AN INSIGHT INTO ADAPTATION: SELF-REGULATORY MECHANISMS AS A DRIVER OF ADAPTIVE PERFORMANCE OVER TIME

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ABSTRACT

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As the workplace becomes more complex there is an increasing need to further our understanding of the adaptive process that occurs in order to maintain the effectiveness of individuals facing changing circumstances. This study is an extension of previous work in the performance adaptation literature investigating the effect of training inductions and self-regulatory variables on individual performance trajectories after an adaptive change in a lab-based computer simulation. Bivariate latent difference score models were used for analyses and revealed that trainings that encouraged errors were most beneficial for the adaptation of individuals. Furthermore, when individuals were not informed to avoid errors but were given an opportunity to learn the task through exploration, they adapted better than if they were given step-by-step instructions. With regard to the self-regulatory processes, individuals who were able to identify the origin of the change in the task and sought feedback and information that aligned with that change required less of that information over time. When motivation was high, performance was increased; however, less effort was needed to have increased performance when individuals devoted effort to the aspects of the task that changed versus simply increasing their amount of effort. Although this study takes the next step of investigating the self-regulatory processes *during* adaptation, future research should investigate how these processes, taken together, create a cycle of self-regulation that influences the adaptation of individuals.

This work is dedicated to Dr. and Mrs. Paul P. Baard and Mr. William C. Perry.

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INTRODUCTION

As the workplace becomes increasingly complex, individuals and teams are challenged with learning new technologies, adjusting to working with different teams of individuals, and dealing with unexpected changes in the environment (Burke, Stagl, Salas, Pierce, & Kendall, 2006). Researchers have called the latter challenge adaptation or adaptability and have defined it as an individual's ability to maintain performance or to recover from a sudden downturn in performance (Pulakos, Arad, Donovan, & Plamondon, 2000; LePine, 2005; Bell & Kozlowski, 2008). However, there is still a need to more fully understand this concept of adaptation and how it influences performance, as well as the mechanisms that are involved in the process.

Although the literature on adaptation spans many fields and definitions, there are three primary perspectives on adaptation: as a construct, as a performance change, and as a process (Baard, Rench, & Kozlowski, in press). The construct approach refers to adaptation as an individual difference variable (Ployhart & Bliese, 2006) or as a set of adaptive performance dimensions (Pulakos et al., 2000). The construct perspective uses a conceptualization that focuses on a static view of adaptation. Such an approach does not allow for the opportunity to examine the dynamics involved in adaptation, which is evident through an individual's fluid responses to changes in the environment. In order investigate the dynamics involved in adaptation, the phenomenon must be conceptualized as a process that unfolds over time.

Several researchers have examined the mechanisms involved in the learning process, the impact of this process on performance after an adaptive event (e.g., Kozlowski, Gully, Brown, Salas, Smith & Nason, 2001; Bell & Kozlowski, 2008), and how performance after an event changes over time (e.g., LePine, 2003, 2005). Together, this set of research can be referred to as a performance change approach to adaptation, as adaptive performance events are operationalized as a change in performance from a routine scenario or task environment to a novel one (LePine, Colquitt, & Erez, 2000; Bell & Kozlowski, 2008). Several researchers adopting a performance change perspective consider the change in performance from a routine to a novel scenario to be a reflection of how well an individual has gone through the adaptive process (e.g., Bell & Kozlowski, 2008). However, researchers have not yet empirically examined how the adaptation process, or self-regulatory activity that drives the adaptation process (e.g., Bell & Kozlowski, 2008), changes over time after an adaptive event occurs. This results in a gap in our understanding of how this adaptation process unfolds over time.

Given the gaps in the literature, the aims of the study are twofold. First, it will conceptually present how self-regulatory processes serve as one model to understand how individuals engage in the adaptive processes after a change is introduced. Second, it will investigate how these processes unfold over time. Regarding the first aim, self-regulation theory has been used by several researchers to describe the learning process before an adaptive event (Bell & Kozlowski, 2008). Bell and Kozlowski provide insight into how individuals monitor their progress toward a goal. They identify three pathways: cognitive, motivational, and emotional. The longitudinal aspect of this study, the second aim, focuses on the period following a change. It is distinguished from past research in that its objective is to empirically examine how the process of adaptation unfolds over time through the examination of self-regulatory mechanisms that have been identified by previous research as being drivers of adaptation (e.g., Bell & Kozlowski, 2008). This approach differs from earlier research where the central aim was to examine the impact of the learning process on training generalization or transfer, assuming a similar adaptation process occurred after an adaptive environment was presented (Bell & Kozlowski, 2008). This research extends the work by Bell and Kozlowski (2008) by empirically examining the process occurring after the adaptive change is introduced, investigating how the adaptation process unfolds over time.

