively during training. In addition, this research is focused on factors that influence the acquisition of complex skills. For example, Smith et al. (1995) examined an integrated model of learning in an environment where individuals had responsibility for choosing their own practice exercises. They predicted that the goal orientation of the learner would influence the activities they engaged in during training to master a complex, decision-making task. These learning activities were expected to impact multiple learning outcomes, which would in turn influence the transfer of training to a more difficult version of the trained task.

Smith et al. (1995) found that mastery orientation was positively related to metacognitive activities during training. Metacognition was positively related to the learning outcomes of final training performance and self-efficacy. In addition, mastery orientation was found to be positively related to self-efficacy, while performance orientation was negatively related to self-efficacy. The use of specific practice

strategies during training were positively related to several learning outcomes. Finally, the three learning outcomes of knowledge, final training performance, and self-efficacy were all positively related to transfer of training.

Kozlowski et al. (1995) examined how individual differences and training design factors affected multiple learning outcomes and adaptive transfer. Individual differences included cognitive ability, mastery orientation, and performance orientation. This study focused on two training interventions to orient individuals to learning objectives for skills critical to the development of expertise. Specifically, they examined how sequenced mastery training goals and advance organizers influenced multiple learning outcomes. Distinct theoretical mechanisms were conceptualized for these two interventions, and different learning outcomes were expected to be influenced by each. An outcome of particular interest in this study was the structure of the knowledge developed during learning. It was expected that providing mastery goals to trainees would be especially beneficial in building effective knowledge structures. With few exceptions (Kraiger & Salas, 1993; Nason, Gully, Brown, & Kozlowski, 1995), training research has tended to assess knowledge in a simpler form through verbal knowledge tests. This study extended training research by examining the unique impacts of declarative and structural knowledge, in addition to skills and self-efficacy, on transfer to a more complex version of the trained tasks.

Results of this study indicated that transfer of training was independently predicted by declarative knowledge, knowledge structure, training performance, and self-efficacy. Advance organizers were found to affect more traditional learning outcomes of declarative knowledge and final training performance. Mastery training

goals led to more rapid acquisition of declarative knowledge, and also affected the development of knowledge structures across training sessions. Mastery goals also influenced the development of self-efficacy over training sessions.

These studies provided the basis for the form of the conceptual model examined in the present study. Specifically, similar to these previous studies, the present model examines how individual differences and training design interventions influence learning and transfer of training. A general conceptual heuristic is presented in Figure 1. As in previous research, this study takes a multi-dimensional perspective to learning by identifying several learning outcomes that will influence adaptive transfer. The model in Figure 1 is a general overview and does not display the specific hypotheses to be tested.

In reviewing cognitive and instructional research, discovery learning methods and metacognitive processes were identified as two factors that will increase the responsibility of the learner for acquiring knowledge and skills through their own interpretive and constructive processes. This active participation by the learner is conceptualized to lead to greater adaptive transfer of this knowledge and skill. The research conducted by Kozlowski et al. (1995) indicated that mastery goal training is another method for building expert knowledge that will lead to greater transfer. In addition, the study by Smith et al. (1995) indicated that metacognitive activity is also relevant when learners have control over instructional events. Although mastery goals and learner control are operationalized differently than the training interventions examined in this study, it is clear that each of these training interventions influence learning and transfer through engaging the learner in more active processing of

training material. Hypothesis-testing, problem-solving, and self-regulation are processes that are consistent with more active engagement in learning.

The present study is focused on how to structure training materials to facilitate adaptive transfer. However, training events are controlled by the instructional medium in this study. Learners are not given control over the sequence, complexity, or number of exercises to complete, although this is acknowledged as another possible method to achieve learning and transfer. In addition, mastery goal training has traditionally focused more generally on the motivational effects of particular goals on learning regardless of the structure of the training environment (e.g., Dweck & Leggett, 1988). In contrast, the interventions in the present study are focused on the specific training content and skills being learned. Individuals are expected to learn differently based on the amount of information and guidance provided during training (discovery learning intervention) and whether or not they are instructed on how to monitor, diagnose, and evaluate specific skills learned during training (metacognitive instruction).

Several learning outcomes are identified as mediators of the effects of these instructional methods on adaptive transfer. A multidimensional perspective on learning outcomes (Kraiger, et al., 1993) is used to hypothesize the learning mechanisms that lead to adaptive transfer. For example, allowing individuals to explore and experiment with tasks should lead to the development of more detailed verbal knowledge about the task. Also, discovery learning methods and metacognitive instruction should lead to knowledge structures that are better developed and more integrated compared to more passive learning methods.

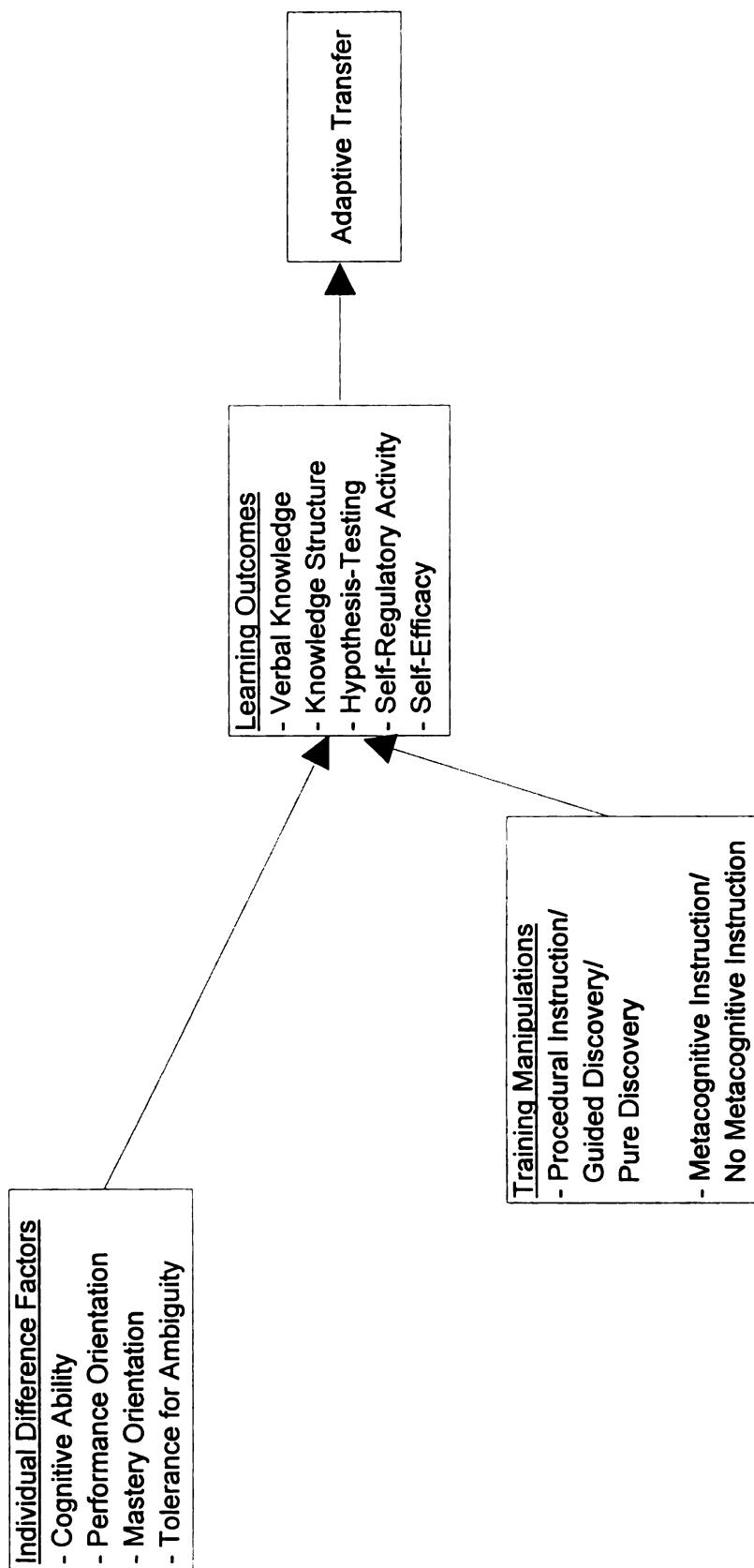


Figure 1. A Conceptual Heuristic of the Impact of Individual Differences, Discovery Learning, and Metacognitive Instruction on Learning and Adaptive Transfer.

Second, researchers have suggested that discovery learning methods and metacognitive training provide individuals with learning strategies that enable them to adjust their task knowledge and skills to handle novel circumstances (McDaniel & Schlager, 1990). The two learning activities identified as critical for adaptive transfer are hypothesis-testing and self-regulatory skills.

Finally, self-efficacy is identified as a learning outcome that should have a motivational impact on adaptive transfer. Self-efficacy is expected to lead to greater persistence in trying to succeed on the adaptive transfer task. Self-efficacy is a central concept in models of self-regulated learning (Schunk, 1989; Zimmerman & Bandura, 1994). Self-efficacy and self-regulated learning processes are expected to be reciprocally related to one another during learning activities. Researchers have found that aspects of self-regulation during learning lead to increased beliefs in self-efficacy (Bandura & Wood, 1981). The model examines how metacognitive instruction may lead to greater self-efficacy at the end of training that then affects adaptive transfer.

In addition, this model examines the impact of both individual differences and instructional interventions on learning and transfer. Baldwin and Ford (1988) criticized training research for examining individual differences and design factors in isolated studies. Recent training research provides some exceptions (Gist, Rosen, & Schwoerer, 1988; Kanfer & Ackerman, 1989). In the present model, tolerance for ambiguity and mastery orientation are identified as theoretically important individual difference factors to consider when examining learning outcomes and adaptive transfer. Cognitive ability and performance orientation are also included in the model to control for any impacts they may have on learning and transfer.

The final outcome examined in this model is adaptive transfer. In this model, adaptive transfer refers to the adjustment of knowledge and skills learned in training to a novel task. Novelty is defined as new stimuli in the transfer task that require individuals to modify task strategies learned in training to achieve successful transfer.

This study will expand research on discovery learning and metacognition by generalizing it to a complex, decision-making task that has relevance for organizational tasks. The task used in this study is a computer simulation of a radar tracking task. In addition, this study will build on traditional training principles by including sufficient opportunities for practice of skills, feedback on performance, and a training sequence that builds from simple to complex skills. In this way, this study will be examining how design elements such as discovery learning opportunities and metacognitive processing can add benefit to traditional training approaches. This perspective is also consistent with the argument that individuals can be taught to actively process and interpret knowledge and skills while practicing and refining them at the same time (Salomon & Perkins, 1989). The training manipulations, individual differences, and learning and transfer outcomes are described in detail next.

Discovery Learning, Guided Discovery, and Procedural Instruction

One major focus of this model is the opportunity for individuals to engage in discovery learning. Allowing individuals to explore and experiment during training should lead to greater adaptive transfer than traditional instructional methods. Unfortunately, complete discovery learning may not be an efficient way to train since it usually takes more time for individuals to inductively learn rules or principles than

to practice and apply instructor-provided rules. An early review (Hermann, 1969) suggested that guided discovery is more effective than pure discovery learning.

In the present study, guided discovery learning is defined as directing individuals to engage in hypothesis-testing. During initial practice, individuals will be provided with a description of a simple task situation and the strategy they should use to respond to the situation. In addition, they will be instructed to explore the task on the first simple trial so that they can see how a scenario unfolds. This will provide initial structure to the task and an introduction to the task parameters that may require attention. Next, individuals will have to make predictions about what parameters may change in the task to make it more complex. They will then have practice opportunities to explore more complex situations, discover if their predictions were correct, and develop the best strategies to handle the more complex situations.

In contrast, a pure discovery condition will provide little structure to learners in how to approach the task. Individuals will be presented with the same task situations in sequence of increasing complexity, but they will be left completely on their own to learn strategies for performing the task under different task situations. The guided and pure discovery conditions will be compared to a procedural instruction condition as well. This condition will be consistent with current training practices, as individuals will be presented descriptions of the different task situations and the strategies they should use to effectively perform the task. Then participants will be provided with opportunities to practice and apply these specific procedures.

It is expected that guided discovery learning will lead to greater adaptive transfer compared to pure discovery and procedural instruction. In addition, pure

discovery learning is expected to lead to greater adaptive transfer than procedural instruction. The two discovery conditions should lead to greater adaptive transfer than procedural instruction because individuals are provided with opportunities to explore and experiment with the task, and they are responsible for developing their own understanding of the task and their own strategies for performing it. In addition, the guided discovery condition should be more effective than the pure discovery condition, because individuals are directed to aspects of the task in the low complexity situation and prompted to test hypotheses in more complex situations. Individuals may differ in their capability to develop a systematic learning approach when given total responsibility to learn about a task. This may lead to inefficient exploration of the task. In contrast, individuals who are provided some guidance in generating predictions and thinking about task strategies will still achieve the benefits of exploration, but in a more systematic way.

Hypothesis 1. Guided discovery learning will lead to greater adaptive transfer compared to pure discovery learning and procedural instruction. Pure discovery learning will also lead to greater adaptive transfer than procedural instruction.

Metacognitive Instruction

Metacognitive instruction is a second focus of this study. Metacognition is defined as the self-regulatory processes of planning, monitoring, and evaluating task behavior. Metacognitive instruction will be operationalized as having individuals set a learning goal for practice, devising a plan for achieving the goal, and monitoring and evaluating their progress relative to the goal. A concern in the literature on these self-regulatory processes is that individuals may not have the attentional resources required to self-regulate early during skill acquisition (Kanfer & Ackerman, 1989). Initial

learning of an unfamiliar task requires attention that may not be available for monitoring and evaluating this learning. Therefore, this study will introduce the metacognitive instruction after individuals have had initial opportunities to practice simple task situations. In addition, the prompts for individuals to set a learning goal and plan will occur after individuals have had one trial to experience the moderate task situation. Individuals will be asked to use the feedback they have received from this first trial, as well as their experience in performing it, to diagnose any difficulties they are having in learning the task. They are then asked to develop a goal and plan for the next trial to improve their understanding. A similar process will occur when individuals move to the most complex training situation.

It is expected that instruction on metacognitive planning, monitoring and evaluation of task strategies will lead to greater adaptive transfer. Individuals who are instructed to plan, attend to, and evaluate their understanding should notice any errors in their performance and find ways to avoid these errors in the future. Thus, by attending to their learning and trying to improve it, these individuals are more likely to be flexible in adapting their skills to novel circumstances.

Hypothesis 2. Individuals who receive metacognitive instruction should perform significantly better on an adaptive transfer task compared to individuals who do not receive metacognitive instruction.

The first two hypotheses are general predictions based on theory and research from the instructional and educational psychology literatures. Previous research has not examined the interaction between discovery learning manipulations and metacognitive instruction. It is expected that there will be an interaction between these two instructional conditions in predicting adaptive transfer. Specifically, it is expected

that metacognitive instruction will lead to greater adaptive transfer in the guided discovery and pure discovery conditions compared to no metacognitive instruction; however, metacognitive instruction is expected to have little or no added benefits in the procedural instruction condition.

Metacognitive instruction may be especially important in helping learners to cope with more exploratory learning environments. Discovery learning environments put high metacognitive demands on novice learners (Veenman et al., 1994). In addition, individuals in discovery learning situations are likely to commit errors that require greater diagnosis compared to individuals in procedural instruction conditions. Frese and Altmann (1989) have distinguished between different types of errors, and two that are relevant to discovery v. procedural instruction are slips and mistakes. Slips are errors which result from wrong plans but right intentions. Mistakes occur when the intentions were wrong but the plan conformed to the intention (Norman, 1984). Individuals receiving procedural instruction should be less likely to commit errors overall, as they are provided with information on the correct strategy to use to perform the task. In addition, if they do commit errors, they are more likely to commit slips. They are presented with the correct strategy for task performance, but they may apply it incorrectly. In contrast, individuals in discovery learning conditions must discover the correct strategy for task performance. Discovery learning environments are designed so that individuals will commit more errors overall. In addition, they are more likely to commit mistakes where they choose and apply an incorrect task strategy.

When individuals receiving procedural instruction perform poorly during practice, it should be fairly obvious to them what errors they may have committed. They have the correct task strategy to study, and they can determine to what extent their actions during practice matched the strategy they should have been practicing. In contrast, when individuals in discovery learning conditions commit errors, the reasons for the errors are not as obvious. The individual may have committed a mistake in terms of trying out the wrong task strategy, or the individual may have committed a slip in terms of an error in applying the correct task strategy. Thus, discovery learning environments should benefit more from instruction and guidance on how to monitor and diagnose difficulties during learning. This should help them increase their understanding of correct and incorrect task strategies that will then lead to greater adaptive transfer.

Hypothesis 3. An interaction between discovery learning conditions and metacognitive instruction will significantly influence adaptive transfer. Metacognitive instruction will lead to greater adaptive transfer compared to no metacognitive instruction for guided and pure discovery conditions; there will be little or no difference between the presence or absence of metacognitive instruction in the procedural learning condition.

In addition, there are several learning outcomes expected to play intervening roles in the relationships between discovery learning, metacognitive instruction and adaptive transfer. These learning outcomes provide the rationale for the general effectiveness of guided discovery learning and metacognitive instruction on adaptive transfer. These more complex relationships are described next.

Learning Activity

The two instructional manipulations to be examined in this study serve the purpose of teaching individuals effective methods for learning new tasks. Not only does the instruction provide a better method for learning during training, it also provides individuals with practice on more general learning skills that can be applied to performance on the adaptive transfer task. First, guided discovery learning teaches individuals an approach to learning new information that consists of making hypotheses or predictions about the task, exploring the task to test these predictions, and experimenting with task strategies to develop those that are optimal for task performance. It is expected that this type of hypothesis-testing/problem-solving approach to learning is an effective skill for adaptive transfer. Individuals who are successful at developing their own systematic approach to learning in the pure discovery condition are also likely to get some practice in this hypothesis-testing activity. This is in contrast to the less active approach of receiving explicit instruction on task strategies and applying them to the situation at hand. Thus, individuals in the procedural instruction condition will have little opportunity to engage in this hypothesis-testing activity.

Therefore, individuals in the guided discovery condition are more likely to report that they practiced and used a hypothesis-testing approach during instruction compared to the pure discovery and guided discovery conditions. One may question the validity of self-reports of learning activities, but it is expected that self-reported hypothesis-testing is a satisfactory measure of learning activities. Previous research has shown that self-reports of learning strategies are related to important learning

outcomes. For example, Pokay and Blumenfeld (1990) found that self-reported use of geometry-specific learning strategies and effort management strategies predicted grades early in the semester in a geometry class.

Thus, it is expected that individuals who are instructed on a hypothesis-testing approach in the guided discovery condition will report greater practice and use of hypothesis-testing methods during training compared to the pure discovery and procedural instruction conditions. In addition, because they are left on their own to develop an understanding of the task, individuals in the pure discovery condition should report greater use of a hypothesis-testing approach to practice compared to individuals receiving procedural instruction. It is also expected that the self-reported use of hypothesis-testing will be positively related to adaptive transfer.

Hypothesis 4. Individuals in the guided discovery condition will report significantly greater use of hypothesis-testing activities during practice compared to individuals in the pure discovery condition, who will report significantly greater use of these activities compared to the procedural instruction condition.

Hypothesis 5. Self-reported use of hypothesis-testing activities will be positively related to adaptive transfer.

Metacognitive instruction provides individuals with practice on a second learning activity that should be effective for adaptive transfer. Individuals in the metacognitive instruction condition will learn how to pay attention to and monitor their task performance, to identify any difficulties, and to develop learning goals and plans to improve their performance. The opportunity to practice these skills will make it more likely that they will apply these skills to an adaptive transfer task. In contrast, individuals in the condition without metacognitive instruction will have no explicit

opportunities to practice this self-regulatory approach to learning. Thus, individuals in the metacognitive instruction condition should report greater use of self-regulatory activity compared to the condition without metacognitive instruction.

Research has provided some evidence for the validity of self-reports of self-regulatory activity during learning. For example, Pintrich and DeGroot (1990) found that self-reports of self-regulated learning were positively related to academic performance in terms of classwork, exams/quizzes, essays/reports, and average grade. Pokay and Blumenfeld (1990) found that self-reported metacognition was negatively related to achievement early in the semester, but positively related to achievement late in the semester. Finally, Smith, et al. (1995) found that self-reported metacognition during learning was positively related to performance on a final training trial. Therefore, it is expected that metacognitive instruction will lead to reports of greater use of self-regulatory activities during practice, and this self-regulation should be positively related to adaptive transfer.

Hypothesis 6. Individuals who receive metacognitive instruction should report significantly greater use of self-regulatory activities compared to individuals who do not receive metacognitive instruction.

Hypothesis 7. Reported use of self-regulation during learning will be positively related to adaptive transfer.

In addition to providing individuals with learning methods that will assist them during transfer, it is expected that discovery learning and metacognitive instruction will influence other learning outcomes as well. These relationships are explained next.

Verbal Knowledge and Knowledge Structure

A fundamental outcome of any training program is the development of knowledge about the training task. As individuals practice a task, they develop declarative knowledge about the task and its features, and they also develop procedural knowledge on how to perform task components. Researchers have hypothesized that more principled knowledge is one mechanism through which guided discovery instruction leads to better adaptive transfer compared to more traditional instruction. Because individuals are allowed to make errors and learn from them under discovery learning conditions, their knowledge of the task will include not only an understanding of when strategies are appropriate, but also when they will not be successful. This greater depth of understanding should assist individuals when they must transfer their knowledge and skills to a novel task.

It is expected that individuals under guided discovery and pure discovery conditions will develop greater verbal knowledge of the task compared to individuals receiving procedural instruction. In addition, guided discovery should lead to greater knowledge compared to pure discovery learning. Because individuals in the guided condition are prompted to develop and test hypotheses about the task, they should be more likely to develop systematic and principled knowledge about the task. Some support has been found for these hypotheses in previous research; for example, Frese et al. (1991) found that individuals in an error-training condition recalled significantly more word processing commands compared to an error-free training group. Singer and Pease (1976) found that a pure discovery and combination group outperformed a

procedural instruction group on a retention test. Therefore, similar results are expected for a knowledge test in the present study.

Hypothesis 8. Guided discovery learning will lead to significantly better verbal knowledge compared to pure discovery learning, which will in turn lead to significantly better verbal knowledge compared to procedural instruction.

Theory also indicates that metacognitive instruction should lead to greater knowledge about the training task. Greater metacognitive skills should facilitate learning because they allow individuals to monitor their progress, identify any problems they are having during training, and then adjust their learning strategies to try to overcome any difficulties. Research has found that metacognitive instruction leads to greater performance on posttests of knowledge compared to groups receiving no metacognitive instruction (Greiner & Karoly, 1976; Lundeberg, 1987). Therefore, it is expected in this study that metacognitive instruction will lead to greater verbal knowledge compared to a no metacognitive instruction condition.

Hypothesis 9. Metacognitive instruction will lead to significantly better verbal knowledge compared to training without metacognitive instruction.

Finally, it is expected that greater declarative and procedural knowledge about the task, as assessed on a knowledge test, will be positively related to adaptive transfer. Individuals who develop a greater depth of knowledge about the task, by learning when certain strategies and actions are appropriate and inappropriate, should be better able to apply and adapt this knowledge to a novel task. Research on discovery learning and metacognitive training has not tended to examine the relationship between knowledge at the end of training and transfer; instead, it has treated them as different outcomes of instructional interventions. However, in the

present study, knowledge about the task is seen as a prerequisite for the ability to successfully perform in an adaptive transfer task.

Hypothesis 10. Verbal knowledge will be positively related to performance on an adaptive transfer task.

As individuals gain experience with a task, their declarative knowledge not only becomes compiled into procedural rules, it also becomes meaningfully structured in memory (Kraiger et al., 1993). Thus, a second method for assessing the quality and depth of knowledge acquired from training is to determine how individuals relate and link various concepts and actions in their memory. Researchers have developed various concepts to describe this knowledge organization, such as scripts, schema, mental models, and cognitive maps. A general term referring to the organization of knowledge is knowledge structure. Research on experts and novices has found that they differ in the organization of their knowledge structures. For example, experts possess knowledge structures that contain both problem definitions and solutions, whereas novices tend to possess separate knowledge structures for problem definition and problem solution (Glaser & Chi, 1989).

