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Training For Decision Making In Complex Environments: Instructional Methods And Individual Differences

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TRAINING FOR DECISION MAKING IN COMPLEX ENVIRONMENTS: INSTRUCTIONAL METHODS AND INDIVIDUAL DIFFERENCES

by

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ABSTRACT

Increased technology reliance along with today's global fast paced society has produced increasingly complex, dynamic operating environments in disciplines as diverse as the military, healthcare, and transportation. These complex human machine systems often place additional cognitive and metacognitive demands on the operator. Thus, there is a crucial need to develop training tools for all levels of operators in these dynamic systems. The current study was designed to empirically test the effects of four training methods on performance and mental model accuracy in a microworld simulation game. It was hypothesized that process-focused guidance targeting metacognitive level processes as well as combined process and problem focused guidance would result in better performance and mental model accuracy than problem-focused guidance alone or unguided training approaches. Additionally, it was expected that individual differences in prior decision making ability, metacognitive awareness, working memory span, and fluid intelligence would moderate the relationship between the type of instructional guidance and outcomes. Results supported the development of decision-making skills through process-focused instructional guidance, particularly for initially low performing or more novice individuals. Results highlight the importance of individual learner experience prior to training. Similarly, this research aims to expand the literature by providing support for process-focused training as a method to support non-expert decision making skills. While further research needs are outlined, the current research represents an important step forward in both the theoretical literature providing support for instruction designed to support domain general decision making skills in non-experts.

Practical implications regarding improved guidance for future instructional and training systems design, personnel selection, operator and system performance evaluation, and safety are also discussed.

This work is dedicated to those who have loved and supported me in this long journey.

A special dedication goes to my Mom and Dad who taught me to always persevere – thank you for your love and guidance.

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CHAPTER ONE: INTRODUCTION

"Most national security issues that challenge our leaders today require attempting to understand, predict, and influence the behavior of complex systems" (Lafond & DuCharme, 2011, p.1)

"No intervention in a complex system such as a human society can have only one effect." (Aoi, de Coning and Thakur, 2007, p.3)

Decision making is a cognitive task that characterizes each of our lives, yet the increasingly complex environments in which we live has created situations where often even seemingly simple decisions lead to multiple, far-reaching, and unforeseen consequences (Aoi, de Coning and Thakur, 2007; Sherden, 2011). From business to the military, modern operating environments are often characterized by delicate interrelationships as cultures and economies of one country intertwine with other cultures and economies around the world producing a single complex global system. Yet the human ability to foresee the consequences of even simple actions within such complexity has failed to meet the growing demands of this globalization. In high stakes operating environments such as the military, government, medical, or even business negative unintended decision consequences can lead to critical losses (Aoi, de Coning and Thakur, 2007; Sherden, 2011). Just as businesses had to adjust to the increasing demands and complexities with industrialization; today governments and militaries are faced with the changing requirements of the increasingly complex and fast moving environments of today's global society. As witnessed across wars and national security measures in the last decade, the fragility of this global system presents ever changing and growing challenges. For the military this increasing complexity and global focus has created a shift in mission focus, operating conditions, and ultimately the focus and approach to military training.

Current Military Operating Environments

Today military operations are increasingly characterized by diverse, complex, and ambiguous environments creating an increased need for decentralized decision-making and adaptability across the ranks (Conway, as cited in Vogel-Walcutt, Carper, Bowers & Nicholson, 2010). Soldiers must be trained for and adapt to changing conditions while focusing on mission objectives, which may range from offensive and defensive force and Counterinsurgency efforts to Stability, Peacekeeping, and Aide or any combination of these (Spain, 2010). With multiple lines of effort across the globe and often multiple cultural influences within a single country, Soldiers must go beyond simple identification of friend or foe and consider the impact of their actions with regard to the various social, economic, political, and cultural influences of the local citizens.

In today's operating environments Soldiers are often faced with ambiguous, ill-defined goals, which may or may not be achieved through the use of previously defined tactics, techniques, and procedures (Spain, 2010). Additionally modern wars have increasingly relied upon counterinsurgency operations that add a layer of operating ambiguity even at a basic level of determining friend from foe. Counterinsurgency operations have also moved modern military operations toward the use of decentralized decision making. Such decentralization has transitioned critical decision making power from the traditional higher level officers and commanders to Soldiers across the ranks, placing decision making demands on Soldiers across the echelons (Conway, as cited in Vogel-Walcutt, Carper, Bowers & Nicholson, 2010). To successfully meet these new demands, Soldiers must develop and maintain an understanding of the many nuances in the various cultures, social and political networks, and leadership hierarchies in each new and evolving operating environment. While in traditional warfare commanders would hand down specific decisions, directives, and TTPs, in today's environment of counterinsurgency operations Soldiers on the ground must be able to quickly and accurately identify and prioritize mission goals and sub-goals within the cultural, political, and logistic parameters of the current, and often changing operational environment. To achieve success Soldiers must develop flexible operational plans which consider not only the immediate effects of their actions but also the second and third order consequences of any potential action or inaction (Spain, 2010). Finally the dynamic and complex nature of these new environments calls for flexibility in mission planning as Soldiers must recognize unexpected consequences as well as the changing needs and situational demands and adjust mission goals and plans accordingly.

New Training Needs

As operating environments grow increasingly complex and ill-defined, the cognitive and metacognitive training needs have changed. Decisions in well-defined situations typically have clear problem spaces and goals as well as correct solutions. In contrast, ill-defined decision environments often have vague goals and end points as well as many interrelated variables that may produce unexpected consequences that are often removed in time or space from the immediate decision consequence. Research suggests that operating in such ill-defined problem situations requires different cognitive and metacognitive skills than well-defined problem situations (Jonassen, 1997; Shin, Jonassen, & McGee, 2003; Shraw, Dunkle, & Bendixen, 1995; Spain, 2010). The complexity inherent in ill-defined situations requires an individual to have the ability to seek out and organize extensive information, formulate and adjust goals and subgoals, and monitor and adjust based on the outcomes of their own decisions as well as changing operational conditions. Today's Soldiers must be prepared to operate in novel situations that are stressful, complex, and dynamic (McAlinden, Gordon, Lane, & Pynadath, 2009). Individuals across the echelons must be equipped with the knowledge, skills, and abilities necessary to adapt to new and rapidly changing situations. This requires a unique combination of cognitive, interpersonal, and cultural knowledge and skills which combine to allow the individual Soldier to make appropriate judgments and decisions in today's complex, dynamic environments (Department of the Army, 2011). Given these new operational demands, Lussier, Shadrick, and Prevou (2003) suggest that today's training needs to go beyond training Soldiers what to think and instead focus more efforts on training Soldier how to think.

Today the transition to training individuals how to think is embraced in the Army Learning Concept for 2015 (ALC 2015) (Department of the Army, 2011) which includes not only cognitive, but critical metacognitive skills as key Soldier competencies. Among these skills, the ALC 2015 highlights the need for Soldiers to exhibit the ability to adjust to new and changing operating environments, use self-regulated learning skills, critical thinking and problem solving, and self-awareness during operations. To meet these training needs the ALC 2015 suggests that training should increasingly incorporate technology-based instructional tools (e.g. simulations, games, etc.) and problem solving exercises with instructional components tailored to the individual Soldiers learning needs and skill-level. It is thought that this shift in training paradigm will begin to develop Soldiers who are adaptable and possess the skills and ability to learn, understand, and operate in new and changing environments.

Meeting the New Training Needs

Simulation and game-based training have a long and storied history in military training (Smith, 2010). These types of training environments offer the advantage of modeling real-world characteristics allowing for mission planning, practice, and performance evaluation. While early forms of simulation and game-based military training often took the form of sand tables and board games, today's training embraces the same simulation or experiential approach within technology-based delivery methods (i.e. computer, digital game, portable computing device, etc.). With a call for increased accessibility to training for today's Soldiers the utilization of technology-based training applications such as games, simulations, and virtual world environments are at the forefront of the Army's new learning model (Department of the Army, 2011).

While the ALC 2015 highlights the utility of technology-based training approaches, it also points to the need for tailoring training to the learner. Despite the trend in academic and military training toward experience-based learning tools such as games and simulations, a number of researchers have argued against a purely inquiry based approach to instruction (Kirschner, Sweller, & Clark, 2006; Mayer, 2004). Instead, these researchers suggest that, while experience is important, in order to deliver effective and efficient learning experiences instructional guidance designed to fit the needs of the individual learner must be provided within the experience (Sweller, 2003).

Based on Cognitive Load Theory (CLT) it is this tailored guidance that allows learners to acquire and organize information in a meaningful way without the risk of overloading the limited capacity working memory system (Sweller, 2003; Sweller, van Merrienboer, & Paas, 1998). As learners gain experience they develop a framework for the organization of similar information and thus require less guidance when learning similar material in a new environment. Perhaps the best illustration of this process comes from Sweller (2003) who describes the process of learning from a map. Without previous map reading experience, or basic information about an area, a traditional map may be of limited utility as an instructional tool. Yet with additional guidance in how to use the map, as well as current and goal locations, the map may be used as an instructional tool to learn a new area or route to a destination. In contrast, for an individual familiar with map reading and aware of their current location the map may be a sufficient instructional tool for learning a route or the local area without further guidance. Thus the development of such tailored training requires an understanding not only of the training needs, but also an understanding of the learner and the processes by which the desired skills are acquired.

Purpose of Current Research

Current military training needs call for decision making in complex, dynamic environments by Soldiers of varying degrees of expertise. Yet, as Jonassen (2012) highlights, “there has been little attention paid to designing instruction in support of decision making” (p. n.p.). While previous research on decision making offers accounts of how experts make decisions in their field of expertise (Klein, Calderwood, & Clinton-Ciricco, 1988) as well as how the decision processes of “good” and “bad” decision makers differ (Dörner, 1996; Brehmer, 1992), far less consideration has been given to the issue of how to develop decision skills. Perhaps most notable in the current context is a lack of research regarding the development of decision skills in non-experts. Theorists of macrocognition (e.g. Klein et al, 2003) and situated cognition (e.g.Choi & Hannafin, 1995) posit that decision skills for real world problems must be developed within the decision situation or context. Yet researchers such as Dörner and Brehmer offer descriptions of good decision making behaviors (e.g. asking more “why” than “what” questions, and knowing when to adjust their decision goals and strategies) in non-domain experts and problem-solving researchers offer empirical evidence supporting the utility of metacognitive and process focused training for performance improvement (e.g. Berardi-Coletta, Buyer, Dominowski, & Rellinger, 1995; Chi & VanLehn, 2010). The current research seeks to explore these seemingly contradictory theories and answer the question of whether metacognitive support in the form of process-focused guidance or task specific support will better aid in performance and learning within a complex and dynamic decision task.

Instructional research has often focused on investigations of the need for guidance versus discovery learning, the control of instruction (e.g. Corbalan, Kester, & Van Merriënboer, 2008) and the format or structure of instruction (Mayer, 2004; Sweller, Van Merriënboer, & Paas, 1998). An examination of the literature suggests that an equally important and far less considered aspect of effective instruction is the consideration of whether instruction should be designed to support cognitive processes or the higher level metacognitive processes. For example, Berardi-Coletta, Buyer, Dominowski, and Rellinger (1995) found that in laboratory-based problem solving activities participants performed better when they were provided instruction focused on guiding them in the process of problem-solving rather than specific problem-level guidance. Such process-level supports guide the individual at the metacognitive level instead of offering direct cognitive level guidance. As Durlach and Ray (2011) highlight, one of the roles of a human tutor is to support the learner not only at the cognitive level, but also at the metacognitive level. Much like the suggestion of Lussier, Shadrick, and Prevou (2003) these process-level supports might be said to support the development of how to approach or complete a task rather than focusing on the task specific information. Yet it is unclear if similar effects will be found in more complex, dynamic situations which are likely to impart a heavy load on working memory. Given the importance of the meta-level of processing recognized by skilled tutors as well as the role of meta-level processes in good decision making, the first step in developing effective training for decision making should be to determine whether instructional guidance must support cognitive and/or metacognitive processes for optimal skill development.

Given Sweller's (2003) description of matching instruction to the needs of the learner it follows that, while offering instructional guidance at the process-level might optimally support one individual at a given stage of experience or skill, that this same level of support may be sub-optimal for a different learner or even the same learner at different stages of learning. Thus when considering what level of support a learner may need it is equally important to consider what aspects of that learner's experience or ability might impact the effectiveness of the support. Toward this, a review of the literature necessitates not only the identification of key aspects of decision making skills to be supported by training, but also critical individual differences that could impact the relationship between the type of training an individual receives and their overall decision making performance and mental model development.

Jonassen (2012) highlights the need for increased attention to the development of instruction for decision making and even offers suggestions of general instructional approaches for developing decision making skills. However, more concrete empirically-driven guidelines are necessary to begin to develop a solid theory of training for general decision making skills in complex environments. Thus the goal of the current research is to examine through direct empirical comparison the effectiveness of unguided, problem-focused guidance, and process-focused guidance instruction for the development of decision making skills in a complex, dynamic environment. Based on the descriptive work of Brehmer (1992), Dörner (1996), and empirical work in problem solving by Berardi-Coletta et al (1995), it is hypothesized that instruction supporting metacognitive processes through the inclusion of process-focused instructional prompts will lead to overall better performance and mental model development than problem-focused or unguided instruction. Additionally, this research explores how individual differences in pre-training decision making skill, metacognitive awareness, working memory span, and abstract reasoning moderate the relationship between the instructional approach and training outcomes. It is expected that the results of this investigation will extend both theoretical and practical understanding on how to develop decision making skills for complex situations. Specifically this work offers a direct comparison of the role of metacognitive versus domain specific instruction in the development of complex, dynamic decision making skills. Results from the individual differences measures are further expected to guide future research and development into how the type of guidance can be tailored to fit an individual's current learning needs.

CHAPTER TWO: BACKGROUND

Technology-based Training

Military organizations require training that is both effective and efficient (Fletcher, 2009). For many decades technology-based solutions have been among the primary foci to meet this need. Since the 1950s military training has sought new training tools in computer-simulation, video and computer games, and intelligent tutoring systems (Fletcher, 2009). These various technologies offer several advantages over traditional schoolhouse training. Technology-based simulations allow individuals to acquire and practice critical skills in a safe environment that models real-world complexities and demands. Additionally, the delivery of today's technology-based training solutions is often more flexible than traditional classroom instruction. While technology-based simulations once focused on skills such as target detection and marksmanship or pilot skills, today technology-based training is utilized for the development of a wide variety of both physical and cognitive skills.

While simulations provide a safe environment which models real world demands making them suitable for the development of complex skills, simulations alone do not provide for training. When simulations include sound instructional supports, however, these technologies can offer a powerful training tool (Vogel-Walcutt, Carper, Bowers, & Nicholson, 2010). Without these tools the experiential nature of the simulation provides for little more than a practice environment. The need for instructional support is not unique to simulation. In fact it is a call echoed by educational researchers highlighting the role of guidance in instruction (Kirschner, Sweller, Clark, 2006; Mayer, 2004). While these educational researchers do not negate the role of experience or active learning, the research they provide suggests that a guided approach affords a more effective approach to learning compared to pure discovery. Many studies have utilized microworld simulations, which are computer models designed to represent allow the experimentation of how dynamic changes occur between interrelated variables, without guidance to study the behavior of decision makers in complex and dynamic environments (Brehmer, 1992; Dörner, 1996; Gonzalez, Vanyukov, & Martin, 2005). Yet appropriate guidance needs to be identified and incorporated into these simulations to move the use of microworlds from pure experimental tools to effective training solutions for the development of general decision skills across domains.

Technology-based models of complex environments appear across the literature in the study of complex and dynamic decision making (Gonzalez, Vanyukov, & Martin, 2005) These authors and others suggest that microworld simulations, used for research offer a balance between the richness of the dynamics and complexity of real-world settings with experimental control similar to laboratory settings (Brehmer & Dorner, 1993; Gonzalez et al, 2005). While researchers have turned to mircoworld simulations for investigations into how individuals make decisions, fewer instances are available describing the use of these simulations as training. In the few instances describing microworlds as modeling decision making learning or as learning environments, a variety of instructional approaches have been utilized. For example, Gonzalez, Lerch, and Lebiere (2003) describe the use of a microworld to model instance based learning where specific instances of decision situations and outcomes are utilized to develop the recognition of expertise based decision making. Leutner (1993) explored the development of decision-making in a microworld with various types of cognitive instruction that successfully supported domain knowledge acquisition. Yet while these instances support domain specific learning within microworld simulations, current training needs call for the development of generalizable decision making skills. Thus it is important to consider what type of instruction within a microworld simulation could support the current needs for skill development.

Purpose of Instruction

From the perspective of cognitive psychology learning can be thought of as following along a continuum from novel, unlearned material to familiar, well-learned material (Sweller, 2003). As an individual moves along this continuum he or she develops new knowledge and critical organizational structures or schemas that aid in performance. The purpose of instruction within this model is to assist the learner as they progress along the continuum. In the development of decision-making skills for complex environments, this continuum can be defined both in terms of a learner's task performance and the organization of their knowledge and understanding of the task environment.

Sterman (1994) describes learning in complex systems as a process of learning from feedback, yet often in these complex and dynamic environments feedback is misperceived. Due to the systems nature of these complex environments a consequence of one action may be easily attributed to a different action. To operate in, understand, and control these types of systems an individual must develop not only an understanding of the system components, but also of the interrelationships or dynamics between the system components. Thus to aid in the development of decision making in complex environments, instruction must aid in the development of mental models or schemas of both the structural and dynamic properties of the environment.

Human Cognitive Architecture in Instruction

A critical step in developing instruction is to understand the role of the underlying cognitive architecture that supports learning and performance. Theories of cognitive architecture suggest that human memory consists of two primary memory components, Long Term Memory (LTM) and Working Memory (WM) (Sweller, 2003; Sweller, van Merrienboer, & Paas, 1998). While LTM provides extensive storage both in terms of length of time and capacity it is not a directly accessible form of memory. Instead LTM is reliant upon WM both for storage of new information and retrieval of existing information. Thus learning requires not only the organized storage of information, but also the ability to retrieve and utilize the information stored in LTM. The role of intermediary between external stimuli or response and LTM falls to Working Memory. Despite its importance in cognitive processing, research indicates that the processing of WM is quite limited both in time and capacity (Baddeley & Hitch, 1974). Thus the meaningful organization of information and attention to well-designed instruction become increasingly important in successfully learning new information.

In order to successfully aid learning it is vital to consider the task demands placed on working memory during the learning process. Across the last three decades researchers have developed a better understanding of the role of working memory and working memory load during learning as they have focused on the development of cognitive load theory (CLT). This theory suggests that while LTM provides for the long-term storage of learned material, LTM relies upon the limited capacity WM processes to acquire new information, as well as to retrieve and manipulate previously learned material (Sweller, van Merrienboer, & Paas, 1998). According to this theory of cognitive architecture, long term memory remains at a largely unconscious level while working memory is the conscious process by which we obtain, access, manipulate, and store information. The limited capacity of WM requires particular attention to the role of instruction as WM is easily overloaded leading to a decrease in learning and/or the efficiency of learning.

In order to aid WM, learned information is stored in LTM as meaningful and related organizations known as schemas (Sweller, van Merrienboer, & Paas, 1998). The purpose of such schemas is twofold. First they aid organization and retrieval of information in LTM, but perhaps more important in the context of instruction; schemas reduce the capacity load on WM as each activated schema is treated as a single chunk. Thus instruction, particularly for learning in complex environments, which have inherently high task WM load, should be designed to aid schema development and activation. In order to support schema development while avoiding WM overload cognitive load researchers suggest instructional support be designed for the specific needs of the individual learner (Sweller, 2003). While such individualized support has often focused on the organization or amount of information or guidance provided, more recently the processing level targeted by instructional guidance has been brought into consideration.

Cognitive vs. Metacognitive Processes

Mental Processes are thought to occur at multiple levels. In such a multi-level model task knowledge and skill may be attributed to the cognitive or object level, while at a higher, meta-level are the processes which are thought to act as both monitor and control mechanisms for the cognitive level (Osman, 2010). Schraw and Dennison (1994) describe these meta-level or metacognitive processes as, “the ability to reflect upon, understand and control one’s learning” (p. 460). As Schraw (1998) explains, “cognitive skills are necessary to perform a task, while metacognition is necessary to understand how the task was performed” (p. 113).

Metacognition is commonly described by two key components – namely the knowledge of cognition and regulation of cognition (Schraw & Dennison, 1994). Knowledge of cognition may be further broken down into the declarative, procedural, and conditional knowledge an individual possesses about their own cognition – that is what an individual understands about the knowledge and strategies they possess as well as when, where, how to utilize such knowledge and strategies. In contrast, the Regulation of Cognition component describes control processes that oversee the cognitive level. For example, higher-order processes such as planning, monitoring understanding, and performance self-evaluation are each encompassed by the regulation of cognition component.

Kalyuga (2009) examines the meta-level of processing within the cognitive load paradigm as higher-level schemas in LTM. In this view, meta-level processes provide flexibility to cognitive responses by acting as executive guides in new or unique situations. While acting as an executive guide these meta-level processes provide the structure needed to acquire new cognitive level schemas or adapt existing schemas to new situations. Across the cognitive load literature, instruction is largely thought to take the role of an executive guide. Kayluga's (2009) recognition of a meta-level schema acting as an executive guide suggests a new consideration for instructional developers. Specifically, instruction should both support and adjust to an individual learner's meta-level development.

Level of Guidance

Instructional guidance has often been delivered as learning aids such as hints or prompts, worked examples, and feedback. Following models of cognitive architecture, these aids most typically offer guidance designed to align the learner with the cognitive model of an expert. Guidance in these models most often provides specific information targeting the cognitive level of processing. However, increasing attention has been focused on the role of Metacognition in everything from comprehension to problems solving. Schraw (1998) suggests that metacognitive skills are both domain-general in nature and malleable. These characteristics have drawn extensive interest to the topic of metacognition in training for both well-defined and ill-defined domains.