First, I will present a framework to categorize previous research in the adaptation literature in order to identify gaps that remain in our understanding of this phenomenon. Second, I will present the theoretical argument for this study by describing more recent work in adaptation and how self-regulation theory has impacted our understanding of adaptation. The study will proceed to address how active learning and error framing induce these self-regulatory mechanisms that are reflective of the adaptation process and how these mechanisms fluctuate over time. As the primary aim of this experiment is to examine the process of adaptation, hypotheses will refer to self-regulatory activities and performance *after a change is introduced into the environment*. This change will necessitate an adaptive response, and the self-regulation mechanisms will provide the opportunity to unpack this process. First, hypotheses will reflect the influence of active learning and error framing on initial levels of self-regulatory activities after a change is introduced into the environment that requires an adaptive response, replicating previous work within in the adaptation literature (e.g., Kozlowski, Gully et al., 2001; Bell & Kozlowski, 2008). Second, expected fluctuations in self-regulatory activities following an adaptive change will be examined. Finally, an overall model will be introduced to analyze the relationships between the self-regulatory mechanisms, as well as their influence on performance over time, after a change.

ADAPTATION – Extant Research

As the workplace becomes more complex and dynamic, individuals and teams must be able to quickly respond to, or adapt to, new demands (Kozlowski, Gully, Salas, Cannon-Bowers, 1996; Chan, 2000; Kozlowski, et al., 2009). Adaptability has been identified as a key component of both individual and team effectiveness, resulting in a growing body of research attempting to understand this phenomenon (e.g., Chan, 2000; Pulakos, Schmitt, Dorsey, Arad, Hedge & Borman, 2002; Ployhart & Bliese, 2006; Bell & Kozlowski, 2008). However, research investigating adaptation has fragmented into several theoretical perspectives, with each approach making contributions in different areas (e.g., training and selection; Baard et al., in press). Therefore, in order to add to our understanding of adaptation, the three general perspectives on adaptation, identified above, will be discussed in turn.

Three Conceptualizations of Adaptation

Baard, Rench, and Kozlowski (in press) have proposed that the literature on adaptation can be separated into three general perspectives or approaches: adaptation as a construct, as a performance change, and as a process. Each of these perspectives will be explicated, but it is important to note that these conceptualizations fall within different domains. The construct perspective, which focuses on adaptability as an individual difference or a type of performance, falls into a domain-general approach which suggests that the adaptive capacity of individuals is situation-spanning. In other words, the individual difference of adaptability described by Ployhart and Bliese (2006) does not change significantly from one domain to the next. By contrast, the performance change and process approaches are domain-specific, suggesting that specific task knowledge is required in order for an individual to adapt. Although the overall process of adaptation may be conceptually the same across situations (e.g., scanning, interpreting and responding; Burke et al., 2006), the way in which adaptation manifests itself depends on the domain (e.g., business or combat or laboratory) and whether the individual has the knowledge, skills, and abilities associated with that specific domain.

The Construct Approach

The construct approach investigates adaptability in two ways: as a type of performance or as a relatively stable individual difference trait.

Performance construct. As pioneers of this conceptualization, Pulakos, Arad, Donovan and Plamondon (2000) were the first to map out the dimensions of adaptive performance, arguing that there is a need to understand the adaptive requirements of the performance environment in which individuals operate. Through analyzing 767 critical incidents of adaptive performance from 21 different jobs within the military, private sector organizations, and federal and state governments, they identified eight dimensions of adaptive performance: 1) handling emergencies or crisis situations; 2) handling work stress; 3) solving problems creatively; 4) dealing with uncertain and unpredictable work situations; 5) learning work tasks, technologies, and procedures; 6) demonstrating interpersonal adaptability; 7) demonstrating cultural adaptability; and 8) demonstrating physically oriented adaptability. The authors then created the Job Adaptive Inventory (JAI) which was specifically designed to examine the adaptive elements of each dimension. This measure was further refined through examining U.S. Army personnel in a variety of specialties, resulting in a 68 item instrument rated on a 5-point Likert scale. After administering the final measure to more than 3,000 telecommunication employees, 300 Army personnel, and several research scientists, results show the JAI to be a reliable measure with alphas ranging from .89 to .97. Furthermore, the exploratory factor analysis revealed the best fit when all eight dimensions were specified. However, when the scale was refined to 24 items, both the exploratory and confirmatory factor analyses revealed a single adaptive performance composite (Pulakos, Schmitt, Dorsey, Arad, Hedge & Borman, 2002).