Patel and Groen (1991), in a study of medical expertise, also found distinct differences between novices, intermediates, and experts. They distinguish between experts and intermediates in terms of generic expertise. "A distinguishing trait of experts, even outside their domain of specialization, is knowledge of what not to do" (p. 121). Intermediates possess the specific domain knowledge that experts possess (i.e., what to do given a particular task situation), but they do not know what not to do. This leads them to conduct irrelevant searches, be distracted by irrelevant clues,

and access unnecessary knowledge from their memory. Novices do not conduct these irrelevant searches because they do not know what to do. This research suggests that experts possess more complex knowledge structures that not only contain information on correct task strategies given a particular task situation, but also information on strategies that would be errors. From their considerable experience with the task, experts are likely to have made errors and developed an understanding of these errors. They are then able to avoid these errors in the future.

Researchers have suggested that allowing individuals to engage in discovery learning processes will lead to better developed and integrated knowledge structures. By exploring the task and making mistakes, individuals should develop a better operative mental model of the task (Frese et al., 1988). For example, Egan and Greeno (1973) interpret the results of their study to indicate that learning by discovery leads to "external connectedness" of one's knowledge structure. Because individuals learning by discovery performed better at problems involving more interpretation, the new structural components developed during learning became well integrated into existing cognitive structure. Individuals who learn by discovery must use their previous knowledge to help them understand the task to be learned, whereas individuals learning under rule application conditions can merely add these new elements to their cognitive structure without reorganizing it (Egan & Greeno, 1973).

While an integrated knowledge structure has been described as an outcome of discovery learning methods, research has not explicitly measured knowledge structures at the end of training to test this hypothesis. Instead, recall or retention tests have been used to assess the amount of knowledge acquired (e.g., Singer & Pease, 1976).

However, cognitive psychologists have examined a number of ways to assess knowledge structure. Measurement of knowledge structure has included card sorting tasks, as well as making judgments of similarity or relatedness among a number of predefined elements. Structural assessment is the strategy of submitting judgments of similarity to a clustering or scaling algorithm (Kraiger et al., 1993).

Recently, interest has been focused on different statistical methods to represent the structural properties of knowledge. Goldsmith, Johnson, and Acton (1991) examined a new algorithm for representing knowledge structure, Pathfinder. The Pathfinder scaling algorithm transforms a matrix of relatedness (proximity) ratings into a network structure. In this structure, each element is represented by a node in the network, and the relatedness between the elements is depicted by how closely they are linked. Based on this network representation, they developed an index of closeness (C) that measured how similar a student's knowledge structure was to that of an expert (i.e., the instructor) in a statistics course. This was compared to correlational measures of similarity derived from the raw proximity data and to structures derived from MDS. These three measures of similarity were related to course performance on exams and papers in the statistics course. The correlation between C and course performance was a better predictor than the raw rating data or the MDS measure. Results indicated that when the other indices were held constant, the C index still captured unique predictive variance in course grades (Goldsmith et al., 1991).

Subsequent research has provided further construct validity for the Pathfinder method of measuring knowledge structure. Several studies have found instructional interventions to predict knowledge structure. For example, Kraiger and Salas (1993)

found C scores to discriminate between individuals who participated in a Naval aircrew coordination training program and a group of control participants. Kraiger (1993) found that providing training goals before training led to greater C scores than presenting training goals after training. Finally, Kozlowski, et al. (1995) used the Pathfinder algorithm to assess the coherence of knowledge structures after various training interventions. Coherence measures the extent to which relations among pairs of concepts are logically consistent across all concepts that were rated. Kozlowski et al. (1995) found that the coherence of knowledge structures increased significantly over training sessions for individuals provided advance organizers or mastery goals.

Thus, having individuals make relatedness ratings among a set of concepts and submitting these ratings to the Pathfinder algorithm is an effective way to measure knowledge structure. This is the operationalization of knowledge structure to be used in the present study. Participants' knowledge structures will be compared to an expert knowledge structure to create the index of closeness, C. It is expected that the discovery learning and metacognitive instruction interventions will affect C scores.

Consistent with theoretical explanations (Egan & Greeno, 1973; Frese et al., 1988), it is expected that guided discovery and pure discovery learning will lead to more accurate knowledge structures compared to procedural instruction. Individuals in the two discovery conditions must actively generate their own understanding of the task and how to respond to it. This should lead to a better integrated and more complex knowledge structure. Because they are likely to make errors in their responses to the task, they are likely to develop a more elaborated knowledge structure as well. In contrast, individuals in a procedural instruction condition do not have to

actively construct an understanding of the task; rather, they are explicitly provided a description of each task situation and how they should respond. Therefore, they will be applying this knowledge in a more passive manner that does not require them to generate their own explanations of the task. It is expected that guided discovery will also result in a better knowledge structure compared to pure discovery learning. While both groups must develop their own understanding of the task, the guided discovery group is directed to the important features of the task on which they should focus their attention. They should develop more accurate knowledge structures than the pure discovery learners, who may develop a less systematic understanding of the task.

Hypothesis 11. Guided discovery learning will lead to a significantly better knowledge structure compared to pure discovery learning, which will in turn lead to a significantly better knowledge structure compared to procedural instruction.

Research on metacognition has not explicitly considered the role of self-regulatory processes in the development of well-structured knowledge. However, it has been hypothesized that metacognitive activity should lead to more principled knowledge (Salomon & Perkins, 1989). It can be hypothesized that individuals who engage in self-regulatory activities during learning should develop a more integrated and elaborated understanding of the task. By planning their activities, and monitoring and diagnosing errors in their performance, they should develop an operative knowledge structure that tells them when certain task strategies are appropriate, when they will lead to errors, and why this is so.

Hypothesis 12. Metacognitive instruction will lead to a significantly better knowledge structure compared to training without metacognitive instruction.

Finally, it is expected that knowledge structure will be positively related to performance on the adaptive transfer task. Previous research has shown the positive relationship between knowledge structure and class performance (Goldsmith et al., 1991), and between knowledge structure and skill generalization to a more complex transfer task (Kozlowski et al., 1995). Individuals who have developed a more richly integrated knowledge structure concerning the task and the range of possible strategies will have a better repertoire of responses to try out when faced with a task in which they must adapt this knowledge.

Hypothesis 13. Knowledge structure will be positively related to performance on the adaptive transfer task.

Self-Efficacy

Self-efficacy is one's confidence that one can successfully perform a given task (Bandura, 1977). Self-efficacy can be differentiated from similar constructs such as self-esteem because self-efficacy perceptions are task-specific. In contrast, self-esteem is usually considered a trait that reflects an individual's global, affective evaluation of the self (Gist & Mitchell, 1992). Social cognitive theories of self-regulation highlight the role that self-efficacy plays during self-regulated learning (Schunk, 1989). Self-efficacy influences self-regulatory processes, and is influenced by them as well (Bandura, 1991). Research on self-efficacy and self-regulation has usually examined self-efficacy as an antecedent variable that affects how individuals self-regulate their performance. For example, Zimmerman and Bandura (1994) found self-efficacy to positively influence goals set by students in a writing course.

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However, a few studies have also examined how self-regulatory activity influences self-efficacy as a learning outcome (Bandura & Schunk, 1981; Sawyer et al., 1992). These studies provided conflicting results. It is hypothesized in this study that providing individuals with skills for monitoring their performance, noticing errors, and identifying ways to correct these errors should enhance their confidence that they can succeed at the task. For example, Gist (1989) found that including a cognitive modeling component during a training course did improve self-efficacy over lecture and practice alone. This cognitive modeling intervention included the self-monitoring and self-correcting features of self-regulation.

Of particular interest in this study is the individual's self-efficacy for handling the task if it changes and becomes more complex. Thus, self-efficacy in this study is targeted at an individual's confidence that he or she can successfully perform the task under circumstances not experienced before. This definition of self-efficacy was chosen to tap into the idea that self-efficacy may have a resiliency component (Bandura & Cervone, 1986). Bandura and Wood (1989) argued that self-efficacy provides resilience in the face of failures and setbacks, and predisposes individuals to view obstacles as challenges rather than reflections of personal inadequacies. This resilience and persistence is expected to be an important influence on the capability to succeed in the adaptive transfer task. Thus, self-efficacy for unseen or novel task situations should enable individuals to persist in the challenging adaptive transfer task.

It is expected that individuals who have received instruction on self-regulation of learning will develop greater self-efficacy compared to individuals who have not received this guidance. Individuals who have developed proficiency in monitoring and

diagnosing their performance should believe that they have certain skills that will assist them in adapting to novel and complex circumstances. Therefore, they should feel more confident that they can adapt to changing task demands compared to individuals who have not received instruction on these self-regulatory skills.

Hypothesis 14. Metacognitive instruction should lead to significantly greater self-efficacy at the end of training compared to no metacognitive instruction.

The discovery learning literature has not examined self-efficacy as an outcome of instruction. Therefore, no clear hypotheses can be derived from past literature on possible relationships between the two variables. In fact, it is not clear that the two guided discovery conditions will lead to greater self-efficacy compared to the procedural instruction group. For example, the guided discovery group and the procedural instruction group may develop similar self-efficacy beliefs by the end of training. However, their self-efficacy beliefs are based on different task experiences. The guided and pure discovery groups are likely to base their self-efficacy perceptions on skills that are more useful for adaptive transfer. The procedural instruction group may feel self-efficacious as well at the end of their training, because they have been explicitly guided through strategies to deal with the task at various levels of complexity. However, their perceptions of self-efficacy are likely to be based on insufficient skills for adaptive transfer. Nonetheless, no clear difference in the level of self-efficacy is predicted for different discovery learning groups.

Finally, self-efficacy is expected to lead to greater adaptive transfer. Individuals who are more confident in their capability to handle novel circumstances should show greater resilience when faced with the demands of the adaptive transfer

task. Previous research provides support for the prediction that self-efficacy will positively affect transfer to a more complex task (Kozlowski et al., 1995).

Hypothesis 15. Self-efficacy will be positively related to adaptive transfer.

In summary, it is generally expected that guided discovery learning and metacognitive instruction will be effective instructional interventions for achieving various learning outcomes and adaptive transfer. In addition to these design factors, the conceptual model examines how individual differences may also impact learning outcomes and adaptive transfer. These factors are described next.

Individual Difference Factors

This study will examine how individual differences in ability, personality and motivation for learning affect learning outcomes and adaptive transfer. Cognitive ability has been shown to interact with the amount of structure in the learning environment to affect learning outcomes. In addition, mastery and performance orientations to learning were identified as motivational factors that may impact learning and transfer. Finally, tolerance for ambiguity was identified as a personality construct that is relevant to situations where individuals must adapt to complex or novel circumstances.

Cognitive ability. Research has shown that cognitive ability affects early skill acquisition (Ackerman, 1988). Therefore, the present study will measure and control for the effects of ability on adaptive transfer. Ability should also impact the learning outcomes of knowledge, knowledge structure, hypothesis-testing, self-regulatory activity, and self-efficacy.

Of greater interest in this study is whether certain dispositional factors will affect learning and adaptive transfer after controlling for the effects of ability. The goal orientation of the learner and tolerance for ambiguity were identified as individual differences that may affect learning and transfer of knowledge and skills.

Goal orientation factors. Mastery and performance orientations to learning represent different ideas of success and different reasons for engaging in learning (Ames, 1992; Dweck, 1986). A mastery orientation includes the belief that effort leads to improved outcomes, and that ability is malleable. Individuals with a mastery orientation engage in learning activities with the purpose of trying to understand new tasks (Ames, 1992; Dweck, 1986). In contrast, individuals with a performance orientation to learning believe that ability is demonstrated by performing better than others; therefore, a learning situation is a means through which the individual can publicly achieve greater success compared to others (Ames, 1992).

Research indicates that a performance orientation is related to the belief that success requires high ability, while a mastery orientation is related to the belief that success requires interest, effort, and collaboration (Duda & Nicholls, 1992). Kroll (1988) found that mastery orientation is positively related to tolerance for ambiguity, thoughtfulness, and open-mindedness. Performance orientation is negatively related to tolerance for ambiguity, thoughtfulness, complexity, and individualism.

Classroom settings emphasizing mastery goals lead students to use more effective learning strategies, to prefer challenging tasks, to have a more positive attitude towards the class, and to have a stronger belief that success follows from effort. In contrast, classrooms emphasizing performance goals lead students to focus

on their ability, to evaluate their ability negatively, and to attribute their failures to lack of ability (Ames & Archer, 1988). Mastery goals lead to greater persistence in the face of difficulties, whereas performance goals led to the avoidance of challenging tasks (Dweck, 1986; Dweck & Leggett, 1988; Elliott & Dweck, 1988).

Two studies have shown the impact of mastery and performance orientations on the learning of a complex, decision-making task. Smith et al. (1995) found mastery orientation to be positively related to metacognitive activity during training. Kozlowski et al. (1995) and Smith et al. (1995) found mastery orientation to be positively related to self-efficacy at the end of training. In addition, Smith et al. (1995) found performance orientation to be negatively related to self-efficacy at the end of a training program where individuals were responsible for choosing practice exercises. The two goal orientation factors were not related to transfer of training in either study after controlling for instructional factors and learning outcomes. It should be noted that performance orientation was negatively correlated with transfer performance in the Smith et al. (1995) study, but this relationship became nonsignificant after controlling for learning strategies and learning outcomes.

Based on theoretical distinctions between the two goal orientation factors, it is expected that mastery orientation will be positively related to both hypothesis-testing activity and self-regulatory activity during training. Previous research has shown that mastery orientation is related to various learning strategies for trying to understand new tasks such as metacognitive activity during training (Ames & Archer, 1992; Smith et al., 1995). Individuals with a mastery orientation tend to use deep processing strategies that require cognitive effort but lead to understanding; in contrast,

performance orientation is related to more short-term and surface-level processing strategies (Meece, 1994). Individuals with a mastery orientation to learning are more likely to formulate hypotheses about the task and test them out during practice. They are also more likely to monitor and evaluate their progress to assess their level of understanding. Consistent with previous findings, performance orientation is not expected to influence the use of hypothesis-testing and self-regulatory activities.

Hypothesis 16. Mastery orientation will be positively related to hypothesis-testing activity.

Hypothesis 17. Mastery orientation will be positively related to self-regulatory activity.

Mastery orientation is also expected to be positively related to general knowledge about the task, as well as the individual's knowledge structure. Because mastery-oriented individuals are focused on learning new skills and understanding the task, they should develop a better understanding of the task overall, as well as a better understanding of the relationships among concepts and actions they are presented during training. Consistent with previous research, performance orientation is not expected to influence an individual's knowledge or knowledge structure.

Hypothesis 18. Mastery orientation will be positively related to verbal knowledge.

Hypothesis 19. Mastery orientation will be positively related to knowledge structure.

Mastery goal orientation is also expected to impact self-efficacy at the end of training. Individuals who are focused on developing new skills during training are likely to develop greater confidence in their abilities at the end of training. In fact,

previous research has found a positive relationship between mastery orientation and self-efficacy (Smith et al., 1995).

Hypothesis 20. Mastery orientation will be positively related to self-efficacy.

Previous research has shown inconsistent results for the impact of performance orientation on self-efficacy. While Kozlowski et al. (1995) found little or no impact of performance orientation on self-efficacy, Smith et al. (1995) found a negative relationship between performance orientation and self-efficacy. In the Smith et al. study, individuals were required to choose the level of complexity and sequence of exercises they were to practice. Individuals with a higher performance orientation may have had difficulty in taking this active responsibility for learning activities, and thus were less confident in their capabilities by the end of training. In the present study, the learning activities and sequence of exercises are prescribed for the learner; therefore, performance orientation is not expected to have an impact on self-efficacy. No specific hypotheses are made concerning the role of performance orientation in learning and transfer. Instead, any effects for performance orientation will be controlled for prior to testing study hypotheses.

Tolerance for ambiguity. The term tolerance for ambiguity can be traced to Frenkel-Brunswik (1949), who used this concept to describe an individual's emotional and cognitive orientation towards life. She was interested in whether individuals who were prejudiced or rigid in their attitudes would show similar rigidity on perceptual tasks. Budner (1962) was interested in tolerance for ambiguity as a construct in its own right, and developed a definition of this construct in terms of several component dimensions. He defined intolerance of ambiguity as ". . . the tendency to perceive (i.e.

interpret) ambiguous situations as sources of threat," and tolerance of ambiguity as ". . . the tendency to perceive ambiguous situations as desirable" (Budner, 1962, p. 29).

He described three types of situations that define ambiguity: (1) a new situation where there are no familiar cues; (2) a complex situation where a great number of cues must be considered; and (3) a contradictory situation in which different elements suggest different structures. In other words, ambiguous situations are characterized by novelty, complexity, or insolubility (Budner, 1962).

Budner (1962) developed a scale to measure intolerance for ambiguity, and found it to be positively related to measures of authoritarianism and conventionalism, and negatively related to Machiavellianism. He also found a marginally significant tendency for medical students intolerant of ambiguity to choose relatively structured specialties, and those tolerant of ambiguity to choose relatively unstructured specialties.

Crandall (1968) provided additional evidence for the task preferences of individuals tolerant and intolerant of ambiguity. Participants in the study were required to learn pairs of CVC syllables. Crandall (1968) found that individuals intolerant of ambiguity preferred stimuli that were familiar and had the strongest confirmation value. In contrast, individuals tolerant of ambiguity lost interest in stimuli at higher levels of repetition. Crandall (1968) interpreted the results to indicate that individuals intolerant of ambiguity prefer stimuli that are useful for providing closure or consolidating knowledge, rather than expanding it. Individuals tolerant for ambiguity welcome extension of their cognitive system, whereas individuals intolerant of ambiguity prefer definition of their systems.

Blake, Perloff, Zenhausen, and Heslin (1973) found that individuals intolerant of ambiguity viewed atypical consumer products as newer than individuals tolerant of ambiguity. Perceived product newness was positively related to willingness to buy among tolerant participants, but negatively related to willingness to buy among intolerant participants (Blake et al., 1973). Frone (1990) conducted a meta-analysis to examine intolerance of ambiguity as a moderator of the occupational role stress-strain relationship. He expected that the role stress-strain relationship would be stronger among high intolerant of ambiguity individuals (IOA) than low IOA individuals. Results supported the moderating role of tolerance for ambiguity (Frone, 1990).

Surprisingly, very little research has been conducted that examines the relationship between tolerance for ambiguity, instructional methods, and learning outcomes (Jonassen & Grabowksi, 1993). Ebeling and Spear (1980) did examine whether tolerance for ambiguity would impact performance on two tasks of varying ambiguity (a decoding task v. a creativity task of thinking of different uses for common objects). They found that individuals high on tolerance for ambiguity performed better on both levels of task ambiguity compared to individuals low on tolerance for ambiguity. Even though previous research has shown that tolerance for ambiguity is in fact related to preferences for novel and ambiguous stimuli, Ebeling and Spear's (1980) study suggests that high tolerance for ambiguity individuals may perform tasks better regardless of their task preferences.

Tolerance for ambiguity is an important factor to consider when examining adaptive transfer. Individuals high on tolerance for ambiguity welcome the challenge of ill-structured, novel, and complex situations. It is expected that tolerance for

ambiguity will be positively related to adaptive transfer. Individuals who view ambiguous situations as desirable are likely to perform well in a transfer situation that requires them to learn about and adapt to a new feature of the task. Individuals low on tolerance for ambiguity may have difficulty adjusting to new task demands.

Hypothesis 21. Tolerance for ambiguity will be positively related to adaptive transfer.

The literature on tolerance for ambiguity has not examined what mechanisms lead to greater learning or transfer by individuals high on tolerance for ambiguity. Researchers have suggested that individuals tolerant of ambiguity will perform well when faced with situations that are novel or unstructured, because they are able to hypothesize well and provide their own structure. It is assumed that individuals high on tolerance for ambiguity are better able to make logical inferences concerning task cues, and that these inferences facilitate success in task performance (Chapelle & Roberts, 1986). In contrast, individuals low on tolerance for ambiguity may have difficulty providing their own structure to ambiguous learning situations (Jonassen & Grabowski, 1993). Thus, one mechanism that may account for the positive relationship between tolerance for ambiguity and adaptive transfer is hypothesis-testing skill. Individuals high on tolerance for ambiguity may engage in greater hypothesis testing while learning tasks that enables them to perform well when faced with novel circumstances. Previous research has not tested the learning mechanisms that facilitate the success of high tolerance for ambiguity learners (Chapelle & Roberts, 1986), and the present study will examine whether tolerance for ambiguity does in fact lead to greater hypothesis-testing during learning.

Hypothesis 22. Tolerance for ambiguity will be positively related to hypothesis-testing skill.

It is expected that tolerance for ambiguity will be related to knowledge acquired during training. Researchers suggest that individuals low on tolerance for ambiguity may be more detail-oriented and unable to view situations in global terms (Jonassen & Grabowski, 1993). Chapelle and Roberts (1986) provided some indication that tolerance for ambiguity is related to knowledge. They found that tolerance for ambiguity was positively related to proficiency in English as a second language for foreign students. After controlling for initial proficiency, anxiety, and motivation, tolerance for ambiguity was positively related to the acquisition of English structure and listening comprehension by the end of the semester. Therefore, it is expected that tolerance for ambiguity will be related to verbal knowledge about the task as assessed on a test at the end of training. A tentative hypothesis is made that tolerance for ambiguity will be related to the quality of one's knowledge structure for a new task. Individuals low on tolerance for ambiguity may develop a less-integrated knowledge structure because they have difficulty viewing a complex task in global terms.

Hypothesis 23. Tolerance for ambiguity will be positively related to verbal knowledge.

Hypothesis 24. Tolerance for ambiguity will be positively related to knowledge structure.

A final learning outcome that may be influenced by tolerance for ambiguity is self-efficacy. It is suggested that tolerance for ambiguity is related to motivation and persistence in the face of ambiguity (Jonassen & Grabowski, 1993). Individuals who welcome and are challenged by novelty, ambiguity, and complexity are likely to feel

more self-confident in their capabilities to adapt to these types of situations. In contrast, individuals low on tolerance for ambiguity are characterized as those who do not enjoy taking risks (Birckbichler & Omaggio, 1978). Thus, they may report low self-efficacy for being able to succeed in ambiguous situations.

Hypothesis 25. Tolerance for ambiguity will be positively related to self-efficacy.

Table 1 summarizes the hypotheses to be tested in this study. Although each hypothesis could be tested separately as a univariate relationship between factors, this study will test sets of hypotheses in a more integrated fashion. Specifically, hypotheses concerning the same dependent variable will be tested in one overall analysis. In this way, a particular hypothesis will be tested after controlling for all other relevant factors in the model. For example, hypotheses 4, 16, and 22, which are concerned with factors that influence hypothesis-testing activity, will be tested in one overall analysis. This will provide a rigorous test of specific relationships in the conceptual model.

In addition, the conceptual model presented in Figure 1 indicates that the learning outcomes are expected to mediate the relationship between individual differences, training manipulations, and adaptive transfer. While not stated as an explicit hypothesis, this mediation will also be tested for in the analyses.

Table 1

Summary of Study Hypotheses

Hypothesis	Independent Variables	Dependent Variable
1	Discovery Learning (Pure discovery v. guided discovery v. procedural instruction)	Adaptive transfer performance
2	Metacognitive Instruction (yes or no)	Adaptive transfer performance
3	Discovery Learning X Metacognitive Instruction	Adaptive transfer performance
4	Discovery Learning (Pure discovery v. guided discovery v. procedural instruction)	Hypothesis-testing activity
5	Hypothesis-testing activity	Adaptive transfer
6	Metacognitive Instruction (yes or no)	Self-regulatory activity
7	Self-regulatory activity	Adaptive transfer
8	Discovery Learning (Pure discovery v. guided discovery v. procedural instruction)	Verbal knowledge
9	Metacognitive Instruction (yes or no)	Verbal knowledge
10	Verbal knowledge	Adaptive transfer
11	Discovery Learning (Pure discovery v. guided discovery v. procedural instruction)	Knowledge structure
12	Metacognitive Instruction (yes or no)	Knowledge structure
13	Knowledge structure	Adaptive transfer
14	Metacognitive Instruction (yes or no)	Self-efficacy
15	Self-efficacy	Adaptive transfer
16	Mastery orientation	Hypothesis-testing activity
17	Mastery orientation	Self-regulatory activity
18	Mastery orientation	Verbal knowledge
19	Mastery orientation	Knowledge structure
20	Mastery orientation	Self-efficacy
21	Tolerance for ambiguity	Adaptive transfer
22	Tolerance for ambiguity	Hypothesis-testing activity
23	Tolerance for ambiguity	Verbal knowledge
24	Tolerance for ambiguity	Knowledge structure
25	Tolerance for ambiguity	Self-efficacy

METHOD

Sample

Participants were undergraduate students at Michigan State University enrolled in psychology courses who received extra credit in their course for participation in the experiment. One hundred sixty-nine individuals participated in this experiment. However, eight participants were eliminated from the sample. Six participants were eliminated because of extreme difficulty in understanding the task. Two other participants were eliminated after it was discovered that they did not engage any targets on the transfer task (it appeared that they were looking up information randomly but not making a single decision during the nine-minute transfer trial). Therefore the sample used in this study included 161 participants, with cell sizes ranging from 26 to 29 individuals.