In recent years, researchers such as Mathan and Koedinger (2005) have offered support for providing guidance following an intelligent novice model. This intelligent novice model builds on the idea that while an individual may be a novice in a domain, they likely enter training with general skills which can aid in the development of new domain knowledge. Skills such as performance monitoring and self-evaluation represent general meta-level skills which set a skilled novice apart from a pure novice. If such skills can aid in learning and performance across domains, instruction should target the support of these critical skills. Mathan and Koedinger (2005) investigated the difference in feedback delivery based on the Intelligent Novice Model and a traditional expert model in an Intelligent Tutor focused on teaching spreadsheet formulas. Specifically, their Intelligent Novice Model Tutor targeted the support and scaffolding of the meta-level skills of error detection and correction. In an empirical comparison these researchers found that participants trained with the Intelligent Novice Model outperformed participants trained with a more traditional Expert Model in measures of problem solving, conceptual knowledge, transfer, and retention. Additionally participants utilizing the Intelligent Novice Tutor showed more efficient learning.

Chi and VanLehn (2010) provide similar support for training specific meta-level skills within an intelligent tutor. In their study learners were given traditional cognitive level instruction in probability or were taught a meta-level domain-independent problem-solving strategy while learning probability. The results of this study show that while meta-level strategy training did not improve the performance of individual's scoring high on pre-test abilities, those individuals scoring low on pre-test performed significantly better when receiving the meta-level strategy training. This supports the notion similar to that of Mathan and Koedinger (2005) that some learners are better prepared for learning than others, and specifically that what makes these individuals more successful is likely the meta-level skills supported by the instruction in these studies.

A series of experiments by Berardi-Colette, Buyer, Dominowski, and Rellinger (1995) further supports this notion by examining the effects of process-focused and problem-focused instruction on the problem solving processes and outcomes of undergraduate student participants in two laboratory-based activities (Tower of Hanoi and the Katona Card Problem). Across a series of four experiments Berardi-Colette, et al found consistent evidence suggesting that prompting participants to focus on the process of problem-solving leads to better performance than participants guided to focus on problem-specific information or participants not receiving instructional guidance. Additionally, verbal protocol analyses suggested that participants did not utilize a process-focused approach in problem-solving unless instructional guidance to utilize such a focus was presented. Targeting a process-focused approach in training generally led to better transfer performance. Thus these findings are important both in highlighting the benefits of a process-focused approach and in supporting that training such behaviors can lead to better problem-solving behaviors beyond training.

Yet while each of these researchers has provided critical grounding for the use of meta-level or process-focused guidance it is as of yet unclear whether training individuals in a process-focused approach will translate from laboratory tasks to more complex, dynamic simulations of real-world environments and problems. While topic areas such as algebra and other mathematics present a well-defined problem space with known solutions and solution paths, increasingly real-world training is focusing on domains lacking such structure. Ill-defined tasks such as negotiation, leadership, and decision-making are increasingly important in training settings from business to the military. These studies offer support for guidance targeting the meta-level of processing in well-defined domains, yet evidence is still needed to support the utility of meta-level process guidance in training for complex ill-defined domains. Training for the ill-defined domain skills is difficult to develop, standardize, and computerize. While training for ill-defined domains such as complex decision making has traditionally focused on the development of domain-specific knowledge, if domain general strategies and skills such as those represented by Metacognition can promote more successful self-directed domain level learning training approaches for ill-defined domains training could focus more on developing the individual and less on the domain. As reviewed in the following sections, these meta-level skills also appear closely tied to “good” decision making behaviors. Therefore, from a theoretical viewpoint, developing meta-level processes could prove a critical aspect of training for better decision-making in complex, dynamic environments. To understand this theoretical link between meta-level processes in decision making it is critical to consider what is known about the cognitive and metacognitive demands of decision making in complex environments.

The Role of Individual Differences in Instruction

As learners advance in their knowledge and schema development, instruction that supports learning early in schema development may interfere with processing or overload WM. In what has become known as the Expertise Reversal Effect (Kayluga, 2007; Kayluga, Ayres, Chandler, & Sweller, 2003) or Aptitude Treatment Interactions, research has shown that a learner’s skill level is often a critical component of how successful or unsuccessful a given instruction intervention will be. These effects often demonstrate that one type of support (whether modality or level of processing) supports learners with one level of experience while learners with a different level of experience show no benefits or even a decline in performance with the same instructional support.

While much of the research into the Expertise Reversal Effect has focused on cognitive level instruction, findings such as Chi and VanLehn (2010) and Mathan and Koedinger (2005) support the notion that lower level learners may need a different type of support than higher level learners. In an expertise reversal type pattern, Batha and Carroll (1998) found that individuals with lower level decision skills, as measured by a paper-based task, improved with meta-level training while those at an intermediate level did not improve and those at a high level decreased slightly. Similarly a review by Alexander and Judy (1988) suggests that in a variety of domains, strategic or meta-level knowledge and training aided the performance specifically of domain novices.

While it is thus evident that general meta-level skills aid in performance across many domains, it is important to consider that instruction focused on this level of processing must adjust for the needs of the individual learner. Yet there is little specific evidence to support how and when the level of instruction should adjust to learner when targeting the development of decision skills in complex environments. Empirical data are needed examining not only the effects of different types of instruction, but also the impact of learner characteristics on the relationship between instruction and learning outcomes. Towards this, the next section is designed both to build an understanding of the instructional domain and skills to be developed as well as an opportunity to identify potential individual differences that may impact the type of instruction that best aids in the development of those skills.

CHAPTER THREE: LITERATURE REVIEW

Decision Making In Complex, Dynamic Environments

Definitions and Terminology

Decision making in complex, dynamic environments requires not a single decision action, but rather involves a series of interconnected decisions where information and results from one decision effect later decisions, though these results may not be immediately visible to the decision maker (Edwards, 1962). Additionally dynamic decisions occur in changing environments where both the decision maker's actions and environmental changes influence potential future decisions. In these dynamic situations it is the long-term result that is of primary interest, thus poor short-term decisions may lead to an optimal outcome or seemingly good short-term decisions may lead to a less than optimal outcome. Research describing this type of decision making in complex environments can be found under terms as diverse as complex problem solving, dynamic decision making, complex decision making, naturalistic decision making, complex dynamic control, and process control (Osman, 2010). While each of these concepts share similarities in focus on how humans perform in complex, dynamic environments characterized by multiple interrelationships, feedback loops, delays, and ill-defined goal paths (Brehmer, 1992; Osman, 2010), the specific research questions and methodologies from these various efforts often diverge. Two primary thrusts, which are reviewed here, have emerged in the field of Complex Decision Making and Problem Solving. The terminology for these paradigms is adopted from Frensch and Funke (1995) who describe differences in the American domain-specific approaches which have focused largely on the role of expertise and the European approaches which have examined complex, but novel problem situations thereby highlighting the general skills of decision makers.

American Approach to Decision Making

The American approach to decision making offers a number of theoretical models of decision making as well as a few approaches to developing decision making skills. Models such as the Recognition Primed Decision Model of Klein, Calderwood, and Clinton-Ciricco (1988), the Recognition/Metacognition Model of Cohen, Freeman, and Wolf (1996), and the Instance Based Learning Theory of Gonzalez, Lerch, and Lebiere (2003) largely focus on single, specific real-world domains and suggest that successful decision making in complex, dynamic environments stems from an expertise based recognition process. Theoretical grounding for the American approach traces its roots to the expertise-based problem solving research of Simon and colleagues (e.g. Chase and Simon, 1973). In their research, Chase and Simon examined expert – novice differences in chess player's abilities to recognize and replicate real and random chess board configurations. Their findings indicated that expert players were significantly better at replicating the configuration of a real chess game board compared to novice or intermediate level players, yet when random board configurations were presented no differences were observed between the different levels of players. This work suggests that domain-specific expertise aids performance by providing the long-term memory organization providing for recognition of familiar patterns and situations. In more recent decades this expertise-based recognition has provided the theoretical foundation for multiple models of real-world complex decision making.

A key aspect of the American approach to Decision Making is the factor of time pressure which is inherent many real-world decision situations. Klein, Calderwood, and Clinton-Ciricco (1988) examined expert decision making within the naturalistic task environment of firefighting. They found that decisions were most often made by matching the characteristics of the decision situation to a similar situation in memory in what the researchers termed a prototype match. In this case the fire commanders did not consider multiple courses of action, but instead acted quickly upon the prototype match. If a decision situation had more than one potential course of action the researchers observed that the expert decision makers would select their course of action not by deliberating on all features of each, but by considering a few critical components such as risk and time. Finally in unfamiliar situations the fire commanders would generate possible courses of action, thus completing a longer deliberation process. These findings led to the development of Klein et al.'s Recognition-Primed Decision Model (RPD). In this model they proposed that real-world decision making, particularly those decisions made under time pressure, call on previous experiences in similar situations which guide expectancies and their expected course of action. Klein et al. further suggest that the competency of a decision maker in situations of extreme time pressure is determined in large part by their ability to quickly match situation characteristics to previous experience prototypes. While the RPD offers explanations of the behavior an expert displays both when a prototype is matched and when presented with a novel situation, it provides greater theoretical detail to the case of a matched prototype as this was the most frequently observed case. In the present work the topic of greater interest, however, are the processes and behaviors present in the case of a novel situation, which could also represent the case of expertise development.

Expanding on the previous recognition based decision theories, Cohen, Freeman, and Wolf (1996) highlighted the need to understand how decision makers operate in the novel or uncertain (multiple or partial recognition matches) situations. In their Recognition/Metacognition (R/M) model of decision making, Cohen et al. describe expert decision making as interplay between expertise-based recognition and meta-level recognition processes which guide and refine pattern recognition. While Cohen et al. recognize the role of pattern matching in expert decision making, they suggest that these matches must be critiqued and often corrected to fit the current decision situation. These critiquing and correction processes are thought to occur at the meta-level and thus are collectively referred to by the authors as meta-recognition skills.

According to the R/M model, decision making begins with the real world problem which is compared to previous experiences through pattern matching in an effort to formulate a course of action. If the recognition process fails to produce a match, Cohen et al. (1996) suggest decision makers develop so called “structured situation models” as a framework for gathering and organizing critical information to form a model of the situation. As the decision maker forms their situation model, either through pattern matching or using structured situation models, potential course(s) of action are identified and subsequently verified by the meta-level in a “quick test” which determines whether time should be taken for further critiquing and correction of pattern match and/or course of action. This “quick test” stage consists of key factors such as the time allowed for decision making, the risk involved, and the confidence in the accuracy of the initial plan of action. In situations where time allows, the risk involved if an error occurs is substantial, and/or the situation is novel the decision maker is likely to proceed with a more complete critique of their understanding of the situation and possible outcomes from their potential courses of action as well as any corrections or modifications necessary to refine their model of the situation and course of action. The authors suggest that these meta-level skills represent a key difference in novice and expert performance in decision making.

Developing expertise based decision skills for a specific domain is a lengthy process, often requiring a decade or more of domain specific experience (Ericsson & Charness, 1994; Chase & Simon, 1973). Yet in many situations decisions must be made prior to the accumulation of such vast experience. Thus the question of interest might be that of how novice and intermediate decision makers gain necessary experience and maintain adequate performance while acquiring vital experience in a new domain. Perhaps the obvious answer is through training, yet from a practical standpoint, developing effective and efficient training first requires understanding the progression of decision processes across the levels of domain.

Departing from other American researchers in research methodology, but still interested in the role of recognition-based decision making, Gonzalez, Lerch, and Lebiere (2003) investigated the development of decision making skills through domain-specific practice utilizing microworld simulations. Gonzalez and her colleagues concluded over a series of laboratory studies that while novice decision makers often utilized heuristics or experience-based rules in making decisions, that as they gained more experience decision makers relied less on heuristics and more on their previous experience (Gonzalez, et al., 2003). That is, as decision makers gained experience they moved from rule-based decision processes to recognition-based decision making. As illustrated in the next section, however, meta-level processing skills or schemas may provide for good general decision-making skills prior to the development of recognition-based decision skills. In bridging the two approaches to the study of decision making it might thus be considered that a general meta-level decision skill develops first to aid in the development of later expertise driven recognition.

European Approach to Decision Making

Frensch and Funke (1995) describe the European approach to complex problems as following two primary lines of research. The first is represented by Broadbent's work on the cognitive processes of complex problem solving in complex, but constrained tasks (Frensch & Funke, 1995). The second line of research representing the European approach is that of German research Dörner (1996; Dörner & Wearing, 1995). This second approach is characterized by the complexity of numerous interconnected variables. This complexity limits problem solving utilizing analytic approaches and provides a better model of real world decision situations. While the European Approach to Decision Making represented by the work of Dörner models complexity approaching that of real-world task, the research contrasts the American Approach both theoretically and in research paradigm. From a methodological standpoint, European investigations of Decision Making have largely involved descriptive studies conducted in microworld simulations. This research paradigm has resulted in what Sternberg (1995) notes as largely task-focused field that has somewhat neglected theory development. As Sternberg (1995) notes however, perhaps the greatest contribution of the European approach has been the description of how individuals from a more diverse population (non-experts) behave in the context of complex, dynamic environments and how individual differences influence these behaviors.

Utilizing this approach, researchers such as Dörner (1996) have collected evidence which suggests that not all complex decision environments require domain expertise. Empirical work investigating complex decision making in microworld simulations has shown that even in situations where individuals appear to have no specific domain expertise advantage, individuals with more decision experience are often more successful at decision making in complex control tasks than individuals with less decision experience (Dörner, 1996). Specifically, Dörner points to behaviors that distinguish "good" decision makers from "bad" decision makers. These are behaviors such as asking more "why questions" than "what questions" when developing an understanding of the complex system. This indicates that individuals with "good" decision making skills approach the new situation with a framework for how they should build an understanding of the system. These decision makers recognize they must find and understand information about the system that they currently lack in order to guide the system progression. Dörner described this understanding of our own knowledge and skills as operative intelligence, in broader literatures these skills would be considered meta-level decision skills. In essence these individuals possess the monitoring of their own knowledge and control their actions and information seeking behaviors in a goal directed fashion to further develop their understanding – that is they possess the strong meta-level skills necessary to understand their performance as part of the complex system.

In contrast to the "good" behaviors described by Dörner (1996), Brehmer (1992) enumerates five key behaviors of "bad" decision makers stemming from work conducted in the European paradigm. Specifically, Brehmer suggests that two key behaviors of poor decision making result in poor goal development. These decision makers often shifted goals frequently during decision making or presented the contrast behavior of being inflexible once they defined a goal and thus failing to alter or refine their goal. In addition to weak goal development, bad decision makers presented a resistance in learning from their own experiences. In this case decision makers might refuse to make a decision, fail to delegate responsibilities, or refuse to accept accountability for poor decisions.

In more recent research conducted using military personnel in role-playing exercises, Brehmer and Thunholm (2011) further describe weaknesses in dynamic decision behaviors. From this research, the authors suggest that a well-developed and accurate model of the situation is the primary requirement for successful decision making. This situation model must be specific and consider both structure and dynamics, including delays. This model may then be transitioned into an action plan, however the quality of the plan is fully reliant upon the foundation model. Yet this paper reaches beyond simple description of decision making weaknesses and explores potential avenues for improving decision behaviors and skill through training. Specifically the researchers began by training individuals to formulate a model of the assumptions of the situation, then through wargaming individuals were taught to monitor the success of their plan and adjust the plan according to changing needs. Despite these efforts, the researchers observed that often plans were weak and failed to model the true dynamics (such as delays) of the system.

This highlights the need to support not only the static knowledge of the system, but perhaps more importantly the dynamic components of the system.

Skill Development in Complex Environments

While many disciplines from education to management have turned in recent years to the concept of system thinking, a review of such literature should begin at the purer foundation of general systems theory developed in the last century largely through the work of biologist Von Bertalanffy (1972). General Systems Theory represented a quest to explain in mathematical formulation the behavior of so called open dynamical systems. Similar to the gestalt school of psychology this systems approach suggests that the organism as a whole (when applied in biology) is more than an amalgamation of its pieces. It is the combination and interaction of those parts that are of key importance. While Von Bertalanffy originally described the biological system, the general systems theory has been extended to describe everything from technological to social systems. It is in these realms that we find the importance of general systems theory in the present review. As Von Bertalanffy (1972) describes the holistic approach of general systems theory has become necessary as a paradigm for study and control of the vastly complex interrelations of today's society. Fields such as control systems, cybernetics, and systems thinking can be viewed as applications built from general systems theory in technological and social systems. In decision making research Brehmer (1992) utilizes a similar control theory as a likeness in developing a framework for the study of decision-making in complex dynamic environments. In this effort Brehmer describes the four preconditions for controlling a system as

1) having a goal, 2) observability of the system state, 3) ability to affect change in the system, and 4) the decision maker must have a model of the system. From Brehmer's framework the importance of building a malleable mental model of the system structure and dynamics with the understanding of one own agency in the system dynamics becomes apparent. Yet Brehmer is not the only researcher to make the connection between the systems paradigm and critical decision-making skills.

More recently the systems paradigm has been translated in the form of systems thinking. Here researchers such as Sweeney and Sterman (2000) have suggested the importance of understanding the behavior of a system, not just the components. Specifically Sweeney and Sterman highlight the need for individuals to understand system dynamics such as how the behavior of a system builds from the interaction of its components over time, understand how delays impact a systems behavior, understand linear and especially nonlinear system component relationships, and how feedback relationships impact system behavior.

Utilizing Richmond's (1993) model of systems thinking, Maani and Maharaj (2004) examined the links between systems thinking and complex decision making. Richmond details systems thinking as seven types of thinking skills including dynamic thinking, system-as-cause thinking, forest thinking, operational thinking, closed-loop thinking, quantitative thinking, and scientific thinking. He further suggests that these skills are developed in a linear fashion such that a skill such as forest thinking is dependent upon lower levels of thinking (dynamic thinking and system-as-cause thinking). In an effort to add empirical evidence to the link between these systems thinking skills and complex decision making, Maani and Maharaj utilized a microworld simulation decision task and recorded think aloud protocols from a small sample of participants.

Results show little support for the overall amount of systems thinking being linked to decision making performance, however the data do suggest that higher levels of systems thinking are likely associated with higher levels of performance.

Arndt (2006) suggest that a key role of traditional education is to prepare individuals to successfully operate in complex real world situations. Specifically Arndt points to the need for developing systems thinking skills as a catalyst for performance in complex situations. Following the work of Richmond (1993), Arndt highlights four dimensions critical for the development of systems thinking. Namely, these researchers suggest that a systems thinking approach involves the construction and use of mental models of the situation, the ability to predict future behavior of the system, the ability to integrate individual components and their interrelationships into a meaningful whole, and finally the ability to operate in complex decision systems. Arndt offers examples of how systems thinking might be promoted in educational environments, however as noted by the author, additional empirical support would be necessary to determine the validity of these instructional methods.

Much like Arndt; Shute, Masduki, and Donmez (2010) address the teaching of systems thinking in an educational context through game-based learning environments. Utilizing an educational game in which students are given a mission of assisting a park ranger in discovering the cause and solution to a decline in fish, Shute and colleagues provide students with opportunities to utilize key aspects of systems thinking within the game. Specifically, in completing the game-based missions students are expected to utilize key systems thinking aspects such as defining the system problems, components, and relationships; identifying possible solutions or courses of action; and finally modeling and testing the solutions. While not identified as meta-level processes by Shute et al., these phases of the systems thinking process closely follow the theoretical components outlined in the literatures of metacognition.

Role of Metacognitive Skill in Decision Making

Given the meta-level processes often represent higher-order domain independent processes, researchers are increasingly turning to investigations of the role of meta-level processes in complex, and often ill-defined cognitive tasks such as complex problem solving and decision making. Ford, Smith, Weissbein, Gully, and Salas (1998) point to metacognitive skills as a critical component in successful self-regulation of learning, particularly in learning environments which promote self-directed or learner controlled instruction. Within a complex, decision-making task, the research or Ford et al. showed support for the hypothesized links between Metacognition and training outcomes when using a learner controlled instructional approach. Specifically, regression analyses supported Metacognition as a significant predictor in performance on a post-training knowledge test, in the final training performance, and in the trainee's level of self-efficacy for the training task. Berardi-Coletta, Buyer, Dominowski, and Rellinger (1995) offer additional early empirical evidence supporting the importance of metacognitive skills in problem solving. In a series of four experiments these researchers examined metacognitive skills from the perspective of a process-orientation as opposed to a more cognitive level problem-based approach to problems solving. Using "think-aloud" protocols during a turn-based problem solving activity, these researchers compared the use of prompting participants with problem-focused questions such as "What are the rules of the problem?", process-focused metacognitive questions such as "How are you deciding which disk to move?", process-focused if-then prompts such as "tell me where you are going to move the disk, and why", with general protocol prompts such as "think out loud while you are solving this problem.", or with no talk-aloud prompting (Berardi et al., p. 207). Results from their initial study indicate that the process-focused groups (metacognitive and if-then) outperform control and problem-focused groups in training, however in a more complex transfer problem only differences between the process-focused and control groups remained statistically significant indicating an advantage of prompted process oriented thinking during problem solving.

The Role of Individual Differences

Across work as varied as Sweller's (2003) learning models to Dörner's (1996) descriptions of "good" and "bad" decision making the importance of individual differences is commonly highlighted. Within the complex decision making literature, however, no specific studies were identified examining the impact of individual differences on the relationship between instructional interventions and training outcomes in a complex, dynamic decision task. However, a review of the literature suggests an important role of individual differences in training decision making skills in a paper-based scenario (Batha & Carroll, 2007). Following the theoretical foundations of ATI research and the expertise reversal effect, Batha and Carroll found that training outcomes following metacognitive strategy training varied based on an individual's level of decision making skill prior to training as measured by a Kline's (1996) Decision Making Questionnaire. While similar analyses were not conducted to examine the ATI effects based on an individual’s level of metacognitive awareness prior to training, pre-training measures of decision making skill and metacognitive awareness showed a moderate positive correlation (r=.389, p <.001). Further research is necessitated to exam how these two key individual difference variables impact the relationship between the level of guidance provided during training and training outcomes in a more complex and dynamic decision task. While significantly correlated, the level of the correlation is such that both pre-training levels of decision skill and metacognitive awareness could provide unique information in targeting the level of training an individual needs.