Although this work provided insight into how the performance domain can be expanded to include adaptive performance dimensions, the lack of convergence seen in the measurement suggests that there is still ambiguity associated with the underlying dimensionality of adaptive performance. Additionally, the performance construct perspective focuses on the different types of adaptive performance and the characteristics of individuals who are more capable of responding to those conditions (e.g., high cognitive ability and openness to experience; Pulakos et al. 2000, 2002). However, what is lacking in the performance construct approach is research investigating *how* individuals respond to adaptive situations (i.e., what *processes* individuals engage in).

Individual difference construct. Ployhart and Bliese (2006) theoretically examined the differences between individuals in their ability to adapt their behaviors to environmental requirements. They proposed that "individual adaptability represents an individual's ability, skill, disposition, willingness, and/or motivation, to change or fit different task, social, and environmental factors" (p. 13). This perspective suggests that an individual is adaptive regardless of what situation he or she is presented with; in other words, an individual can be proactive and change before the environment requires that behavior, or reactive and respond to a change. Some researchers have conceptualized this individual difference of adaptability as a combination of several traits (e.g., behavior flexibility, openness to experience, proactivity, past experience of change and change receptiveness; Griffin & Hesketh, 2005). Ployhart and Bliese distinguish themselves by describing the construct of adaptability as a compound trait of knowledge, skills, and abilities that is distinguished from any other individual difference trait. They propose that adaptability is a relatively stable individual difference that manifests itself in multiple performance contexts and does not necessarily need to be in response to a change but could be evident through small changes, such as becoming more familiar with an environment or task.

Ployhart and Bliese (2006) used the dimensions identified by Pulakos et al. (2000) to create their measure (the I-ADAPT). However, few studies have used this measure as a means of investigating adaptation. Wang, Xhan, McCune & Truxillo (2011) investigated five of the eight dimensions of the I-ADAPT and discovered that the uncertainty dimension had a direct impact on job satisfaction and turnover intention. The cultural, interpersonal, learning and work stress adaptability dimensions impacted job satisfaction, turnover intention, and supervisor-related job performance indirectly through organizational fit variables. Given the scarcity of research using this individual difference construct approach, it is difficult to establish whether this construct adds additional explanation to performance differences between individuals in the face of a changed situation. Ployhart and Bliese (2006) suggest that the individual difference of adaptability influences performance through a mediating process of situation perception and appraisal, strategy selection, self-regulation and coping, and knowledge acquisition. However, they neither empirically examined the influence of this mediating process nor has research building upon their work investigated the process. Therefore, although this set of research provides initial evidence that individuals have predispositions towards adaptation, the mechanisms involved in how this predisposition impacts performance are not well examined.

The Performance Change Approach

One of the earliest conceptualizations of adaptation is found in the performance change approach where adaptation is broadly defined as effective performance after a change is introduced into the environment (Smith, Ford, & Kozlowski, 1997). These authors extended previous work that focused on developing routine expertise to include adaptive expertise, which is developed through understanding and applying the principles underlying the trained task in order to adjust to a new situation. Some refer to this adaptive expertise as adaptive transfer where individuals display their adaptive capabilities through their performance on a training generalization or novel task (Kozlowski, Gully, Brown, Salas, Smith & Nason, 2001).

Generally speaking, a novel environment is differentiated from routine environments through a significant increase in level of complexity. A novel situation requires individuals to utilize the knowledge and skills previously developed on the job or in training in a new way, thus displaying adaptive expertise. Research in the adaptation literature has utilized Wood's (1986) typology of task complexity to provide an operational definition of the requirements of the adaptive environment (e.g., Kozlowski, Gully et al., 2001; Bell & Kozlowski, 2008). The three types of complexities Wood identifies are: component complexity (where the number of elements in the environment increases), coordinative complexity (where the timing or frequency of interactions is intensified), and dynamic complexity (where there is a shift in the relationship between inputs and products such that knowledge and skills must be adjusted; Wood, 1986). An adaptive environment will have either more elements to attend to or require a more complex set of behaviors (e.g., Bell, 2002). Adaptive performance is evident in an individual's ability to minimize a downturn in performance after an increase in complexity is introduced.