Design

The study was a 3 (discovery instruction) X 2 (metacognitive instruction) fully-crossed factorial design. The three levels of discovery instruction were pure discovery, guided discovery, and procedural instruction. The second factor was the presence or absence of metacognitive instruction. A power analysis was conducted to determine the sample size necessary to detect a moderate effect size with power of .80, and a significance level of .05 (Cohen, 1977). For a 3 X 2 factorial design, cell sizes of 25

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(i.e., a total sample size of 150) would result in power of .78 for detecting an interaction using $p < .05$ as the level of significance for rejecting the null hypothesis. Based on this power analysis, the sample size of 161 participants was judged to be sufficient for examining the study hypotheses.

Task

The task individuals learned was a revised version of TANDEM (Tactical Naval Decision Making System; Dwyer, Hall, Volpe, Cannon-Bowers, & Salas, 1992). TANDEM is a simulation software program that depicts targets on a screen. Trainees were placed in the role of Radar Operator of a U.S. Navy Aegis-class cruiser. The Operator was to "hook" a target on the radar screen and then collect information to classify the target's Type, Class, and Intent. Then the Operator decided to shoot hostile targets and clear peaceful targets from the screen. The goal of the task was to correctly identify and process each target in the shortest amount of time possible. Individuals learned how to prevent targets from entering critical zones surrounding their own ship. If individuals allowed targets into these "penalty circles," they would lose points. Individuals learned to check the speed and range for each target to prioritize the targets they would engage first. Trainees practiced task scenarios that varied in the number of targets, the proportion of dangerous targets surrounding each penalty circle, and their order of entry into the penalty circles. Three different scenarios were presented, sequenced from low to moderate to high complexity.

The design of the scenarios focused on increasing the component and coordinative complexity of the task (Wood, 1986) as they increased from low to moderate to high complexity. Specific descriptions of the scenarios are provided in

Appendix D (under Procedural Instruction section). As scenarios increased in complexity, the number of targets surrounding the penalty circles was greater to increase the component complexity of the task. By increasing the number of targets, the number of distinct acts required by participants to assess these targets was also increased. In addition, the coordinative complexity of the task was increased over scenarios by making the sequence of the prosecution of targets more important. As scenarios increase in complexity, a greater proportion of targets were dangerous, and individuals had to zoom in and out more frequently to prosecute targets in the correct sequence. After training, individuals were tested on an adaptive transfer task that was different on the dimension of dynamic complexity (Wood, 1986).

Procedure

The experiment was conducted over two consecutive days. The first day comprised the training manipulation. When participants first arrived, they read and signed a consent form that described the experiment (see Appendix A). They then completed an individual differences questionnaire that assessed their tolerance for ambiguity, mastery orientation, and performance orientation, as well as certain demographic and experience variables. Next, participants watched a brief demonstration by the experimenter on how to perform the basic functions of the task (hooking targets, accessing information from the menus, making decisions about targets, and zooming in and out on the radar screen). Participants had ten minutes to read a short manual describing these functions in more detail (see Appendix B). Then participants performed a 9 minute trial and a 4.5 minute trial to practice hooking

targets, calling up information about these targets to classify their Type, Class, and Intent, and making Final Engagement decisions.

Participants learned a simplified version of the task in which they only needed to access one information cue to make each of the Type, Class, and Intent decisions. They used a table from the manual to determine the correct classification to choose for each of the Type, Class, and Intent decisions. This portion of the task was simplified so that the decision criteria and decision sequence could be learned quickly. The training manipulations focused on a more complex skill, prioritization of targets to prevent them from entering two penalty circles.

After individuals practiced the basic rules for classifying targets, the discovery learning manipulation was introduced. All participants were told that the goal of the next portion of training was to learn how to prevent targets from entering two penalty circles surrounding their ship, and that they would practice scenarios at low, medium, and high levels of complexity (see General Task Instructions in Appendix C). After this general introduction to the training, participants received instructions for the pure discovery, guided discovery, or procedural instruction condition (explained in more detail in the Discovery Learning Manipulation section below). Participants then practiced the low complexity scenario for three trials. The number of practice trials that were sufficient for individuals to learn each scenario were determined in a pilot study. Each practice trial lasted 4.5 minutes. For the low complexity trials, the score was turned off during the scenario. This was done so that all groups were focused on a mastery-oriented approach to learning and were not too focused on their performance

during initial learning. At the end of each practice trial, participants received feedback concerning the number of targets they allowed to enter each penalty circle.

After practicing the low complexity scenario, participants in the metacognitive instruction condition received training on how to self-regulate their learning, and why it was important (see Metacognitive Instruction section for more details). In addition, participants were presented with instructions for the medium complexity scenario that varied by discovery learning condition. For the moderate and high complexity scenarios, the score was turned back on during the practice trials so that individuals could monitor their progress.

Participants completed one trial of the medium complexity scenario. For the metacognitive instruction group, participants were presented with the first set of questions they were to answer to regulate their learning. Participants completed three additional practice trials, with metacognitive questions answered between trials for the metacognitive instruction group.

After the medium complexity scenario, participants received a short break. Finally, participants were presented with the high complexity task scenario. Before practice, participants received instructions consistent with their discovery learning condition. After the first practice trial, participants in the metacognitive instruction condition began answering questions to guide them in self-regulating their learning. Participants completed a total of 5 trials to practice the high complexity scenario.

When participants finished practicing the high complexity scenario, they completed a questionnaire concerning their use of hypothesis-testing and self-regulation during the training session. This first day of training lasted for 3 hours.

Participants returned one day later to perform on the adaptive transfer task. On the second day of the experiment, participants first completed a self-efficacy questionnaire. They then completed ratings to assess their knowledge structure, followed by a short, multiple-choice verbal knowledge test. Participants next completed a test of general cognitive ability. Finally, they performed the adaptive transfer task, which was 9 minutes in length. The second experimental session took one hour to complete.

Discovery Learning Manipulation

The discovery learning manipulation determined the type of learning strategy or approach used by the learner to develop an understanding of the task. Participants in the pure discovery condition received instructions that told them they would face a scenario of low complexity. They were instructed to explore the task in order to discover the best strategy to deal with the situation and prevent targets from entering the penalty circles. Similar instructions were presented prior to practice on the medium and high complexity scenarios as well.

Participants in the guided discovery condition were presented with an explicit description of the low complexity scenario, and the task strategies they should use to handle it. However, for the first low complexity scenario trial, participants were asked to just check speed and range on targets and learn where the penalty circles were. They were told not to make decisions about targets so that targets remained on the screen and participants would be able to learn what happens when targets entered the penalty circles. Then for the remaining two low complexity trials, participants were asked to practice the task strategy appropriate for that scenario.

For the medium and high complexity scenarios, the guided discovery group was directed to hypothesize what aspects of the task might change to increase the complexity of the task. Then they were asked to identify how they would respond to these changes in their strategy for performing the task. They recorded their answers to these questions on a sheet provided to them. They were instructed to explore the task to test out their hypotheses and their task strategies. In this way, they could determine what were the important features of the scenario and how they should respond to them. Thus, individuals in the guided discovery condition were provided with explicit procedural instruction on the low complexity scenario to provide a knowledge base for their own hypothesis-testing on the medium and high complexity scenarios.

Participants in the procedural instruction condition received explicit description of the scenario and the task strategy to use for each of the low, medium, and high complexity scenarios. They were instructed to focus their attention on practicing the task strategy outlined for them. The specific instructions provided to each instructional condition are detailed in Appendix D.

Metacognitive Instruction

The metacognitive guidance provided learners with a way to improve the effectiveness of their performance strategies to handle the different task situations they faced. Individuals in the metacognitive instruction condition received training on planning, monitoring, and evaluating their task strategies. Metacognitive instruction was introduced before practice of the moderate complexity task. Participants were taught what it meant to plan, monitor and evaluate their task performance in order to find ways to improve it. Consistent with previous research on metacognitive

instruction, participants were also told why these self-regulatory processes are important. The specific instructions provided to participants can be found in Appendix E. After the first trial of practicing the moderate complexity task, participants in the metacognitive instruction condition were asked to record how many intrusions they allowed in each penalty circle on a sheet provided to them. Participants were asked to think about their feedback from the last trial, and identify any difficulties or problems upon which they could improve. They were then asked to develop a learning goal for the next trial to improve their understanding, and a plan for accomplishing that goal. They recorded these on the sheet provided (see Appendix E). They were told to monitor their practice with regard to their goal. This process was repeated three times for the moderate complexity scenario and four times for the high complexity scenario trials.

Participants in the condition not receiving metacognitive instruction were instructed that they could do as they like to prepare for the next practice trial, and they sat quietly between trials for several minutes. For initial trials, where the self-regulation questions took longer to answer, participants in the no-metacognition instruction group were given three minutes to sit quietly. For later trials, where the self-regulation questions were answered more quickly, participants in the no-metacognition instruction condition had two minutes to sit quietly between trials.

Measures

Participants completed several survey measures at the beginning and end of the training program. Cognitive ability was assessed with a computerized test on the second day of the experiment. Two measures of knowledge were also collected the

day after the training portion of the experiment. Finally, performance on the adaptive transfer test was assessed on the second day of the experiment. Table 2 presents the means, standard deviations, reliabilities, and intercorrelations of the measures used in this study. The specific measures and their development are described next.

Participants completed a questionnaire at the beginning of the experiment, which included questions with regard to their age, sex, GPA, and previous video game experience. A problem with the GPA measure arose during the study, as many participants were freshmen in their first semester of college so that they did not yet have a GPA. This variable, therefore, was not included in the study. Specific questions can be found in Appendix F.

Gender. Participants were asked to indicate their gender. Gender was coded as 1 = male and 2 = female.

Age. Participants indicated one of ten categories for their age. See Appendix F for the specific categories which ranged from "17 or younger" to "26 or older."

Video game experience. Participants answered the item "how often do you play with video games" using a 5-point scale ranging from (1) never to (5) always.

Cognitive ability. General cognitive ability was measured with a computerized version of the Wonderlic Personnel test. This was a short form test of general cognitive ability, consisting of 50 items arranged in order of difficulty. The items included word comparisons, disarranged sentences, sentence parallelism, following directions, number comparisons, number series, analysis of geometric figures, and math or logic story problems. Participants were given 12 minutes to complete as

Table 2
Means, Standard Deviations, Reliabilities, and Intercorrelations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Adaptive Transfer Score	---															
2. Guided Discovery ^a	-.06	---														
3. Pure Discovery ^a	.12	-.50**	---													
4. Metacognitive Instruction ^b	.04	-.01	.01	---												
5. Tolerance for Ambiguity	.11	-.01	-.01	-.14	(.66)											
6. Ability	.26**	.01	.08	.06	.04	---										
7. Mastery Orientation	.03	.00	.08	-.13	.27**	.17*	(.80)									
8. Performance Orientation	.02	-.10	-.05	-.10	-.02	-.04	.26** (.75)									
9. Verbal Knowledge	.28**	.07	.06	.07	.03	.46**	.12	-.06	(.68)							
10. Knowledge Structure	.07	-.01	-.03	.02	.04	.24**	.06	.04	.07	---						
11. Hypothesis-Testing/ Self-Regulatory Activity	.07	.24**	-.06	-.07	.22**	.20*	.35**	-.02	.25**	.03	(.90)					

Table 2 (cont'd)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
12. Self-Efficacy	.10	.00	-.02	-.01	.35**	.20*	.33**	.14	.05	.02	.43** (.85)					
13. Prioritization of Targets	.90**	-.04	.10	.03	.09	.25**	.05	.01	.35**	.07	.07	.10	---			
14. Gender	-.19*	.00	.01	-.04	-.18*	-.07	-.09	.19*	-.09	.00	-.14	-.17*	-.11	---		
15. Age	-.35**	-.02	.00	-.14	-.08	.03	.21**	.02	-.04	.14	.07	.00	-.29**	-.17*	---	
16. Video Game Experience	.33**	-.06	.11	.03	.17*	.09	-.06	-.11	.20**	.06	.14	.14	.29**	-.47**	-.07	---
M	230.37	0.32	0.35	0.51	4.17	24.93	5.50	5.61	6.68	0.17	5.51	5.22	11.32	1.69	3.18	2.08
SD	455.35	0.47	0.48	0.50	0.97	4.77	0.72	0.77	2.16	0.06	0.87	0.98	2.72	.46	1.92	0.98

* Guided Discovery is a dummy-coded variable where Guided Discovery = 1, Pure Discovery = 0, and Procedural Instruction = 0. Pure Discovery is dummy-coded so that Guided Discovery = 0, Pure Discovery = 1, and Procedural Instruction = 0.

^b Metacognitive Instruction is coded as Metacognitive Instruction = 1 and No Metacognitive Instruction = 0.

N = 161

many items as possible. Scores on the Wonderlic test have been shown to be highly related to scores on longer tests of cognitive ability. In addition, test-retest reliabilities have ranged from .82 to .94, and internal consistency reliabilities (based on correlating odd and even items) have ranged from .88 to .94 (Wonderlic Personnel Test & Scholastic Level Exam User's Manual, 1992). Participants completed this test on the second day of the experiment.

Participants completed a questionnaire at the beginning of the experiment to assess three individual difference factors: tolerance for ambiguity (10 items); mastery goal orientation (8 items); and performance goal orientation (8 items). These individual differences are conceptually distinct. However, to test the empirical independence of these three constructs, the 26 items making up these three measures were subject to a common factor analysis with varimax rotation. A three-factor solution was specified. Table 3 displays the rotated factor matrix.

The three factors accounted for 42 percent of the total variance. The predicted factor structure was maintained to some extent. The first factor was made up of mastery orientation items. The third factor was made up of tolerance for ambiguity items. However, the second factor was made up of all performance orientation items along with four items from the tolerance for ambiguity scale. Item 6 from the tolerance for ambiguity scale also loaded on both the first factor and the third factor.

In addition, the scree plot indicated the possibility of a six-factor solution. A factor analysis was run with a six-factor solution as well; results of the six factor solution did not conform well to the conceptualization of these constructs. The mastery orientation and performance orientation items separated into four factors, and

Table 3

Rotated Factor Matrix for Individual Differences Items

	Factor		
	1	2	3
Mastery Orientation 5	<u>.76</u>	.21	.02
Mastery Orientation 6	<u>.72</u>	.13	-.03
Mastery Orientation 4	<u>.68</u>	-.14	.24
Mastery Orientation 7	<u>.64</u>	.01	.28
Mastery Orientation 3	<u>.61</u>	.25	-.01
Mastery Orientation 8	<u>.58</u>	.19	-.05
Mastery Orientation 1	<u>.38</u>	.03	.19
Mastery Orientation 2	<u>.36</u>	.01	.25
Performance Orientation 5	-.06	<u>.65</u>	-.14
Performance Orientation 8	.26	<u>.62</u>	-.13
Tolerance for Ambiguity 7 ^a	-.01	<u>-.61</u>	.39
Performance Orientation 6	.15	<u>.60</u>	.20
Tolerance for Ambiguity 8 ^a	.08	<u>-.52</u>	.39
Tolerance for Ambiguity 3 ^a	.07	<u>-.52</u>	.28
Performance Orientation 4	.16	<u>.49</u>	.03
Performance Orientation 3	.07	<u>.46</u>	.04
Performance Orientation 2	.12	<u>.45</u>	.15
Performance Orientation 1	.03	<u>.38</u>	.19
Performance Orientation 7	.19	<u>.36</u>	.02
Tolerance for Ambiguity 2 ^a	.11	<u>-.27</u>	.20
Tolerance for Ambiguity 10	.14	-.01	<u>.64</u>
Tolerance for Ambiguity 9	.24	-.27	<u>.52</u>
Tolerance for Ambiguity 1	-.06	.00	<u>.50</u>
Tolerance for Ambiguity 6 ^a	.38	-.15	<u>.44</u>
Tolerance for Ambiguity 4	.03	.05	<u>.43</u>
Tolerance for Ambiguity 5	.17	.13	<u>.36</u>

^a These items were dropped from final scales.

four tolerance for ambiguity items separated from the performance orientation items. The five tolerance for ambiguity items that loaded together in the first factor analysis remained a clear factor in the six-factor solution.

It was decided that the scales would be developed based on the results of the three-factor solution. The tolerance for ambiguity scale was made up of the five items from the third factor in Table 3 that loaded cleanly on this one factor. The five items that loaded on other factors were dropped from the scale. The eight items making up the mastery orientation scale and the eight items making up the performance orientation scale were retained. This decision was based on several previous studies that had shown the construct validity and psychometric properties of these two scales (Button, Mathieu, & Zajac, 1995; Kozlowski et al., 1995; Ford et al., 1995). In addition, reliability analyses for these scales indicated adequate internal consistency for the mastery and performance orientation scales.

Table 1 displays the intercorrelations between these three scales. As found in previous research (Kroll, 1988), tolerance for ambiguity was positively related to mastery orientation ($r = .27, p < .01$). Tolerance for ambiguity was not significantly related to performance orientation ($r = -.02, p > .05$). In addition, consistent with some research (Kozlowski et al., 1995), mastery orientation and performance orientation also exhibited a significant, positive correlation ($r = .26, p < .01$).

It should be noted that other research has not found a significant relationship between mastery and performance orientation (Smith et al., 1995). When corrected for attenuation, the intercorrelations between tolerance for ambiguity, mastery orientation, and performance orientation were as follows: tolerance for ambiguity and mastery

orientation, $r_{\text{true}} = .37$; tolerance for ambiguity and performance orientation, $r_{\text{true}} = -.03$; and mastery orientation and performance orientation, $r_{\text{true}} = .34$. These small to moderate correlations after correcting for attenuation indicate that the scales measure distinct constructs.

Also, while tolerance for ambiguity and performance orientation were not significantly related to cognitive ability, mastery orientation did exhibit a significant, positive correlation with ability ($r = .17$, $p < .05$). These scales also exhibited differential relationships with gender, age, and previous video game experience. The differential relationships provide evidence for the construct validity of these three scales.

Tolerance for ambiguity. Tolerance for ambiguity was measured with a 10-item scale adapted from Major (1990). Items can be found in Appendix G. Participants responded to these items on a seven-point scale ranging from (1) strongly disagree to (7) strongly agree. Based on factor analysis results, the final scale was made up of five items. Coefficient alpha for this scale was .66.

Mastery orientation. Participants completed an eight-item scale developed by Button, et al. (1995). Items can be found in Appendix H. Participants responded to these items on a seven-point scale ranging from (1) strongly disagree to (7) strongly agree. Coefficient alpha for the scale was .80.

Performance orientation. Participants completed an eight-item scale developed by Button et al. (1995). Items can be found in Appendix H. Participants responded to these items on a seven-point scale ranging from (1) strongly disagree to (7) strongly agree. Coefficient alpha for the scale was .75.

At the end of training, participants completed two scales measuring learning activities, hypothesis-testing activity (6 items) and self-regulatory activity (6 items). In addition, when participants returned on the second day of the experiment, they completed an eight-item self-efficacy scale. These twenty items were subjected to a common factor analysis. A three-factor solution was specified and rotated to a varimax criterion. The rotated factor matrix is presented in Table 4. The three factors accounted for 63 percent of the total variance. However, the scree plot indicated that a two-factor solution was also appropriate, and the first two factors accounted for 57 percent of the variance.

Table 4 shows that factor 1 included all self-efficacy items. Factor 2 included all self-regulation items and three hypothesis-testing items. Factor 3 was made up of the remaining three hypothesis-testing items. However, the items from Factor 3 also loaded fairly strongly on factor 2 as well. These results suggested that self-regulation and hypothesis-testing were not distinct constructs. In fact, the correlation between the two original scales was found to be .74. When corrected for attenuation, this correlation became .90. Therefore, it was decided to combine these 12 items into one scale that measured hypothesis-testing/self-regulatory activity.

The correlation between hypothesis-testing/self-regulatory activity and self-efficacy was .43 ($p < .01$). After correcting for attenuation, the correlation between hypothesis-testing/self-regulatory activity and self-efficacy was .49. Although these scales were significantly correlated, Table 2 shows that the hypothesis-testing/self-regulation and self-efficacy scales were differentially related to the discovery learning manipulation. In addition, hypothesis-testing/self-regulatory activity was positively

Table 4

Rotated Factor Matrix for Learning Activity and Self-Efficacy Items

	Factor		
	1	2	3
Self-Efficacy 6	<u>.86</u>	.15	.22
Self-Efficacy 5	<u>.85</u>	.14	.08
Self-Efficacy 8	<u>.84</u>	.23	.04
Self-Efficacy 3	<u>.83</u>	.11	.02
Self-Efficacy 4	<u>.83</u>	.22	-.03
Self-Efficacy 1	<u>.78</u>	.12	.12
Self-Efficacy 7	<u>.75</u>	.21	.23
Self-Efficacy 2	<u>.72</u>	.16	.26
Self-Regulation 1	.16	<u>.75</u>	.11
Self-Regulation 4	.00	<u>.74</u>	.05
Self-Regulation 5	.16	<u>.72</u>	.20
Self-Regulation 6	.20	<u>.62</u>	.19
Hypothesis-Testing 4	.32	<u>.57</u>	.22
Self-Regulation 2	.23	<u>.56</u>	.30
Self-Regulation 3	.21	<u>.55</u>	.30
Hypothesis-Testing 5	.16	<u>.46</u>	.23
Hypothesis-Testing 6	.07	<u>.45</u>	.32
Hypothesis-Testing 3	.15	.47	<u>.56</u>
Hypothesis-Testing 2	.20	.35	<u>.55</u>
Hypothesis-Testing 1	.06	.31	<u>.55</u>

related to verbal knowledge ($r = .25, p < .01$), while self-efficacy was not significantly related to verbal knowledge ($r = .05, p > .05$). These differential relationships provide evidence for the construct validity of these scales.

Hypothesis-testing/self-regulatory activity. Self-reported hypothesis-testing and self-regulation during training was assessed with 12 items developed for this study. Although originally conceptualized as separate constructs and scales, factor analysis and correlational results suggested a single construct. Several items on this scale were adapted from a metacognition measure developed by Smith et al. (1995). This scale measured the extent to which individuals made and tested predictions about changes in scenario complexity, and explored the task and experimented with different task strategies. This scale also measured the extent to which individuals set learning goals and plans for their practice trials, and monitored and evaluated their understanding. Participants in this study rated items on a 7-point Likert-type scale ranging from (1) *strongly disagree* to (7) *strongly agree*. Items for this scale can be found in Appendix I. Coefficient alpha for this scale was .90.

Self-efficacy. Self-efficacy was measured on the second day of the experiment by a modified version of an 8-item scale developed by Smith, et al. (1995) and Kozlowski, et al. (1995). Items were adapted to reflect a focus on the subject's confidence that they could handle the task if the situation they faced was complex and one that they had never experienced before. Participants rated the 8 items on a 7-point Likert-type scale ranging from (1) *strongly disagree* to (7) *strongly agree*. Self-efficacy items are presented in Appendix J. Coefficient alpha for the scale was .85.

Verbal knowledge. Participants completed a 14-item multiple choice test to assess their declarative and procedural knowledge of the task. Questions assessed their understanding of the location of the penalty circles, the use of the zoom function, and how to prioritize the order of prosecuting targets. The test questions can be found in Appendix K. A reliability analysis was conducted to assess the internal consistency of the test items. The coefficient alpha for the original 14-item scale was .58. Based on an analysis of internal consistency statistics, 4 items were dropped from the scale which exhibited low corrected item-total correlations and low squared multiple correlations. These four items were eliminated from the test to form the final 10-item knowledge test used in the study. Coefficient alpha for this 10-item test was .68.

Knowledge structure. The knowledge structure measure was collected at the end of training. The organization of each subject's knowledge was measured by having them make relatedness ratings between 13 concepts and actions important for task performance. Thus, participants made a total of 78 ratings indicating how related they thought two items are on a 9-point scale ranging from (1) *unrelated* to (9) *related*. These ratings were submitted to the Pathfinder algorithm to derive a Pathfinder network. Each subject's network was compared to an expert structure derived from the primary experimenter. A closeness index, C, was computed for each subject's network. This index examined the degree to which the same item in each of the two networks (subject and expert) was surrounded by a similar neighborhood of items. This neighborhood comparison was made for each item in the network, and the results were averaged across all items to compute the overall index of closeness

(Goldsmith et al., 1991). This closeness index can range from 0.0 to 1.0. Instructions and items that were rated can be found in Appendix L.