While Batha and Carroll (1998) represents the sole article identified investigating key individual differences in metacognitive training for decision making, individual differences have been identified as significant predictors of decision-making performance in microworld simulations when training is not present (Gonzalez, Thomas, & Vanyukov, 2005). Specifically, Gonzalez et al. examined the role of fluid intelligence or abstract reasoning as measured by the Raven’s Advanced Progressive Matrices test and visual working memory span as measured by the VSPAN in predicting task performance in two individual and one team microworld simulation tasks. Results of their investigation found that while both the Raven’s and VSPAN could independently predict performance in all three microworld tasks, the Raven’s did not add much prediction power to the prediction of the VSPAN in two of the three tasks. Yet in the third task the researchers found the combined model to be the best predictor. Thus it was concluded that different types of microworld tasks create slightly different cognitive demands. Thus it might be construed that with no prior classification or comparison between microworlds both individual difference variables testing the cognitive demands of the task provide potentially useful information both in defining the task and in extending the role of these cognitive skills into the realm of identifying learner needs.

Current Research

Goals

Today's complex and dynamic operating environments require that Soldiers of all echelons be prepared with the skills to consider not only the immediate, but the second and third order consequences of their decisions and actions. To meet these demands effective and efficient training providing general skills in understanding and controlling complex environments through decision making must be developed. While considerable research is available describing both expertise driven recognition based decision making in real world settings (e.g. Klein, Calderwood, & Clinton-Ciricco, 1988) and "good" and "bad" decision making behaviors in microworld simulations (e.g. Dörner, 1996; Dörner & Wearing, 1995), little focus has been given to the best way in which to prepare individuals for decision making in a variety of complex and rapidly changing environments. Previous findings from across the literature do, however, indicate that learners with meta-level skills providing for the acquisition, monitoring, and assessment of knowledge outperform individuals without these skills, even without the benefit of domain specific knowledge, in a variety of tasks. Additionally, work by Berardi-Coletta, Buyer, Dominowski, and Rellinger (1995) suggests that individuals receiving meta-level process-oriented support during problem solving outperform individuals receiving problem-focused support. Despite the wealth of evidence in support of meta-level processes both in problem solving and decision-making, no prior research was identified examining how the use of meta-level prompts in a complex, dynamic environment compares to more traditional discovery and cognitive or problem-focused instructional methods. Thus the current research represents a unique contribution to the literature in suggesting that developing an individual's meta-level skills through process-focused instruction will lead to an individual better prepared with the knowledge (mental model) and skills to both perform within the training environment and to adapt to the demands of a new domain. Additionally this research advances both theoretical and applied knowledge by identifying how key individual differences impact the relationship between the level of instruction and training outcomes. The examination of these individual differences, while stemming from existing literature, represent a new exploration within the task environment and across training approaches and thus demonstrate their own unique addition to the literature.

Research Questions

The current research is driven by two primary research questions:

Question 1

What type of training approach leads to the best decision making performance and mental model accuracy when training for complex decision making skills in a microworld simulation? To answer this question the current research examined four training approaches. The first training approach was an unguided practice approach common to simulation-based training. The second, problem-focused approach, examined the use of prompts to highlight how specific system relationships impact the outcome variable(s). The third approach, the process-focused approach, examined the use of meta-level prompts to guide the participant in how to think and monitoring their own decision processes in this type of environment. The final approach combines both process-focused and problem-focused prompting offering guidance targeting two levels of processing. This research question thus offers a direct comparison of task specific learning, as theories of situated learning highlight (e.g. Choi & Hannafin, 1995), with a domain general approach that would offer support to metacognitive and process-focused theories.

Question 2

Do individual differences moderate the relationship between the type of training and the level of decision making performance or mental model accuracy? This question explored how individual differences such as pre-training decision making skill level, pre-training metacognitive awareness level, general fluid intelligence, or working memory span might help explain or highlight aptitude treatment interactions. Previous research has suggested that the success of different training interventions often depends on individual characteristics of the learner. For example, Batha and Carroll (2007) found that metacognitive strategy instruction helped individuals with low pre-training levels of decision making skills improve, yet individuals high on pre-training levels of decision making skills showed declines. Theories such as the Expertise Reversal Effect (Kayluga, Chandler, & Sweller, 2000; Sweller, 2003) highlight the importance of considering the individual when developing any new training. Thus the second thrust of the current project sought to lay the groundwork for future training development efforts by investigating how four key individual difference variables identified in the literature moderate the relationships between the three training interventions and training outcomes.

Implications

While offering unique contributions to the theoretical literatures of both decision making and training, the current research also offered many important implications for application. The primary motivator of this research is new and evolving training needs of the military. Toward this, the findings are expected to inform future training development including laying the foundation for adaptive training methods based on the findings of the individual differences moderation analyses. Finally, the development and refinement of decision support systems may draw from the findings of this research. If findings support the utility of meta-level processes as expected, these prompts could easily be transitioned from the training environment to a decision aid for use in the field.

CHAPTER FOUR: METHODOLOGY

Participants

Power Analysis

A power analysis was conducted using the software package G*Power. With limited evidence available in the literature to determine the expected effect size for the current study, a medium effect size was selected for conducting the power analysis based on recommendations by Cohen (1988) as well as Bausell and Li (2002) for estimating expected effects. Based on the G*Power analysis, to achieve 0.80 Power level at a p=.05 alpha level, it was determined that 120 participants were necessary to show a medium effect.

Recruitment and Assignment

Participants were recruited from the University of Central Florida as well as the surrounding area. The primary recruitment tool was SONA, the UCF Psychology Department's Research Participation System (ucf.sona-systems.com). Participants were required to be 18 years of age or older with normal or corrected to normal vision and the ability to read English as well as use a standard keyboard and mouse. Participants were not required to be students. All participants completed the same pre-training measures in phase 1 of the study. Participants were randomly assigned to one of four training conditions upon scheduling a time for Phase 2.

Description of Study Participants

A total of 141 participants (71 males, 70 females) completed both phases of the research in a laboratory setting at the University of Central Florida. Participants ranged in age from 18 years to 48 years, with a mean age of 19.28 (*SD* = 3.263). Only one participant reported not being currently enrolled as a college student. While recruitment was expected to draw largely from the undergraduate general psychology course, participants reported belonging to over 40 different primary major areas of study for their undergraduate area focus. Over 62% of participants reported being in their first year of their undergraduate career while 17.2% reported being in their second year, 10% in their third year, 10% in their fourth year, and a single participant reporting to be in their fifth year of studies as an undergraduate student.

Materials

Phase one was completed on computers in the lab utilizing SurveyMonkey's survey administration and data collection software. This allowed participants to complete the demographics questionnaire, the metacognitive awareness inventory, and the decision making questionnaire prior to the face-to-face portion of the experiment. The measures completed in phase one did not require special training or administration and thus were easily adapted to an online environment without requiring format changes.

Experimental Task

For the current study, two independent complex decision making scenarios were developed within the Complex Decision Making Experimental Platform (CODEM). Each of these scenarios presented a complex, ill-defined, dynamic situation containing six interrelated variables. The turn-based CODEM system modeled both the direct and indirect consequences of user decisions as changes in the status levels of each of the six system variables. Direct consequences of a user's decision created changes in related system variables. As the status of system variables change, these changes in turn affected changes in the levels of related system variables. In addition to these direct and indirect consequences, environmental effects were also modeled within the scenarios (e.g., the landfall of a hurricane in the training scenario).

Participant Task Experience

From the participant's perspective a scenario began with a brief description of the task situation and goals. In keeping with the ill-defined nature of most complex decision tasks, participants were initially introduced to the scenario situation and given only general task goals (i.e., "Your advice is needed on how to focus preparation efforts"). Participants were then presented the situation screen illustrating the six system variables, descriptions of each variable, and the current level of each variable. Participants were informed that as part of their task goal they should attempt reach a strong level for all variables as represented by the green region on the status bar of each variable. Next participants could select to move to the relations screen where the participant may explore the details of the system variable interrelationships, or the participant could choose to move to the decision screen where the participant may explore the various intervention options as well as execute their decision/intervention for that turn. Before concluding the turn and advancing to the next turn, participants were given feedback on how each of the system variables changed following their intervention as well as the catalyst of the change (participant intervention, system variable influence, etc.). Following the delivery of feedback, users were prompted to continue to the next turn, with the next turn commencing on the updated situation screen.

As is typical of this type of problem, multiple solution paths and strategies existed for obtaining the desired outcome. Thus learning outcomes for the current project included the participant's understanding of the system of variables (mental model structure), how the system variables changed dynamically (mental model dynamics), as well as the participant's ability to develop control of over the system (performance). Each of these outcome measures is explored in more detail later in this chapter.

Experimental Platform

CODEM, the computer-based microworld system utilized in this experiment, offered a flexible experimental environment with extensive authoring capabilities and data capture. From the experimenters' perspective, CODEM offered a scenario development tool which allows for scenario authoring and editing. For the current project this allowed for the development of two independent scenarios - one for training and a second for transfer testing. The two scenarios represented two different domains and as such contained different variables, interrelationships, and possible interventions. Within the training scenario, the authoring capabilities of CODEM also provided for the customization of instructional features, such as prompting, delivered within the system and tailored to each experimental condition.

In addition to the flexibility of authoring capabilities, the CODEM system offered a robust selection of data output logs capturing everything from the time a participant spent on each individual screen to the decisions made across the course of the scenario. Generated and saved automatically by the CODEM system, these .xml log files offered an easily accessible trace of the participant's interaction with the system. For the current study these files provided for the performance outcome data discussed below.

Training Scenario

The experimental training scenario modeled six key factors in a hurricane preparation and disaster recovery effort across 13 simulated days (where 1 turn = 1 simulated day). Prior to beginning the training scenario, participants completed a single turn introductory scenario designed to review the system knobology as well as a 5-minute introductory video which provided an introduction to the training scenario. This introduction introduced the training task as follows:

> It is mid September, the peak of the North Atlantic Hurricane Season. The National Weather Service is monitoring a large storm expected to become a major hurricane in the next few days and has issued warnings along the forecast track which currently indicates the likelihood of a direct landfall in the coastal town of Terpido. Your assistance has been requested for guiding the pre-storm preparations and potential post-storm recovery efforts as needed. Based on current forecasts you have approximately five days in which to help the citizens and government of Terpido prepare for the landfall of Hurricane Florenz. Your advice is needed on how to focus preparation efforts.

The training scenario contained six variables that might be encountered during hurricane preparation and recovery efforts, namely: Civilian Compliance, Communications, Infrastructure, Interagency Coordination, Public Safety and Security, and the overall level of the Response Effectiveness. These variables could be influenced directly by the decision interventions of the participant, indirectly through the interrelationships with other system variables, or by external environmental events – such as the landfall of the hurricane. Within the training scenario, decision intervention effects resulted from the allocation of manpower points to each of three lines of effort on the decision screen (Response Effort, Response Logistics, and Services and Support). These lines of effort each directly impacted the level of one or more variables. In total the points allocated to these lines of effort directly impacted five of the six system variables. As the status of these five variables changed from the effects of the intervention, the status of these variables in turn affected changes in the status of other related system variables. For example, if a participant allocated a certain number of points to the Services and Support line of effort the direct effect of their decision might help increase the levels of Interagency Coordination as well as Public Safety and Security. The levels of these two variables in turn influenced a change in the levels of other variables. If we followed the effects of the participant's decision on Interagency Coordination we would see that the results of that decision filter through to influence the levels of Communications, Infrastructure, Response Effort, Public Safety and Security, and even feedback to alter its own level. Just as the variable Interagency Coordination influenced the levels of each of these other variables, the changes in these second order variables also influenced the levels of other related variables – thus creating a complex web of interrelationship and indirect decision consequences. The participant's goal in this task was to attempt to reach the green or optimal level for each variable in the system by controlling the system with a series of decision interventions.

Transfer Scenario

The transfer scenario followed the same structure and format as the training scenario, but represented a different task domain with different system variables. In the transfer scenario, participants were introduced to the task in a brief (approximately 45 second to 1 minute) video that described the task situation as follows:

> The country of Tasbak is a small developing nation. A severe drought has limited their traditional agricultural production and caused widespread food shortages. Tasbak has traditionally been a primarily tribal society and only recently has it adopted a democratic

central government. Not all citizens in Tasbak support this democratic government, especially with the recent food shortages. This has led to multiple demonstrations and unrest, particularly in the capital city, by citizens calling for governmental changes. You have been asked to take the lead on advising the government on a short term plan to help stabilize the situation. You have thirteen days in which to mobilize aid resources and move the country toward stability.

While the general complexity of the transfer scenario was similar to that of the training scenario, the variables, interventions, and specific relationships within the transfer scenario were completely new to the participant. Much like the training scenario, the transfer scenario consisted of six key variables and three lines of intervention. The three lines of intervention include Military Support, Non-Governmental Aid, and Public Support Abroad. The addition of manpower points to each of these lines of effort would lead to direct and indirect changes in the six system variables which include Crime, Foreign Aid, Social Issues, Economic Growth, Infrastructure, and Stability. As in the training scenario, the goal of the transfer scenario was to reach the green or optimal level of each system variable. Participants were again advised that they would have 13 days (turns) to help stabilize the current situation.

Experimental Design

The foundation of the research design was a four group between-subjects design where each group received one of the four instructional approaches - unguided practice, problem-focused instruction, process-focused instruction, or a combined problem and process-focused instruction. With multiple training iterations utilizing the same scenario, a 4x2 (instructional condition x training scenario) Mixed Model approach was adopted for examination of performance outcomes during training. Other performance and mental model analyses utilized only the 4 instructional conditions. Finally, analyses of the individual difference variables each followed a 4x2 design with the two grouping variables representing the instructional condition and a high/low median split grouping of the level of the individual difference variable of interest.

Experimental Conditions

Unguided Practice

The "unguided practice" experimental condition was designed to represent the experimental control and lowest level of instructional guidance. Participants first completed the single turn knobology training scenario and the 5-minute scenario introductory video. Following the introductory video participants logged into the CODEM system and completed two iterations of the training scenario with a total of 13 turns per iteration. No additional instruction was provided during the scenario. As part of their mission participants were instructed that they should attempt to reach a strong level for each system variable. Both iterations of the mission began with the same system start state and contained the same system parameters. Due to the dynamic nature of the system, however, it was unlikely that participants would follow exactly the same path to mission completion across iterations.

Upon starting the mission, participants were presented a screen displaying the various system variables and their current level. Participants were also given access to view graphical representations of system relationships and specific relationships between individual variables. Finally, participants could explore how their own decision interventions would affect different system variables. While these various system features indicating the current state of the decision situation, the interrelations between variables, relationships between decision options and related variables and feedback following each decision turn were all available to participants, no specific instructional guidance was provided to participants during the mission.

Problem-Focused Training

The "problem-focused training" experimental condition built upon the basic system features available to participants in the unguided practice condition by offering direct prompts or hints specifying direct and indirect relationships in the system. These prompts directly targeted the cognitive level of processing by providing information that was necessary to have in working memory when deciding what intervention to make (see Appendix B).

Similar to participants in the Unguided Practice condition, participants in the problem-focused training condition started with the knobology training and video introduction to their mission. Upon logging into the CODEM system participants completed two iterations of the same 13-turn mission as participants in the unguided practice condition. Unlike the unguided conditions' experience, participants in the problem-focused training condition began each turn with a prompt providing them with the details the direct and/or indirect effects related to one of the three lines of effort or interventions. Participants were then allowed to explore the system including the current state/level of the system variables, the structural relationships between the variables, specific graphical representations of variable relationships, and the relationship between potential decision interventions and the various system variables.

Process-Focused Training

Much like the problem-focused training condition, the process-focused experimental condition built upon the basic system features available in the unguided condition by adding instructional prompts to the training. While the focus of the problem-focused training condition was to target the cognitive level of processing by directly highlight specific effects of a decision, the process-focused training condition targeted activation at the meta-level of processing (see Appendix C). Thus prompts in this condition were designed to be more general and are oriented toward guiding participants to consider what information they knew, what information they needed, and the strategies and approaches they were taking in deciding what intervention to make.

Following the protocol of the unguided and problem-focused conditions, participants in the process-focused condition began their training with the knobology scenario and introductory video. In the process-focused training condition participants were presented a prompt at the beginning of each turn designed to activate the meta-level of processing. These prompts guided participants to consider how they were developing an understanding of the system variables and dynamics as well as guiding participants to monitor and adjust their own cognitive processes as needed. Following the instructional prompts participants were allowed to review the system data including the current state of system variables and specific relationships between those variables. Participants then proceeded to the decision intervention. Once participants logged their intervention, they were presented a feedback screen showing the specific direct and indirect effects of the decision. Participants then moved to the next turn and another prompt.

Combined Problem/Process Training

The final experimental condition followed the same introductory procedures as the other three conditions beginning with the knobology walkthrough and video based scenario introduction. In this combined condition, once in the training scenario, participants received both the problem-focused and process-focused prompts. At the beginning of each turn these prompts were presented in two separate pop-up screens within the game-system. Prompt order was counterbalanced such that half of the turns presented the problem-focused prompt followed by the process-focused prompt while the alternating turns presented the process-focused prompt first followed by the problem-focused prompt.

Dependent Variables

Performance

The first dependent variable of interest was decision-making performance within the CODEM system. Performance on decision making tasks in turn-based games or microworlds can be measured in a number of ways. For the current study performance was examined as the level of goal attainment across all system variables. A specific description of how goal attainment was calculated for the current research can be found in Appendix D. This method of performance evaluation followed established procedures from the previous literature (Lafond & DuCharme, 2011) and was calculated as the distance from the "green-zone" of one or more key variables. If multiple variables are used to calculate the level of goal attainment then the distance from goal is averaged across all variables. This measure was calculated for both training mission attempts as well as the transfer mission.

In the current study participants were not only tasked with achieving a goal state, but with maintaining that state if and when it was achieved. The number of turns per mission attempt was held constant across participants.

Mental Model Accuracy

Sterman (1994) suggested that for learning to occur in complex systems individuals must develop an accurate understanding of both the structure and dynamics of the system. Thus in addition to performance measures taken within the CODEM system, the current study sought to measure the accuracy of the participant's mental model of the system structure and system dynamics. Toward this, following completion of the training missions and again following completion of the transfer mission participants were given a paper-based measure which showed the variables of the just completed mission (see Appendices D and E). In order to measure participants' knowledge of the surface structure of the system, participants were asked to draw arrows depicting the various relationships of the system. This structural test of mental model accuracy was scored by giving one point for each correct relationship depicted on the graphic. Errors of omission and commission were treated equally with zero points added or deducted. To test the dynamic understanding of the system participants were then given a depiction of a current state of the same system along with a set of intervention values. Given this information participants were asked to predict what the value of the system variables would be after the given intervention. This measure was scored as the absolute distance between the predicted change and actual change across the six system variables, thus a lower score indicated better understanding of the dynamics of the system.

Individual Difference Variables

Multiple independent measures of training outcomes including performance and mental model accuracy were collected to determine differences between training conditions. Pre-training measures of multiple individual difference variables were conducted to address the second question of potential aptitude treatment interactions.

Metacognitive Awareness Inventory (MAI)

The Metacognitive Awareness Inventory (MAI) is a 52-item self-report questionnaire which required approximately 10 minutes to complete and measured both an individual's Knowledge of Cognition and their Regulation of Cognition (Shraw & Dennison, 1994). The first dimension of the MAI, Knowledge of Cognition, includes a combination of declarative, procedural, and condition knowledge. Shraw and Dennison described this dimension as knowledge about yourself, your strategies, how to use those strategies, and finally when and why different strategies should be used. The second dimension of Metacognitive Awareness represented an individual's regulation of their own cognition and included aspects of planning, performance monitoring, and self-evaluation behaviors (Shraw & Dennison, 1994). Across two experiments utilizing undergraduate participants Shraw and Dennison found their two factor MAI provided a reliable measure of both knowledge and regulation of cognition (with internal consistencies ranging from .88 to .93) and while significantly correlated (r = .45 to r = .54) the two factors were deemed to each represent "a unique contribution to cognitive performance" (p. 471).

Decision Making Questionnaire (DMQ)

The DMQ (Kline, 1996) included two decision scenarios, one focused on tactical decision making and the second on strategic decision making. Each scenario required the participant read a brief story and rank the potential actions of the individual described in the scenario. Additionally, participants were asked to rate their own confidence in the correctness of their rankings. Shortened to the current two scenario format through a series of psychometric analyses, Kline's (1996) DMQ was deemed a valid measurement of tactical and strategic decision making based on item-to-total correlations, retention of non-significant correlations, and higher strategic decision scores than tactical. A primary advantage of this shortened form was an administration time of 10-15 minutes.

Working Memory Span Task

Lin's (2007) Web-OSPAN task was utilized to measure the individual difference of working memory span. Similar to the Operation-Word span tasks described by Turner and Engle (1989), Conway, et al. (2005), and De Neys, d'Ydewalle, Schaeken, and Vos (2002), this task presented participants with a series of simple arithmetic problems in the form (a * b) – c = d where the first operand can be a multiplication or division operation and the second operand can be either an addition or subtraction. Participants were then asked to identify whether the provided answer was correct or incorrect. Following each arithmetic operation the participant was presented a high frequency English word (e.g. "ball") for 800 milliseconds. Following a series of two to six operation-word pairs the participant was then asked to provide the words in the order they were originally presented. Each level (2 to 6) was presented three times with different stimuli to obtain an accurate measure of an individuals' WM span. To ensure participants do not use memory strategies an 85% or better accuracy for the arithmetic operations must be maintained throughout the task.