Given the increasing complexity associated with the workplace, research moved toward investigating how individuals could be better prepared for a novel situation by examining the effectiveness of different training programs. Ivancic and Hesketh (2000) and Kozlowski, Gully, Brown, Salas, Smith, and Nason (2001) were among the first to empirically investigate the impact of training techniques on the psychological processes and adaptive performance of individuals by introducing a novel change in controlled laboratory settings. Ivancic and Hesketh (2000) studied individuals performing a simulated driving task where participants were required to learn specific driving techniques. They manipulated whether or not the individuals were presented with errors during their training trials. When an adaptive transfer trial was presented, results suggested that individuals who were exposed to errors during training made fewer errors during the adaptive task and chose a safer driving speed than those with errorless training. This suggests that knowledge of errors allows individuals to more completely understand their tasks and capabilities within a domain.

Kozlowski, Gully et al. (2001) investigated the impact of mastery versus performance training goals on adaptive performance through a computer-based radar simulation platform. The mastery training goals significantly increased knowledge structure coherence and self-efficacy, which led to enhanced adaptive performance. Furthermore, individuals with higher learning orientation had higher self-efficacy, whereas individuals with higher performance orientation did not experience any increase in training outcomes. Finally, those with higher academic ability had higher declarative knowledge, training performance and adaptive performance. These studies provided some initial steps in developing an understanding of how adaptive performance is influenced by both training inductions as well as through self-regulatory mechanisms. However, neither Ivancic and Hesketh (2000) nor Kozlowski, Gully et al. (2001) investigated the process of adaptation directly. Instead, they assumed that individuals who had higher performance in the adaptive transfer trial underwent the adaptation process. Furthermore, as only one performance trial was presented after the adaptive change, fluctuations in performance could not be examined.

LePine (2003, 2005) responded to this need to investigate how performance fluctuates over a period of time after an adaptive change is introduced. Through two studies, he examined the impact of changes in communication and coordination patterns on performance in a computer-based team task. The basic premise of the task was to establish a way of communicating among team members to disseminate information that was critical for team performance. After several trials, the communication link between two team members was abruptly severed, resulting in a need to adapt. Adaptation was evident in the team's ability to recognize the need to shift behaviors and choose a new and effective pattern of communication, with their performance dependent on how well they adapted to that change. Results suggested that teams of individuals with higher cognitive ability, greater achievement, more openness, and lower dependability performed better after the change (LePine, 2003). LePine's second study investigated how a gradual (versus an abrupt) change in the degradation of communication influenced adaptive performance. Similar to the previous study, communication patterns were established among the team members during the first few trials. Following that period, the communication between two members began to break down but was not fully severed for several trials. When the link was fully severed, adaptation was seen in how rapidly the team members were able to adapt to a new pattern of communication. The results identified that teams of higher learning-oriented individuals who were given difficult goals had more rapid growth in their performance after the change (LePine, 2005).

One important insight that is gained from the work by LePine (2003, 2005) is that performance after a change does not remain constant over time. This suggests that research examining adaptation would be well-advised to consider how performance fluctuates after a change is introduced. However, one critical limitation of the work by LePine is the lack of investigation about what psychological processes were *driving* the different trajectories of performance after a change.

Moving Toward a Process Approach

Researchers have responded to this need for developing a deeper understanding about how the process of adaptation influences performance by examining how self-regulatory mechanisms drive responses to a change (e.g., Kozlowski, Gully, Salas, & Cannon-Bowers, 1996). Self-regulation is one way of understanding how individuals monitor their environments, set goals, and adjust their behaviors in order to progress toward those goals (Bandura, 1991). Karoly (1993) describes the inherent link between self-regulation and adaptation in that "the processes of self-regulation are initiated when routinized activity is impeded or when goal-directedness is otherwise made salient" (p. 25). Self-regulation theory has been discussed through three categories of functions: 1) the cognitive appraisal of one's actions, its causes, and its effects; 2) the motivational and effortful progress toward a goal; and 3) the affective evaluation of reactions (Bandura, 1991). Therefore, work conducted in the adaptation literature with self-regulatory mechanisms in mind has identified three pathways: cognitive, motivational, and affective (Bell, 2002; Bell & Kozlowski, 2002a, 2002b; Kozlowski & Bell, 2006; Bell & Kozlowski, 2008).

Kozlowski and colleagues established a research stream investigating how active learning influences adaptive performance through impacting the self-regulatory mechanisms involved in the learning process (Bell & Kozlowski, 2010). Kozlowski, Toney et al. (2001) described a conceptual Adaptive Learning System that incorporated self-regulatory mechanisms (such as self-monitoring and self-evaluation) to build a theoretical model to guide the design of Active Learning interventions to enhance domain-specific adaptive performance. Work progressed to empirically investigating how active learning techniques enact the self-regulatory mechanisms involved in the process of learning and adapting through a series of studies utilizing undergraduates engaging in a computer-based radar-tracking simulation (TANDEM). As described earlier, Kozlowski, Gully et al. (2001) investigated the impact of mastery versus performance training goals on adaptive performance and found that mastery training goals significantly increased knowledge structure coherence and self-efficacy which led to enhanced adaptive performance. This work provided initial insight into understanding how training goal orientation impacted the self-regulatory processes and subsequent adaptive performance of individuals.