Reliability information for this measure was not available. However, research does indicate that individuals who are trained on a task exhibit knowledge structures that are significantly closer to an expert structure compared to a control group that did not receive training (Kraiger & Salas, 1993). Also, Kozlowski et al. (1995) found that, with training, these knowledge structures become more coherent over time.

Adaptive transfer. Adaptive transfer was measured by the score achieved on a novel transfer task. As in training, participants gained 40 points for accurate decisions, and gained fewer points or lost up to 40 points when some or all the decisions were incorrect. More importantly, participants lost 100 points for each target allowed into either of the two penalty circles. While the training trials lasted 4.5 minutes, the transfer task was 9 minutes in duration. This transfer task required adaptability because participants were presented with "pop-up" targets that suddenly appeared on the screen. During training trials, all targets were present on the screen for the whole scenario, so that once participants assessed each target's speed and range they would know the situation that they faced. In contrast, the pop-up targets appearing throughout the transfer task dynamically altered the situation over the course of the scenario. In the beginning of the scenario, the targets on the screen indicated that the most dangerous targets were on the outer penalty circle and that individuals should focus their attention on prosecuting targets there first. However, targets suddenly appeared at both the inner and outer penalty circles for the duration of the scenario, which required individuals to continually assess new targets and adjust their strategy

for prioritizing targets. These "pop-up" targets required participants to frequently zoom in and out to prosecute targets on the inner and outer penalty circles. Thus, this task included a new stimulus feature, pop-up targets, that required individuals to continually assess and re-assess the situation at each penalty circle. This scenario was higher on dynamic complexity (Wood, 1986) compared to the training scenarios. A task high on dynamic complexity requires individuals to frequently adapt to changes in cause-effect relationships during performance of the task. Instructions for the adaptive transfer task are found in Appendix M.

RESULTS

Data Analysis

The psychometric properties of the tolerance for ambiguity, hypothesis-testing/self-regulatory activity, and self-efficacy scales were assessed prior to testing the conceptual model. In addition, it was found that two participants failed to complete the six items assessing self-regulatory activity. Their value on the hypothesis-testing/self-regulation scale was based on their answers to the six hypothesis-testing items.

The hypotheses in this study were tested using hierarchical regression analyses (Cohen & Cohen, 1983). In all analyses, cognitive ability and performance orientation were entered in the first step as control variables. In addition, variables prior to or concurrent with variables in the model were entered to control for the effects of all other factors when assessing the hypothesized relationships. Variables were entered in an order consistent with the conceptual model in Figure 1. Individual difference factors were entered into the regression first because they were conceptualized as stable characteristics that individuals brought to the training. The discovery learning and metacognitive instruction manipulations were entered next to examine the role of training on the dependent variable. The discovery learning manipulation was represented by two dummy-coded variables. First, guided discovery was a variable coded 1 for the guided discovery group and 0 for the other two groups. Pure discovery was coded 1 for the pure discovery group and 0 for the other two groups.

Metacognitive instruction was also coded as 1 for the presence of the instruction and 0 for its absence from the training.

Verbal knowledge. Hierarchical regression analysis was used to examine how individual differences, discovery learning, and metacognitive instruction influenced the acquisition of verbal knowledge about the task. The first step in the regression controlled for the effects of cognitive ability and performance orientation. The second step in the regression contained the individual differences of tolerance for ambiguity and mastery orientation. The third step assessed the main effects for the discovery learning and metacognition manipulations. Table 5 presents results of the analysis.

Results indicated that cognitive ability and performance orientation accounted for a significant amount of variance in verbal knowledge ($R^2 = .21$, $F = 20.93$, $p < .01$). Beta-weights indicated that cognitive ability was positively related to verbal knowledge ($\beta = .45$ at step 1). Hypotheses 18 and 23 predicted that mastery orientation and tolerance for ambiguity, respectively, would positively affect verbal knowledge. The second step in the regression, containing these individual difference factors, did not account for a significant amount of variance in verbal knowledge. Hypotheses 18 and 23 were not supported by these results.

Hypothesis 8 predicted that guided discovery would lead to greater verbal knowledge compared to pure discovery, which would lead to greater verbal knowledge compared to procedural instruction. Hypothesis 9 predicted that metacognitive instruction would lead to greater verbal knowledge compared to no metacognitive instruction. The third step in the regression, which contained the main effects for these training manipulations, did not account for a significant amount of variance in

Table 5

Hierarchical Regression Analysis Results for Verbal Knowledge

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.45**	.43**		
	Performance Orientation	-.04	-.04	.21**	.21**
2	Tolerance for Ambiguity	-.01	.01		
	Mastery Orientation	.07	.06	.21**	.00
3	Guided Discovery	.10	.10		
	Pure Discovery	.07	.07		
	Metacognitive Instruction	.05	.05	.22**	.01

* $p \leq .05$; ** $p \leq .01$

verbal knowledge. Therefore, hypotheses 8 and 9 were not supported by the regression results. Overall, the variables in the regression accounted for 22 percent of the variance in verbal knowledge ($F(7,153) = 6.30, p < .01$).

Knowledge structure. A hierarchical regression analysis was run to examine how individual difference factors, discovery learning manipulations, and metacognitive instruction influenced the structure of knowledge developed about the training task. The effects of cognitive ability and performance orientation were controlled for in the first step in the regression analysis. Tolerance for ambiguity and mastery orientation were entered in the second step, followed by the training manipulations in the third step in the regression.

Results are presented in Table 6. Cognitive ability and performance orientation accounted for a significant amount of variance in knowledge structure ($R^2 = .06, F = 4.91, p < .01$), and beta-weights indicated that ability was the influential factor ($\beta = .24$). Hypotheses 19 and 24 predicted that mastery orientation and tolerance for ambiguity would be positively related to knowledge structure. The second step in the regression, containing these factors, did not account for a significant amount of variance in knowledge structure. These results did not support hypotheses 19 and 24.

Hypothesis 11 predicted that guided discovery would lead to a better knowledge structure compared to pure discovery learning, which would lead to a better knowledge structure than procedural instruction. Hypothesis 12 predicted that metacognitive instruction would lead to a better knowledge structure compared to no metacognitive instruction. The step containing the training manipulations did not account for significant variance in knowledge structure, which did not support hypotheses 11 and

Table 6

Hierarchical Regression Analysis Results for Knowledge Structure

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.24**	.24**		
	Performance Orientation	.05	.04	.06**	.06**
2	Tolerance for Ambiguity	.04	.03		
	Mastery Orientation	-.01	.00	.06*	.00
3	Guided Discovery	-.04	-.04		
	Pure Discovery	-.07	-.07		
	Metacognitive Instruction	.02	.02	.06	.00

* $p \leq .05$; ** $p \leq .01$

12. When all factors were entered into the regression, they no longer accounted for a significant amount of variance in knowledge structure ($F(7,153) = 1.48, p > .05$).

Hypothesis-testing/self-regulatory activity. A hierarchical regression analysis was run to examine the impact of individual differences and training manipulations on hypothesis-testing/self-regulatory activity during training. Cognitive ability and performance orientation were controlled for in the first step in the regression analysis. Tolerance for ambiguity and mastery orientation were entered in the second step, followed by the training manipulations in the third step. Results are presented in Table 7.

Cognitive ability and performance orientation accounted for a significant amount of variance in the dependent variable ($R^2 = .04, F = 3.20, p < .05$). The beta-weights indicated that cognitive ability was positively related to hypothesis-testing/self-regulation ($\beta = .20$ at step 1). Hypotheses 16/17 predicted a positive relationship between mastery orientation and hypothesis-testing/self-regulatory activity. Hypothesis 22 predicted a positive relationship between tolerance for ambiguity and hypothesis-testing. The second step in the regression analysis accounted for a significant amount of variance in the dependent variable ($\Delta R^2 = .13, \Delta F = 12.16, p < .01$). Beta-weights indicated that mastery orientation was positively related to hypothesis-testing/self-regulation ($\beta = .32$ at step 2). Although tolerance for ambiguity exhibited a significant zero-order correlation with hypothesis-testing/self-regulation ($r = .22, p < .01$), this relationship became nonsignificant once the influence of the other individual differences were controlled. These results did not support hypothesis 22, but they did support hypotheses 16/17.

Table 7

Hierarchical Regression Analysis Results for Hypothesis-Testing/Self-Regulation

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.20*	.13		
	Performance Orientation	-.01	-.07	.04*	.04*
2	Tolerance for Ambiguity	.13	.13		
	Mastery Orientation	.32**	.31**	.17**	.13**
3	Guided Discovery	.25**	.25**		
	Pure Discovery	.03	.03		
	Metacognitive Instruction	-.02	-.02	.22***	.06*

* $p \leq .05$; ** $p \leq .01$

* R^2 values do not add up due to rounding of numbers.

Hypothesis 4 predicted that guided discovery would lead to greater hypothesis-testing compared to pure discovery, which would lead to greater hypothesis-testing compared to procedural instruction. Hypothesis 6 predicted that metacognitive instruction would lead to greater self-regulatory activity compared to no metacognitive instruction. The third step in the regression, containing these training manipulations, accounted for a significant amount of variance in hypothesis-testing/self-regulation ($\Delta R^2 = .06$, $\Delta F = 3.71$, $p < .05$). Beta-weights indicated that guided discovery led to greater hypothesis-testing/self-regulation compared to pure discovery and procedural instruction ($\beta = .25$). The predicted cell means after controlling for individual differences were: guided discovery, $X = 5.79$; pure discovery, $X = 5.38$; procedural instruction, $X = 5.33$. These results provided partial support for hypothesis 4. Guided discovery did lead to greater reported use of hypothesis-testing/self-regulation compared to pure discovery and procedural instruction. However, the pure discovery group did not report greater use of hypothesis-testing/self-regulation compared to the procedural instruction group. Hypothesis 6, predicting an effect for metacognitive instruction, was not supported by the regression results. Overall, variables in the equation accounted for 22 percent of the variance in hypothesis-testing/self-regulation ($F(7,153) = 6.34$, $p < .01$).

Self-efficacy. A hierarchical regression analysis was run to examine the relationships between individual differences, training manipulations, and self-efficacy. The effects of cognitive ability and performance orientation were controlled for in the first step in the regression. Tolerance for ambiguity and mastery orientation were

entered in the second step, followed by discovery learning and metacognitive instruction in the third step. Results are presented in Table 8.

The first step in the regression did account for significant variance in self-efficacy ($R^2 = .06$, $F = 5.27$, $p < .01$). Beta-weights for the step indicated that both cognitive ability ($\beta = .20$ at step 1) and performance orientation ($\beta = .15$ at step 1) were positively related to self-efficacy. Hypotheses 20 and 25 predicted that mastery orientation and tolerance for ambiguity would be positively related to self-efficacy. The second step in the regression, containing these factors, did account for significant variance in self-efficacy ($\Delta R^2 .15$, $\Delta F = 15.17$, $p < .01$). In addition, beta-weights for the step indicated that both tolerance for ambiguity ($\beta = .29$ at step 2) and mastery orientation ($\beta = .20$ at step 2) were positively related to self-efficacy. These results supported hypotheses 20 and 25.

Hypothesis 14 predicted that metacognitive instruction would lead to greater self-efficacy compared to no metacognitive instruction. The third step in the regression, which contained the metacognitive instruction factor as well as the discovery learning manipulations, did not add a significant increment in R^2 .

Hypothesis 14 was not supported by these results. The full regression equation accounted for 22 percent of the variance in self-efficacy ($F(7,153) = 6.16$, $p < .01$).

Adaptive transfer. A regression analysis was run to examine how individual difference factors, discovery learning, metacognitive instruction, and learning outcomes were related to adaptive transfer. Results are presented in Table 9. Cognitive ability and performance orientation were entered first to control for their effects on adaptive transfer. In the second step, tolerance for ambiguity and mastery orientation were

Table 8

Hierarchical Regression Analysis Results for Self-Efficacy

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.20**	.15*		
	Performance Orientation	.15*	.11	.06**	.06**
2	Tolerance for Ambiguity	.29**	.30**		
	Mastery Orientation	.20*	.21**	.22***	.15**
3	Guided Discovery	-.01	-.01		
	Pure Discovery	-.04	-.04		
	Metacognitive Instruction	.06	.06	.22**	.00

* $p \leq .05$; ** $p \leq .01$

* R^2 values do not add up due to rounding of numbers.

entered into the regression. The main effects for the discovery learning manipulation and metacognitive instruction were entered in the third step. The fourth step contained the interaction between discovery learning and metacognitive instruction. The four learning outcomes were entered in the fifth step of the regression.

Results indicated that cognitive ability and performance orientation accounted for a significant amount of variance in adaptive transfer ($R^2 = .07$, $F = 5.61$, $p < .01$). The beta-weights revealed that cognitive ability was the influential factor which was positively related to adaptive transfer ($\beta = .26$ at step 1). Hypothesis 21 predicted that tolerance for ambiguity would be positively related to adaptive transfer. The second step, containing tolerance for ambiguity and mastery orientation, did not account for a significant amount of variance in adaptive transfer. These results did not support hypothesis 21.

Hypothesis 1 predicted that guided discovery would lead to greater adaptive transfer compared to pure discovery, which would lead to greater transfer compared to procedural instruction. Hypothesis 2 predicted that metacognitive instruction would lead to greater adaptive transfer than no metacognitive instruction. The third step in the regression, containing the main effects for discovery learning and metacognitive instruction, did not add a significant increment in R^2 to the prediction of adaptive transfer. Therefore, hypotheses 1 and 2 were not supported by the regression.

Hypothesis 3 predicted that the discovery learning manipulations would interact with metacognitive instruction to affect adaptive transfer. The fourth step in the regression, containing the interaction terms, did account for a significant amount of variance in adaptive transfer ($\Delta R^2 = .05$, $\Delta F = 4.03$, $p < .05$).

Table 9

Hierarchical Regression Analysis Results for Adaptive Transfer

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.26**	.17		
	Performance Orientation	.03	.04	.07**	.07**
2	Tolerance for Ambiguity	.12	.12		
	Mastery Orientation	-.06	-.07	.08*	.01
3	Guided Discovery	.00	-.22		
	Pure Discovery	.11	-.06		
	Metacognitive Instruction	.04	-.23	.09*	.01
4	Guided Discovery X Metacognitive Instr.	.38**	.32*		
	Pure Discovery X Metacognitive Instr.	.28*	.25	.14**	.05*
5	Verbal Knowledge	.17	.17		
	Knowledge Structure	.03	.03		
	Hypothesis-testing/Self-regulation	.00	.00		
	Self-Efficacy	.04	.04	.16*	.02

* $p \leq .05$; ** $p \leq .01$

Figure 2 plots the predicted means for each group to examine this interaction. These means are based on the regression equation containing the individual difference factors and the training manipulations (i.e., before entering learning outcomes into the regression). The figure reveals that, for the guided discovery group, metacognitive instruction led to greater adaptive transfer compared to no metacognitive instruction. This was consistent with hypothesis 3. Surprisingly, the figure reveals that for the procedural instruction group, metacognitive instruction led to poorer adaptive transfer compared to no metacognitive instruction. This was not as hypothesized, as it was expected that metacognitive instruction would have little impact on the procedural instruction group. In fact, the interaction reveals that the metacognitive instruction had the least impact on the pure discovery group. The results also show that the procedural instruction group without metacognitive instruction, and the guided and pure discovery groups with metacognitive instruction performed at a similar level on the transfer task. Possible explanations for these results are presented in the discussion.

Hypotheses 5, 7, 10, 13, and 15 predicted that adaptive transfer would be influenced by hypothesis-testing, self-regulation, verbal knowledge, knowledge structure, and self-efficacy, respectively. Hypotheses 5 and 7 were combined in the analysis as hypothesis-testing/self-regulation was examined as a single construct. The fifth step in the regression analysis, which contained these learning outcomes, did not account for significant variance in adaptive transfer. It should be noted that verbal knowledge exhibited a significant zero-order correlation with adaptive transfer; however, when entered into the regression, it did not add a significant increment in R^2 .

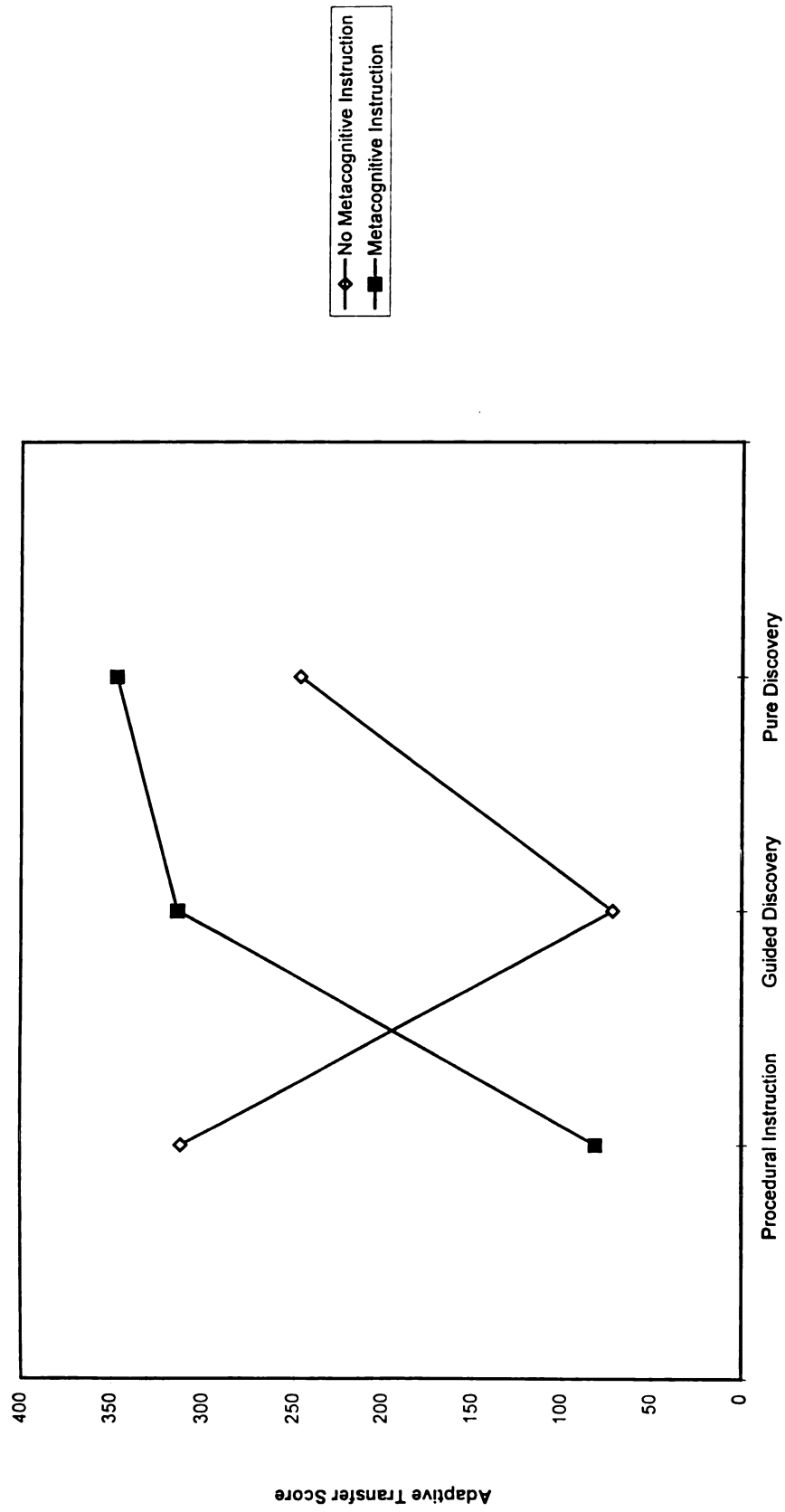


Figure 2. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Adaptive Transfer.

after controlling for prior factors in the causal model. Therefore, results did not support hypotheses 5/7, 10, 13, and 15. The variance in adaptive transfer accounted for by all variables in the equation was 16 percent ($F(13,147) = 2.17, p < .05$).

Follow-up analyses were conducted to try to understand how the interaction of metacognitive instruction and discovery learning influenced adaptive transfer. In addition, these analyses were conducted to better understand the zero-order correlation between verbal knowledge and adaptive transfer. A second measure of adaptive transfer was assessed which focused solely on the extent to which individuals were able to prevent targets from entering the penalty circles. The total score on the adaptive transfer task included both points for making correct decisions about targets, as well as points lost for targets entering the penalty circles. Performance with regard to the penalty circles was isolated from the total score because this skill was the focus of the training manipulations in the study. The second adaptive transfer outcome was labelled **prioritization of targets**. This outcome assessed the number of targets that individuals prevented from entering the penalty circle on the adaptive transfer task. This outcome was strongly related to the total adaptive transfer score ($r = .90$). The same regression analyses presented for adaptive transfer score were run with the second transfer outcome. Results are presented in Table 10.

In the first regression analysis, results indicated that the interaction between discovery learning and metacognitive instruction accounted for a significant amount of variance in prioritization of targets in the adaptive transfer task ($\Delta R^2 = .05, \Delta F = 3.89, p < .05$). Figure 3 plots the predicted cell means for this dependent variable to examine the nature of the interaction. Again, this plot is based on the regression

Table 10

Hierarchical Regression Analysis Results for Prioritization of Targets

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.25**	.11		
	Performance Orientation	.02	.02	.06**	.06**
2	Tolerance for Ambiguity	.08	.08		
	Mastery Orientation	-.02	-.04	.07*	.01
3	Guided Discovery	.00	-.21		
	Pure Discovery	.09	-.04		
	Metacognitive Instruction	.03	-.20	.08	.01
4	Guided Discovery X Metacognitive Instr.	.39**	.29*		
	Pure Discovery X Metacognitive Instr.	.22	.18	.12**	.05*
5	Verbal Knowledge	.27**	.27**		
	Knowledge Structure	.03	.03		
	Hypothesis-testing/Self-regulation	-.02	-.02		
	Self-Efficacy	.06	.06	.17**	.05 ^b

* $p \leq .05$; ** $p \leq .01$ ^a R^2 values do not add up due to rounding of numbers.^b $p = .06$

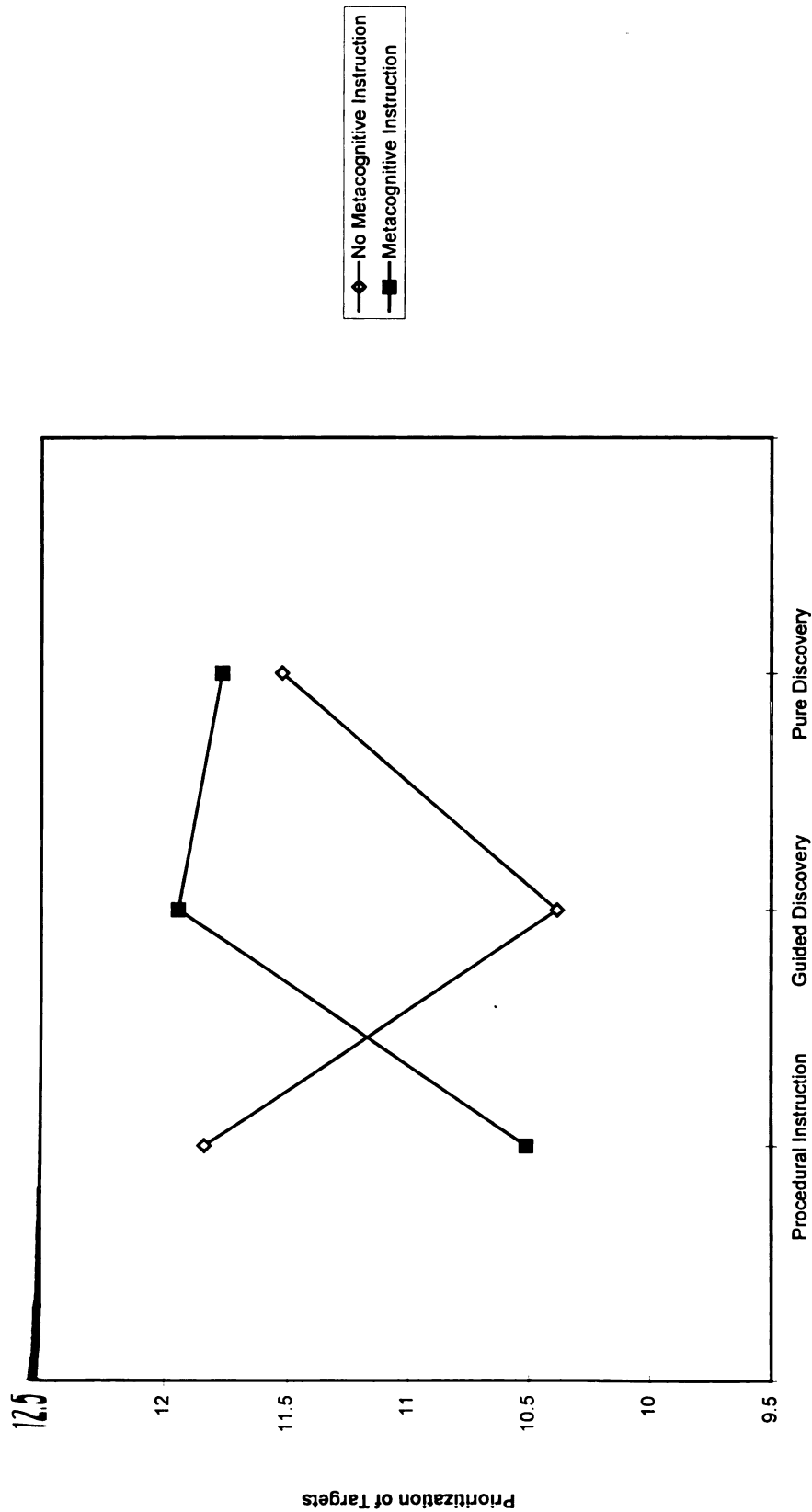


Figure 3. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Prioritization of Targets.

equation before learning outcomes are entered. Results are similar to that found for the adaptive transfer score. Metacognitive instruction led to better prioritization of targets for individuals in the guided discovery group. However, metacognitive instruction led to poorer prioritization of targets for the procedural instruction group compared to the absence of metacognitive instruction. For the pure discovery group, metacognitive instruction had no significant effect on prioritization of targets.