Ravens Progressive Matrices- Short-form

The Raven's Advanced Progressive Matrices was utilized as a measure of fluid intelligence. The version used in the current research (Bors & Stokes, 1998) was a short-form consisting of 12 items of progressive difficulty (specifically items 3, 10, 12, 15, 16, 18, 21, 22, 28, 30, 31, and 34 shown below) of the Raven's Advanced Progressive Matrices (Raven, Court, & Raven, 1988). Each item presented a 3x3 grid of patterns with one pattern missing from the grid. Participants were asked to select the pattern from 8 possible alternatives that best completes the grid. The primary advantage of the short-form and the precipitous of its development was a substantial time savings. The traditional full version of the Raven's APM required approximately 40-60 minutes to administer, while the shortened form required only 20 minutes to administer. Tests of the reliability and validity of this shortened form of the Ravens APM indicated that the 12 item measure is of adequate reliability (0.82 based on test-retest; internal consistency alpha = .73) and maintained adequate convergent validity in its new form (Bors & Stokes, 1998).

Procedure

The current study was conducted in two experimental sessions across no more than one week. Upon signing up to participate in the study participants were asked to schedule times for both phase 1 and phase 2 with the second session following one to seven days after the completion go the first session. All participants were randomly assigned to one of the four experimental conditions when the participation times were scheduled and confirmed.

Prior to beginning each Phase all participants were provided with both short written and descriptions of the tasks they would be asked to perform as part of the consent process. All participants were informed and agreed that their participation was strictly on a voluntary basis and could be concluded at any time during the experiment if the participant wished. Additionally, researchers explained to participants that any compensation for participation, including academic credit or cash payment, would be determined and awarded on the basis of every completed 30 minute segment of the study.

Phase One

Phase 1 was conducted on computers in a laboratory setting and consisted of the demographics questionnaire, the Metacognitive Awareness Inventory, the Decision Making Questionnaire, the Web OSPAN, and the short-form of the Raven's Advanced Progressive Matrices. This approach offered a number of experimental advantages. First both the decision making questionnaire and metacognitive awareness inventory were closely related to experimental interventions which raised concerns of participants learning from the pre-training measures or manipulating their performance based on the pre-training measures. It is thought that the time between these measures and introduction to the experimental platform is likely to reduce this possibility. Secondly, having participants complete these measures in a separate phase shortened the experimental session time for Phase 2 and thus may reduce the potential introduction of fatigue effects.

When participants first arrived at the laboratory for Phase 1, they were asked to read the informed consent document and verbally inform the experimenter if they voluntarily agreed to participate and whether they wished to receive monetary or credit compensation for their participation in that phase. Following the consent process participants were first asked to complete the demographics questionnaire (see Appendix A) which included questions about the participant's age, gender, ethnicity, education and math background, and prior computer and gaming experience. Following completion of the demographics questionnaire participants were asked to rate each of 52-items on the Metacognitive Awareness Inventory (Shraw & Dennison, 1994). These items, which measure an individual's knowledge and regulation of their own cognition, each provide a statement about an individual's learning followed by a 5-point Likert scale which ranges from "*Never true of me*" to "*Always true of me*". Finally, participants were asked to complete the two scenarios of the Decision Making Questionnaire (Kline, 1996). These scenarios, representing tactical and strategic decision making situations respectively, required participants to first read a brief scenario presenting a decision situation. Each scenario was followed by five action statements. Participants were asked to rank these action statements from the most appropriate response to the situation to the least appropriate response. Additionally, participants were asked to rate their own confidence in these rankings. Finally, participants were asked to follow a link to log into the Web-OSPAN. Modeled after Turner and Engle's (1989) series of WM span tasks and more specifically the computer based GOSPAN (De Neys et al., 2002) this task presented a series of 2 practice and 15 test trials consisting a mathematical equation followed by an answer to that equation. Here participants were required to respond whether the answer was correct or incorrect. On the next screen the participant was presented a high frequency English language word. After a series of three to seven equation letter pairs the participant was asked to recall in order what letters they had been presented. Completion of the entire working memory task requires approximately 10-20 minutes. Following this series of computer-based tasks, participants completed a paper-based shortened form of the Raven's Advanced Progressive Matrices (Bors & Stokes, 1998). The shortened form of the RAPM contains 2 practice items to familiarize participants with the procedure, followed by 12 test items. Each item consists of a 3x3 matrix of abstract patterns with one pattern missing. Participants are then asked to select the one pattern from a series of eight patterns that best completes the matrix. The shortened form of the RAPM measures a participant's fluid intelligence or abstract reasoning skill and requires approximately 20 minutes to complete. Phase 1 required approximately 1-1.5 hours for which participants could elect to receive 0.5 credits per half hour in SONA (for students in the UCF Psychology Department) or $5 per half hour payment.

Phase Two

Phase 2 of the study was conducted in the same laboratory setting as Phase 1 on the University of Central Florida's main campus. Upon arrival participants were briefed on the tasks they would be asked to complete in this phase of the study and were asked to review the informed consent if they agreed to participate in Phase 2 of the study. Participants then completed a single turn knobology scenario in the CODEM system. This system introduction was led by the experimenter and provided participants with a hands-on walkthrough of the various system features they would be presented and allowed to utilize during the session. This system walkthrough was then followed by a short (approximately 5 minute) video introducing participants to the background story and variables they would encounter during the training scenario. Following knobology training participants were logged into the CODEM system by an experimenter. Participants completed the 13 turn training scenario twice. After the second completion of the training scenario participants were asked to complete both the structural and then dynamic components of the mental model test for the training scenario (Appendix D). Participants were then asked to take a 10 minute break. Upon returning from the break participants viewed a brief (approximately 1 minute) video introducing the transfer scenario background story. The experimenter then logged each participant into the 13-turn transfer scenario, which was completed without guidance by all participants. At the completion of the transfer scenario participants were asked to complete the two part mental model test for the transfer scenario (Appendix E). Finally participants were asked to complete a paper-based questionnaire examining the participant's strategy in the game, what strategies they believed did and did not work for decision making in the game, and what features of the game they deemed most important. After completing this final measure, participants were given a summary of the research, thanked for their participation, and granted the appropriate compensation.

Experimental Hypotheses

H1: The process-focused training intervention will lead to better performance than the other training interventions

Prediction 1: Process-focused, Problem-focused, and Combined guidance based training will lead to significant improvements in performance across time while no change will be observed across time in the Unguided training

Prediction 2: Process-focused training and combined guidance will lead to significantly higher levels of goal attainment at the end of training than problem-focused training or unguided practice

Prediction 3: Process-focused and combined guidance training will lead to significantly higher goal attainment in the transfer scenario than Problem-focused training or unguided practice

H2: The process-focused training intervention will lead to better mental model accuracy than the other training interventions

Prediction 1: Process-focused and combined guidance training will lead to better mental model accuracy in training than problem-focused training which will have better accuracy than unguided practice

Prediction 2: Process-focused and combined guidance training will lead to better mental model accuracy in transfer than problem-focused training which will have better accuracy than unguided practice

While the type of training intervention provided was expected to play a direct role in the performance and mental model accuracy developed by participants in this complex problem solving task, previous research points to the importance of considering the differential impact of such training methods across different participants. While group research is commonplace in both educational and experimental psychology studies, the key role of individual differences and the individualization of instruction have experienced a resurgence of research interest in recent decades. While ongoing work by Cronbach and Snow (1977) has long pointed to the importance of potential aptitude treatment interactions in instruction, more recently work in the areas of intelligent tutoring and adaptive training have brought new awareness to such individual differences. From a training development standpoint, individual differences become critical factors if they can be targeted to identify the best training for an individual to produce improved training effectiveness and/or efficiency. With this goal in mind the following section of the research sought to identify possible key factors for the future development of tailored training methods through a series of moderator analyses.

Based on previous findings from the literature, four primary variables were identified for an exploratory moderator analysis in the current study. Specifically, Batha and Carroll (2007) demonstrated that participants with low pre-training levels of decision making ability as measured by Kline's (1996) Decision Making Questionnaire (DMQ) benefited from metacognitive strategy training while average and high level participants saw no improvement or even declines in decision making ability with strategy training. While this indicated a differential impact across experience levels within a metacognitive training condition, it did not address what type of training, if any, would better support learners across the range of skill development. In the same study, Batha and Carroll further demonstrated a positive moderate relationship (r = 0.389) between Kline's DMQ and Shraw and Dennison's (1994) Metacognitive Awareness Inventory (MAI). While the positive nature of this correlation suggested possible relationships between both the decision making skill measured by the DMQ and the level of Metacognitive Awareness, the moderate level of the relationship warranted further investigation of both variables as potential moderators in the current study. Thus the current moderator analyses explored how pre-training domain skill and metacognitive awareness level might be utilized to identify what level of guidance is best for different levels of learners.

H3: Individual differences in pre-training levels of decision making skill and metacognitive awareness will moderate the relationship between the level of guidance provided and the training outcomes of performance and mental model accuracy such that individuals lower in pre-training skill and awareness show greater benefits from guidance.

Prediction 1: *It is predicted that individuals with lower levels of pre-training decision making skill will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Prediction 2: *It is predicted that individuals with lower levels of pre-training metacognitive awareness will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

While the first two individual difference variables of interest examine variables previously identified as potentially informing instruction, the second set of variables was founded in the complex decision making performance literature. Specifically, these analyses examined the potential impact of fluid intelligence or analytical reasoning skills and working memory capacity. These variables were previously identified by Gonzalez, Thomas, and Vanyukov (2005) as predictors of performance in microworld simulations. However, their utility in determining the best type of training support for different level individuals represented a new avenue of investigation. Thus while the moderator analysis was expected to provide important information both for future research and development.

H4: Individual differences in working memory capacity and fluid intelligence will moderate the relationship between the level of guidance provided and the training outcomes of performance and mental model accuracy

Prediction 1: *It is predicted that individuals with lower working memory spans will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Prediction 2: *It is predicted that individuals with lower levels of fluid intelligence will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

CHAPTER FIVE: RESULTS

Data Cleaning and Treatment

Prior to data analysis the complete data set was examined first for critical missing data followed by an outlier analysis by experimental condition.

Missing Data

The first of these examinations showed that of the 141 participants completing both phases of the research one case was missing performance data and no missing Mental Model data. Due to the isolated nature of missing data these cases were excluded from further analyses. Examination of the individual difference variables showed no missing data for the Decision Making Questionnaire, Metacognitive awareness Inventory, or the Raven's Advanced Progressive matrices short-form, however 1 participant was missing data for the WEB-OSPAN.

Outlier Analysis and Description of Final Data Set

An outlier analysis was conducted utilizing the Explore function in SPSS. Examination of performance by condition initially showed significant deviations from normality for the process-focused condition in the first training scenario. Based on these analyses a total of six extreme outliers were removed from the process-focused condition. Additionally, four cases identified as outliers in the second training were removed from the combined guidance condition. The final data set thus contained a total of 129 cases with 36 cases in the unguided condition, 35 cases in the problem-focused condition, 28 cases in the process-focused condition, and 31 cases in the combined guidance condition. While this left unequal n across conditions, the standard deviation of the smallest group (the process-focused) was noted to be the smallest deviation of the four groups with the next smallest group size (the combined guidance) having the next smallest standard deviation for performance. Thus parametric analyses were determined to be suitable even with the potential violation of the assumption of equality of covariance matrices (Tabachnik & Fidell, 2006).

Analysis Approach

An initial correlational analysis was conducted prior to hypothesis testing with two primary goals; first to determine the most suitable statistical techniques for analysis, and second to identify potential covariates to be utilized during hypothesis testing. In examining the correlations across the dependent variables it is important to note that better levels of performance on the structural mental model task and goal attainment are represented by higher numbers while better performance on the dynamic mental model is represented by lower numbers. Thus negative correlations between a measure of dynamic mental model and goal attainment or the structural mental model task represent a relationship in which both variables show performance in the same direction (e.g. good performance on both or poor performance on both). While the first correlation analysis (Table 1) shows the expected relationship between the three performance variables, it did not support a relationship between the structural and dynamic components of the Mental Model tasks for either training (r = -.091) or transfer (r = -.150) scenarios. Thus while a mixed between within ANOVA is suitable for the analysis of the first hypothesis, separate ANOVA analyses, not MANOVA were utilized to examine the effects of instructional approach on the separate aspects of participants' mental models for the scenarios.

Table 1. Dependent variable correlation analysis

	Structural Mental Model Training	**Dynamic Mental Model Training**	**Structural Mental Model Transfer**	**Dynamic Mental Model Transfer**	**Final Goal Attainment Training 1 (T1)**	**Final Goal Attainment Training 2 (T2)**	**Final Goal Attainment Transfer (T3)**
Structural Mental Model Training	**1**						
Dynamic Mental Model Training	**-.091**	**1**					
Structural Mental Model Transfer	**.414****	**.016**	**1**				
Dynamic Mental Model Transfer	**-.241****	**.357****	**-.150**	**1**			
Final Goal Attainment Training 1 (T1)	**.125**	**-.232****	**.220***	**-.149**	**1**		
Final Goal Attainment Training 2 (T2)	**.114**	**-.428****	**.105**	**-.157**	**.644****	**1**	

	Structural Mental Model Training	Dynamic Mental Model Training	Structural Mental Model Transfer	Dynamic Mental Model Transfer	Final Goal Attainment Training 1 (T1)	Final Goal Attainment Training 2 (T2)	Final Goal Attainment Transfer (T3)
Final Goal Attainment Transfer (T3)	**.261****	**-.222****	**.191***	**-.512****	**.363****	**.357****	**1**

***. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).**

The second correlational analysis (Table 2) examined relationships between a series of variables from the demographics questionnaire and each of the dependent variables. Demographics questions included in this analysis were selected to highlight prior skill experience that might impact learning and performance during the experiment. From this analysis, the variable measuring an individual's frequency of game play specific to turn-based strategy games was found to be moderately and significantly correlated with all independent variables except for the structural mental model task which followed immediately after training. Additional analysis of variance tests examining the potential for interaction between the frequency of turn-based strategy game play and the experimental manipulation of instructional condition, however, eliminated the utility of the frequency of turn-based strategy game play variable as a covariate as a significant interaction was confirmed ($F(1,122)=3.013, p = .033$, $\eta^2_p=.069$). Still considered a variable of interest, I will return to the influence of prior turn-based strategy game play on performance in later sections of this chapter.

Table 2. Correlation analysis to identify potential covariates

	Age	Math Confidence	Weekly Hours on Computer	Frequency of Game Play	Frequency of Turn-based Strategy Game Play	Structural Mental Model Training	Dynamic Mental Model Training	Structural Mental Model Transfer	Dynamic Mental Model Transfer	Final Goal Attainment Training 1	Final Goal Attainment Training 2	Final Goal Attainment Transfer
Age	**1**											
Math Confidence	**.020**	**1**										
Weekly Hours on Computer	**.179***	**-.038**	**1**									
Frequency of Game Play	**.002**	**.116**	**.261****	**1**								
Frequency of Turn-based Strategy Game Play	**.043**	**.190***	**.043**	**.293****	**1**							

	Age	Math Confidence	Weekly Hours on Computer	Frequency of Game Play	Frequency of Turn-based Strategy Game Play	Structural Mental Model Training	Dynamic Mental Model Training	Structural Mental Model Transfer	Dynamic Mental Model Transfer	Final Goal Attainment Training 1	Final Goal Attainment Training 2	Final Goal Attainment Transfer
Structural Mental Model Training	.089	.111	.171*	.200*	.366**	1						
Dynamic Mental Model Training	.124	-.036	.056	.020	-.110	-.091	1					
Structural Mental Model Transfer	.024	.278**	-.107	.023	.294**	.414**	.016	1				
Dynamic Mental Model Transfer	.270**	-.154	-.060	-.097	-.245**	-.241**	.357**	-.150	1			
Final Goal Attainment Training 1	-.138	.071	-.086	.160	.300**	.125	-.232**	.220*	-.149	1		

	Age	Math Confidence	Weekly Hours on Computer	Frequency of Game Play	Frequency of Turn-based Strategy Game Play	Structural Mental Model Training	Dynamic Mental Model Training	Structural Mental Model Transfer	Dynamic Mental Model Transfer	Final Goal Attainment Training 1	Final Goal Attainment Training 2	Final Goal Attainment Transfer
Final Goal Attainment Training 2	**-.107**	**.038**	**-.076**	**.038**	**.258****	**.114**	**-.428****	**.105**	**-.157**	**.644****	**1**	
Final Goal Attainment Transfer	**-.038**	**.075**	**.086**	**.079**	**.366****	**.261****	**-.222****	**.191***	**-.512****	**.363****	**.357****	**1**

***. Correlation is significant at the 0.05 level (2-tailed).**

****. Correlation is significant at the 0.01 level (2-tailed).**

Table 3. Correlation analysis for individual difference variables

	Metacognitive Awareness Inventory Knowledge	**Metacognitive Awareness Inventory Regulation**	**Decision Making Questionnaire Tactical**	**Decision Making Questionnaire Strategic**	**Operation Span Task**	**Ravens Fluid Intelligence**
Metacognitive Awareness Inventory Knowledge	1					
Metacognitive Awareness Inventory Regulation	.691**	1				
Decision Making Questionnaire Tactical	.010	-.052	1			
Decision Making Questionnaire Strategic	.073	-.010	.135	1		
Operation Span Task	-.011	-.069	-.056	-.006	1	
Ravens Fluid Intelligence	-.085	-.223*	-.041	-.125	.120	1

***. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).**

Hypothesis One

H1: The process-focused training intervention will lead to better performance than the other training interventions

Table 4. Final Goal Attainment Means and Standard Deviations

Condition	Training T1 Goal Attainment	Training T2 Goal Attainment	Transfer Goal Attainment
Unguided	52.9167 (25.6238)	58.4433 (24.8421)	52.5123 (20.1559)
Problem	47.8036 (25.7957)	50.0000 (24.9632)	50.6881 (20.0433)
Process	61.5104 (10.6503)	64.6205 (14.9994)	50.3264 (17.6901)
Combined	55.8938 (22.5023)	57.0161 (15.8615)	52.4368 (19.7658)

Prediction 1: Process-focused, Problem-focused, and Combined guidance based training will lead to significant improvements in performance across time while no change will be observed across time in the Unguided training

The first prediction tested the interaction of the instructional intervention with the change in performance from the first training scenario to the second. Support for this hypothesis would first be expressed by a significant Time by Condition interaction and then by simple effects showing a significant time 1 to time 2 performance change in training for each of the three guidance conditions but no significant change in the unguided condition.

Examination of the level of goal attainment at the conclusion of each training scenario (see Figure 1) showed no significant interaction between time and condition ($F(3,126)=0.338, p = .798$, $\eta^2_p=.008$). Main effects for time were also non-significant ($F(1,126)=3.229, p = .075$, $\eta^2_p=.025$), however a significant main effect for condition was observed ($F(3,126)=2.708, p = .048$, $\eta^2_p=.061$).

Figure 1. Goal attainment by condition across training (T1 and T2)

Prediction 2: Process-focused training and combined guidance will lead to significantly higher levels of goal attainment at the end of training than problem-focused training or unguided practice

The second prediction tested the simple effects for condition on performance at the conclusion of the second training scenario. Support for this hypothesis would be shown by significantly higher performance scores at T2 for Process (C3) and Combined (C4) Guidance compared to Unguided (C1) and Problem (C2) guidance. A univariate analysis of variance was utilized to test this prediction. Results indicate a marginally significant effect for condition (F(3,126)=2.541, p = .059, η^2_p=.057) when examined across all participants. Post hoc analysis with Bonferroni correction indicate that this difference can be attributed to participants in the Process Guidance condition outperforming participants in the Problem-focused condition (Mean difference = 14.621, SE = 5.365, p = .044).

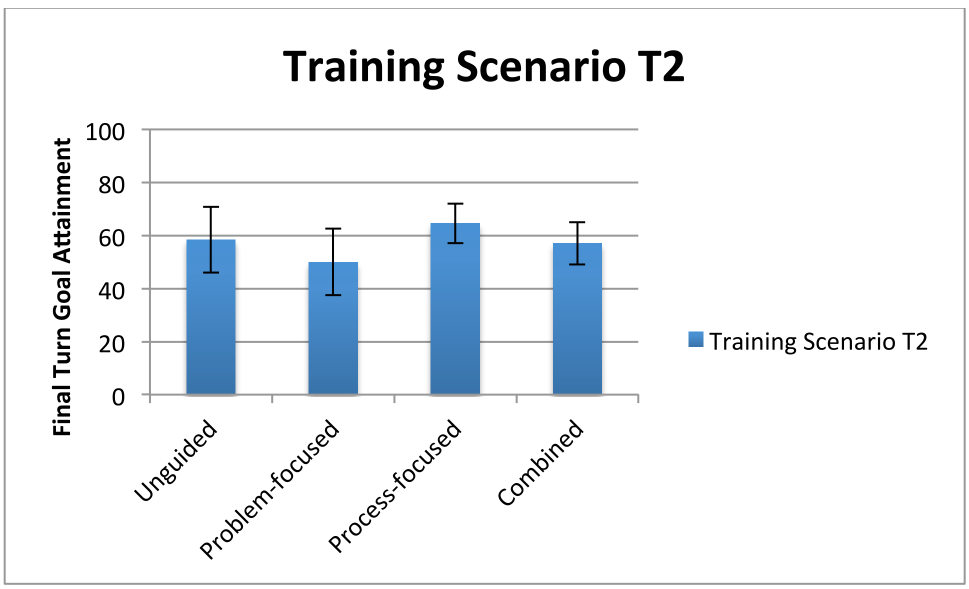


Figure 2. Goal attainment by condition on the final turn of Training Scenario 2

Prediction 3: Process-focused and combined guidance training will lead to significantly higher goal attainment in the transfer scenario than Problem-focused training or unguided practice

The third prediction tested the effects of condition on goal attainment at the conclusion of the transfer scenario. Again a univariate analysis of variance was utilized to test this hypothesis. Support for this analysis would show higher levels of goal attainment on the final turn of the transfer scenario for Process (C3) and Combined (C4) Guidance compared to Unguided (C1) and Problem (C2) guidance. Results failed to show support for this hypothesis with no significant differences being apparent by condition ($F(3,126)=0.110$, $p = .954$, $\eta^2_p=.003$). It is noted, however that the lack of differences by condition in the transfer is largely the result of a significant decline in performance by participants in the process-focused condition ($t(27)=2.870$, $p=.008$) from training (T1) to transfer (T3) while participants in the other three conditions showed no significant change in performance.