Research expanded to investigate the influence of an individual's trait goal orientation on adaptive performance. Bell and Kozlowski (2002b) found that cognitive ability moderated the influence of trait goal orientation on adaptive performance. When cognitive ability was low, both self-efficacy and adaptive performance were not impacted by learning orientation; however, among those with high cognitive ability, learning orientation had a significantly positive impact on both self-efficacy and adaptive performance. Contrarily, when investigating the impact of individuals with a higher performance orientation, those with low cognitive ability had decreased self-efficacy whereas individuals with high cognitive ability had decreased adaptive performance

(Bell & Kozlowski, 2002a). This research suggests that in addition to the impact of training programs and individual differences serve as predictors of the self-regulatory mechanisms involved in adaptation.

Further work examined the impact of active learning techniques. Bell and Kozlowski (2002b) investigated how adaptive guidance, or training that focuses on assisting individuals to make effective decisions while learning, impacted their self-regulatory processes and adaptive performance. Results indicated that adaptive guidance led to higher levels of self-efficacy early in training, and although adaptive guidance did not have a significant effect on on-task cognition, it did have a significantly positive effect on individual study and practice sequences. Furthermore, adaptive guidance had a positive impact on basic knowledge early in training and strategic knowledge later in training. Similarly, adaptive guidance had a significantly positive impact on basic performance early in training and strategic performance later. Finally, after a change was introduced, adaptive guidance was found to have a significantly positive impact on strategic performance, but a non-significant relationship with basic performance (Kozlowski, Gully, et al., 2001). This suggests that adaptive guidance enhances the motivation and the development of cognitive strategies as individuals had higher self-efficacy early on and higher strategic knowledge and performance later in the training.

Kozlowski and Bell (2006) investigated the influence of goal framing, content, and proximity, and found positive effects for all three on self-regulatory activities, particularly with goal-content training. This study also found that individuals who spent more time exploring the environment, and individuals who had higher levels of self-evaluative activity, had higher basic and strategic knowledge, as well as enhanced adaptive performance.

More recently, Bell and Kozlowski (2008) presented a complex model of how self-regulatory mechanisms are involved in adaptation through understanding how active learning training improved self-regulatory processes and subsequent adaptive performance. They developed three training inductions that targeted one of the three self-regulatory pathways: cognitive, motivational, and affective.

In the investigation of the cognitive pathway, they examined the impact of guided exploration versus proceduralized instruction. Guided exploration is an intervention that requires an individual to explore the environment and learn the rules that govern it with very little guidance whereas proceduralized learning provides very detailed instruction that leads the individual step-by-step through key task procedures. Bell and Kozlowski (2008) found that guided exploratory training enacted the self-regulatory mechanisms of metacognitive activity, self-evaluative activity, and strategic knowledge which led to higher performance after an adaptive event than proceduralized training. Furthermore, they identified the individual difference of cognitive ability as a moderator of the impact of the training induction on self-regulatory mechanisms. They concluded that guided exploration was more effective than proceduralized training at increasing metacognitive activity (moderated by cognitive ability) which drove self-evaluative activity, strategic knowledge formation, and adaptive performance, suggesting that the training induction effectively increased those self-regulatory mechanisms which allowed individuals to be more adaptive.

In the investigation of the motivational pathway, Bell and Kozlowski (2008) examined error encouragement versus error avoidance training where the former portrays errors as learning opportunities and the latter frames errors as hindrances to the learning process. Error encouragement framing was found to be more effective at enacting the self-regulatory mechanisms of state goal orientation, self-efficacy and intrinsic motivation which led to increased levels of adaptive performance as compared to error avoidance framing. In addition,, they identified trait goal orientation as an individual difference that moderates the impact of error framing on the self-regulatory process. They concluded that error encouragement framing was more effective than error avoidance framing at impacting state goal orientation and self-efficacy. This suggests that error framing enhances self-regulatory mechanisms which, in turn, impact how individuals are able to adapt to the change.