Step 5 in the regression analysis contained the four learning outcomes. Learning outcomes accounted for 5 percent of the variance in prioritization of targets after controlling for all prior factors, but this step just missed statistical significance ($\Delta F = 2.28, p = .06$). The beta-weights indicated that verbal knowledge was positively related to the dependent variable ($\beta = .27$). When all variables were entered into the regression, they accounted for a total of 17 percent of the variance in prioritization of targets ($F(13,147) = 2.34, p < .01$).

Follow-up analyses for verbal knowledge. Based on the post-hoc analyses with prioritization of targets as the dependent variable, an additional regression analysis was conducted with verbal knowledge as the dependent variable. A fourth step was entered in the regression that contained the interaction between discovery learning and metacognitive instruction. It was expected that this interaction term would account for significant variance in verbal knowledge. This expectation was consistent with the theoretical rationale for the hypothesized effect for adaptive transfer. It was expected that individuals in the discovery learning groups would be able to learn from their mistakes and incorrect task strategies when they were provided metacognitive

instruction. This rationale suggests that they would develop greater knowledge about correct and incorrect task strategies, and about important features of the task.

Results of this follow-up analysis are presented in Table 11. Results revealed that the interaction between the discovery learning and metacognition manipulations did account for significant variance in verbal knowledge ($\Delta R^2 = .04$, $\Delta F = 4.15$, $p < .05$). Figure 4 plots the cell means in order to examine this relationship. The plot reveals a similar pattern of results to those found for Adaptive Transfer Score and Prioritization of Targets. Individuals in the guided discovery group acquired more verbal knowledge when also provided metacognitive instruction compared to no metacognitive instruction. In contrast, individuals in the procedural instruction group performed worse on the verbal knowledge test if they also received metacognitive instruction. Metacognitive instruction had no impact on verbal knowledge for the pure discovery group.¹

Tests for mediation. It was expected in this study that the learning outcomes would mediate the relationships between the individual differences, training manipulations and adaptive transfer. However, tolerance for ambiguity and mastery orientation did not exhibit significant zero-order correlations with adaptive transfer. Therefore, there was not a significant relationship between these factors and adaptive transfer that could be mediated by learning outcomes.

¹ Previous research has suggested that cognitive ability and the degree of discovery learning during training will interact to affect learning (Cronbach & Snow, 1977). Therefore, regression analyses assessing the outcomes of adaptive transfer score, prioritization of targets, verbal knowledge, and knowledge structure were re-run with the addition of this interaction term. The interaction between cognitive ability and the discovery learning manipulation did not account for significant variance in any of the four outcomes.

Table 11

Follow-Up Regression Analysis for Verbal Knowledge

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.45**	.43**		
	Performance Orientation	-.04	-.06	.21**	.21**
2	Tolerance for Ambiguity	-.01	.02		
	Mastery Orientation	.07	.07	.21**	.00
3	Guided Discovery	.10	-.14		
	Pure Discovery	.07	-.04		
	Metacognitive Instruction	.05	-.19	.22**	.01
4	Guided Discovery X Metacognitive Instr.	.37**	.37**		
	Pure Discovery X Metacognitive Instr.	.18	.18	.26**	.04*

* $p \leq .05$; ** $p \leq .01$

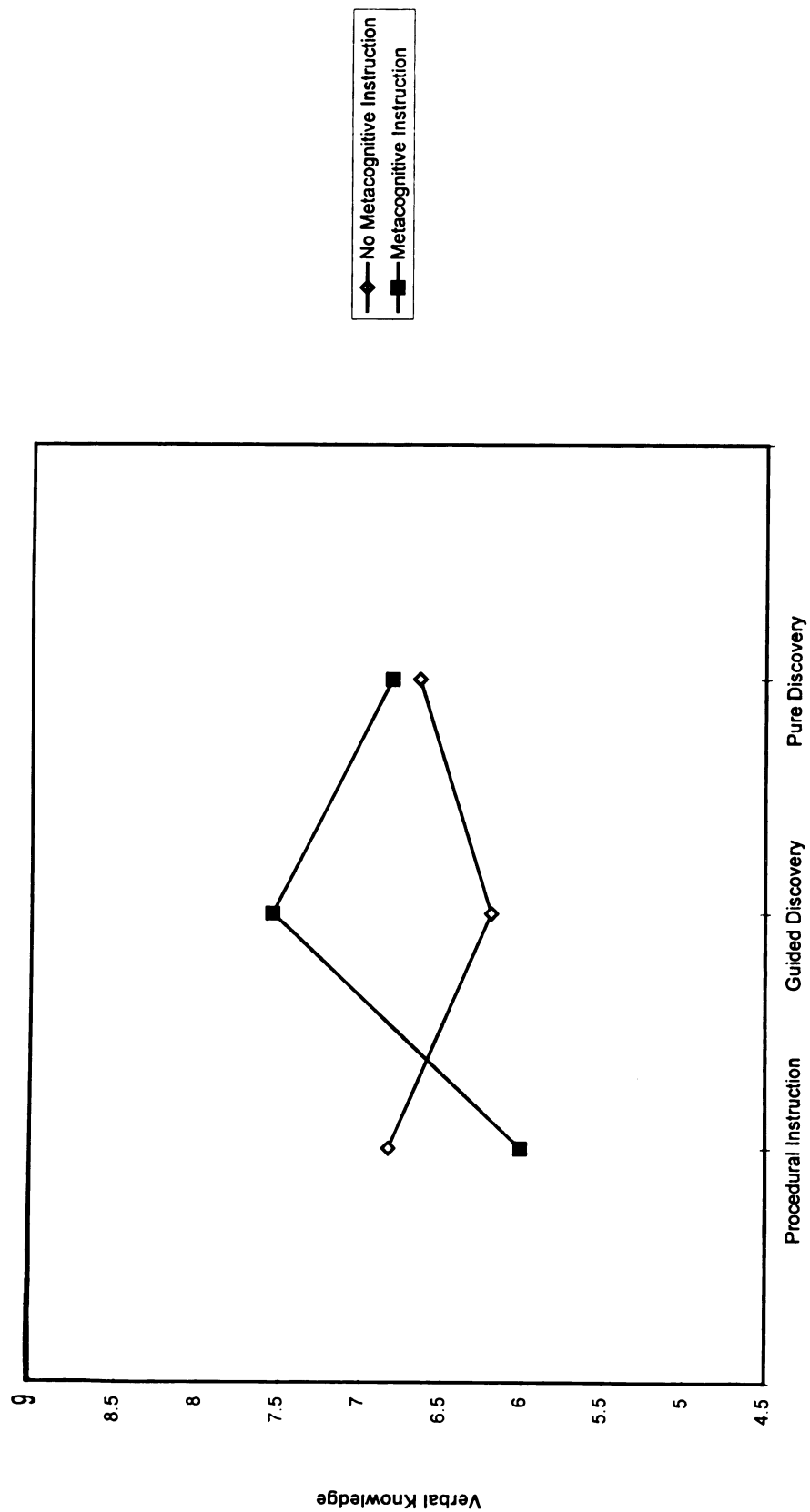


Figure 4. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Verbal Knowledge.

On the other hand, results did show that the training manipulations interacted to affect adaptive transfer. In addition, one learning outcome, verbal knowledge, was significantly correlated with adaptive transfer. However, this relationship became nonsignificant once all other factors were controlled for in the regression analysis (see Table 9). These results did not satisfy the requirements for mediation (James & Brett, 1984). Nonetheless, a hierarchical regression analysis was run with adaptive transfer as the dependent variable. The order of entry was reversed so that the learning outcomes were entered prior to the training manipulations and their interaction. This allowed for an assessment of whether the variance accounted for by the interaction between the manipulations became nonsignificant after controlling for the learning outcomes. Results are presented in Table 12. The results indicated that the interaction between the discovery learning groups and metacognitive instruction no longer accounted for significant variance in adaptive transfer after controlling for the learning outcomes.

A similar analysis was conducted for prioritization of targets. One condition for mediation was satisfied as the training manipulations interacted to influence prioritization of targets. In addition, verbal knowledge also showed a positive relationship with the dependent variable when all factors were controlled for in the regression (although the step containing the learning outcomes just missed statistical significance). Finally, the follow-up analyses for verbal knowledge indicated that the interaction between discovery learning and metacognitive instruction influenced verbal knowledge.

Table 12

Hierarchical Regression Analysis Results for Adaptive Transfer
(Mediation Analysis)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.26**	.17		
	Performance Orientation	.03	.04	.07**	.07**
2	Tolerance for Ambiguity	.12	.12		
	Mastery Orientation	-.06	-.07	.08*	.01
3	Verbal Knowledge	.22*	.17		
	Knowledge Structure	.01	.03		
	Hypothesis-testing/Self-regulation	-.04	.00		
	Self-Efficacy	.06	.04	.12*	.04
4	Guided Discovery	-.01	-.22		
	Pure Discovery	.10	-.06		
	Metacognitive Instruction	.02	-.23	.13*	.01
5	Guided Discovery X Metacognitive Instr.	.32*	.32*		
	Pure Discovery X Metacognitive Instr.	.25	.25	.16*	.03

* $p \leq .05$; ** $p \leq .01$

A test for mediation was conducted using hierarchical regression. The order of entry was reversed so that the learning outcomes were entered before the training manipulations in the regression predicting adaptive transfer. If the learning outcomes mediated the relationship between the training manipulations and adaptive transfer, the step containing the interaction between the manipulations should become nonsignificant once the learning outcomes are controlled (James & Brett, 1984). Results are presented in Table 13. The interaction between the discovery learning groups and metacognitive instruction no longer accounted for significant variance in prioritization of targets after controlling for the learning outcomes. Although this suggests that learning outcomes might be mediators, the fact that learning outcomes did not account for significant variance when entered last in the regression did not provide definitive results for this prediction. These follow-up analyses did provide some limited support for hypothesis 10 that verbal knowledge would significantly affect adaptive transfer.

Demographic factors. Participants in this study indicated their gender, age, and video game experience at the beginning of the experiment. No specific relationships or predictions were made about these factors; these variables were collected as descriptive information about the sample used in the study. As Table 3 shows, these demographic factors were significantly correlated with some learning outcomes, adaptive transfer score, and prioritization of targets. These relationships were not conceptualized as part of the theoretical model examined in this study. However, because these relationships were found, post-hoc analyses were conducted in which these three demographic factors were controlled for in each regression analysis. These

Table 13

Hierarchical Regression Analysis Results for Prioritization of Targets
(Mediation Analysis)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Ability	.25**	.11		
	Performance Orientation	.02	.02	.06**	.06**
2	Tolerance for Ambiguity	.08	.08		
	Mastery Orientation	-.02	-.04	.07*	.01
3	Verbal Knowledge	.31**	.27**		
	Knowledge Structure	.02	.03		
	Hypothesis-testing/Self-regulation	-.06	-.02		
	Self-Efficacy	.07	.06	.14**	.07*
4	Guided Discovery	.00	-.21		
	Pure Discovery	.09	-.04		
	Metacognitive Instruction	.01	-.20	.15**	.01
5	Guided Discovery X Metacognitive Instr.	.29*	.29*		
	Pure Discovery X Metacognitive Instr.	.18	.18	.17**	.02

* $p \leq .05$; ** $p \leq .01$

analyses provided a very rigorous test of the conceptual model, as they were not considered in the hypotheses or in the power analysis for the study.

Tables 14 through 19 present regression analyses that repeat the analyses presented earlier with the demographic factors entered in the first step. Table 14 presents a hierarchical regression analysis in which verbal knowledge is regressed on the independent variables. Results were similar to those presented in Table 11. Although the demographic factors did not account for significant variance in verbal knowledge, beta-weights indicated that video game experience was positively related to verbal knowledge ($\beta = .17$). Figure 5 plots the interaction effect for the training manipulations. This figure reveals similar results to those obtained without controlling for demographics.

Table 15 presents analyses with knowledge structure as the dependent variable. These results show similar effects to those reported in Table 6. In addition, the three demographic factors did not account for a significant amount of variance in knowledge structure. It should be noted that the beta-weight for the relationship between age and knowledge structure was positive and statistically significant.

Table 16 presents analyses with hypothesis-testing/self-regulatory activity as the dependent variable. Results are slightly different compared to analyses presented in Table 7. Specifically, the step containing ability and performance orientation no longer accounted for significant variance in the dependent variable. Although the addition of the demographic factors changed the regression results somewhat, these factors did not account for significant variance in hypothesis-testing/self-regulation.

Table 14

Hierarchical Regression Analysis Results for Verbal Knowledge
(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.01	.03		
	Age	-.02	-.03		
	Video Game Experience	.20*	.17*	.04	.04
2	Ability	.44**	.42**		
	Performance Orientation	-.02	-.05	.24**	.20**
3	Tolerance for Ambiguity	-.05	-.02		
	Mastery Orientation	.10	.10	.24***	.01
4	Guided Discovery	.10	-.13		
	Pure Discovery	.05	-.08		
	Metacognitive Instruction	.04	-.20	.25**	.01
5	Guided Discovery X Metacognitive Instr.	.35**	.35**		
	Pure Discovery X Metacognitive Instr.	.20	.20	.29**	.04*

* $p \leq .05$; ** $p \leq .01$

^a R^2 values do not add up due to rounding of numbers.

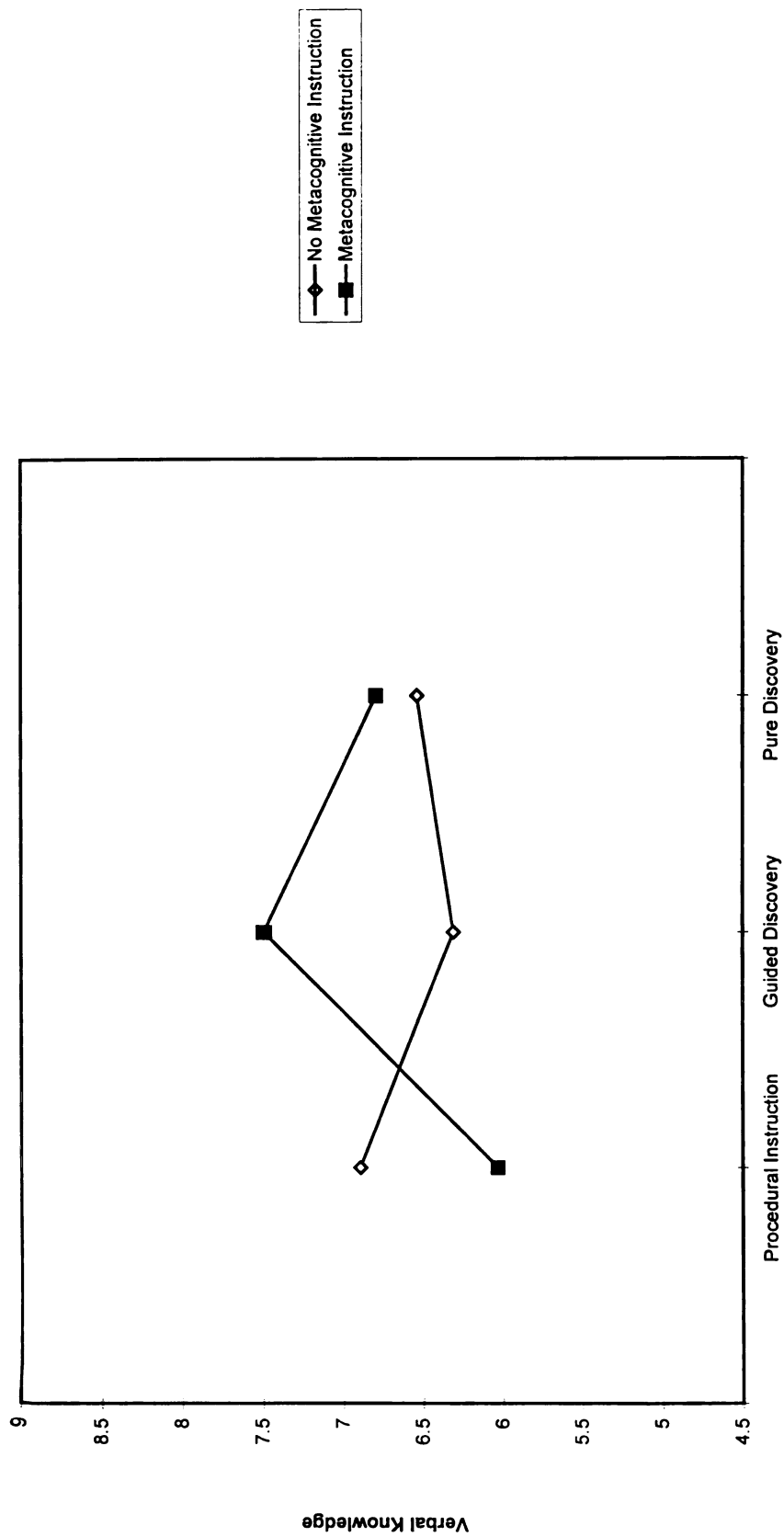


Figure 5. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Verbal Knowledge (Controlling for Demographic Factors).

Table 15

Hierarchical Regression Analysis Results for Knowledge Structure
(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	.08	.09	.03	.03
	Age	.16*	.17*		
	Video Game Experience	.10	.09		
2	Ability	.23**	.24**	.08*	.05*
	Performance Orientation	.04	.04		
3	Tolerance for Ambiguity	.06	.06	.08*	.00
	Mastery Orientation	-.03	-.02		
4	Guided Discovery	-.04	-.04	.09	.01
	Pure Discovery	-.08	-.08		
	Metacognitive Instruction	.04	.04		

* $p \leq .05$; ** $p \leq .01$

Table 16

Hierarchical Regression Analysis Results for Hypothesis-Testing/Self-Regulation

(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.08	-.01		
	Age	.06	.02		
	Video Game Experience	.10	.13	.03	.03
2	Ability	.18*	.12		
	Performance Orientation	.01	-.05	.06	.03
3	Tolerance for Ambiguity	.11	.11		
	Mastery Orientation	.33**	.31**	.18**	.12**
4	Guided Discovery	.25**	.25**		
	Pure Discovery	.02	.02		
	Metacognitive Instruction	-.03	-.03	.24**	.06**

* $p \leq .05$; ** $p \leq .01$

Table 17 presents analyses with self-efficacy as the dependent variable. The demographic variables did not account for significant variance in self-efficacy, and the results of this follow-up analysis were similar to those found in Table 8.

Table 18 presents analyses with adaptive transfer score as the dependent variable. The results were similar to those found in Tables 9 and 12. Results also indicated that age was negatively related to adaptive transfer score ($\beta = -.38$), and video game experience was positively related to adaptive transfer score ($\beta = .20$). These demographic factors accounted for 23 percent of the variance in adaptive transfer score. When all factors were entered in the regression, they accounted for 35 percent of the variance in adaptive transfer ($F(16,144) = 4.77, p < .01$).

Figure 6 plots the predicted cell means for the interaction effect before learning outcomes are entered into the regression. The pattern of results is similar to that presented in Figure 2, except that the guided discovery and pure discovery groups with metacognitive instruction are not predicted to perform quite as well.

Table 19 presents results with prioritization of targets as the dependent variable. The results in this analysis were mostly similar to those found in Tables 10 and 13. When gender, age, and video game experience were controlled for, the learning outcomes no longer accounted for significant variance in the dependent variable when entered before the training manipulations. This change in the results limits the implications of the results presented earlier. The demographic factors accounted for 16 percent of the variance, with age negatively related to prioritization of targets ($\beta = -.30$) and video game experience positively related to prioritization of targets ($\beta = .19$).

Table 17

Hierarchical Regression Analysis Results for Self-Efficacy

(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.13	-.08	.03	.03
	Age	-.02	-.04		
	Video Game Experience	.07	.07		
2	Ability	.19*	.14*	.10**	.07**
	Performance Orientation	.19*	.13		
3	Tolerance for Ambiguity	.26**	.26**	.23**	.13**
	Mastery Orientation	.21**	.22**		
4	Guided Discovery	.00	.00	.24***	.00
	Pure Discovery	-.05	-.05		
	Metacognitive Instruction	.04	.04		

* $p \leq .05$; ** $p \leq .01$ ^a R^2 values do not add up due to rounding of numbers.

Table 18

Hierarchical Regression Analysis Results for Adaptive Transfer

(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.14	-.15		
	Age	-.36**	-.38**		
	Video Game Experience	.24**	.20*	.23**	.23**
2	Ability	.24**	.18*		
	Performance Orientation	.09	.06	.29**	.06**
3	Tolerance for Ambiguity	.00	.01		
	Mastery Orientation	.05	.05	.29**	.00
4	Guided Discovery	-.01	-.20		
	Pure Discovery	.08	-.08		
	Metacognitive Instruction	-.03	-.27*	.30**	.01
5	Guided Discovery X Metacognitive Instr.	.32*	.29*		
	Pure Discovery X Metacognitive Instr.	.25*	.24	.34**	.03*
6	Verbal Knowledge	.10	.10		
	Knowledge Structure	.07	.07		
	Hypothesis-testing/Self-regulation	-.01	-.01		
	Self-Efficacy	-.01	-.01	.35**	.01

Table 18 (cont'd)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.14	-.15		
	Age	-.36**	-.38**		
	Video Game Experience	.24**	.20*	.23**	.23**
2	Ability	.24**	.18*		
	Performance Orientation	.09	.06	.29**	.06**
3	Tolerance for Ambiguity	.00	.01		
	Mastery Orientation	.05	.05	.29**	.00
4	Verbal Knowledge	.14	.10		
	Knowledge Structure	.06	.07		
	Hypothesis-testing/Self-regulation	-.04	-.01		
	Self-Efficacy	.00	-.01	.31**	.02
5	Guided Discovery	-.01	-.20		
	Pure Discovery	.08	-.08		
	Metacognitive Instruction	-.04	-.27*	.32**	.01
6	Guided Discovery X Metacognitive Instr.	.29*	.29*		
	Pure Discovery X Metacognitive Instr.	.24	.24	.35**	.03 ^a

* $p \leq .05$; ** $p \leq .01$

^a $p = .056$

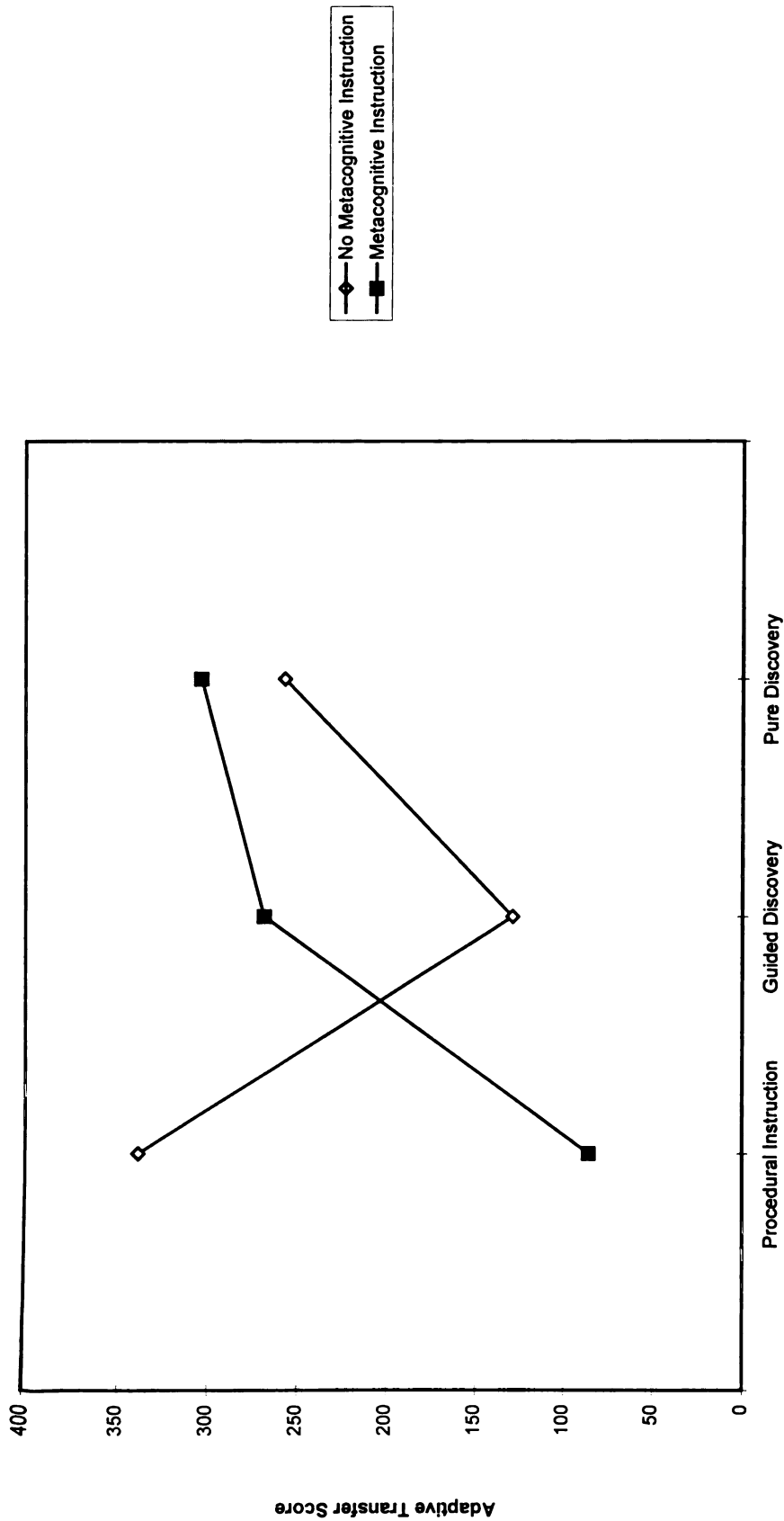


Figure 6. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Adaptive Transfer (Controlling for Demographic Factors).