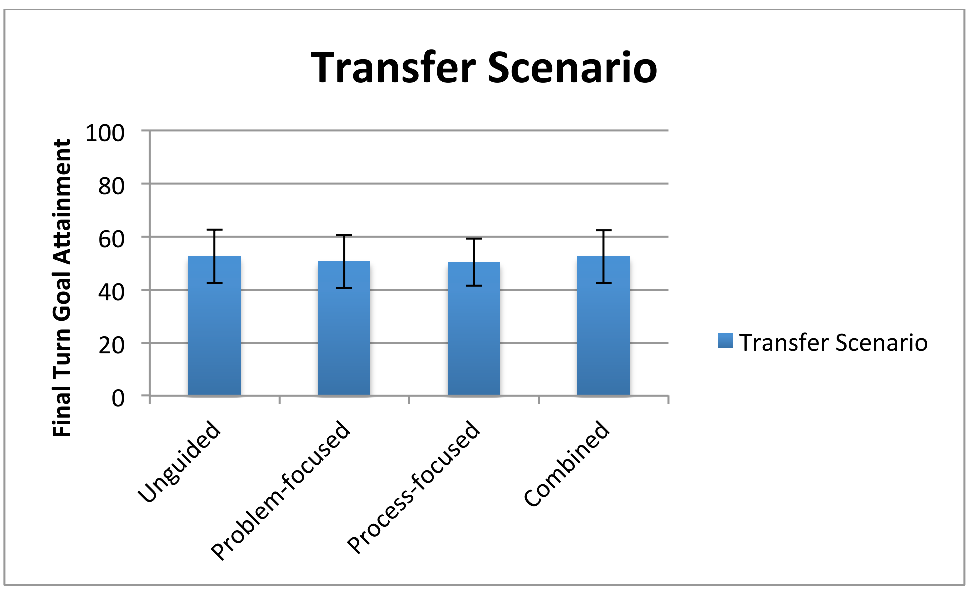


Figure 3. Goal attainment by condition on the final turn of the Transfer Scenario

Hypothesis Two

H2: The process-focused training intervention will lead to better mental model accuracy than the other training interventions

As reviewed in the previous correlational analyses above structural and dynamic aspects of the mental model tasks were found to be unrelated. As such, the second hypothesis was tested via a series of univariate analysis of variance tests. In the structural mental model task higher scores indicate mental models closer to the actual system model, thus a higher score is better. In the dynamic mental model task, a participants' score is calculated as the absolute difference in system change from the actual system change and thus a lower score represents a more accurate mental model of the system dynamics.

Table 5. Structural Mental Model Means and Standard Deviations

Condition	Structural MM Training	Structural MM Transfer
Unguided	10.36 (3.244)	11.42 (2.989)
Problem	9.63 (3.282)	10.57 (3.534)
Process	10.64 (3.841)	11.50 (2.560)
Combined	11.55 (2.731)	12.03 (2.302)

Table 6. Dynamic Mental Model Scenario Means and Standard Deviations

Condition	Dynamic MM Training	Dynamic MM Transfer
Unguided	17.09 (3.592)	10.94 (5.565)
Problem	19.97 (4.756)	12.09 (5.695)
Process	19.54 (4.004)	12.18 (5.086)
Combined	18.32 (4.134)	12.29 (5.330)

Prediction 1: Process-focused and combined guidance training will lead to better mental model accuracy in training than problem-focused training which will have better accuracy than unguided practice

A Univariate Analysis of Variance was utilized to examine differences by condition for each the structural and dynamic mental model tasks completed following training. No significant differences were observed across the four conditions for structural mental model task ($F(3,126)=1.917, p = .130, \eta^2_p=.044$). However, tests of the dynamic mental model task indicated significant differences by instructional condition ($F(3,126)=3.323, p = .022, \eta^2_p=.074$). Specifically, post hoc analyses with Bonferroni corrections indicate that these differences can be attributed to participants in the unguided condition showing a better understanding of the dynamics of the system than participants in the problem-focused condition (Mean difference = -2.89, *SE* = 0.992, *p* = .026).

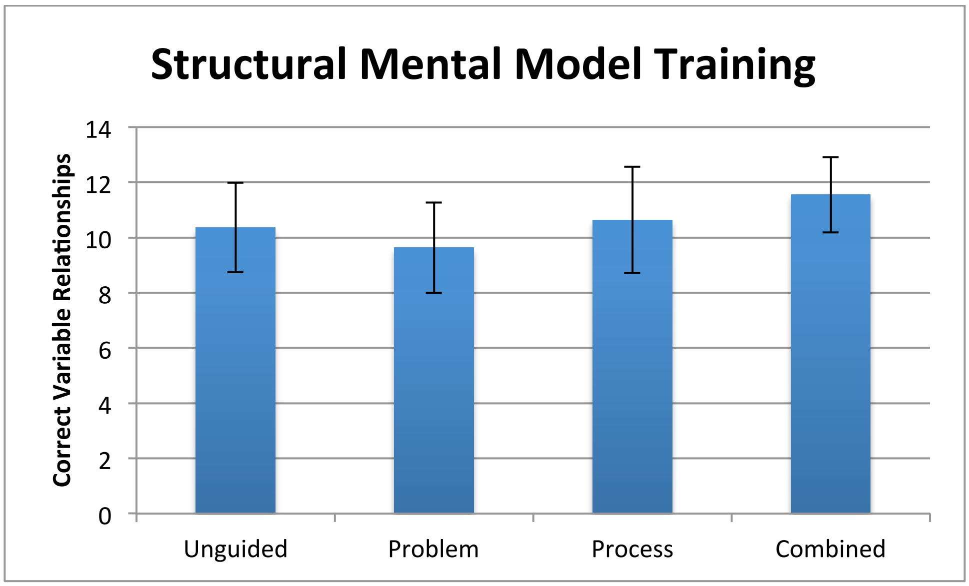


Figure 4. Structural Mental Model Score (correct relationships) by condition for training scenario

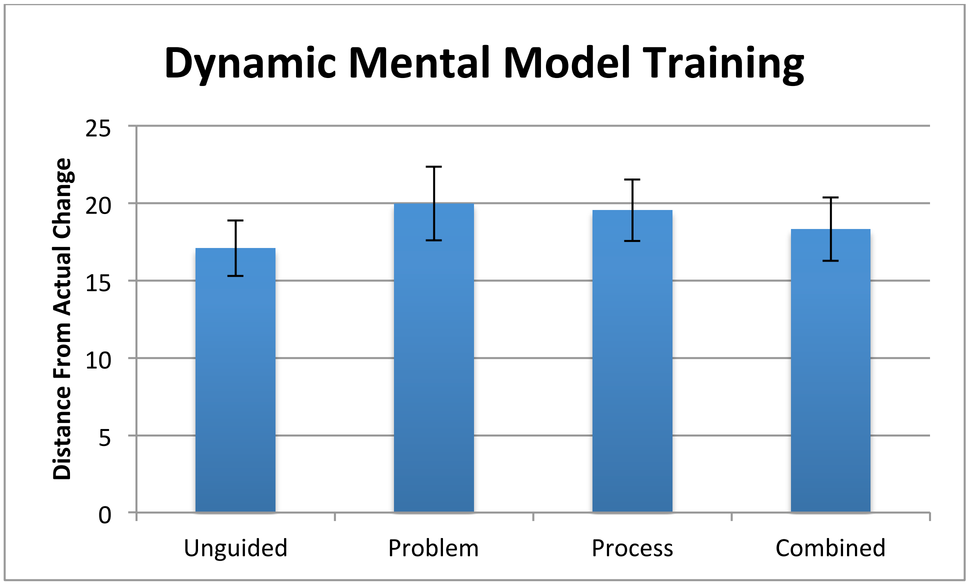


Figure 5. Dynamic Mental Model Score (deviation from actual) by condition for training scenario

Prediction 2: Process-focused and combined guidance training will lead to better mental model accuracy in transfer than problem-focused training which will have better accuracy than unguided practice

Independent Univariate Analysis of Variance tests showed no significant differences by condition for either the structural ($F(3,126)=1.426, p = .238, \eta^2_p=.033$) or the dynamic ($F(3,126)=0.457, p = .713, \eta^2_p=.011$) mental model tasks for the transfer task.

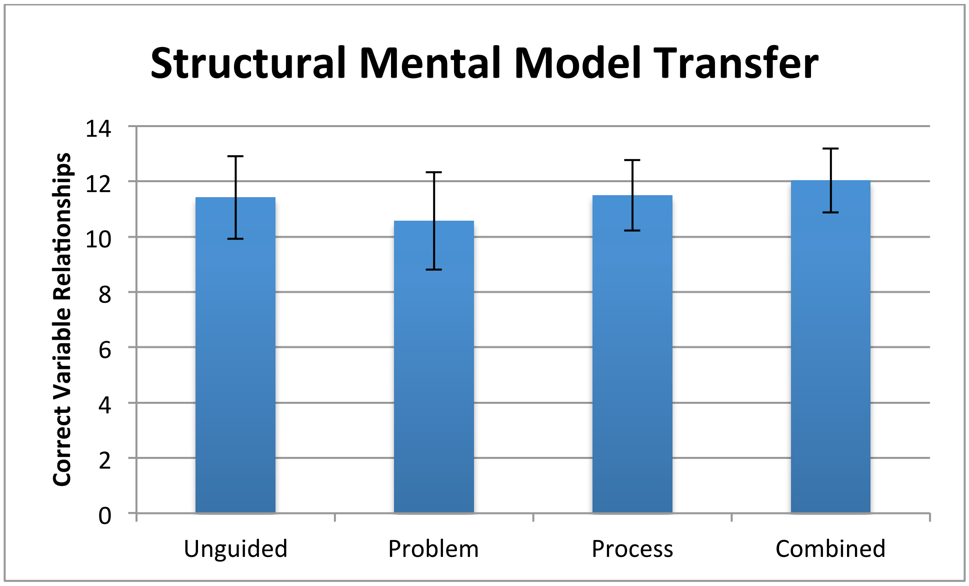


Figure 6. Structural Mental Model Score (correct relationships) by condition for transfer scenario

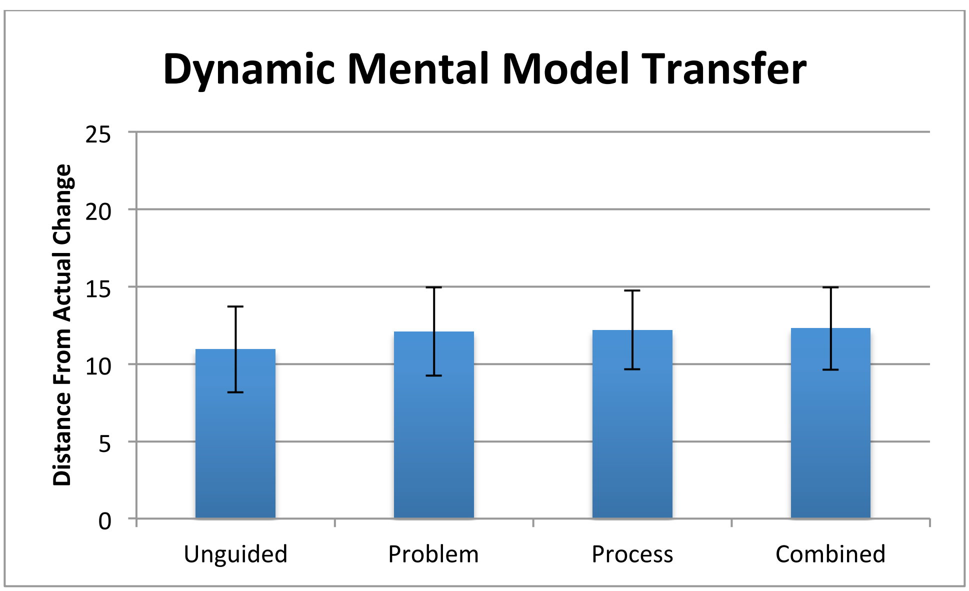


Figure 7. Dynamic Mental Model Score (deviation from actual) by condition for transfer scenario

Hypothesis Three

H3: Individual differences in pre-training levels of decision making skill and metacognitive awareness will moderate the relationship between the level of guidance provided and the training outcomes of performance and mental model accuracy such that individuals lower in pre-training skill and awareness show greater benefits from guidance.

Prediction 1: *It is predicted that individuals with lower levels of pre-training decision making skill will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Table 7. Goal Attainment for Low and High pre-training Decision Making Skill by Condition

	Low DMQ	**High DMQ**
Unguided	58.2589 (27.8150)	58.5606 (23.4430)
Problem	47.8399 (28.6510)	52.5651 (20.3597)
Process	57.0711 (17.3544)	64.7059 (16.1235)
Combined	49.3403 (14.0941)	67.6442 (11.6965)

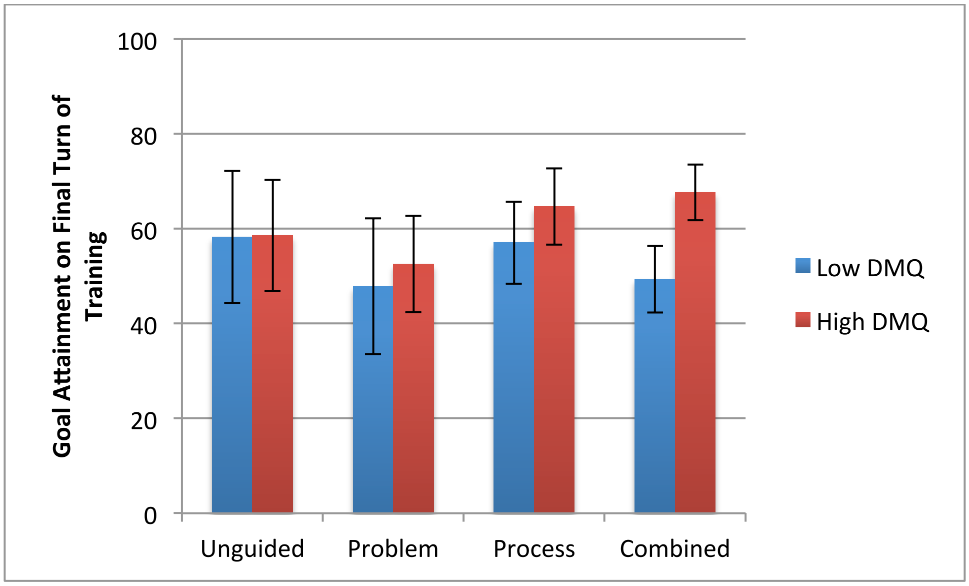


Figure 8. Goal Attainment for Low and High pre-training Decision Making Skill by Condition

To test the first prediction of this hypothesis a univariate analysis of variance was conducted to test for an interaction between the condition and participants grouped as high or low in pre-training levels of decision making skill as measured by the two part Decision Making Questionnaire (Kline, 1996). With a range of 11 points on a 12 point scale (M = 5.8, SD = 2.3) the median split included individuals with scores less than 6 as low pre-training decision skill while those with a score of 6 or higher were classified as initially high levels of decision making skill. Initial support for this prediction would be shown first by a significant interaction between condition and prior decision making skill. The univariate analysis of variance showed no significant interaction between the pre-training level of decision making and instructional condition ($F(3,129)=1.049, p = .373, \eta^2_p=.024$), however it did show a significant main effect for the pre-training level of decision making ($F(3,129)=4.498, p = .036, \eta^2_p=.034$). Specifically, this main effect showed that individuals with higher levels of pre-training decision skill reached better levels of goal attainment overall regardless of the type of training they received. While these findings fail to support the hypothesis they do suggest that the pre-training level of decision making skill may be an important aspect of final performance.

Prediction 2: *It is predicted that individuals with lower levels of pre-training decision making skill will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Table 8. Goal Attainment for Low and High pre-training Metacognitive Awareness by Condition

	Low MAI	**High MAI**
Unguided	55.4444 (29.0340)	60.5853 (21.8709)
Problem	55.3516 (24.6032)	45.4934 (25.0152)
Process	58.5636 (17.5606)	63.8333 (16.2353)
Combined	57.8438 (17.1834)	55.5114 (13.7801)

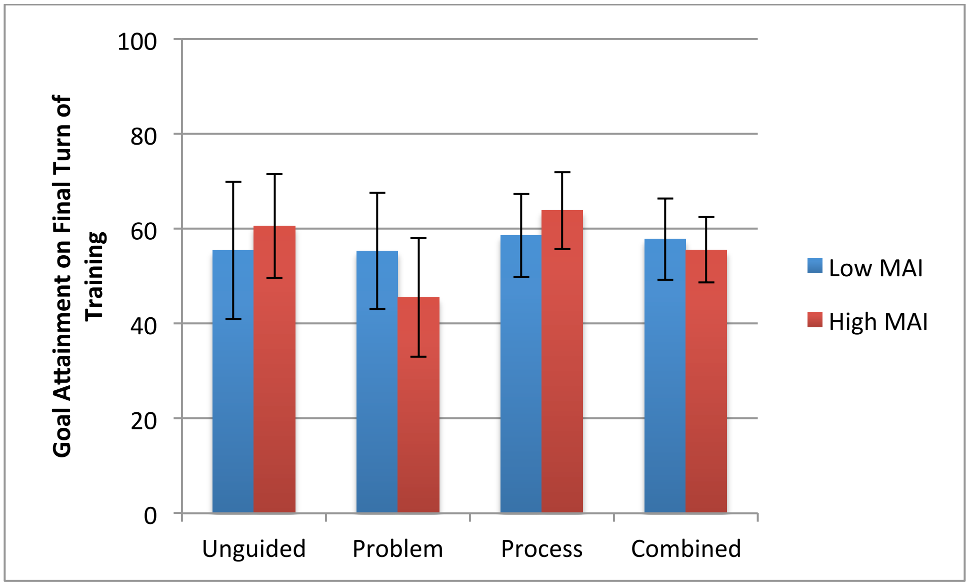


Figure 9. Goal Attainment for Low and High pre-training Metacognitive Awareness Skill by Condition

To test the second prediction a univariate analysis of variance was utilized to test for a significant interaction between high and low levels of pre-training metacognitive awareness as measured by the 52 item Metacognitive Awareness Inventory and the instructional condition during training. Scores on the Metacognitive Awareness Inventory were totaled across the two scales (M= 198.3, SD = 22.2) and split at the median of 196.5 with individuals scoring higher than the median classified as high and individuals under the median as low. The independent variable of interest was again the final goal attainment during the second training. Results of this analysis failed to support a significant interaction ($F(3,129)=0.979, p = .405, \eta^2_p=.022$).

Hypothesis Four

H4: Individual differences in fluid intelligence and working memory capacity will moderate the relationship between the level of guidance provided and the training outcomes of performance and mental model accuracy

Prediction 1: *It is predicted that individuals with lower levels of pre-training metacognitive awareness will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Table 9. Goal Attainment for Low and High pre-training Working Memory Span by Condition

	Low WMS	**High WMS**
Unguided	59.9653 (26.1046)	56.9213 (24.1704)
Problem	45.8724 (24.8687)	53.4759 (25.1756)
Process	58.4524 (16.2162)	62.4561 (18.1150)
Combined	56.9712 (19.4180)	57.0486 (13.3347)

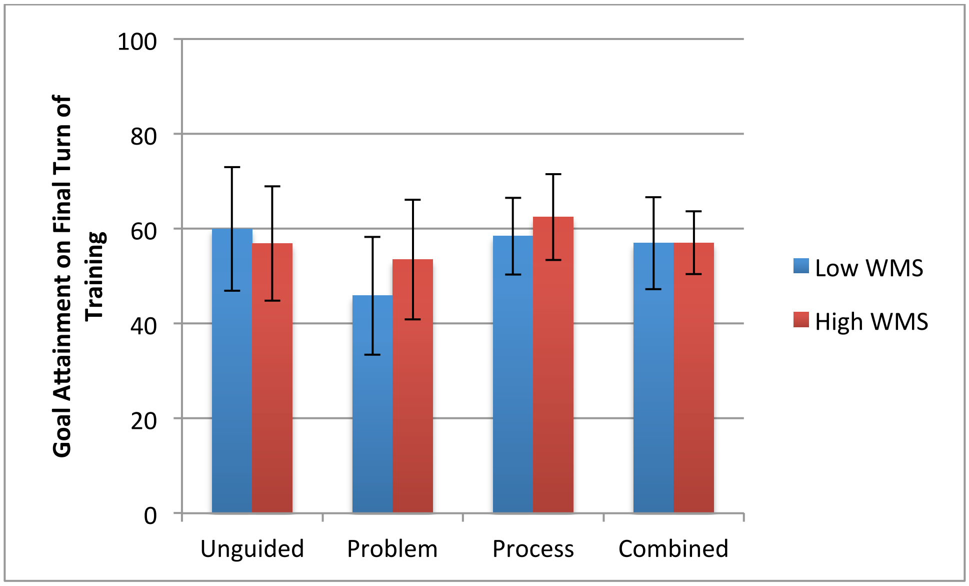


Figure 10. Goal Attainment for Low and High pre-training Decision Making Skill by Condition

Much like the prior two analyses, this prediction expected an interaction between the individual difference variable of working memory span and instructional condition. Working memory span ranged from a total memory span of 4 to 48 (M = 24, SD = 9.6) and a median split classified individuals at 23 and under as low working memory span and those over 23 as high. A univariate analysis of variance test showed no significant interaction between the level of working memory span and the instructional condition ($F(3,129)=0.402, p = .752, \eta^2_p=.009$).