Finally, in the investigation of the affective pathway, Bell and Kozlowski (2008) trained an emotion-control strategy that was directed at reducing the frequency of negative thoughts and increasing positive thoughts. The emotion-control strategy was found to significantly reduce state anxiety, and trait anxiety moderated that effect. Emotion-control training was not found to be directly related to adaptive performance but increased self-efficacy through decreasing anxiety.

Bell and Kozlowski made two key contributions to the study of adaptation. They provided initial work mapping the self-regulatory mechanisms involved in the learning process prior to an adaptive change which assists in the understanding how differences in the self-regulatory process impact adaptive performance after a change. They also identified training interventions that were able to enact these self-regulatory processes which then influenced adaptive performance. A limitation in this work was that adaptive performance was measured at only one point in time which does not allow for the investigation of how individuals change over time (as seen in LePine's work, 2003, 2005). Also, although this research described the self-regulatory mechanisms that are present during learning, it is unclear whether they are reflective of an adaptive process as the mechanisms were not measured after a change. Finally, as these studies did not investigate the self-regulatory mechanisms or adaptive performance over multiple points in time, our understanding is limited on how these processes influence performance over time after an adaptive change is introduced.

Chen, Thomas and Wallace (2005) also attempted to measure how self-regulatory processes impact performance after a change. They investigated how knowledge, skills, and efficacy impacted goal choice and striving activities at both the individual and team levels. They measured knowledge, skills and efficacy after a series of training trials before any performance trials. After a period for planning, individuals completed measures of goal choice activities (the individual level construct) and transition processes (team level construct), followed by the adaptive trial. After the adaptive trial the individuals completed the goal striving activities (individual level) and action processes (team level). This last step distinguishes the work of Chen and colleagues from previous work in the performance change approach as they attempted to gather information about the processes occurring *after* an adaptive change. They found that goal choice and striving self-regulatory activities mediated the impact of self-efficacy on individual level adaptive performance. Although they did not investigate the dynamics of adaptive performance for a longer period of time after a change, Chen et al. (2005) added insight into how self-regulatory mechanisms are useful in the understanding of adaptation through measuring goal striving *after* the change and finding a significant impact of this mechanism on adaptive performance.

The theoretical conceptualization about the process of adaptation (e.g., Kozlowski et al., 1996; Burke et al., 2006) have the common theme of directing attention towards the importance of understanding *how* individuals respond to a change in their environment. However, each of the previously described approaches falls short of being able to address this need. That is, the extant research fails to empirically investigate the fluctuations in the self-regulatory mechanisms involved in the adaptation process after a change is introduced. The performance construct approach identifies different adaptive performance types and characteristics of individuals that may be more suited to deal with adaptive situations, but this stream of research does not describe how (i.e., through what mechanisms) individuals respond. The individual difference construct approach identifies adaptive characteristics of individuals, but this perspective does not examine how individuals can be trained to become more effective at handling a changed environment. Finally, the performance change approach investigates differences in performance after an adaptive event, but fails to empirically examine the underlying process of adaptation after the change nor does it describe how the process of adaptation unfolds over time.

ADAPTATION – New Direction

Given the need for further understanding of the phenomenon of adaptation, the next step is to extend the theoretical conceptualizations of the process of adaptation with an empirical design that is intended to unpack the process. A way forward is through the investigation of how the self-regulatory mechanisms, that have been previously established by research (e.g., Bell & Kozlowski, 2008), unfold over time after a change in complexity is introduced. In other words, this study will build upon research conducted in the adaptation literature using self-regulation theory as an explanatory mechanism for understanding the process of adaptation, as well as using the extant self-regulation and cognitive processing literatures to increase our understanding of how these mechanisms fluctuate over time. Therefore, this research contributes to the adaptation literature in two ways: first, by unpacking the process of adaptation by investigating the trajectories of the self-regulatory mechanisms involved and second, by examining performance trajectories after a change. This will allow for the examination of how those self-regulatory mechanisms drive the adaptation process and performance over time.

As described earlier, adaptation is the regulation of thoughts, behaviors, and motivation in response to a change (Bell & Kozlowski, 2008). Research has shown that training inductions can successfully influence self-regulatory mechanisms which impact adaptive performance (e.g., Bell, 2002; Keith & Frese, 2005). Therefore, the following sections will describe the two self-regulatory pathways that are conceptualized as driving the adaptation process (cognitive and motivational) as well as how two training inductions will influence the enactment of these mechanisms, how the self-regulatory constructs relate to each other over time, and how they impact adaptive performance trajectories.