Table 19

Hierarchical Regression Analysis Results for Prioritization of Targets

(Controlling for Demographic Factors)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.05	-.05		
	Age	-.28**	-.30**		
	Video Game Experience	.24**	.19*	.16**	.16**
2	Ability	.23**	.12		
	Performance Orientation	.06	.02	.22**	.06**
3	Tolerance for Ambiguity	-.02	.00		
	Mastery Orientation	.08	.07	.22**	.01
4	Guided Discovery	-.01	-.19		
	Pure Discovery	.05	-.07		
	Metacognitive Instruction	-.03	-.23	.23**	.00
5	Guided Discovery X Metacognitive Instr.	.34*	.26*		
	Pure Discovery X Metacognitive Instr.	.21	.18	.26**	.03*
6	Verbal Knowledge	.21*	.21*		
	Knowledge Structure	.06	.06		
	Hypothesis-testing/Self-regulation	-.03	-.03		
	Self-Efficacy	.02	.02	.29**	.03

Table 19 (cont'd)

Step	Predictors	β at Step	Final β	R^2	ΔR^2
1	Gender	-.05	-.05		
	Age	-.28**	-.30**		
	Video Game Experience	.24**	.19*	.16**	.16**
2	Ability	.23**	.12		
	Performance Orientation	.06	.02	.22**	.06**
3	Tolerance for Ambiguity	-.02	.00		
	Mastery Orientation	.08	.07	.22** ^a	.01
4	Verbal Knowledge	.24**	.21*		
	Knowledge Structure	.05	.06		
	Hypothesis-testing/Self-regulation	-.06	-.03		
	Self-Efficacy	.03	.02	.27**	.04 ^b
5	Guided Discovery	-.02	-.19		
	Pure Discovery	.04	-.07		
	Metacognitive Instruction	-.04	-.23	.27**	.00
6	Guided Discovery X Metacognitive Instr.	.26*	.26*		
	Pure Discovery X Metacognitive Instr.	.18	.18	.29**	.02

* $p \leq .05$; ** $p \leq .01$

^a R^2 values do not add up due to rounding of numbers.

^b $p = .06$

When all factors were entered into the regression equation, they accounted for 29 percent of the variance in prioritization of targets ($F(16,144) = 3.69, p < .01$).

Figure 7 plots the predicted cell means for the interaction effect. Similar to the results found for adaptive transfer score, the guided discovery and pure discovery groups with metacognitive instruction performed a little more poorly after demographic factors are controlled.

Summary of results. The results of this study provided limited support for the conceptual model that was tested. Analyses provided strict tests of study hypotheses by controlling for prior factors in the model before assessing a particular effect. Because hypothesis-testing and self-regulation were examined as a single construct, the analyses tested a total of 23 hypotheses. Three of these hypotheses received clear support from the analyses. Specifically, mastery orientation was found to be positively related to hypothesis-testing/self-regulatory activity during training. Both mastery orientation and tolerance for ambiguity were positively related to self-efficacy.

Two hypotheses received partial support from the regression analysis. First, the discovery learning manipulation and metacognitive instruction were found to have a significant interactive effect on adaptive transfer. However, the nature of the interaction was somewhat different than hypothesized. Second, guided discovery was found to lead to significantly greater hypothesis-testing/self-regulation compared to pure discovery and procedural instruction, although the latter two groups were not found to differ on this variable.

The remaining hypotheses were not supported by the regression analysis. There was the suggestion that verbal knowledge mediated the relationship between the

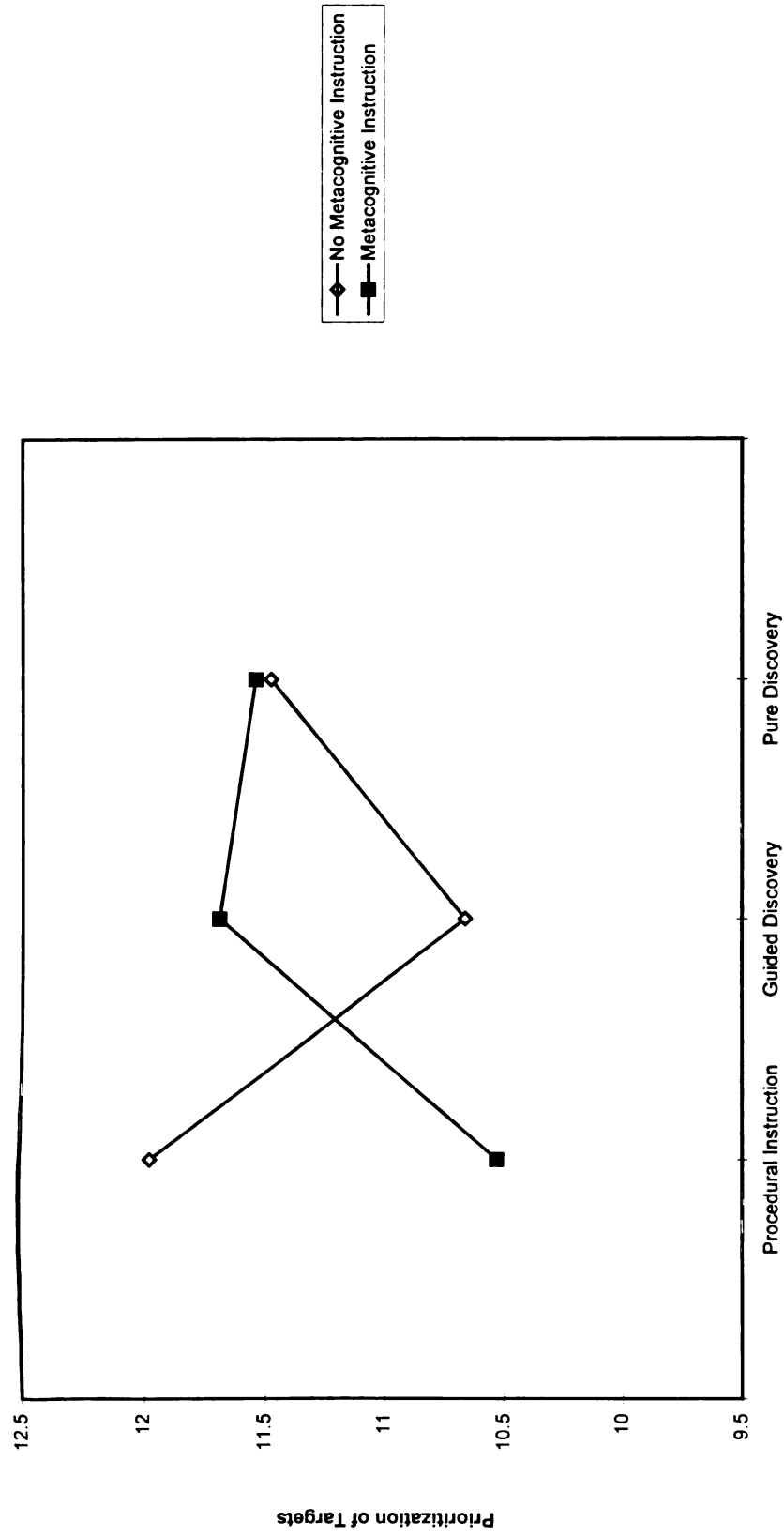


Figure 7. Predicted Cell Means for the Interactive Influence of Discovery Learning and Metacognitive Instruction on Prioritization of Targets (Controlling for Demographic Factors).

interaction of the training manipulations and prioritization of targets. The regression analyses did not support a strict interpretation of mediation; however, the plot of the means for each training group did show a similar pattern for verbal knowledge and adaptive transfer score.

There were some interesting results for factors not identified in explicit hypotheses. For example, cognitive ability was found to be positively related to verbal knowledge, knowledge structure, and self-efficacy. It was also positively related to adaptive transfer score after demographic factors were controlled. Surprisingly, demographic factors had influences on several learning outcomes and adaptive transfer. Age was found to be negatively related to adaptive transfer score and prioritization of targets. Video game experience was positively related to these two transfer outcomes. Video game experience positively influenced verbal knowledge, and age positively influenced knowledge structure.

DISCUSSION

The purpose of this study was to examine how individual difference factors, discovery learning, and metacognitive instruction would influence multiple learning outcomes and adaptive transfer. Tolerance for ambiguity and mastery orientation were identified as key individual difference factors when examining learning and adaptive transfer. Cognitive ability and performance orientation were also included as control variables based on previous research linking these variables to learning processes. Two training interventions were examined as likely methods for facilitating learning and the capability to adapt to novel task situations: discovery learning and metacognitive instruction. Learning outcomes hypothesized to mediate the influence of the individual differences and training manipulations on adaptive transfer were also identified. Verbal knowledge, knowledge structure, hypothesis-testing/self-regulatory activity, and self-efficacy were each expected to influence adaptive transfer. A conceptual model was tested in which individual differences and training manipulations led to particular learning outcomes, which then affected performance on an adaptive transfer task.

Results provided support for limited portions of the model. Results indicated that the discovery learning and metacognitive instruction manipulations interacted to affect performance on the adaptive transfer task. Similar results were obtained for

overall score on the adaptive transfer task, as well as when performance on the prioritization skill was isolated. The nature of the interaction was somewhat different than hypothesized. As expected, metacognitive instruction did lead to greater adaptive transfer compared to no metacognitive instruction for the guided discovery group. Prompting individuals to make hypotheses and predictions about the task in the guided discovery manipulation was not enough to help them adapt their skills to the transfer task. Individuals may have pursued incorrect or less important hypotheses about the task, or were unsystematic in their testing of predictions when not required to explicitly evaluate their understanding. Without guidance on monitoring and evaluation, individuals may have had difficulty recognizing errors they were making during practice. Asking individuals to reflect on their practice trials seems to have made the exploration process more systematic in the guided discovery condition.

The impact of metacognitive instruction on the procedural instruction group was not as expected. Metacognitive instruction led to poorer performance on the adaptive transfer task compared to no metacognitive instruction. It is difficult to explain why instructing individuals to attend to their understanding of the task would lead to poorer transfer. The different effect of metacognitive instruction on the guided discovery and procedural instruction conditions may have depended on what learners were focusing on in their self-regulatory efforts. It may be that individuals in the procedural instruction group felt that they already comprehended the task strategies for prioritizing targets because this information was provided to them before practice trials. They may have then directed their attention to improving other aspects of task performance and thus spent less time and effort on improving their prioritization skill. A second

possibility is that individuals who were provided the correct task procedure and then asked to self-regulate their learning focused their attention on developing very efficient and streamlined performance of the strategies. This focus on effectively applying a known strategy may have made it difficult for these individuals to adapt to a task that required more dynamic processing and change in task strategies. This second explanation, however, does not explain why the procedural instruction group that did not receive metacognitive instruction performed well on the adaptive transfer task.

Another reason for the detrimental effect of metacognitive instruction may deal with attentional processes. For example, Kanfer and Ackerman (1989) found that prompting individuals to engage in self-regulatory processes led to decrements in performance early in skill acquisition. Because of this research, the present study did not introduce the metacognitive instruction until after the individuals had practiced the low complexity scenario and thus had some exposure to the nature of the skills they were learning. However, it is possible that individuals were still in very early stages of skill acquisition where asking them to focus on self-regulation may have presented additional processing requirements that were overwhelming to them.

Yet Kanfer and Ackerman's (1989) theory that there are limited resources available for self-regulation early in skill acquisition does not seem to explain why the metacognitive instruction hurt the procedural instruction group, but not the guided discovery group or the pure discovery group. It would seem that, from this perspective, the two discovery groups would have less attention available to engage in self-regulatory activities because they had to engage in more active learning to develop their own understanding of the task.

However, Allport (1989) has proposed a different perspective on the role of attentional processes which he calls selection-for-action. His theory is opposed to the notion of attention as a limited resource. Basically, this perspective states that we are faced with multiple goals in any particular situation, and that these goals are assigned different priorities. The purpose of the attentional system is to ensure coherence of behavior under multiple and often conflicting goals. Attention is selectively engaged for goals with high priority, and attention to lower priority goals is inhibited. In the case of the guided and pure discovery groups, the metacognitive instruction is likely to have been compatible with the overall goal of exploring the task and experimenting with strategies for dealing with it. In fact, the self-regulatory activities may have focused this activity and made it more systematic. In contrast, the instruction to consciously monitor and evaluate one's understanding may have been in conflict with the overall goal of the procedural instruction group to apply and practice the explicit strategies for task performance. The application of known strategies was likely a more rote and passive learning process (Frese et al., 1988), and adding the self-regulatory activity may have confused trainees or provided them with additional work that did not increase their understanding.

Overall, the results suggested that there were several methods for training individuals to achieve a similar level of performance on the adaptive transfer task. Procedural instruction without metacognitive instruction, guided discovery with metacognitive instruction, and pure discovery with metacognitive instruction all produced similar levels of adaptation. The results, therefore, do not resolve some of the varying results for discovery learning instruction in previous research (e.g., Carlson

et al., 1992; Kamouri et al., 1986; Singer & Pease, 1976). Alternatively, this may suggest problems with the nature of the adaptive transfer task used in this study. Adaptive transfer was operationalized at a moderate level of novelty where a new feature of the task required individuals to reconfigure the strategies learned in training. This task may not have been novel enough to detect differences in adaptability across the discovery learning groups.

Results did not support hypotheses predicting that the learning outcomes would influence performance on the adaptive transfer task. Knowledge structure, hypothesis-testing/self-regulation, and self-efficacy were not found to be significantly related to adaptive transfer. Although verbal knowledge was positively correlated with adaptive transfer, this relationship became nonsignificant once all the other factors were entered in the regression analysis. Nonetheless, this positive correlation was intriguing and led to some post-hoc analyses to try to understand the role of verbal knowledge in the conceptual model.

In fact, the follow-up analysis suggested that the interaction of the training manipulations was significantly related to verbal knowledge. The pattern of means for the training groups was similar to that found for the adaptive transfer outcomes. Metacognitive instruction was especially beneficial for the guided discovery group. Prompting individuals to make predictions about the task and to test out different strategies was not enough guidance to help individuals understand the task. They also needed to be taught to explicitly monitor and evaluate their progress in developing effective task strategies.

Contrary to hypotheses, the training interventions did not impact knowledge structure. Also, knowledge structure did not influence performance on the adaptive transfer task. The lack of results for knowledge structure is likely due to a deficiency in the measure itself. For example, one would have expected some correlation between the verbal knowledge measure and the knowledge structure measure, as both measures tap into the content of trainee's knowledge. A significant correlation was not found between the verbal knowledge and knowledge structure measures used in the present study, although verbal knowledge was correlated with adaptive transfer. This suggests that the knowledge structure measure may not have been tapping into critical task concepts or the linkages among them. The low mean closeness index ($C = .17$) found between the study participants and the expert knowledge structure suggests that the structure used as the measure of a high-quality structure may not have been tapping into an effective representation of the task.

The representation used as the expert structure in this study was based on how the experimenter designed the task. It was expected that certain aspects of the task would be most critical for understanding the task and performing it well. However, due to the complex and dynamic nature of the task, trainees may have developed alternate knowledge representations and task strategies that proved just as effective for adaptive transfer.

A second possibility for the deficiency of the knowledge structure measure is the range of concepts and actions that were rated by trainees. In the present study, the task was simplified to some extent so that individuals were focused on learning about a single domain of task performance. Thus, the concepts and actions that were rated

in the assessment of knowledge structure all tapped into one task domain. It may be that individuals rated all concepts and actions as highly related because they all referred to this particular aspect of task performance.

In a previous study, a measure of knowledge structure was found to differentiate instructional groups as well as to affect performance on a transfer task (Kozlowski et al., 1995). However, the difference between the Kozlowski et al. (1995) study and the present one is that Kozlowski and colleagues trained individuals on two important aspects of task performance that were distinct from one another. Therefore, individuals in that study who learned the task well would have clearly differentiated these domains by having two separate clusters of concepts in their knowledge representation. In the present study, the nature of the knowledge structure would not have led to distinct clusters of concepts, but rather to a structure that differed on the degree to which certain concepts and actions were important for task performance. The method used to assess knowledge structure in this study may not have been sensitive enough to capture this distinction.

Individual differences in tolerance for ambiguity and mastery orientation were not found to influence verbal knowledge and knowledge structure after training. Also, tolerance for ambiguity was not related to performance on the adaptive transfer task. One issue with the tolerance for ambiguity measure was its low internal consistency reliability. This may have limited the extent to which a relationship could be detected in the study. In terms of mastery orientation, the results suggested that being motivated by the desire to learn new things did not lead individuals to acquire more

knowledge about the task. Instead, cognitive ability was found to be an important individual difference factor in this study for predicting knowledge.

Results showed that individual differences and the discovery learning manipulation did affect the learning activities that trainees engaged in during practice. Mastery orientation was related to reports of greater hypothesis-testing and self-regulatory activity during training. Also, guided discovery learning led to greater hypothesis-testing/self-regulation compared to pure discovery and procedural instruction. Thus, a mastery orientation to learning and the discovery learning manipulation did influence how individuals approached the learning task. These individuals were more willing to test out hypotheses about the task, monitor their understanding of the task, and set learning goals to improve their knowledge. It should be noted, however, that even the procedural and pure discovery groups reported a relatively high degree of hypothesis-testing/self-regulation during learning.

In contrast to hypotheses, this learning activity was not found to be related to performance on the adaptive transfer task. One rationale for the benefits of discovery learning was that it allows individuals to use more analytic learning strategies that then may be available to use to learn how to handle a novel transfer task (e.g., Singer & Pease, 1976). Greater practice at these activities did not help individuals when faced with the novel transfer task. Yet hypothesis-testing/self-regulatory activity was positively correlated with verbal knowledge. While not an effect examined in the study, this does suggest that engaging in these learning activities will lead to greater knowledge about the task.

As predicted, results indicated that tolerance for ambiguity and mastery orientation were positively related to self-efficacy. Cognitive ability was also positively related to self-efficacy. Thus, dispositional factors and ability led individuals to have greater confidence in their capability to handle changing task demands. However, the metacognitive instruction did not lead to higher levels of self-efficacy compared to no metacognitive instruction. This is in contrast to research by Bandura and Schunk (1981), but it is consistent with results found by Sawyer et al. (1992). The lack of a relationship may have been due to the results of the self-regulatory activities for different individuals. If individuals were unable to improve their understanding through self-regulatory activities, then this activity was probably unrelated or possibly negatively related to self-efficacy. It is possible that the relationship between metacognitive instruction and self-efficacy was moderated by the success of these metacognitive activities for facilitating learning.

Self-efficacy was not found to be related to adaptive transfer. This result is in contrast to several studies that have found self-efficacy to influence transfer of training (Kozlowski et al., 1995; Smith et al., 1995). This result may be explained in some part by some issues brought up in the introduction. It was not expected that the discovery learning manipulations would lead to differential self-efficacy by the end of training. In fact, it was suggested that the procedural instruction, guided discovery, and pure discovery groups may have developed similar levels of self-efficacy by the end of training. However, these self-efficacy beliefs would be developed based on different task experiences. For example, the explicit rules provided to the procedural group were expected to be less effective strategies for dealing with the adaptive

transfer task. In addition, although the training groups in this study did not differ in their self-efficacy, they did differ in the amount of knowledge acquired and their capability to transfer their knowledge and skills to the adaptive transfer task. Yet self-efficacy was unrelated to performance on the verbal knowledge test in the present study. In previous research that found self-efficacy to predict transfer of training, self-efficacy did exhibit a positive relationship with knowledge (Kozlowski et al., 1995) or performance on a posttest (Gist, 1989). It may be that self-efficacy had no impact on adaptive transfer because individuals were being persistent in applying both effective and ineffective strategies to the task.

Surprisingly, demographic factors of age, gender, and previous video game experience influenced several learning outcomes and adaptive transfer. For example, age was found to be negatively related to performance on the adaptive transfer task, and video game experience was positively related to adaptive transfer. The results for previous video game experience suggested that these individuals were able to use their previous knowledge and experience with a different task and apply it to performing this computer-simulated task. They were able to recognize similar features of previous video games and likely used analogical reasoning processes to learn this new task (Kamouri et al., 1986). The results for age are more difficult to interpret. The range of ages in this study was not varied enough to suppose that there were information-processing differences across people. Also, age was not related to previous video game experience, and affected adaptive transfer after controlling for this experience. One might speculate on another experience-related difference between older and younger participants. It may be that the older participants in this sample had less

experience in using personal computers compared to the younger participants, which affected what they learned and transferred during the study. However, the study did not provide evidence to support this speculation.

Limitations and Directions for Future Research

One limitation raised earlier was the deficiency in the measure of knowledge structure. Future research should consider more fully the extent to which the method used to measure the knowledge structure can capture meaningful differences in knowledge representations. The range of knowledge representations that might be equally effective should also be considered, as should the nature of the domain of knowledge to be assessed. In addition, future research examining this construct could use a different approach to develop a representation of an expert structure. For example, an expert structure could be developed based on the structures from individuals who learn and perform very well on this task. Some average across a group of expert performers could be derived and used as an expert representation. If there are several equally effective knowledge structures for a particular task, then an average representation would not be meaningful.

A second issue that can be debated is the nature of the adaptive transfer task in this study. The task was operationalized at a moderate level of task novelty, in which a new feature of the task was introduced that had not been experienced during practice. This new task feature made the task more dynamic in nature. This change in the task was designed so that individuals would continually have to reprioritize targets in the task. This is in contrast to the practice trials where initial assessment of the task led to a relatively stable understanding of how the task would unfold. However, a

transfer task at the far end of the novelty continuum might require the development of strategies never used in training. Future research should examine whether results are more consistent with the conceptual model when a task of greater novelty is used to assess transfer of training.

A broader concern for future research is the nature of transfer of training and the elements that are necessary for transfer to occur. The present study focused on multiple learning outcomes that were expected to be necessary conditions for adaptive transfer. For example, it was expected that an individual must have extensive knowledge about the task (verbal knowledge) and that this knowledge should be well-organized in memory (knowledge structure). It was also expected that practice in using more active learning approaches such as hypothesis-testing and problem-solving during training would assist individuals when they had to learn what was different about the adaptive transfer task and how they should respond. Finally, it was expected that motivational processes play a part in transfer as well; specifically, it was hypothesized that self-efficacy would allow people to be resilient and to persist in the face of the demands of the adaptive transfer task.