Prediction 2: *It is predicted that individuals with lower levels of pre-training metacognitive awareness will perform better with process-focused instruction while higher level individuals will perform better with unguided instruction*

Table 10. Goal Attainment for Low and High pre-training Working Memory Span by Condition

	Low Fluid Intelligence	High Fluid Intelligence
Unguided	60.9028 (26.8431)	55.9838 (23.1776)
Problem	51.9240 (28.0002)	48.1829 (22.3883)
Process	57.4479 (16.4885)	65.8036 (16.9461)
Combined	58.7660 (12.4092)	55.7523 (18.2002)

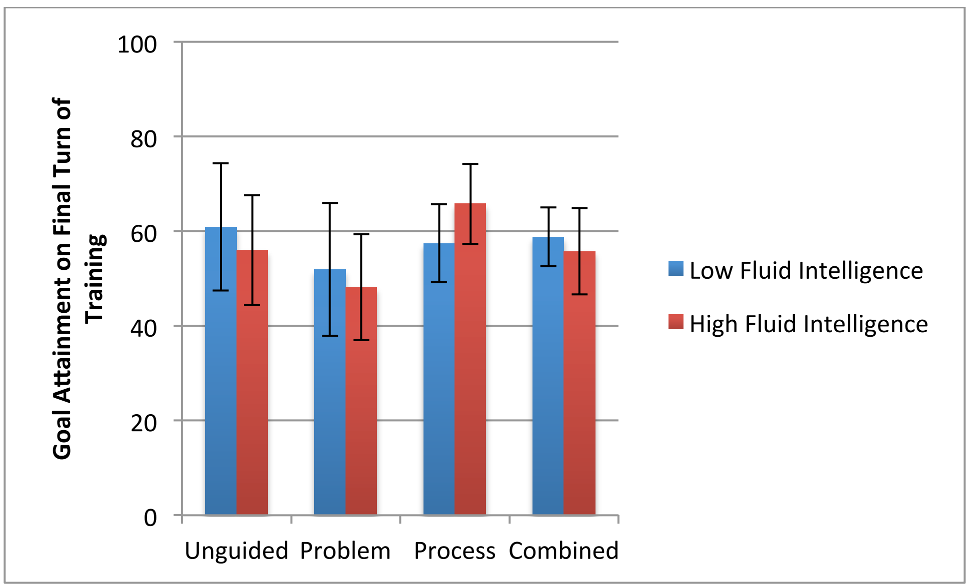


Figure 11. Goal Attainment for Low and High pre-training Fluid Intelligence by Condition

The final prediction tests for the interaction between high and low levels of fluid intelligence with the instructional conditions. Fluid intelligence ranged from 2 to 12 (*M* = 7.5, *SD* = 2.2); individuals scoring 7 or higher were considered high fluid intelligence while those under 7 were considered low. Univariate analysis of variance focused on the final training performance indicate no significant interaction ($F(3,129)=0.693, p = .558, \eta^2_p=.016$) between the variables of interest suggesting no differences in performance by condition when accounting for the pre-training level of fluid intelligence.

Additional Analyses

Early stages of data analysis showed several key aspects that may have impacted hypothesized results. First is the previously mentioned variable of prior experience playing turn-based strategy games. Originally included as part of the demographics questionnaire and investigated as a covariate variable, a significant interaction between this variable and the experimental manipulation of instructional condition ruled out the utilization of this variable as a statistical covariate in the above analyses. Prior research supporting the potential importance of prior experience and skill level (e.g. Batha & Carroll, 1998; Berardi-Colette, Buyer, Dominowski, & Rellinger, 1995; Chi and VanLehn, 2010) prompted the addition of a series of analyses to investigate the difference in the first two hypotheses across individuals who already had exposure to turn-based strategy games and those who did not have this type of experience.

Participants with prior turn-based strategy game experience were first isolated as a group. A mixed between within ANOVA was performed to test the effects of performance across training times by condition for these more experienced participants. Results indicate no significant interaction between time and condition ($F(3,61)=0.731, p = .537, \eta^2_p=.035$) as well as no significant main effects for either time ($F(3,61)=0.614, p = .436, \eta^2_p=.010$) or condition

(F(3,61)=1.061,p = .372, η^2_p=.050). The same analysis was then conducted for participants reporting no prior turn-based strategy game experience. This second analysis again showed no significant interaction for time by condition (F(3,61)=1.028,p = . 386, η^2_p=.040) and no main effect for time (F(3,61)=2.519,p = .118, η^2_p=.048). However, in examining this group of novices alone a main effect for condition was observed (F(3,61)=4.851,p = .004, η^2_p=.193). Post hoc analyses using a Bonferroni correction suggest this difference is the effect of the Unguided (C1), Process-focused (C3), and Combined guidance (C4) conditions significantly outperforming participants in the Problem-focused (C2) condition during the two training scenarios.

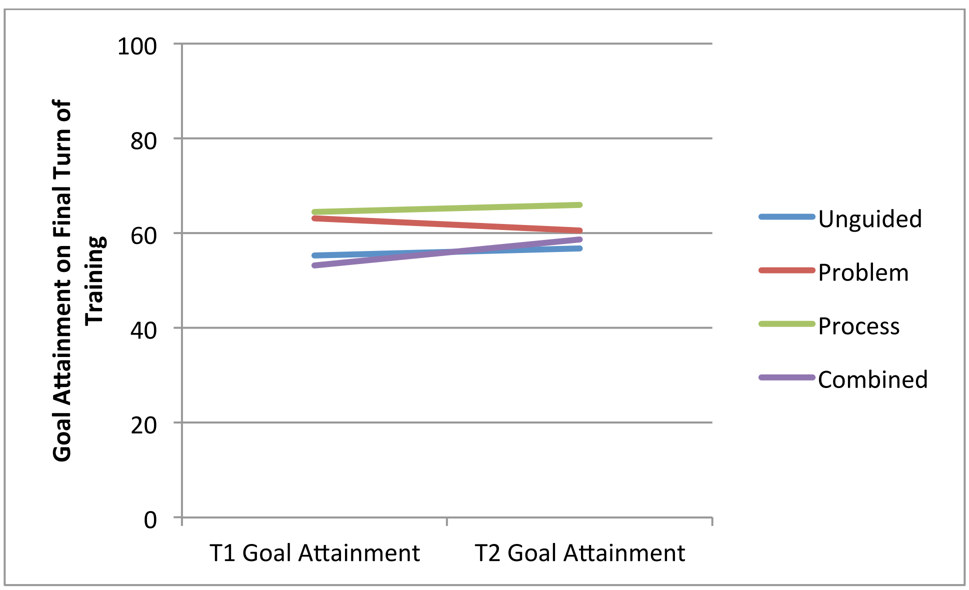


Figure 12. Goal attainment during training for participants with prior turn-based strategy game experience

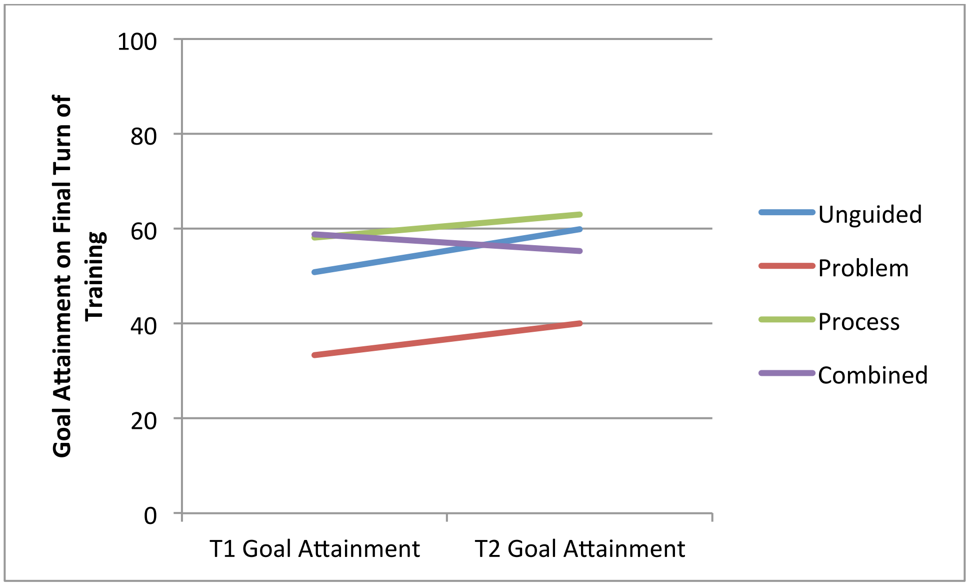


Figure 13. Goal attainment during training for participants with no prior turn-based strategy game experience

Substantial extant literature examining aptitude treatment interactions (e.g. Crohnback & Snow, 1977; Snow, 1989; Park & Lee, 2004) suggests that instruction impacts high and low level performers differently. In the current research it was expected that key differences in the utility of each instructional approach would be closely tied to the level of performance in the initial stages of training. Initial analyses supported few differences by condition across all participants or the expected interaction between training condition and individual differences. Yet a main effect of the DMQ and the impact of prior strategy game experience pointed to the importance of prior general task experience. With theoretical support that experience is often related to differential effectiveness of training approaches it was expected that key differences in the utility of each instructional approach might be closely tied to the level of performance in the initial stages of training. Thus a median split of goal attainment at the mid-point of the first training was conducted to segment two groups, labeled as high and low performers. The median analyses at this mid point of the initial training produced a range of goal attainment scores from 47.5 to 80.42 with the mean goal attainment being 71.04 and a median goal attainment of 72.5. The mid-point was selected as it provided a measure providing enough turns to measure variability in performance, yet with a limited amount of training exposure. While it is recognized that this measure is still potentially confounded by the training interventions, it is expected to provide important insight for future investigations.

An ANOVA examining the impact of initial performance level and training condition on the final training performance supported a significant interaction between the initial performance and the training condition ($F(3, 122) = 4.293$, $p = .006$, $\eta^2_p = .095$). Individual ANOVAs indicate that this interaction is a result of significant difference across training conditions within the initially low performers ($F(3, 60) = 3.461$, $p = .022$, $\eta^2_p = .148$). Post-hoc analyses with Bonferroni correction showed that this significant difference was attributed to individuals in the process training condition showing significantly higher performance during training compared to individuals in the problem focused training condition. (Mean Difference = 24.15, $p = .029$). No significant differences were observed across the training conditions for individuals with initially higher levels of performance ($F(3, 62) = 2.146$, $p = .103$, $\eta^2_p = .094$).

In each training and transfer scenario an external event had a negative impact on the overall system state. While this was a purposeful feature of the system which tests the participant's ability to handle not only direct and known indirect influences on the system, but also unexpected influences on the system, initial review of the data suggests that the negative impact on the system may have led to both a mathematical and psychological impact on performance. This prompted a final series of additional analyses that focus on goal attainment differences at the mid-point of each scenario. An examination of performance as defined as the level of goal attainment for the first half of each training scenario (MidGoalAttainment) showed a significant interaction of time by condition ($F(3,117)=3.03, p = .023, \eta^2_p=.078$). Independent paired samples t-tests, however, indicate no significant change across conditions for either the problem ($t(31)=0.495, p=.624$) or process guidance condition ($t(28)= -0.713, p=.482$). Furthermore, goal attainment was observed to decrease slightly in the combined guidance condition ($t(27)= 2.040$ $p=.051$) and increase significantly in the unguided condition ($t(31)= -2.116, p=.043$). Thus while an interaction is supported, the nature of the interaction is an unexpected finding. Univariate analysis of variance tests of the simple effects for condition indicate a significant difference ($F(3,129)=3.950, p = .010, \eta^2_p=.084$) with participant in the unguided condition having significantly higher goal attainment than participants in the problem-focused condition at the mid-point of the second training (Mean difference = 3.014, SE = 1.021, p = .023) and participant in the problem-focused condition having marginally higher goal attainment than participants in the problem-focused condition (Mean difference = 2.598, SE = 1.014, p = .069). No significant differences were observed between conditions for MidGoalAttainment ($F(3,127)=0.579, p = .630, \eta^2_p=.014$) performance in the transfer scenario.

Table 11. Mid Goal Attainment Means and Standard Deviations

	Training1 MidGoal Attainment	Training2 MidGoal Attainment	Transfer MidGoal Attainment
Unguided	72.4798	73.5753	69.8808
	(3.5336)	(3.7997)	(3.6606)
Problem	71.3290	70.5747	69.1111
	(4.4628)	(5.1224)	(4.0393)
Process	72.9018	73.2887	68.3735
	(2.2637)	(3.5674)	(3.6737)
Combined	72.9630	71.6204	68.7109
	(2.9859)	(3.2297)	(4.5847)

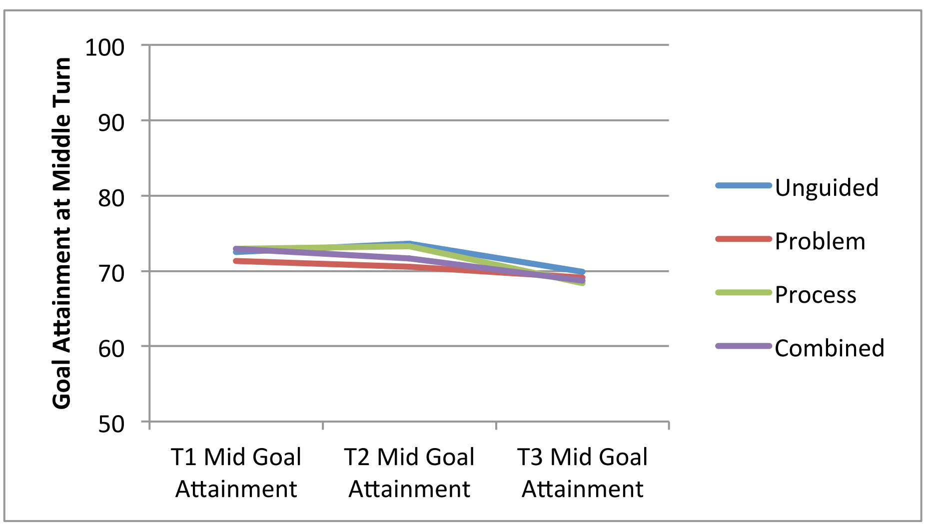


Figure 14. Mid-Goal Attainment by condition across training (T1 and T2) and transfer (T3)

CHAPTER SIX: DISCUSSION

Research Findings and Theoretical Implications

Prior work in the area of complex, dynamic decision making has focused largely on expertise driven decision processes. While extensive critical models of recognition and expertise driven decision making are available in the literature, a need exists both in the theoretical literature as well as in real world settings for an empirically derived understanding of how to develop instruction to support the development of decision making (Jonassen, 2012). While expertise driven decision making and theorists of macrocognition (Klein et al, 2003) and situated cognition (Choi & Hannafin, 1995) suggest that the development of critical decision skills is best achieved within the domain and environment specific to a set of decisions. Yet work in problem solving as well as descriptive accounts of complex dynamic decision making suggest that a set of domain general skills and an understanding of the decision process may greatly aid in performance. In the descriptive work of European decision making researchers (e.g. Brehmer, 1992; Dörner, 1996; etc.) behaviors such as asking "why" questions, goal development and refinement, and learning from one's own experiences have been linked to "good" decision making. These skills closely mirror the components of both the knowledge and regulation aspects of metacognition and suggest that even without domain specific knowledge a guiding mental framework for such tasks aids in performance. Additional support for the role of domain general knowledge within problem solving research (e.g. Berardi-Colette, Buyer, Dominowski, & Rellinger, 1995; Chi and VanLehn, 2010; Mathan & Koedinger, 2005; Batha & Carroll, 1998) suggests that instruction focusing on the process of problem solving at the metacognitive level produces better problem solving than instruction focused on problem-specific or cognitive level support. From this built the theoretical groundings of the current work which posit that instruction supporting the development of a general framework of decision making at the metacognitive level would lead to better performance on a complex, dynamic decision making task. To test the hypothesized efficacy of process-focused guidance versus problem-focused guidance, comparisons were taken in training and transfer sessions for these as well as a combined and an unguided instructional approach.

Analyses of goal attainment at the end of training support the use of process-focused instructional prompts compared to problem-focused prompts. This is an important finding which both supports the translation of problem-solving instructional research to complex, dynamic decision tasks. Process-focused prompts in the current research were designed to activate meta-level processing by prompting key aspects of metacognitive awareness from the literature. Thus this finding also extends support for the importance of active metacognitive processing during decision making in unfamiliar tasks. This latter implication is further refined through examination of the additional analyses examining the role of prior game experience and initial performance level within the task.

As illustrated in earlier sections of this paper, the success of training requires a match between the instructional approach and the needs and skill level of the learner. Unexpectedly a priori hypotheses in the current work that expected differential performance outcomes based on the type of training and individual differences in metacognitive awareness, working memory span, and fluid intelligence were largely unsupported. That is not to say, however, that the prior experience or initial skill level of participants had no effect on the utility of the various training methods. While little support was found for differences based on the a priori selected individual difference variables metacognitive awareness, working memory span, or fluid intelligence, two key analyses reinforce the importance of individual learner characteristics when selecting instructional approaches.

Specifically, additional analyses highlighted the importance of initial performance levels during training. Within the initially low performing group, analyses supported the use of process-focused prompting as substantially better than problem-focused prompting during training. Yet in the initially high performing group no differences were found in the performance outcomes of individuals across the four instructional conditions. While this finding mirrors many earlier findings suggesting instructional supports must match the needs of the learner, it also provides an important step forward in the literature in two facets. First, they support the application of cognitive learning theories such as Sweller (2003) to learning within an ill-defined complex, dynamic decision making task by showing that learners at different skill levels near the beginning of training benefit from different types of instruction. Specifically, low level individuals demonstrate better performance with process-focused guidance that targets the development or utilization of meta-level processes while the type of training support provided is not as critical for higher level individuals. Second, findings from the initially low performance group support the use of process-focused prompt guidance as an important instructional support approach extending previous work with such guidance from the realm of laboratory based problem solving tasks (Berardi-Colette, Buyer, Dominowski, & Rellinger, 1995) to more complex, dynamic decision tasks. Furthermore this supports the notion that while more experienced levels decision making may benefit from domain specific information, in less experienced decision makers metacognitive processes and support for these processes can provide an important foundation for decision making.

While the pattern of results for the initially low performers indicated a benefit of process-focused guidance above problem-focused guidance, intriguingly no differences were observed between the problem-focused guidance and no guidance. Additional analyses examining individuals with no previous strategy game-play experience further suggested a relationship between problem-focused guidance and lower levels of goal attainment compared to other training conditions - in this case goal attainment was also found to be significantly lower than the goal attainment reached by participants in the unguided condition. From these findings it is hypothesized that perhaps the problem-focused guidance imposed greater levels of cognitive load for participants that lacked prior experience or knowledge of the type of task they were asked to complete. As Sweller (2003) points out, the utility of available information depends largely on an individual's ability to incorporate the information into a useful schema or mental model. Without a preexisting decision or task model and without prior experience with the task environment, it is possible that participants discarded or were overloaded with the addition of more cognitive level information while attempting to build a model of the task. While further investigation is still warranted, it is thought that the general nature of the process-focused prompts allowed and encouraged individuals to focus on strategy development within the new task environment. In contrast the problem-focused prompts offered little support for strategy development and instead offered details about system content that may either have had little meaning to the participants without a base structure for organizing the information or may potentially have even impeded exploration and strategy development. While it is beyond the scope of the current work, more detailed analyses of how participants interacted with the system across the different instructional conditions could potentially provide interesting insights into the impact of these various prompt types on decision strategies within the system.

It has been suggested that performance alone is not the sole indicator of decision skill in complex, dynamic tasks such as those utilized in the current research. Beyond performance, Brehmer and Thunholm (2011) point toward the importance of an individual's structural and dynamic understanding of the system model represent critical requirements for successful decision making in complex, dynamic environments. Towards this, the current research examined both structural and dynamic aspects of participants' mental models of the training and transfer scenarios. Specifically, it was expected that like training performance participants receiving process-focused guidance would develop more accurate models of the systems. These predictions were not supported by the research, which found no differences between conditions for either of the structural mental model tasks (training or transfer) or the transfer dynamic task. While significant differences were supported between the conditions for the dynamic mental models in the training scenario, these differences were not in support of process-focused guidance as expected. In contrast these differences suggest that participants receiving unguided training form more accurate dynamic models of the system than either participants trained with process-focused or problem-focused guidance alone. In contrast to the expected support for guided learning, this finding would appear to support the constructivist view of discovery learning whereby individuals are expected to develop a deeper understanding of the learning material when the learner develops or constructs their own meaning of the material (Jonassen, 1991). Yet it is also noted that while participants in the unguided condition performed better than the participants in either the process-focused or problem-focused conditions, that none of the conditions performed exceedingly well with the best performance showing predicted change values an average of nearly 3 points from expected change values. It is also interesting to note that differences were found following two training sessions, no differences were found after a single transfer session. While this could be an artifact of task difficulty or measurement error and thus was not suitable for direct statistical comparison, it does result in potentially interesting avenues for future research. Thus another issue for further investigation is how the structural and dynamic models of these systems develop over time.

Somewhat surprisingly within the individual difference measures of Metacongitive Awareness, Working Memory Span, or General Fluid Intelligence isolated in the current research, little support was for relationships between the four a priori hypothesized individual difference variables and performance and no link was found between the instructional condition and high or low levels of on each of these individual differences. A number of factors could explain the lack of differences. First, it was noted that work by Gonzalez, Thomas, and Vanyukov (2005) suggests that different microworld tasks may create different cognitive demands. Furthermore, the addition of instructional supports in three of the four conditions may have altered the cognitive demands of the task environment. Thus, it is recommended that the relationships between these and other potentially informative individual difference variables with performance within the CODEM task environment be given closer examination without the incorporation of instructional guidance prior to dismissing their potential utility in future research.

Despite only limited support for a priori hypothesized individual difference variables, additional support for the role of prior task general schemas was found in the role of prior turn-based strategy game experience on performance. Much like the previous findings, this series of analyses suggests that participants who report no prior experience playing turn-based strategy games perform better with process-focused guidance than with problem-focused guidance or no guidance. Again mirroring the previous findings participants who report prior experience playing turn-based strategy games show no differences in performance across the different instructional conditions. This suggests that instructional support for individuals with limited task ability and no prior experience with the type of task are likely to benefit from first developing the meta processes needed for “good” general decision skills. Additionally, it highlights the potential pitfalls of adding additional cognitive information and likely cognitive load to individuals already struggling with building task strategies. While limited in scope and generalizability, these findings point to potentially important avenues for further investigation. Specifically, these findings reinforce the importance of understanding the learner and how pre-training experiences and skills influence the instructional needs of the individual and point to the need for future research to isolate the most appropriate individual difference variables within the current task environment.