Cognitive Pathway

Early work in the adaptation literature identified adaptive expertise as a skill an individual develops that consists of a deep understanding of the task domain such that when a novel situation is presented the individual can effectively adapt to the change through performing a new set of behaviors that are extensions of previously learned actions (Smith et al., 1997). Therefore, adaptive expertise is displayed through a cognitive awareness of the changes occurring in the environment as well as a deep, strategic understanding of that domain. One definition of self-regulation is a thoughtful reflection on one's current state compared with one's desired state (Bandura, 1991). This definition implies that cognitive mechanisms are involved with the self-regulatory process that would assist in the identification of a change. In one adaptation process model, Burke et al. (2006) suggest that a change must first be recognized and then behaviors need to be appropriately altered; hence, there must be cognitive self-regulatory processes at work. Given the importance of this cognitive aspect, I will describe how guided exploratory training can activate self-evaluative activity, information gathering behaviors, and strategic effort allocation over time after an adaptive change is introduced.

Guided Versus Proceduralized Learning Yielding Self-evaluative Activity

In the adaptation literature, exploratory and proceduralized learning have had differential effects on the enactment of self-regulatory mechanisms and subsequent adaptive performance (Bell & Kozlowski, 2008). Guided exploratory learning, sometimes referred to as exploratory learning, requires individuals to engage in active learning techniques in order to develop knowledge about a task domain. This knowledge is developed through exploring the task and drawing inferences about the rules governing it (Debowski, Wood, & Bandura, 2001; Bell &

Kozlowski, 2008). In contrast, proceduralized learning provides highly regimented instruction to an individual that informs them about the specific workings of the task. In this learning instruction, individuals are given step-by-step instructions which may result in a more superficial comprehension of the task. Bell and Kozlowski (2008) state "the active learning approach is distinctive, in that it goes beyond simply 'learning by doing' and focuses on using formal training design elements to systematically influence and support the cognitive, motivational, and emotional processes that characterize how people focus their attention, direct their effort, and manage their affect during learning" (p. 297). Through the investigation of the impact of active learning on adaptive performance, Bell and Kozlowski (2008) found that guided exploration, as compared to proceduralized instruction, resulted in higher levels of strategic knowledge and adaptive performance through the mediation of metacognitive activity and self-evaluative activity. These results suggest that guided exploration increases the self-regulatory processes that lead to the acquisition of a deeper understanding of the task.

The findings by Bell and Kozlowski (2008) could also be described through the theory of deep and surface level cognitive processing in that guided exploration yielded deep level processing and proceduralized learning resulted in surface level processing. According to Marton and Säljö, the surface elements of a task are the basic operating features or information that develops declarative knowledge, whereas the deep elements consist of the underlying principles that govern the task, which reflect procedural knowledge, such as the reasons why certain behaviors are rewarded (Phan, 2009). This concept of deep and surface processing is relevant to the task paradigm in the current study, as surface knowledge is evident in the information processing of the basic operating features (e.g., the identification of cues, the decision rules, and other basic operating features), whereas deep knowledge is captured in a strategic or procedural understanding of the task that will impact one's identification of the situation, prioritization of actions, and effectiveness of strategic behaviors (Kozlowski, Toney, et al., 2001). Smith et al. (1997) state that adaptive expertise is a two-step process: First, individuals develop the knowledge and skills required for a basic understanding of the task domain; then, they develop strategic knowledge which allows for the creation of adaptive solutions. These respective surface and deep level aspects of the task domain will be essential in our discussion, and in the understanding of how individuals adapt to an increase in complexity over time.

Smith, Ford and Kozlowski (1997) specifically state that adaptive expertise is displayed through a deep understanding of the task domain such that when a novel situation is presented the individual can effectively adapt to the change through performing a new set of behaviors. In other words, adaptive expertise is displayed through the deep cognitive processing of the task domain. The distinction between deep (or strategic) and surface (or basic) aspects of the task domain will continue throughout the description of the cognitive pathway of the self-regulatory process involved in adapting to a change. In order to effectively adapt to a change, an individual is required to not only understand the basic rules of a task but also the strategic procedures. Attending to the strategic aspects of a task displays a deep, and procedural, understanding of the task domain which facilitates the identification of a change, the interpretation of which behaviors would be effective, and the adaptation to a change. Therefore, the strategic aspects of self-evaluative activity (feedback information upon which an individual reflects concerning the strategic elements of the environment), information gathering (the information that is sought after feedback is received), and strategic effort (the behaviors that are targeted at the elements of the environment that have changed) will be considered evidence of an individual engaging in an adaptive self-regulatory process. By contrast, ineffective adaptation would be seen in a lack of effort devoted to the strategic aspects of the task, as those behaviors would demonstrate a lack of cognitive awareness of the adaptive requirements of the change. In other words, in order to unpack the process of adaptation, I will investigate a set of adaptive self-regulatory behaviors, namely behaviors that reflect an understanding of the strategic aspects of the task domain. The self-regulatory processes that will be investigated in this study are: self-evaluative activity, information gathering, and strategic effort.