However, theories of transfer also highlight the role of similarity in the successful transfer of knowledge and skills. For example, theories presented by Thorndike and Woodworth (1901), Anderson (1993), and Gick and Holyoak (1987) all emphasize that there are certain features that are similar between the training and transfer tasks that will promote transfer. Studies that have examined how this similarity operates have focused on the processes through which individuals recognize similar features and then apply their knowledge and skills to a new task. For example,

Gick and Holyoak (1980, 1983) examined the role of analogical reasoning in the transfer of trained strategies to a novel task.

In this study, individuals were told that they had to apply the knowledge and skills learned in training to a more complex task. Therefore, they did not have to engage in the recognition processes that would occur in more natural transfer situations back on the job. This decision was made so that the study could focus on how individuals prepared themselves during training to learn as much as they could before the transfer task. However, future research should examine whether the training manipulations examined in this study would have similar impacts if individuals were not aware that they were being assessed for their capability to transfer knowledge and skills to a novel task.

Another issue for future research is to understand the somewhat puzzling interaction between the discovery learning manipulations and metacognitive instruction. Examining how metacognitive instruction influences what individuals focus on during practice may reveal why metacognitive instruction had a negative impact on knowledge and transfer for the procedural instruction group. The metacognitive instruction in this study allowed individuals to direct their own self-regulatory activities. Therefore, they may not have chosen the best areas of the task to focus on improving their understanding. In addition, the study provided general feedback on their success at prioritizing targets so they would have to diagnose their own errors in performing the task. This may have been difficult for some individuals to handle. One area for future research is to examine the provision of diagnostic feedback that gives the learner more directed advice for where they are having problems and thus

how they should focus their self-regulatory activity. A related issue is the fact that self-reported level of hypothesis-testing/self-regulation did not influence adaptive transfer. Both of these results suggest that future research should expand our understanding of metacognitive processes during learning to focus on the content and quality of these self-regulatory activities in addition to their presence or quantity.

The results of this study may also have implications for how individuals focus their attention during learning. The different results for the procedural and guided discovery group may suggest that self-regulatory training may create conflicting goals when the task and what is to be done are clearly specified to trainees. Research should focus on understanding how this metacognitive training may have led trainees to attend to different content in the procedural and discovery learning groups.

A final issue for future research is the nature of the task being learned. Previous research on discovery learning and metacognitive instruction have tended to use simpler tasks or focused on academic settings. In this study, a complex and dynamic task was used that was more generalizable to the types of jobs people perform in organizations. Research should examine the effects of these training interventions using other complex tasks to determine the extent to which these interventions have similar impacts across levels of task complexity.

Implications for Practice

Results of this study do not provide very clear implications for training for adaptive transfer. If a training program is developed using a guided discovery learning environment such as the one examined in this study, then there should also be instruction on metacognitive activity and the opportunity to monitor and reflect on

practice activities. In addition, the results suggest that if one is providing explicit procedural training, do not add additional pressures or competing goals by also requiring self-regulatory activity during training. However, the results also showed that procedural instruction with no metacognitive instruction, and pure discovery learning with or without metacognitive instruction may produce similar levels of performance on adaptive transfer tasks. This study cannot resolve some of the inconsistent results found in previous research on discovery learning and training transfer. In addition, the differential effects of the particular metacognitive manipulation in this study need to be understood before making recommendations for including this type of intervention in organizational training programs.

In sum, this study was designed to examine how individual differences, discovery learning, and metacognitive instruction influenced multiple learning outcomes and adaptive transfer. Results found that the interaction between discovery learning manipulations and metacognitive instruction did influence both verbal knowledge and adaptive transfer. However, the nature of the interaction was somewhat different than hypothesized. The individual difference factors of tolerance for ambiguity and mastery orientation were found to have limited influence in the conceptual model.

APPENDICES

APPENDIX A

Consent Form

The study in which you are about to participate is designed to examine how individuals learn and transfer complex, decision-making skills. You will be asked to learn and perform a computer-simulated, radar tracking task in which you will measure the attributes of targets on your screen. You will be asked to collect information about the targets, classify them, and decide what action should be taken for each target. Also, you will learn how to use information about each target to prioritize which targets should be acted upon first. In addition to learning this task, you will be asked to complete a short test of general cognitive ability. You will also answer questionnaires about yourself, as well as provide ratings that will measure your understanding of the task.

This experiment will occur over two consecutive days. The first day of the experiment is expected to last about 3 hours. The second day of the experiment will last approximately one hour. You will receive extra credit in your psychology course for your participation in this experiment. At the end of the experiment, you will be provided with written feedback explaining the purpose of this research in more detail.

Your participation in this research is strictly voluntary. You are free to discontinue participation in this experiment at any time for any reason without penalty. Your responses will be kept completely confidential. In addition, individuals will remain anonymous in an report of research findings. You are free to ask any questions you might have about this experiment at any time. You may ask questions about the outcome of the study at any time by contacting Eleanor Smith through the Department of Psychology by mail or you may call directly at 353-9166.

By signing this sheet, you agree that the researcher has explained the study to you, that you understand the procedures to be used, and that you freely consent to participate.

Date: _____

Name: _____

Signature: _____

APPENDIX B**Learning a Computerized Radar Simulation****Individual Training Manual**

During this experimental session investigating how people learn, you will be operating a naval war fighting simulation.

Scenario

You are the Chief Radar Operator of the USS Intrepid, a U.S. Navy Aegis-class cruiser. You are seated on the bridge of the USS Intrepid where you can receive information from all the ship's sensors on your computerized radar screen. Your mission is to protect your ship and crew from hostile enemy vessels and to avoid destroying peaceful vessels. The decisions you make are critical. You are advising the Captain of the ship on a course of action to take when confronted with other vessels.

Your ship is in the center of the radar scope on your screen. Surrounding your ship are a number of "asterisks" called targets. The sensors on your ship provide you the information you need to classify these targets.

Your goal is to protect the USS Intrepid by correctly identifying the Type, Class, and Intent of a target, and deciding on the correct Engage response corresponding to the target's Intent. You must decide what action the USS Intrepid should take toward each target by deciding whether the Type of the target is Air/Sub/Surface, the Class of the target is Civilian/Military, and the Intent of the target is Peaceful/Hostile. You then Engage the target by advising your Captain to "Clear" Peaceful Targets from the area or "Shoot" Hostile Targets. All the information you collect must be correct for the Captain to be able to respond to the targets on your screen. The Type, Class, and Intent decisions you recommend allow the Captain to order which weapons and communication devices to use to carry out the Shoot or Clear decision. All four decisions you make must be correct to allow the Captain to order the correct response. For example, you might identify a target as Surface, Military, and Hostile, and then recommended that the Captain have the crew shoot the target. But if the target was really an Air target instead of a Surface target, the Captain would order the wrong weapons be used to shoot the target down. You must make sure that all four decisions you make are accurate so that your ship can effectively respond to other vessels in the area.

APPENDIX B

Your Radar Console

The radar console looks and operates like a computer. On the upper left corner of your console, you see the Time, in minutes and seconds, remaining in your simulation. When the Time counts down to zero (0), your simulation will be finished. In the upper right of your console, you see your Score. Your job is to protect your ship by correctly Engaging as many targets as possible to get the highest possible score.

In the center of your console, you see your computerized radar screen with the USS Intrepid in the center surrounded by targets. In the lower left corner of your screen, you see the radius at which your radar console is currently set. This indicates the distance from your ship your console displays. You may enlarge that radius to see targets outside your viewing area by clicking on the Zoom_Out function on the OPER menu.

In the lower right corner of your console, you see the Hooked Track #. Each of the Targets on your console is assigned a Track number. When you "Hook" a Target, by placing the mouse pointer on the Target and clicking the left button, the Hooked Track # changes to correspond to the Target number. When you gather information from your ship's sensors, that information will be given for the target you currently have Hooked. Each target retains the same track # throughout the simulation.

On the far upper right corner of your console, you see OPER, TYPE, CLSS, and ITNT. These are pull-down menus. These menus allow you to gather the information you need to make the Air/Sub/Surface, Civilian/Military, Peaceful/Hostile, and Shoot/Clear decisions. Your console will not allow you to make a Shoot/Clear decision before you have determined a target's Type, Class, and Intent. You must make the **four decisions** in the following order:

- (1) **ID Air/Sub/Surface;**
- (2) **ID Civilian/Military;**
- (3) **ID Peaceful/Hostile;**
- (4) **ENGAGE Shoot/Clear.**

Once you make the Engage decision, the target will disappear from the screen and you cannot change any of your decisions. If you want to go back and change any decision before you make the Engage decision, you need to make that decision and all the decisions that follow it. For example, if you think you made the wrong Type decision, you can go back and change that decision. But then you have to make the Class decision again, followed by the Intent decision as well. Then you can Engage the target.

APPENDIX B

To display the contents of a menu, use the mouse to place the pointer on the menu label and click the **right** mouse button. To display the information gathered by your sensors, place the pointer on the item and press and hold down the right mouse button. The sensor information is displayed in the lower right corner of your console.

In using your mouse, it is more efficient to use one finger for the left mouse button (e.g., your pointer finger), and a second finger to use the right mouse button (e.g., your ring finger). This will help you to avoid clicking on the wrong mouse button to hook targets v. calling up the menu information.

Your console menus contain the following items:

OPER	TYPE	CLSS	ITNT
End_Simulation	Altitude/Depth	Initial_Bearing	Missile_Lock
Start_Simulation	ID_Air/Sub/Surface	ID_Civilian/Military	ID_Peaceful/Hostile
Zoom_In			
Zoom_Out			
ENGAGE_Shoot/Clear			
Range			
Speed			

The first item in the TYPE, CLSS, and ITNT menus provide you the information from your sensors to make the ID_Air/Sub/Surface, ID_Civilian/Military, and ID_Peaceful/Hostile, decisions. When you choose each item, you receive a piece of information in the lower right corner of your console. There are rules to follow to interpret each piece of information and make the correct decision for each target. These rules are outlined in the table on the following page. Use these rules to classify the target's Type, Class, and Intent.

APPENDIX B

INFORMATION VALUES**Type = Air/Surface/Sub**

	AIR	SURFACE	SUB
Altitude/Depth	> 0 feet	0 feet	< 0 feet

Class - Civilian/Military

	CIVILIAN	MILITARY
Initial Bearing	091 - 270 degrees	000 - 090 degrees

Intent - Peaceful/Hostile

	PEACEFUL	HOSTILE
Missile Lock	Clean	Locked

For example, the TYPE menu allows you to gather the information needed to determine whether the Target is Air/Sub/Surface. We will use information about Altitude/Depth to illustrate the rules for making the ID_Air/Sub/Surface decision.

You hook a target and pull down the Type menu to look at the Altitude/Depth. The Altitude/Depth is 100 feet. Compare this value to the table above to determine the target's Type. Since this value is > 0, it indicates the Target Type is Air. You would then select the ID_Air/Surface/Sub option from your menu. A list of choices will appear, and you will select the choice corresponding to the decision you have made by clicking the right mouse button on the decision. In this example, you would classify the target as Air.

Once you make the Type decision, the symbol representing the Target on the screen will change. Air Targets are represented by upper-half symbols (◐). Submarines are represented by lower-half symbols (◑), and surface vessels are represented by whole symbols (◓).

APPENDIX B

When you have made the Class decision, the symbols will change again to reflect Military or Civilian. Civilian targets are represented by curved symbols. Military targets are represented by angular or pointed symbols. These symbols are outlined in the table below.

Symbols

	Air	Surface	Submarine
Civilian	⌒	○	∪
Military	∧	◇	∇

The ITNT menu contains the Missile Lock information necessary to make the Intent decision. When you have examined this information, you may choose the ID_Peaceful/Hostile item from the bottom of the ITNT menu and label the Target as "Peaceful" or "Hostile."

Engage Decision

After making decisions about the Type, Class, and Intent of a Target, you are now able to Engage the Target. Go to the OPER menu and click on ENGAGE_Shoot/Clear. Then choose "Clear" for Peaceful Targets or "Shoot" for Hostile Targets. Remember, you must make all four decisions (ID_Air/Sub/Surface, ID_Civilian/Military, ID_Peaceful/Hostile, and ENGAGE_Shoot/Clear) correctly to successfully engage a Target.

When you choose Shoot or Clear, you will receive feedback on your decisions if you hold your right mouse button down on your choice. Feedback will appear in the lower right corner of your screen, indicating whether your decision was correct or not, the points gained or lost, and the correct Type, Class, and Intent of the target chosen.

Targets disappear from your console after you Engage them so you cannot change your decision after Engaging a target. You can go back and correct your Type, Class, or Intent decisions if you do it **before** you make the final Engage decision.

APPENDIX B

Score

Your score will increase, remain the same, or decrease depending on the correctness of your decisions. Remember that you must make all four decisions correct (Type, Class, Intent, and Engage) to get the maximum score. Points for each completed target are as follows:

All 4 decisions correct	40 points
3 decisions correct	20 points
2 decisions correct	0 points
1 decision correct	-20 points
0 decisions correct	-40 points

For example, you hooked a target and made the Type decision correct, but were incorrect on the Class, Intent, and final Engage decision. You would lose 20 points for that target because only one decision was correct. It is important to be accurate on each decision in order to do well on this task.

Some Target combinations may seem strange, such as Air-Civilian-Hostile. In times of war, any type of target can be used for hostile purposes (for example, a kamikaze civilian aircraft or a research sub).

Summary

In sum, to perform your job as Chief Radar Operator, you must first hook a target by pointing to the target with the mouse pointer and clicking the left mouse button. Then, you gather information from your sensors to make decisions about the target's Type, Class, and Intent. Then, you Engage the Target by choosing to Clear it away or Shoot it. You should continue identifying and engaging Targets until you have Engaged all the Targets in your area. Remember to Zoom_Out to check for Targets that have traveled outside the radius of your radar screen.

APPENDIX C

General Task Instructions

You have had an opportunity to practice the basic procedures for performing this task. You have practiced hooking targets, calling up information on the menus, and making the Type, Class, Intent, and Engage decisions. Now you will be faced with a more complex task skill to learn.

In the next portion of your training, you will be learning how to prioritize the order in which you classify and make decisions about targets on your screen. Certain targets are more important than others because of the presence of two penalty circles on your screen.

Penalty circles refer to the presence of one or more circles surrounding your ship. It is a matter of policy that no targets should enter these zones. If a target enters one of these circles, you will lose points. For example, you don't want targets getting too close to your own ship where they can fire on you. There is a visible penalty circle that indicates this critical range. There is also a second penalty circle that is invisible and further away that will also cost you points if you let targets enter it. This invisible penalty circle indicates a safety zone for the rest of your fleet.

Location of Penalty Circles

The figure on the third page shows you the two penalty circles you will face. The picture on the left hand side shows your radar screen when the scenario begins. The **inner penalty circle** is the circle at **10 n.m.** that is shaded with grid lines. You cannot see the second penalty circle from this screen.

The second, **outer penalty circle** is located at **256 n.m.** If you use the zoom function and zoom out four times, your radar screen will show a radius of 512 n.m. This is displayed in the figure on the right hand side of the page. The second, invisible penalty circle falls halfway between the outer perimeter of your radar screen and your ship. This is highlighted in the figure by the dotted circle. Remember, though, that you will not see this penalty circle in the actual scenario. Also, remember that you need to zoom your radar out to 512 n.m. in order to see targets that are close to entering the outer penalty circle at 256 n.m. You should zoom out and look for targets that are about halfway between your ship and the edge of your screen when you zoom out to 512 n.m.

Using the zoom function will help you to see what is going on close to your inner penalty circle, and to look out in the distance at targets near your outer penalty circle.

APPENDIX C

Penalty Points

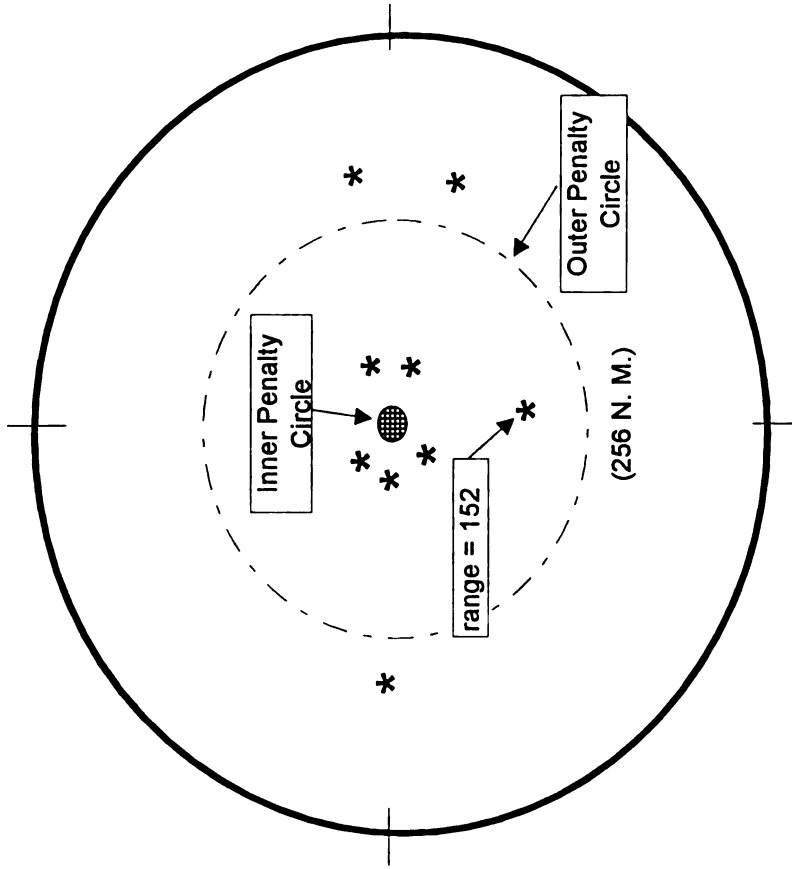
You will lose 100 points for each target that enters the outer penalty circle, and will also lose 100 points for each target that enters the inner penalty circle. So these two penalty circles are equally important for you to defend. Remember, once a target enters a penalty circle, you have already lost points and there is nothing you can do about regaining them. For example, the figure on the right side of the page shows a target with a range of 152. This target is already inside the outer penalty circle (256 n.m.) and far away from the inner penalty circle (10 n.m.). So this target would be a very low priority to choose. But you can try to prevent other targets from entering a penalty circle by choosing targets close to the outside of the penalty circle.

Speed and Range of Targets

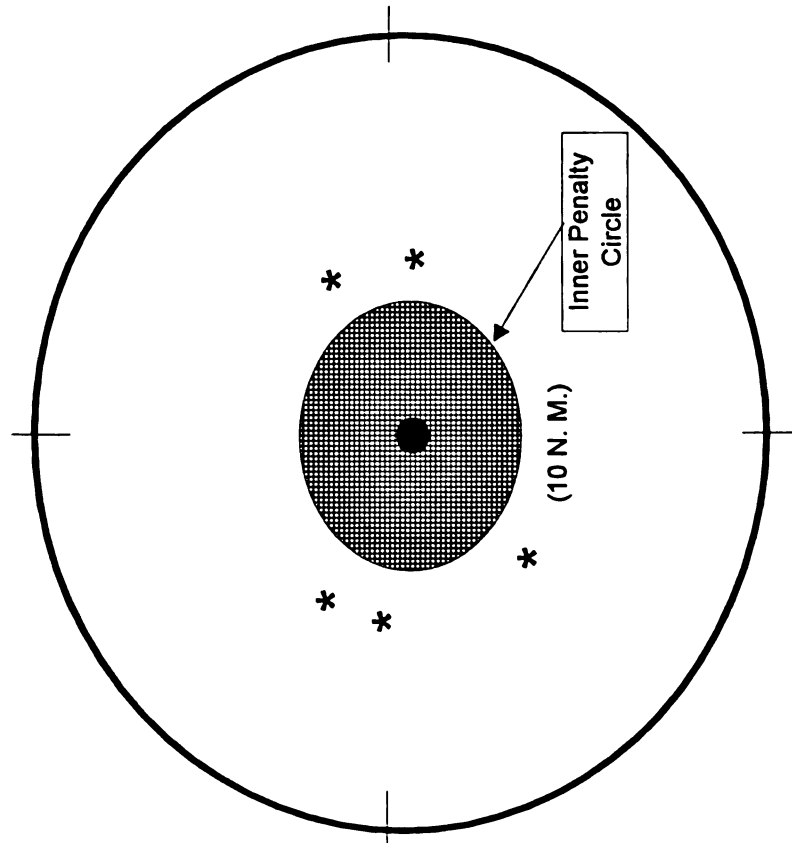
You may have several targets near a penalty circle at the same time. How will you decide which target to make decisions about? **Speed** and **Range** information are available on the **OPER menu**. The **Speed** information tells you how fast the target is travelling towards you -- the higher the number, the greater the speed. The **Range** information indicates how far the target is from your ship. For example, a target with a range of 20 n.m. would be 20 n.m. away from your ship.

You can hook a target and look up its Speed and Range to determine how soon it will enter a penalty circle. Comparing the Speed and Range for several targets will help you identify and prioritize which targets to make decisions about first. You should first choose and engage targets that are close in range and moving towards you quickly. By making the four decisions about a target and removing it from the screen, you will prevent it from entering the penalty circle.

You will now have opportunities to practice these new skills. You will first practice a scenario at a low level of complexity. After this, you will practice a scenario at a moderate level of complexity, followed by a scenario at a high level of complexity.



Radius = 512 N. M.



Radius = 32 N. M.

APPENDIX D

Discovery Learning Instructions

*Low Complexity Scenario*Pure Discovery Learning

You will first be facing a low complexity scenario. An effective method for learning skills is to explore a task and develop your own understanding of it. As you practice the scenario, explore the task to understand what is occurring in the scenario, and to discover the best strategy to deal with the situation. Experiment with different strategies for dealing with the low level of complexity. Remember that your task is to prioritize targets to make decisions about to prevent them from entering the inner (located at 10 n.m.) and outer (located at 256 n.m.) penalty circles.

Guided Discovery Learning

You will first be facing a low complexity scenario. **The scenario is described as follows:** There will be a moderate amount of targets on the screen, with five targets surrounding the inner penalty circle and seven targets surrounding the outer penalty circle. In general, the targets are not very critical, with the majority of targets moving pretty slowly and not too close in range to the penalty circles. However, there will be two critical targets surrounding the inner penalty circle, and one critical target surrounding the outer circle that you must prosecute to prevent yourself from losing penalty points. You will have plenty of time to identify these targets and prosecute them before they enter the penalty circle. In addition, these three critical targets will enter the penalty circles at about the same time.

Your strategy to deal with this is as follows: First, you should check the speed and range values of targets around the inner (located at 10 n.m.) and outer (located at 256 n.m.) penalty circles. It is important for you to check all targets around both circles first to develop a good assessment of the overall situation you will be facing. You will see the targets around your inner circle when the scenario first starts. Make sure that you do zoom out to 512 n.m. to check the targets on the outer circle as well. Determine which targets are critical on the inner and outer circles. Because these three targets will enter the two circles at about the same time, the order of prosecuting these three targets is less important in this scenario. But you must make sure to prosecute these critical targets first. Once you have prosecuted these three targets, prosecute as many additional targets as you can, prioritizing them based on their speed and range values.

APPENDIX D

Low Complexity Scenario (cont'd)

To learn how to handle this scenario, you should spend time checking the speed and range values of all targets around the inner and outer penalty circles. Take time to explore the task and understand what this low complexity scenario is like. Try to figure out what features of this low complexity scenario are important, and why they lead to the strategy described above. Once you are comfortable with your understanding of the scenario, then try out the strategy described above. It is important for you to focus your attention on exploring the task, and trying to understand its features and the strategy you must use to handle it.

Guided Discovery Learning - Trial 1 Instructions

On this first practice trial, I want you to take time to explore the task and to watch how the scenario unfolds. You should practice checking the speed and range information for targets around the inner and outer penalty circles. Focus on understanding what these two pieces of information mean for each target. First, check the speed and range values of the targets on the inner circle. Next, zoom out to 512 n.m. on your screen, and look for your outer penalty circle. Check the speed and range values of all targets around the outer penalty circle. Get a good idea of which targets you think will enter first on the inner circle, and the target that will enter first on the outer circle.