While established theories including cognitive load theory (Sweller, 2003) and the expertise reversal effect, and in practice across multiple studies presented across the literature (e.g. Batha & Carroll, 1998; Chi & VanLehn, 2010; Mathan & Koedinger, 2005, etc.), the present research sought to examine the possibility that these theories should be extended to learning within complex, dynamic decision making as well. Within the current research similar effects were in fact observed when a priori analyses were conducted with high and low initial performers defined by a median split of performance at the mid-point of initial training. With this categorization of learner skills results support very different patterns of performance under the four training conditions for initially low versus high performing decision makers, with process-guidance aiding performance in low level performers while high level performers did equally well in any condition. While further research is needed to confirm the exact relationships of pre-training decision performance, it is expected that the differences found in the current research would extend to pre-training task performance if these measures were included.

Practical Implications

The current research offers important implications for practical application in the realm of complex, dynamic decision making. While additional research is still necessary, which will be discussed below, the benefit of process-guidance beyond problem-focused guidance provides support for the key role of general skills in decision making. While expert decision making is critical in many real-world tasks, the development of the expertise driven recognition skills is often an unreasonable expectation for individuals beyond the highest ranking in the field. Yet there exists a real and critical need for better preparing and aiding decision making in lower echelon non-expert individuals. Findings of the current research support the utility of such general or metacognitive skills, and specifically for supporting these skills through process-focused guidance in lower performing individuals during training. Furthermore, these findings suggest that in complex, dynamic tasks, instructional guidance should not follow the traditional cognitive or problem-focused approach, but instead is better focused on supporting the process of decision making with metacognitive level guidance. From a practical application this is an important contribution as process-focused guidance provides for a more economical training solution as training and aiding supports may easily be ported from one training scenario to another providing reusable training supports.

While further research is necessary, support for metacognitive or process level guidance can be expected to easily extend to the area of decision aiding as well. While the primary focus of the current work was training, a real need also exists beyond the classroom or virtual training environment to provide continued support in the field. Future research should consider the utility of incorporating process-level or metacognitive supports in checklists and technological decision aids in the field. By prompting individuals within the field these aids could support information gathering, goal defining, goal shifting, and strategy selection while reminding individuals to consider both local and global factors and consequences as well as strategies and scenarios from previous decisions that might help formulate better decision actions in future situations. It has also been noted that in some situations, inaction is as detrimental to success as a wrong action. It is hypothesized that process-focused decision aiding, while not providing context specific support, could potentially reduce the consequences of inaction by supporting the development of suitable actions.

The current research highlights the role of previous experiences in training and performance. In practical applications, these factors should be considered as possible selection criteria as well as in the selection of the most appropriate training approaches for individuals of differing backgrounds. Specifically, individuals with prior strategy-game experience may be more adept at the decision processes necessary for complex, dynamic decision making. It is thought that these individuals have likely developed thought frameworks and mental models for the general task environment which supports the acquisition and processing of new information and strategy development necessary to successfully operate within these environments. Alternatively, given the current support for metacognitive prompts, these thought frameworks may simply represent better metacognitive skills within the environment. Both hypotheses represent interesting avenues for future research. If further research extends support for these hypotheses, both selection of individuals with this experience and/or the pre-training exposure to these experiences could potentially accelerate training and strengthen decisions in the field.

Research Limitations and Directions for Future Research

While the current research findings offer a better understanding of the role of instructional support in complex and dynamic decision making, it is important to consider how the limitations of the research design and execution may limit the generalizability of these findings. Paramount among these is the apparent need for additional training experience. As highlighted in the findings, no single condition reached above 65% goal attainment in performance. Additionally, performance on the transfer task was flat or declined. It can be argued that more extensive training would further extend the artificial and laboratory nature of the task as in practical application training time is often quite limited. Yet even with limited training time, notes from the current study suggest that more efficient training schedules may be possible. Thus it is recommended that future research explore the issue of additional training exposure in two approaches. First, small n longitudinal or single subject design research could be utilized to investigate how many training sessions are required to reach learning or performance asymptote. From a theoretic viewpoint this would extend the understanding of performance development and offer a better understanding of idealized training.

Alternatively, research should consider alternative training scenario structures. One avenue for this research would be to expose participants to shorter training scenarios with more iterations of a scenario. For example, training scenarios might be shortened to 7 turns instead of 13 and be completed four times instead of two. It is hypothesized that this could change motivation and frustration levels of participants by essentially giving them a "clean start" earlier in the scenario. Additionally, it is expected that the additional exposures to the same conditions would better support the formation of task strategies more quickly and accurately. From a practical viewpoint research investigating the structure of training would extend the understanding of the best structure or use of available training time.

A key lesson taken from the current research is the criticality of the task difficulty. This was noted both in experimenter notes during the sessions as well as in data analysis which indicated adequate performance by some participants prior to the external impact on the system followed by a decline in performance in all conditions following the external event. While the impact on performance may be an artifact of system destabilization at lower performance levels, it was noted that participant motivation and frustration were commonplace. While no quantitative measures of either motivation or frustration were collected during the current experiment, participant comments logged during the sessions such as "nothing works" in reference to strategies and “I can’t do anything right” or “I just don’t get it” suggested a level of frustration and potential feelings of failure during the session for a number of participants. In extreme cases it was noted that participants simply quit making decisions and instead began to click through the system. While the most extreme cases were eliminated in data analysis, it is unclear exactly how the behaviors and decisions may have been impacted in less extreme cases. In particular it is unclear how levels of frustration and motivation may have influenced participants’ attention to and utilization of the instructional prompts. This is highlighted here both as a potential limitation of the current research and as discussed next an important avenue for future research.

It is hypothesized that an additional effect of shortening the number of turns in the training scenarios is a potential influence on the motivation of participants by giving them a “clean start” sooner. From a theoretical perspective it is proposed that this could more easily build the participant’s mental model of the system by increasing the number of similar iterations as well as provide the opportunity to test different strategies with more similar system dynamic relationships. It is important to recognize that while each scenario structurally contained the same variables, variable relationships, and began at the same start state the system dynamics nature of the task means that the system changes based on the user’s interactions with the system. Thus if one strategy and point allocation is executed in one scenario iteration and a different strategy and point allocation is executed in another scenario iteration the dynamics and system relationships will likely be different based on these different paths. By creating shorter scenarios and completing more iterations of the scenario participants could be given the opportunity to better understand the initial dynamics and how their approach the strategy development impacts the system. It is cautioned, however, that utilization of a single training scenario could lead to problem-specific learning and still fail to develop the general decision skills sought by the current research.

Alternatively, training scenarios could be built to provide part task training by providing a simpler form of the system for initial training and building complexity. Beginning with less difficult scenarios could provide participants with an achievable level of challenge while allowing for development of general task mental models and strategies. More complex scenarios could then be introduced to develop transfer of these general mental models and strategies to new and increasingly complex system dynamics.

Within the individual difference measures isolated in the current research, little support was for relationships between multiple a priori hypothesized individual difference variables and performance and no link was found between the instructional condition and high or low levels of on each of these individual differences. A number of factors may explain the lack of differences. First, it is noted that work by Gonzalez, Thomas, and Vanyukov (2005) suggests that different microworld tasks may create different cognitive demands. Furthermore, the addition of instructional supports in three of the four conditions is expected to have changed the cognitive demands of the task environment. Thus, it is recommended that the relationships between these and other potentially informative individual difference variables with performance within the CODEM task environment be given closer examination without the incorporation of instructional guidance prior to dismissing their potential utility in future research. Unfortunately, the design of the current research did not allow for the extension of such analyses and thus this becomes a topic for future research. However, the lack of relationship between individual difference variables which were found to be related in prior research also adds a note of caution to any interpretation of these findings. Specifically the current research failed to find expected relationships between the MAI and DMQ as reported in Batha and Carroll (1998) and between working memory span and measures of fluid intelligence which were found to be related in Gonzalez et al (2005). It is unclear whether this lack of relationship is a result of measurement error or another unrelated factor.

While the current research failed to support moderating effects of the targeted individual difference variables, additional analyses show both differences in the effectiveness of instructional approaches based on initial performance as well as for individuals lacking prior turn-based strategy game experience. These differences reinforce the importance of considering the impact of prior experience on the effectiveness of various instructional approaches. Further research is needed specifically to target key individual differences that may impact both performance and the relationship between the instructional approach and performance.

Conclusions

The current research provides a critical step forward in both the theoretical and practical knowledge of the role of metacognitive domain general skills in non-expert decision making. While extensive works have focused on expertise driven decision making far less concentration has been given to the issue of successful decision making in non-experts. Yet the practical need for the latter is growing in fields from business to military and medical where increasing complexity and the shifting of decision responsibilities to less experienced individuals is ever increasing. As Jonassen (2012) notes, a critical need has developed to understand how to develop effective instruction to improve decision making. The current research directly addressed this need within a complex, dynamic decision task. The current research extends our theoretical knowledge by reinforcing and extending the findings of Berardi-Colette, Buyer, Dominowski, and Rellinger (1995) from traditional types of problems solving tasks toward more complex, dynamic models of real world decision tasks. While support was not found for the a priori hypothesized individual differences in this study, additional analyses support differences in instructional effectiveness based on learner characteristics such as prior game play experience. Thus the current research further reinforces the need for understanding how learner specific characteristics such as prior similar task experience and task performance impact the efficacy of instruction.

While further research is still necessitated, the findings of this research suggest that reusable decision supports can be developed to aid decision makers in the process of decision making during training. The current research demonstrated that process-focused guidance support better decision performance than problem-focused guidance in individuals with initially low task performance as well as those with no prior strategy game experience. From a practical application this is a critical finding as process-focused guidance is more practical to develop for ill-defined domains which lack one correct solution path. Additionally, the task general nature of process-focused guidance provides for reusable instructional supports that can be ported from one training scenario to another with little or no modification. Together these factors should result in a cheaper, as well as more effective training instructional approach compared to a more traditional problem-focused instruction. Additionally, the current research suggests that further investigations should consider the applicability of process-guidance not only as a training aid, but also as a potentially powerful decision aid in the field.

Despite mixed findings across the a priori hypotheses, the current research provides an important step forward in the theoretical and practical understanding of the role of instructional guidance in the development of complex, dynamic decision making. Specifically this work extended the use of process-focused guidance to complex, dynamic decision tasks. Finally it highlights the importance of individual skill and experience level for selecting the most appropriate training approach for developing both performance and mental models in a complex, dynamic decision task.

APPENDIX A: DEMOGRAPHICS QUESTIONNAIRE

1) Age: _____________ 2) Gender (check): ________Male ________ Female

3) To your knowledge, are you colorblind? Yes No

4) Are you currently enrolled as a student at a college or university? Yes No

5) If you answered yes to question 4,

Degree Sought (e.g. Associates, Bachelors, etc.) _____________________

Major _____________________ Year in School _________________

6) If you are not a current student, what is the highest degree you have completed?

____

7) What is the highest level math course you have completed? _______________________

8) When were you last enrolled in a math course? (year) ______________

9) How confident are you in your math ability?

1	2	3	4	5
Not at all Confident		Somewhat Confident		Very Confident

7) How often do you use a computer?

Daily_____ Several times a week ______ Occasionally_______ Never_______

8) Estimate how many hours per week you use a computer (circle one).

0-9 hours	10-19 hours	20-29 hours	30-39 hours	40+ hours

9) How many hours per week do you currently play video games?

0-9 hours	10-19 hours	20-29 hours	30-39 hours	40+ hours

10) Have you ever played a turn-based strategy game? (circle one) Yes No

11) How often do you turn-based strategy games (e.g., Civilization, Heroes of Might and Magic, etc.)

Never Rarely Monthly Weekly Daily

APPENDIX B: PROBLEM FOCUSED PROMPTS

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
1	The goal of the current task is to reach the green zone for each of the variables on the situation screen. To achieve this goal you need to understand that the points you add on the decision screen lead to direct changes in the levels of • Response Effectiveness • Communications • Infrastructure • Interagency Coordination • Public Safety and Security	Identify problem and relevant information	Identify goals and key system features/variables
2	Note on the decision screen that the more points you add to Response Effort the more positive the direct effect will be on the level of Response Effectiveness.	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the different LOEs and how points allocated to each LOE directly impact system variables
3	The more points you add to Response Logistics the more positive your direct influence will be on Communications, Infrastructure, and Interagency Coordination.	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the different LOEs and how points allocated to each LOE directly impact system variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
4	The more points you add to Services and Support the more positive your direct influence will be on both Interagency Coordination and Public Safety and Security.	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the different LOEs and how points allocated to each LOE directly impact system variables
5	When you add manpower points on the decision screen your decision creates direct changes in the variables • Response Effectiveness • Communications • Infrastructure • Interagency Coordination • Public Safety and Security Changing the level of these variables will in turn lead to additional changes in the status of related variables.	Justify solution(s)/Anticipate consequences of solution,	Understand how points allocated toward an LOE change the system variables both directly and indirectly. Account for these changes in the decision process/strategy, understand system dynamics, predict system change

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
6	To help you achieve your goal review the feedback screen to see exactly how your decision changed the system variables. If your current decision did not help you move toward your goal, try adjusting your decision in future turns.	Determine effects of solution and adapt solution path as needed	Adjust future decisions on this feedback
7	**NO PROMPT- LANDFALL**		
8	The goal of the current task is to reach the green zone for each of the variables on the situation screen. To achieve this goal you need to understand that in addition to direct changes, the points you add on the decision screen also lead to indirect changes in the variables • Civilian Compliance • Response Effectiveness • Communications • Infrastructure • Interagency Coordination • Public Safety and Security	Identify problem and relevant information	Identify goals and key system features/variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
9	The more points you add to Response Effort the more positive the direct effect will be on Response Effectiveness. These changes in Response Effectiveness will then impacts the status of • Civilian Compliance, • Interagency Coordination, • Public Safety and Security.	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the interrelationships between system variables and how a direct change in a system variable filters through to change other variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
10	The more points you add to Response Logistics the more positive the direct effect will be on Communications, Infrastructure, and Interagency Coordination. Changes in these three variables also lead to changes in other variables: • **Communications** effects the status of ○ Civilian Compliance, ○ Interagency Coordination, ○ Public Safety and Security • **Infrastructure** effects the levels of ○ Civilian Compliance, ○ Communications, ○ Public Safety and Security • **Interagency Coordination** impacts the levels of ○ Response Effort, ○ Communications, ○ Infrastructure	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the interrelationships between system variables and how a direct change in a system variable filters through to change other variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
11	The more points you add to Services and Support the more positive your direct influence will be on both Interagency Coordination and Public Safety and Security. Changes in **Interagency Coordination** will then effect the levels of ○ Response Effort, ○ Communications, ○ Infrastructure Changes in **Public Safety and Security** will affect the levels of ○ Civilian Compliance ○ Response Effort.	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the interrelationships between system variables and how a direct change in a system variable filters through to change other variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
12	When you add manpower points to a line of effort your decision creates a direct change in • Response Effectiveness • Communications • Infrastructure • Interagency Coordination • Public Safety and Security Changing the level of each of these variables then leads to additional changes in the levels of related variables.	Justify solution(s)/Anticipate consequences of solution	Understand system dynamics, predict system change
13	To help you achieve your goal review the feedback screen to see exactly how your decision changed the system variables. If your current decision did not help you move toward your goal, try adjusting your decision in future turns.	Determine effects of solution and adapt solution path as needed	Adjust future decisions on this feedback

APPENDIX C: PROCESS FOCUSED PROMPTS

Turn	Process-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
1	How are you defining your task goals and subgoals? How are you determining what information you need to reach these goals?	Identify problem and relevant information	Identify goals and key system features/variables
2	How are you developing an understanding of how the manpower points you allocate on the decision screen directly impacts the system variables? How does understanding these relationships help you move toward your goal?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the different LOEs and how points allocated to each LOE directly impact system variables
3	How are you deciding how many manpower points to allocate to each line of effort on the decision screen?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the interrelationships between system variables and how a direct change in a system variable filters through to change other variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
4	How are you deciding how many manpower points to allocate when a line of effort directly affects more than one variable?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand how points allocated toward an LOE change the system variables both directly and indirectly. Account for these changes in the decision process/strategy
5	Have you developed an understanding of how the manpower points you allocate directly and indirectly impact the system variables?	Justify solution(s)/Anticipate consequences of solution	Understand system dynamics, predict system change
6	How are you deciding whether your decision interventions are successful or unsuccessful? How is this affecting your future decisions?	Determine effects of solution and adapt solution path as needed	Adjust future decisions on this feedback
7	**NO PROMPT- LANDFALL**		
8	How are you adjusting your goals and subgoals as this task progresses? How are you determining what information you need to reach these goals?	Identify problem and relevant information	Identify goals and key system features/variables

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
9	How are you developing an understanding of relationships between variables as shown on the relations screen? How do these relationships relate to your decision making?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the different LOEs and how points allocated to each LOE directly impact system variables
10	How are you developing an understanding of how your decisions cause system variables to change the status of other variables? How has this understanding influenced your decision making process?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand the interrelationships between system variables and how a direct change in a system variable filters through to change other variables
11	How are you developing and understanding of how the number of manpower points you allocate to a line of effort both directly and indirectly change related variables?	Determine relevant information, key features, and constraints/Structure or restructure the problem space	Understand how points allocated toward an LOE change the system variables both directly and indirectly. Account for these changes in the decision process/strategy
12	How are you utilizing your understanding of the direct and indirect effects of an intervention to formulate your decision and anticipate how that decision will change the system?	Justify solution(s)/Anticipate consequences of solution	Understand system dynamics, predict system change

Turn	Problem-Focused Prompt	Instructional Goal (Jonassen, 1997)	Instructional Goal (Context Specific)
13	How are you deciding whether your decisions are successful or unsuccessful? How is this affecting your future decisions?	Determine effects of solution and adapt solution path as needed	Adjust future decisions on this feedback

APPENDIX D: CALCULATION OF GOAL ATTAINMENT

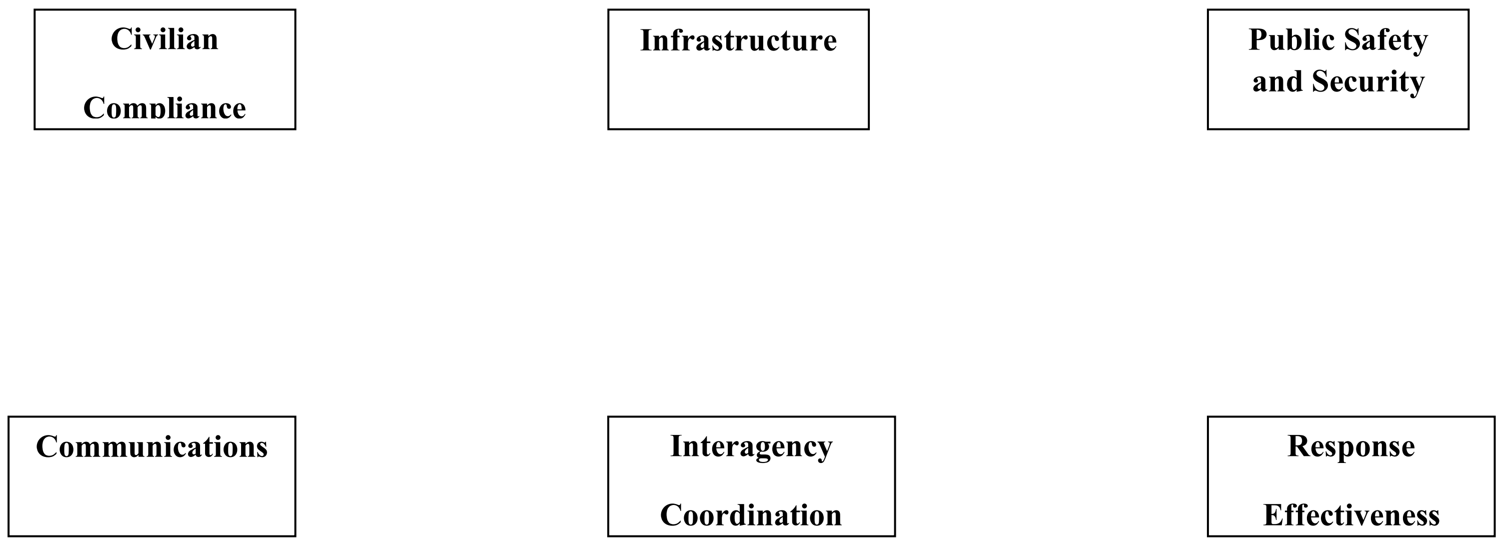
Operationally Defining Performance

Performance within each scenario is defined as the level of Goal Attainment averaged across the six system variables with 0 being the lowest level of Goal Attainment and 100 being the highest level of Goal Attainment. To compute the level of Goal Attainment at each turn, the relative distance between the raw score and the closest score to obtain the optimal range are computed. These relative distance scores are then averaged across the six variables in the system and the average is subtracted from 0. The resulting score is then multiplied by 100 to produce a percentage of goal achievement.

APPENDIX E: TRAINING MENTAL MODEL TASK

Mental Model Task Part 1

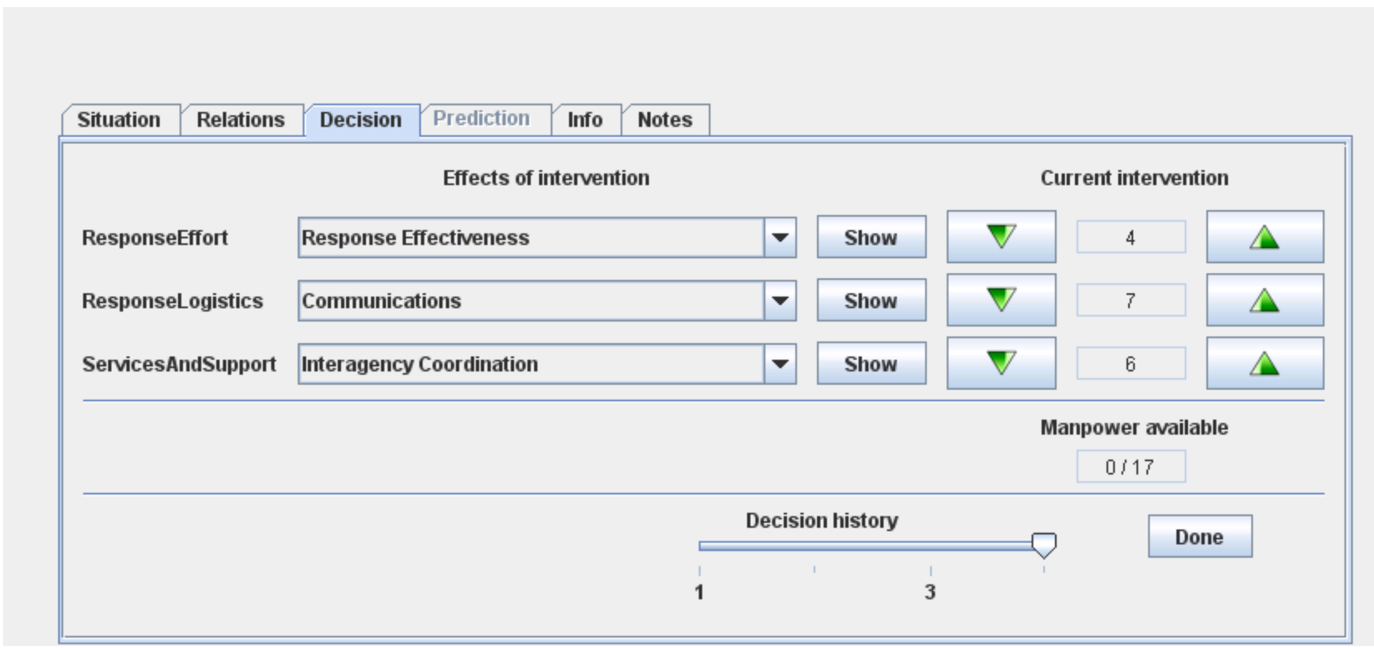
Please indicate with arrows how the variables presented below were related in the scenario you just completed.



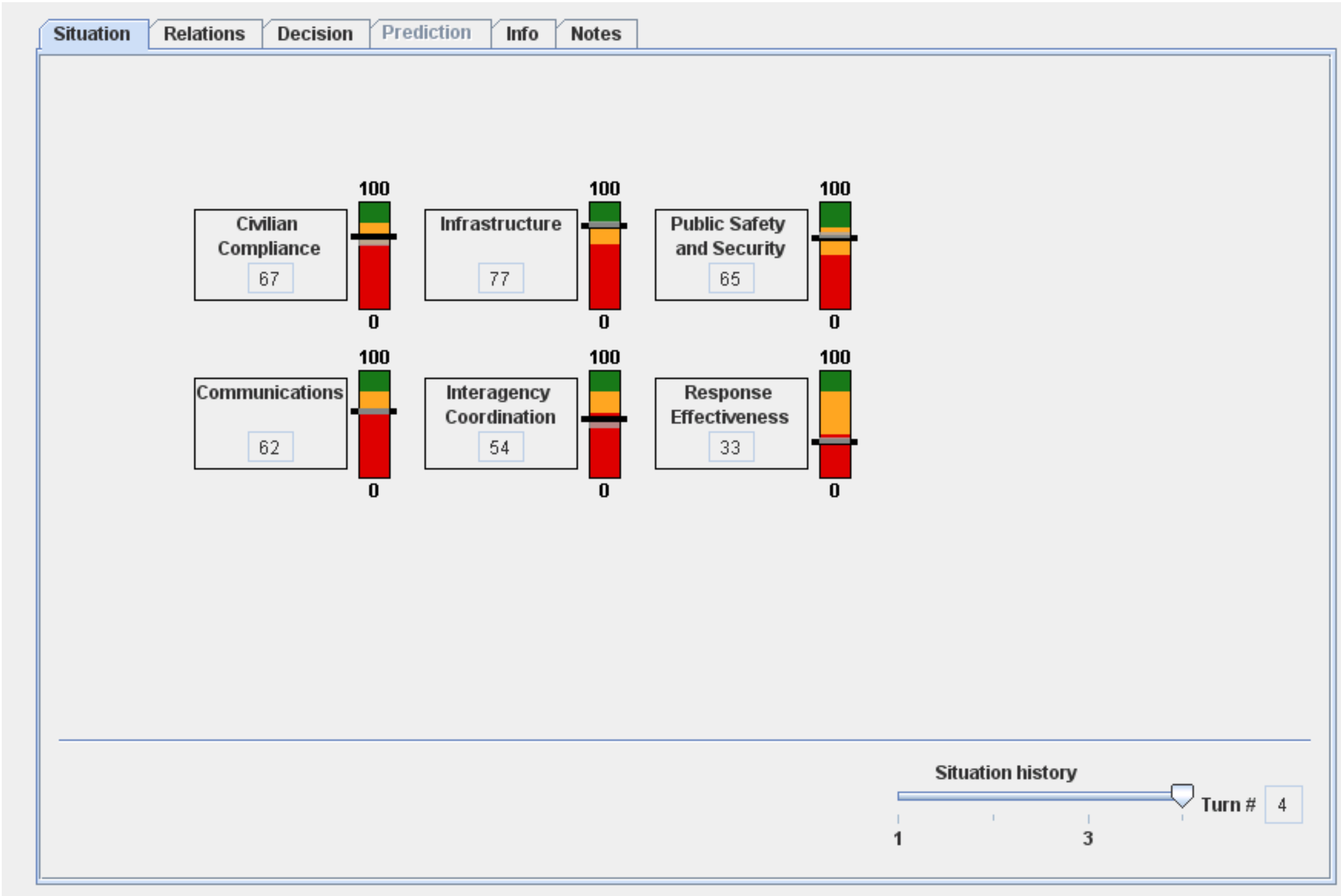
Mental Model Task Part II

Below you will find a representation of the variables and situation you encountered during your mission. The variable relationships and intervention effects are the same as they were during your mission. Please predict the value of each of the variables on the next turn (turn 5) given the intervention shown below. Use the knowledge you have gained of the situation, the interrelationships of system variables, the effects of various interventions, as well as the information provided below indicating the level of all variables on the current turn (turn 4). Please also rank your confidence in the accuracy of your predictions with 1 representing a very low confidence and 5 representing a very high confidence in the accuracy of your prediction. If you have any questions on how to complete this task please feel free to ask the experimenter for clarification.

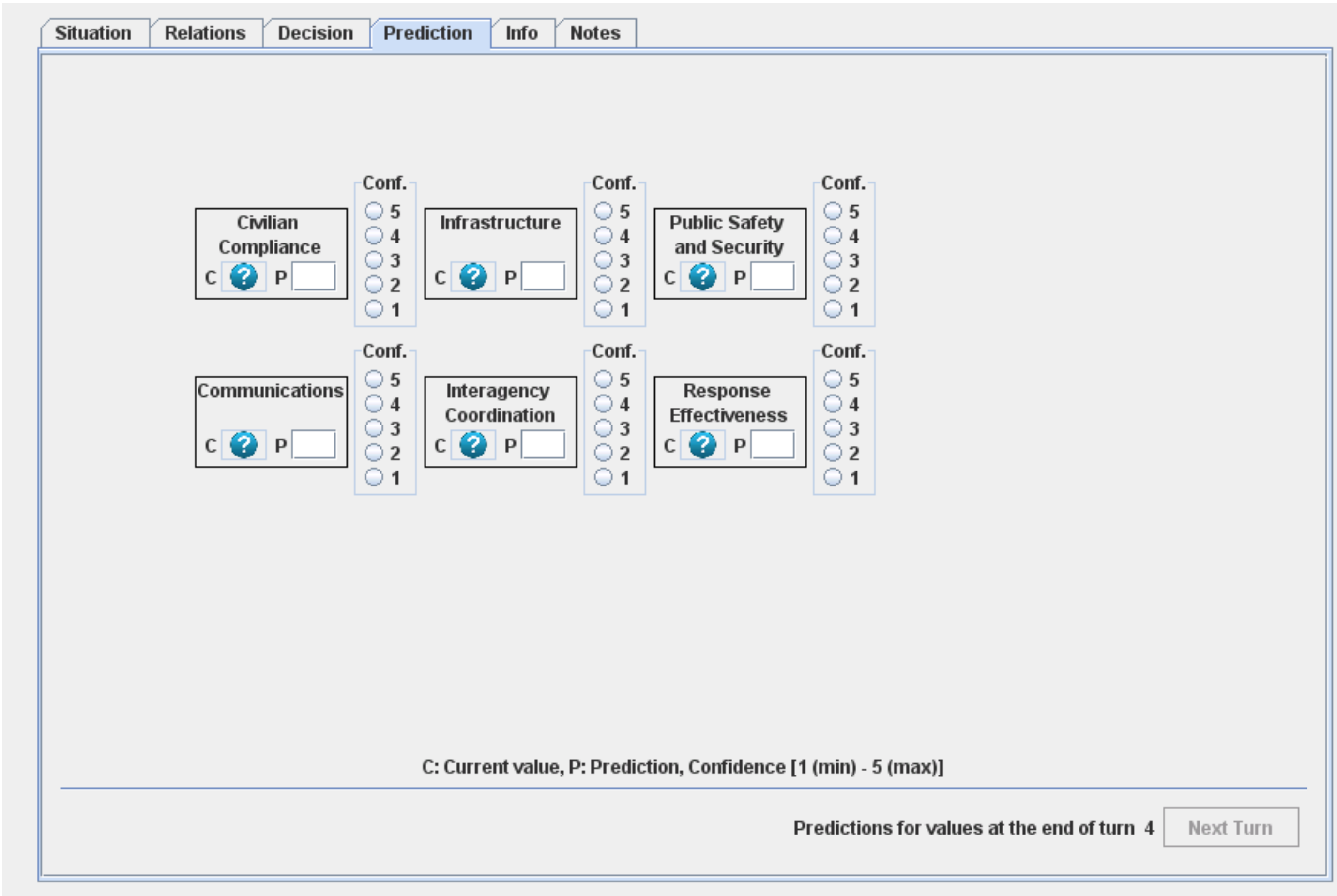
Given the following intervention:



As well as the Current State of the System Variables on turn 4:



Predict the value of each variable at the end of this turn (turn 4) / beginning of the next turn (turn 5):

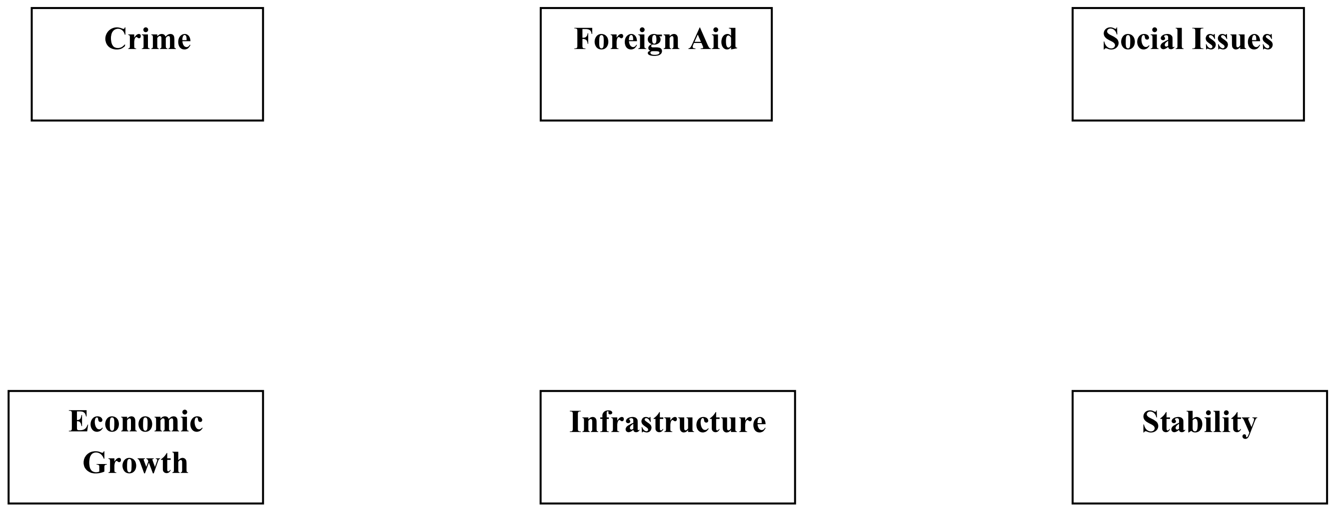


Is there any additional system information you would have used to improve your prediction?

APPENDIX F: TRANSFER MENTAL MODEL TASK

Mental Model Task Part 1

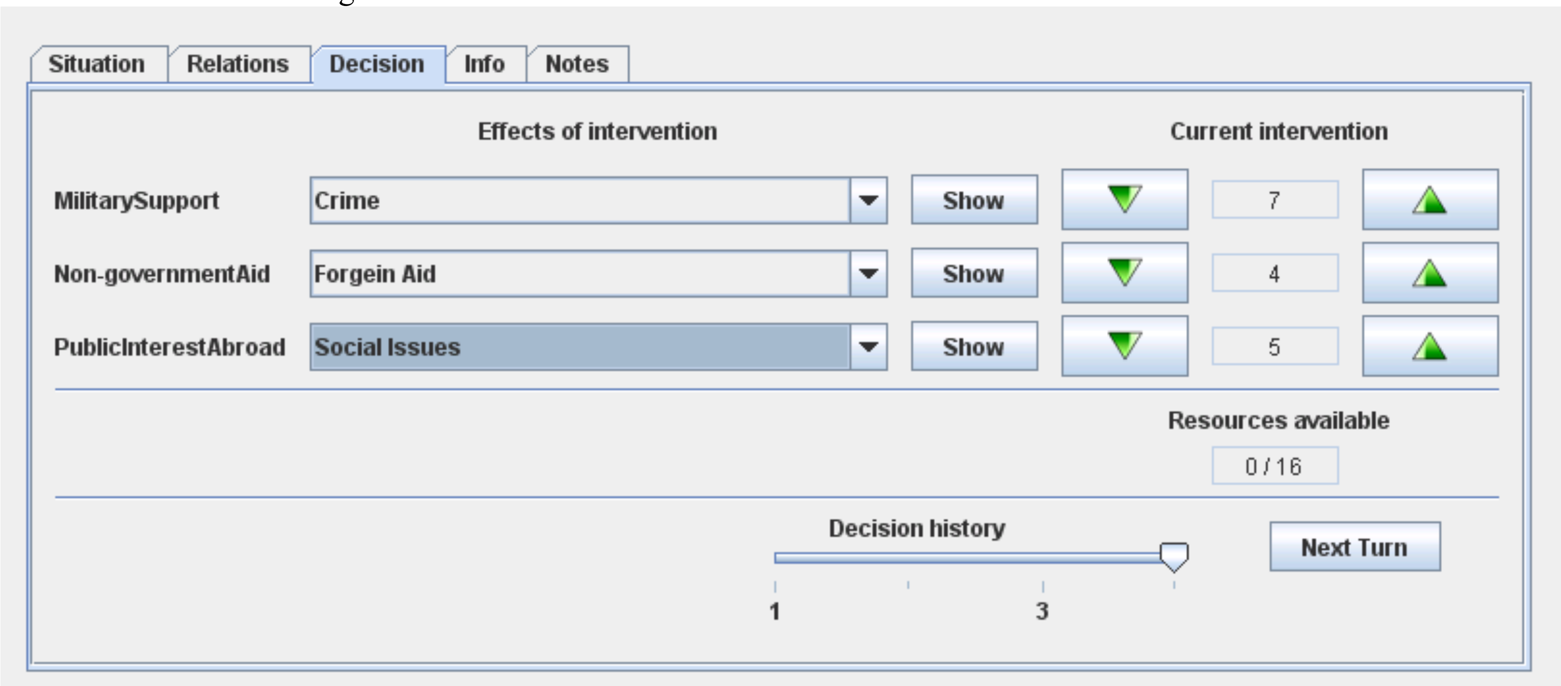
Please indicate with arrows how the variables presented below were related in the scenario you just completed.



Mental Model Task Part II

Below you will find a representation of the variables and situation you encountered during your mission. The variable relationships and intervention effects are the same as they were during your mission. Please predict the value of each of the variables on the next turn (turn 5) given the intervention shown below. Use the knowledge you have gained of the situation, the interrelationships of system variables, the effects of various interventions, as well as the information provided below indicating the level of all variables on the current turn (turn 4). Please also rank your confidence in the accuracy of your predictions with 1 representing a very low confidence and 5 representing a very high confidence in the accuracy of your prediction. If you have any questions on how to complete this task please feel free to ask the experimenter for clarification.

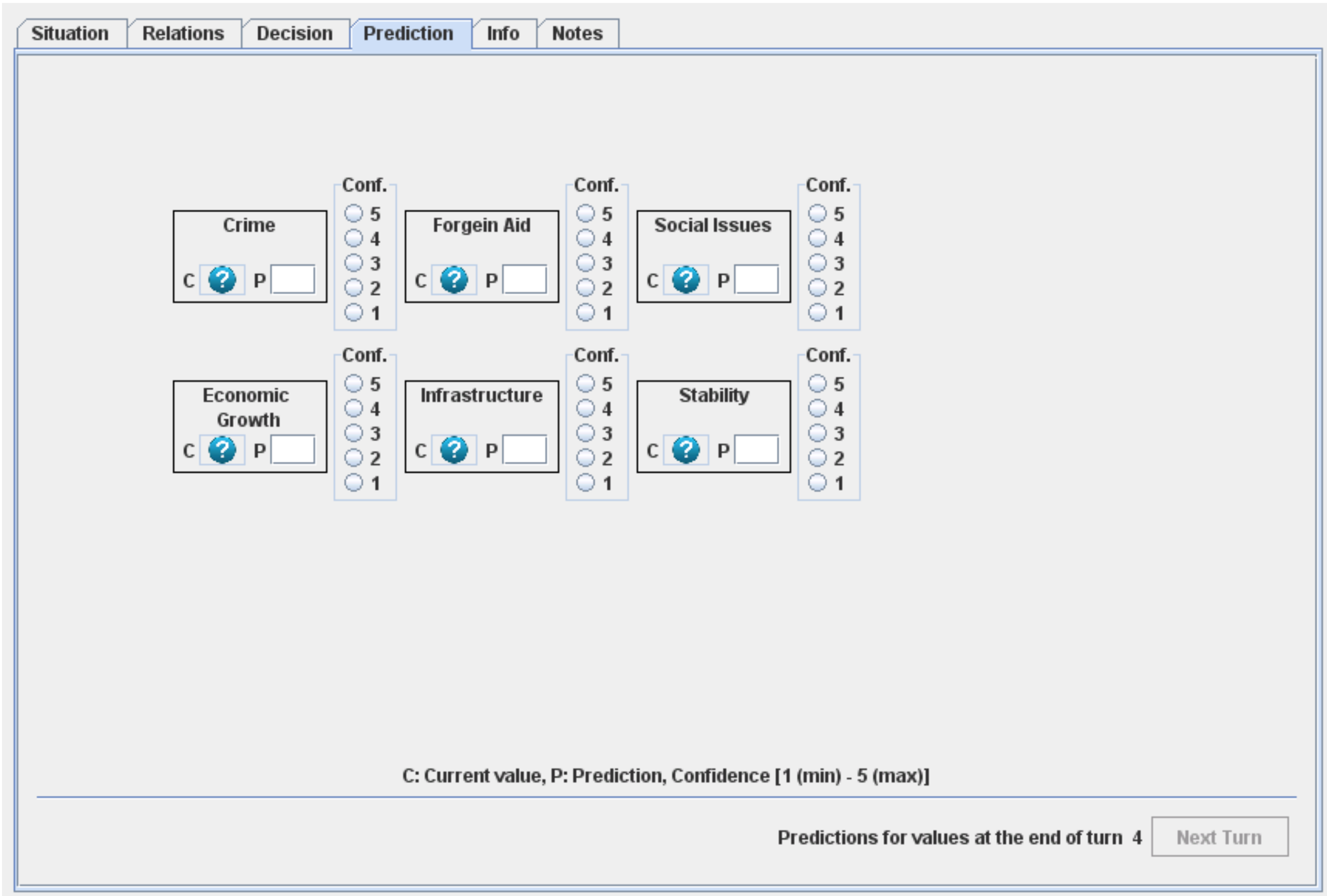
Given the following intervention:



As well as the Current State of the System Variables on turn 4:


Situation
Relations
Decision
Prediction
Info
Notes
Crime
45
Forgein Aid
50
Social Issues
0
Economic Growth
12
Infrastructure
40
Stability
28
100
0
Situation history
Turn #
4
1
3

Predict the value of each variable at the end of this turn (turn 4) / beginning of the next turn (turn 5):



Is there any additional system information you would have used to improve your prediction?

APPENDIX G: INSTITUTIONAL REVIEW BOARD APPROVAL

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Jessica Ray**

Date: **May 21, 2012**

Dear Researcher:

On 5/21/2012, the IRB approved the following minor modifications to human participant research until 03/08/2013 inclusive:

Type of Review:	IRB Addendum and Modification Request Form
Modification Type:	Three students added as research assistants: Annie Makalintal, Andrew Tungate, and Lisseth De La Cruz. Compensation increments have been adjusted to 30 minute increments ($5 per 30 minutes). Revised protocol and experimenter script now include an introductory walkthrough of the game system to train prior to the first scenario. Revised recruiting flyers uploaded and revised Informed Consent documents have been approved for use.
Project Title:	An Investigation of Training Approaches for Decision Making in Complex Environments
Investigator:	Jessica Ray
IRB Number:	SBE-12-08213
Funding Agency:	
Grant Title:	
Research ID:	N/A

The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 03/08/2013, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., CF IRB Chair, this letter is signed by:

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