Don't make decisions on these targets on this first trial (or they will be removed from the screen). Instead, watch how the scenario unfolds, and notice when the targets enter the penalty circles. For the inner penalty circle, it is apparent on your screen when the targets enter the penalty circle. For the outer penalty circle, you must check the range of targets to notice when they have entered the 256 range of the outer circle.

You should explore the task on this first trial to develop a good understanding of the penalty circles, and what the speed and range values mean. You will have several more trials to experiment with and practice getting the targets before they enter the circles later.

APPENDIX D

*Low Complexity Scenario (cont'd)*Procedural Instruction

You will first be facing a low complexity scenario. **The scenario is described as follows:** There will be a moderate amount of targets on the screen, with five targets surrounding the inner penalty circle and seven targets surrounding the outer penalty circle. In general, the targets are not very critical, with the majority of targets moving pretty slowly and not too close in range to the penalty circles. However, there will be two critical targets surrounding the inner penalty circle, and one critical target surrounding the outer circle that you must prosecute to prevent yourself from losing penalty points. You will have plenty of time to identify these targets and prosecute them before they enter the penalty circle. In addition, these three critical targets will enter the penalty circles at about the same time, so it does not matter the order in which you prosecute these targets. But you must make sure to prosecute these critical targets first.

Your strategy is as follows: First, you should check the speed and range values of targets around the inner (located at 10 n.m.) and outer (located at 256 n.m.) penalty circles. Range can be estimated somewhat by looking at targets around the inner circle, but looking up the exact range can help you when it is hard to see which target is closer. On the outer circle, you must look at the range of targets on the outer circle to assess their distance from the outer penalty circle. It is important for you to check all targets around both circles first to develop a good assessment of the overall situation you will be facing. You will see the targets around your inner circle when the scenario first starts. Make sure that you do zoom out to 512 n.m. to check the targets on the outer circle as well.

Determine which targets are critical on the inner and outer circles. Because the three critical targets will enter the two circles at about the same time, you can choose to prosecute these targets in any order. Once you have prosecuted these three targets, prosecute as many additional targets as you can, prioritizing them based on their speed and range values.

An effective method for learning skills is to practice them as often as possible. It is important for you to focus your attention on practicing the strategy described above during the practice trials.

APPENDIX D

*Moderate Complexity Scenario*Pure Discovery Learning

You will now face a task that has increased in complexity to a moderate level. An effective method for learning skills is to explore a task and develop your own understanding of it. As you practice the scenario, explore the task to understand what is occurring in the scenario, and to discover the best strategy to deal with the situation. Experiment with different strategies for dealing with the moderate level of complexity. Remember that your task is to prioritize targets and prevent them from entering the penalty circle.

Guided Discovery Learning

You will now face a task that has increased in complexity to a moderate level. You must identify how the situation has changed, and how you must adjust your task strategy to deal with the changes.

1. Identify at least three aspects of the moderate complexity scenario that might be different from the low complexity scenario. Write your predictions below.

1 _____

2 _____

3 _____

2. Identify how you would respond to these changes. In other words, identify what task strategy you would use to handle each of the changes you identified in the first question. Write these new task strategies below.

1 _____

2 _____

3 _____

APPENDIX D

Moderate Complexity Scenario (cont'd)

An effective method for learning skills is to explore a task and develop your own understanding of it. As you practice the next scenario, you should explore the task to try to identify what is going on and what makes it a moderate complexity task. Watch and discover what is happening on both the inner and outer penalty circles. As you explore the task, check whether or not your predictions about the changes that might occur are correct. Try to understand what these changes mean for how you should perform the task. Once you understand what is going on in the scenario, experiment with and try out different strategies for dealing with the situation. Remember that you must prevent targets from entering the penalty circles so you do not lose points.

Procedural Instruction

You will now face a task that has increased in complexity to a moderate level. **The scenario is described as follows:** There will be six targets surrounding the inner penalty circle and seven targets surrounding the outer penalty circle. A moderate proportion of the targets are critical. Two targets surrounding the inner penalty circle and three targets surrounding the outer circle will be critical, and you must prosecute these targets to prevent yourself from losing penalty points. The two critical targets on the inner circle will enter the circle pretty quickly. The three critical targets on the outer penalty circle will enter towards the end of the scenario.

Your strategy is as follows: First, you should check the speed and range values of targets around the inner and outer penalty circles. Determine which targets are critical on the inner and outer circles. Then prosecute the two targets that are critical on the inner circle. Once these targets have been dealt with, move to the outer circle and prosecute the three critical targets on the outer circle. Once you have prosecuted these five targets, prosecute as many additional targets as you can, prioritizing them based on their speed and range values.

An effective method for learning skills is to practice them as often as possible. Therefore, it is important for you to focus your attention on practicing the strategy described above during the practice trials.

APPENDIX D

*High Complexity Scenario*Pure Discovery Learning

You will now face a task that has increased in complexity to a high level. An effective method for learning skills is to explore a task and develop your own understanding of it. As you practice the scenario, explore the task to understand what is occurring in the scenario, and to discover the best strategy to deal with the situation. Experiment with different strategies for dealing with the moderate level of complexity. Remember that your task is to prioritize targets to prosecute to prevent them from entering the penalty circle.

Guided Discovery Learning

You will now face a task that has increased in complexity to a high level. You must identify how the situation has changed, and how you must adjust your task strategy to deal with the changes.

1. Identify at least three aspects of the high complexity scenario that might be different from the moderate complexity scenario. Write your predictions below.

1 _____

2 _____

3 _____

2. Identify how you would respond to these changes. In other words, identify what task strategy you would use to handle each of the changes you identified in the first question. Write these new task strategies below.

1 _____

2 _____

3 _____

APPENDIX D

High Complexity Scenario (cont'd)

An effective method for learning skills is to explore a task and develop your own understanding of it. As you practice the next scenario, you should explore the task to try to identify what is going on and what makes it a high complexity task. Watch and discover what is happening on both the inner and outer penalty circles. As you explore the task, check whether or not your predictions about the changes that might occur are correct. Try to understand what these changes mean for how you should perform the task. Once you understand what is going on in the scenario, experiment with and try out different strategies for dealing with the situation. Remember that you must prevent targets from entering the penalty circles so you do not lose points.

Procedural Instruction

You will now face a task that has increased in complexity to a high level. **The scenario is described as follows:** There will be six targets surrounding the inner penalty circle and seven targets surrounding the outer penalty circle. A majority of the targets are critical. Four targets surrounding the inner penalty circle and four targets surrounding the outer circle will be critical, and you must prosecute these targets to prevent yourself from losing penalty points. The critical targets on the inner and outer penalty circles will enter the two penalty circles in an alternating fashion. In other words, two of the critical targets on the outer penalty circle will enter first, followed by two targets entering on the inner circle. Then two targets will enter on the outer circle, and two more will follow on the inner circle.

Your strategy is as follows: First, you should check the speed and range values of targets around the inner and outer penalty circles. Determine which targets are critical on the inner and outer circles. Then prioritize the targets and prosecute them in the order outlined below:

1. two on the outer circle;
2. two on the inner circle;
3. two on the outer circle;
4. two on the inner circle.

With any time remaining, prioritize and prosecute the remaining targets on the screen.

An effective method for learning skills is to practice them as often as possible. Therefore, it is important for you to focus your attention on practicing the strategy described above during the practice trials.

APPENDIX E

Metacognitive Instructions

Now that you have had some experience with practicing this task, it is important for you to focus your attention on improving your understanding of the task, and your strategies for accomplishing it. One learning method that is beneficial for identifying and correcting errors in your understanding of a task is called **self-regulation**. Self-regulation is a process of **setting a learning goal**, developing a **plan for achieving the goal**, and **monitoring and evaluating your progress** with reference to the goal. When people are active in self-regulating their learning they are able to continuously improve their understanding.

The first step in self-regulation is **setting a learning goal**. A learning goal tells you what you should focus your attention on while you practice the task. To set a learning goal, you need to identify the specific information or skills that you need to learn more about.

Once you have set a learning goal, you need to **develop a plan** for how you will accomplish that goal. In other words, you will identify the specific thoughts or actions you will engage in during practice to try to achieve that goal.

While you practice the task, you will also be active in **monitoring** your improvement with regard to your learning goal. Are you making progress towards that goal, or have you started focusing on less important issues?

Finally, when you are finished with the practice session, you need to **evaluate** yourself in terms of your progress towards your learning goal. Did you improve your understanding of the task, and did it lead to better outcomes? Once you evaluate your progress, the self-regulatory process begins again. You may still need to work on the same learning goal, or you may identify some new problem that you want to tackle.

Example of Self-Regulation

Let's say I am focused on improving my capability to make accurate Type, Class, and Intent decisions about each target. I have noticed that I am pretty good at remembering the initial bearing information for the Class decision, and the missile lock information for the Intent decision. But I have had some difficulty remembering the ranges of altitude/depth for the Type decision. I decide that my **learning goal** for the next trial is to focus on understanding and memorizing the altitude/depth information. Notice that a learning goal is focused on the specific skills that need improvement, not on overall performance of the task.

APPENDIX E

My **plan** for achieving that goal is to hook ten targets and just make the Type decision on them first. I figure that by practicing that skill ten times in a row without interruptions from the Class and Intent decisions, I may improve my memorization of the altitude/depth information. I will also try to make these ten decisions without looking at the information in the manual. Once I have made these ten decisions, I will go back and make the Class decision and the Intent decision on each of the ten targets.

I believe that this strategy of practicing many Type decisions in a row will improve my understanding. I will **monitor** if this is so by checking the feedback I get when I make the Final Engagement decision. The feedback should match what I decided the Type of the target to be. When the scenario is over, I can also check my final score to see if it has improved due to my focus on the Type decision. I need to remember, though, that the overall score may not be very high because I decided to take extra time to focus on the Type decision. But in general, I can **evaluate** whether my understanding and progress on the task has improved. If I feel that it has, I may set a new learning goal focused on a different aspect of the task.

Instructions for Practice

In your practice sessions, you should be focused on improving your understanding of how to prioritize targets so that they do not enter the penalty circles. So you need to identify any difficulties you are having in this prioritization skill, and come up with a learning goal and plan to improve your mastery of this skill. For self-regulation to be successful, you need to think carefully about your practice exercises, your feedback, and your understanding of the task in order to identify the specific areas that need improvement. A superficial or hasty approach to self-regulation will not help you to improve your learning.

For the next trial, focus on learning the medium complexity scenario. After the trial, you will then have some experience with the task to help you identify difficulties that you need to correct through self-regulation.

Metacognitive Questions

Participants in the metacognitive instruction condition will be asked to answer questions after the first trial practicing the medium complexity scenario, and any subsequent trials to practice this scenario. A similar procedure will occur for the high complexity scenario, where participants will have the first trial to gain an initial understanding of the task, and after this first trial and subsequent trials they will answer questions to guide their self-regulatory learning.

The specific sheet that participants will fill out after each trial is found on the following page.

APPENDIX E

Self-Regulation

Subject # _____
Trial # _____

1. How many targets did you allow into the inner and outer penalty circles?

2. Based on the information above, do you think you have learned about and understand what is occurring in the scenario? Why or why not?

3. Where did you have the most difficulties in understanding the scenario? Be specific.

4. What is your learning goal on the next trial to improve your learning? In other words, what are the knowledge or skills that you want to master?

5. What is your plan to accomplish your goal? In other words, what will you be thinking about or what will you be doing to work towards your learning goal?

On your next practice trial, remember to periodically monitor your progress towards your learning goal and plan. Adjust your behavior if necessary if you do not feel you are making progress towards your goal.

APPENDIX F

Demographics

Please answer the following questions about yourself:

1. What is your gender?

1 = Male

2 = Female

2. What is your age?

1 = 17 or younger

2 = 18

3 = 19

4 = 20

5 = 21

6 = 22

7 = 23

8 = 24

9 = 25

10 = 26 or older

3. What is your overall grade point average?

1 = 0.00 - 0.50

2 = 0.51 - 1.00

3 = 1.01 - 1.50

4 = 1.51 - 2.00

5 = 2.01 - 2.50

6 = 2.51 - 3.00

7 = 3.01 - 3.50

8 = 3.51 - 4.00

4. How often do you play with video games?

1 = Never

2 = Rarely

3 = Sometimes

4 = Frequently

5 = Always

APPENDIX G

Tolerance for Ambiguity (adapted from Major, 1990)

Instructions

Please answer the following questions about yourself. Use the following rating scale to indicate your agreement with each of the following statements:

1	2	3	4	5	6	7
strongly disagree	moderately disagree	slightly disagree	neither agree nor disagree	slightly agree	moderately agree	strongly agree

1. I prefer situations that are unpredictable.
2. I dislike supervisors who expect me to figure out my work assignments on my own.^a
3. I prefer explicit instructions when I'm learning a new task.^a
4. Jobs that have a lot of change and uncertainty are more desirable than jobs with little change and uncertainty.
5. I enjoy learning tasks that are ambiguous.
6. I like working on problems that have more than one solution.^a
7. A good job is one where what is to be done and how it is to be done are always clear.^a
8. I prefer work assignments with specific directions to those with vague directions that require my own interpretation.^a
9. I like trying to figure out tasks when the directions are not very clear.
10. I enjoy dealing with unexpected situations.

^a Based on factor analysis results, these items were dropped from the final tolerance for ambiguity scale.

APPENDIX H

Mastery Orientation and Performance Orientation
(Button, Mathieu, & Zajac, 1995)

Instructions

Please answer the following questions about yourself. Use the following rating scale to indicate your agreement with each of the following statements:

1	2	3	4	5	6	7
strongly disagree	moderately disagree	slightly disagree	neither agree nor disagree	slightly agree	moderately agree	strongly agree

Mastery Orientation Items

1. I do my best when I'm working on a fairly difficult task.
2. When I have difficulty solving a problem, I enjoy trying different approaches to see which one will work.
3. I try hard to improve on my past performance.
4. The opportunity to do challenging work is important to me.
5. The opportunity to extend the range of my abilities is important to me.
6. The opportunity to learn new things is important to me.
7. I prefer to work on tasks that force me to learn new things.
8. When I fail to complete a difficult task, I plan to try harder the next time I work on it.

Performance Orientation Items

1. The things I enjoy the most are the things I do the best.
2. I feel smart when I do something without making any mistakes.
3. I prefer to do things that I can do well rather than things that I do poorly.
4. I like to be fairly confident that I can successfully perform a task before I attempt it.
5. I am happiest at work when I perform tasks on which I know that I won't make any errors.
6. I feel smart when I can do something better than most other people.
7. The opinions others have about how well I can do certain things are important to me.
8. I like to work on tasks that I have done well on in the past.

APPENDIX I

Hypothesis-Testing/Self-Regulatory Activity

Instructions

Please answer the following questions about your activities during the practice sessions. Use the following rating scale to indicate your agreement with each of the following statements:

1	2	3	4	5	6	7
strongly disagree	moderately disagree	slightly disagree	neither agree nor disagree	slightly agree	moderately agree	strongly agree

Hypothesis-Testing Items

1. Before practicing a new scenario, I made predictions concerning how the scenario might be different due to its increased complexity.
2. I identified strategies for dealing with changes that might occur in a scenario of greater complexity.
3. I explored the task to test my predictions about what the scenario would be like.
4. I watched what occurred at both the inner and outer penalty circle to develop a good understanding of how each scenario would unfold.
5. I experimented with different task strategies to handle the level of complexity I faced in a scenario.
6. I thought about how well my predictions about a scenario matched the actual events that occurred during the scenario.

Self-Regulation Items

1. I thought carefully about my performance on the previous practice trial to develop a learning goal for the next practice trial.
2. I developed a specific plan of action to achieve my learning goal during practice.
3. While practicing a scenario, I monitored how well I was learning its requirements.
4. During practice, I monitored closely the areas where I needed the most practice.
5. I noticed where I made the most mistakes during practice and focused on improving those areas.
6. I evaluated the feedback at the end of the practice trial to determine how I would approach the task on the next trial.

Note: These items were originally conceptualized as separate constructs, but factor and correlational analyses indicated that these items tapped into a single construct. Therefore, these 12 items were combined into a single scale for study analyses.

APPENDIX J

Self-Efficacy

Instructions

Please answer the following questions about your activities during the practice sessions. Use the following rating scale to indicate your agreement with each of the following statements:

1	2	3	4	5	6	7
strongly disagree	moderately disagree	slightly disagree	neither agree nor disagree	slightly agree	moderately agree	strongly agree

1. I can successfully meet the challenges of a scenario I have never experienced.
2. I am confident that my knowledge of this task can be adapted to unforeseen situations in the future.
3. I can deal with a task scenario I have never handled before.
4. I am certain I can handle the initial difficulties of a scenario I have not performed before.
5. I believe I will perform well if the task requires me to develop a more complex task strategy.
6. I am confident that I can cope with this simulation if it becomes more complicated.
7. I believe I can develop methods to handle changing aspects of this task.
8. I am certain I can cope with task components competing for my time.

APPENDIX K

Verbal Knowledge Test

1. If a target is outside of the current radius of your screen, you can view it by doing what?
 - a. there is nothing you can do
 - b. wait for the target to enter you screen
 - c. Zoom_Out
 - d. Zoom_In
2. What information should you use to prioritize targets to engage?
 - a. Speed and Initial Bearing
 - b. Speed and Range
 - c. Range and Initial Bearing
 - d. Speed
3. The inner penalty circle is characterized by which of the following features:
 - a. located at 10 n.m. and visible
 - b. located at 32 n.m. and visible
 - c. located at 32 n.m. and invisible
 - d. located at 16 n.m. and visible
4. If you zoom out to 512 n.m.:
 - a. the outer Penalty Circle is visible (is marked on the screen)
 - b. the outer Penalty Circle is invisible and half way between the center and the screen's edge
 - c. the inner Penalty Circle is invisible, and the outer Penalty Circle is visible
 - d. the outer Penalty Circle is around the edge of the screen but invisible
5. At the start of the scenario, there are two targets, one by each Penalty Circle. Both targets are traveling at 250 knots. One target has a range of 14 n.m. and the other has a range of 261 n.m. Which target should be engaged first?
 - a. the target near the inner Penalty Circle
 - b. the target near the outer Penalty Circle
 - c. it does not matter
 - d. engage the target with the highest initial bearing first no matter what

APPENDIX K

6. How many points would you lose if you allowed three targets to enter the inner penalty circle and two targets to enter the outer penalty circle?
- a. 200
 - b. 300
 - c. 500
 - d. 1000
7. If you have three targets,
target (a) with Range = 255 n.m., Speed = 150 knots
target (b) with Range = 260 n.m., Speed = 100 knots, and
target (c) with Range = 25 n.m., Speed = 120 knots,
which target should be engaged first?
- a. target a
 - b. target b
 - c. target c
 - d. engage in any order
8. If you Zoom_Out to find three targets clustered together near the Outer Penalty Circle, how would you determine which to engage first?
- a. check the Ranges
 - b. check the Speeds
 - c. check both Range and Speed for each target
 - d. zoom to 256 n.m. and engage the first target closest to the center (own ship)
9. You have been checking targets around the inner circle and zoom out to look at your outer penalty circle. There are two targets surrounding your outer circle. You check the range on one target and it is 254 n.m. What do you do next?
- a. Make the four decisions for that target so it won't travel near the inner penalty circle.
 - b. Check the target's speed to determine how critical it is overall.
 - c. Zoom back in to the inner penalty circle.
 - d. Hook the second target on the outside circle.

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10. You have checked the speed and range values on targets on your inside and outside penalty circles. Their values are as follows:

	<u>Speed</u>	<u>Range</u>
Target 001	380	22
Target 002	229	26
Target 003	428	45
Target 004	412	262
Target 005	150	261
Target 006	390	280

What four targets would you engage first, and in what order?

- a. 004, 001, 006, 002
 - b. 004, 005, 001, 002
 - c. 003, 004, 006, 001
 - d. 004, 006, 001, 002
11. In which of the following situations would looking up the range of targets be most critical?
- a. To determine which of two targets is closer to the inner penalty circle.
 - b. To compare how close targets are to the outer penalty circle.
 - c. To identify targets that are an equal distance between the inner and outer penalty circles.
 - d. Range is not important to look up in any situation because speed is the critical factor.
12. When a scenario first begins, what should you do?
- a. Prosecute the target that looks closest to the inner penalty circle.
 - b. Choose a penalty circle, compare the speed on 2 or 3 targets around it, and choose the fastest of the targets to prosecute.
 - c. Identify the targets with a Hostile Intent and prosecute them first.
 - d. Check targets on both the inner and outer penalty circle to get an overall assessment of the scenario.

APPENDIX K

13. When dealing with a high complexity scenario, what is the best strategy for preventing targets from entering your penalty circles?
- a. As you look up the speed and range of each target, immediately engage any fast and close ones that you see before checking the rest of the targets.
 - b. Check just the speed of the targets to save time and then prosecute the fastest targets first.
 - c. Frequently zoom in and out to your two penalty circles to continuously monitor what is happening.
 - d. Quickly get rid of all of the critical targets around one circle to have more time to devote to the other penalty circle.
14. When a scenario begins, the radius of the screen is 32 n.m. If you hit the zoom_out button three times, what will be the radius of the radar screen?
- a. 126 n.m.
 - b. 128 n.m.
 - c. 256 n.m.
 - d. 512 n.m.

Note: Items 8, 12, 13, and 14 were dropped from the final knowledge test based on an analysis of the internal consistency of the test.

APPENDIX L

Knowledge Structure

Instructions

Your goal is to make "relatedness" ratings about actions you perform in the radar simulation task. We want you to think about how strongly or weakly pairs of actions "go together" or "are connected" in a meaningful way IN YOUR MIND when you perform the task.

Pairs of actions will be presented by the computer in random order, so the order of presentation is not important -- whether an action is presented as the first or second item in a pair should not affect your ratings of relatedness. We are only interested in how strong or weak YOU THINK the overall connection is between each pair of aspects.

Press SPACE BAR to continue

As you make your ratings, bear in mind that the actions can go together in different ways. For example, your ratings should indicate HOW STRONGLY OR WEAKLY you think taking one action relates to taking another action.

Each pair of actions will be presented on the screen along with a "relatedness" rating scale. Pairs of actions that you think are weakly related should be rated with 1, 2, or 3; moderately related pairs should be rated 4, 5, or 6; and highly related pairs should be rated 7, 8, or 9 by pressing the number on the keyboard -- a bar marker will move directly above the number you pressed. If you wish to change your response, simply press another number. When you are satisfied with your rating, press the SPACE BAR to enter your response. The next pair of items to be rated will be then be displayed.

Press SPACE BAR to continue

Because the task is complex, there are many pairs of actions to be rated -- please make your ratings carefully. It is very important to us that you think about HOW RELATED THEY SEEM TO YOU based on your experience with the task.

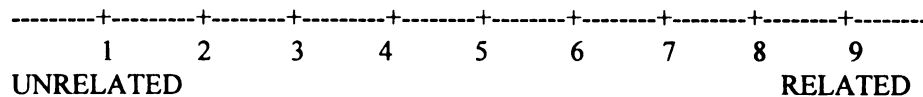
If at any time you feel like taking a break tell the experimenter you are doing so and leave the machine running. Thanks for helping us with this part of the experiment.

Now the complete list of actions to be rated will be presented. This is done to give you a general idea of the types of actions you will asked to rate. Thank you again for your help.

Press SPACE BAR to continue

- Check Speed
- Check Range
- Zoom Out
- Zoom In
- Monitor Penalty Circles
- Proportion of Dangerous Targets
- Number of Targets around Circles
- Order of Target Entry
- Prioritize Targets
- Minimize Point Loss
- Monitor Score
- Assess Scenario Complexity
- Change Performance Strategy

Press the SPACE BAR to begin the ratings.



Enter <1 through 9> followed by <SPACE>

77 Ratings to go.

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APPENDIX M

Transfer Task Instructions

Yesterday you had a number of opportunities to practice dealing with penalty circles. Now it is time for you to perform on a more complex version of this task. Use the knowledge and skills you have gained during the practice exercises to show how well you can perform this task.

In this final task, your score counts. You should concentrate on achieving the best score you can. This session will last nine minutes. You need to engage as many targets as you can. You will earn 40 points when you make all four decisions correctly about a target, and you will gain fewer points or even lose points if some or all of the decisions are incorrect.

More importantly, you will lose 100 points for each target that you allow into either of your two penalty circles. These penalty circles are located at 10 n.m. and 256 n.m.

Your score will be -700 when this task begins. This happens due to the placement of targets on the screen. We will adjust your score at the end of the session by adding those 700 points to the score you achieve.

This scenario will be more challenging than those that you have practiced. The scenario will last twice as long as the practice trials. You will no longer have feedback on the accuracy of your decisions after you make the Engage decision. In addition, the scenario will be more dynamic than any you have faced so far.

Do you have any questions? If not, let's begin the final session.

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