Guided exploratory learning is associated with an increase in the deep cognitive processing of individuals in multiple types of laboratory environments. Researchers have identified that when individuals are exposed to a change, this active learning strategy yields a faster identification of the effective strategy that is required (McDaniel & Schlager, 1990; Debowski et al., 2001). Therefore, individuals who are provided with the opportunity to develop their own understanding of the environment – through drawing their own inferences by guided exploratory learning – are able to develop a deeper understanding of the task domain which increases the speed with which they can identify which elements in their environment changed.

Feedback is one way an individual can assess whether they have developed a deep understanding of their task domain, as feedback allows for the assessment of whether a change in complexity was due to the surface aspects (e.g., an increase in the number of problems that need to be solved) or deep aspects (e.g., a change in the rewards associated with certain actions). Feedback has been discussed in the self-regulation literature as a critical mechanism of self-regulatory process as it provides individuals with information about their progress toward a goal. This feedback information provides individuals with an opportunity to analyze their strategy and redistribute their effort (Karoly, 1993; Bandura, 1991). Feedback Intervention Theory (Kluger & DeNisi, 1996) suggests that individuals have a limited number of attentional resources available for use at any one time, and those attentional resources are focused at reducing the feedback-standard gap. This gap is identified through the investigation of feedback and the comparison of their past performance to the goal they had set. When an adaptive change occurs, the previously established goals will most likely not be reflected in the performance. Therefore, attention needs to be devoted to understanding what aspects of the task changed and how that change impacted their performance. As attentional resources are limited when receiving feedback (Kluger & DeNisi, 1996), it is critical for individuals to prioritize where time and attention are allocated, suggesting that resources devoted to investigating the basic aspects of feedback will be resources not available to examine strategic aspects.

Research conducted using the task paradigm that this study employs, utilizes the term *self-evaluative activity* to refer to the feedback evaluation period (Bell, 2002; Bell & Kozlowski, 2008). Self-evaluative activity is a self-regulatory mechanism that is centered on analyzing the feedback which then influences how an individual is able to adapt to a change. Bell and Kozlowski (2008) investigated the effects of guided exploration on several self-regulatory mechanisms and determined that this form of active learning had a positive impact on metacognition, which in turn impacted self-evaluative activity, strategic knowledge and adaptive performance.

However, one limitation of past work was the lack of differentiation between self-evaluative activities that are reflective of a strategic understanding of the task domain, versus self-evaluative activities that are focused on basic aspects. As discussed above, the distinction will assist in our understanding of how strategic self-evaluative activity is reflective of an effective adaptation strategy. By contrast, continued focus on the basic aspects of self-evaluative activity will reflect a surface understanding of the domain, which would yield a less effective adaptation process. Based on the definition of adaptive expertise described earlier (Smith, Ford & Kozlowski, 1997), a deeper understanding of the task results in more adaptive expertise and better adaptive performance. This suggests that strategic self-evaluative activity will be a key mechanism in the adaptation process.

Research has established the positive effect of guided exploration on self-evaluative activity through the enhancement of metacognitive activity (Bell & Kozlowski, 2008). In addition, self-evaluative activity was positively related to strategic knowledge and adaptive performance. The study by Bell and Kozlowski (2008) provided evidence that individuals who were given the opportunity to learn through actively exploring their environment were more knowledgeable about the strategic elements of the task domain. Therefore, guided exploration will better equip individuals to focus their attention on feedback that addresses the strategic elements, as they will have a deeper understanding of the task, resulting in higher levels of strategic self-evaluative activity once a change is introduced. By contrast, those given proceduralized learning will not have as deep or strategic of an understanding of the task domain, which will result in an initial lack of focus on strategic self-evaluative activity once a change is implemented. In other words, those with proceduralized learning will not as quickly identify the strategic elements of the feedback. However, as exposure to the changed task environment increases, individuals will be forced to develop a strategic understanding of the task (if they have not done so) as the nature of the change requires strategic knowledge of the task domain in order for adaptation to occur. Therefore, individuals will show an increase in strategic self-evaluative activity over time in general. This is supported by Bandura's work which posits that an individual utilizes information from the environment to understand internal patterns of thought, emotions, and behavior when receiving feedback (Bandura, 1991). However, given that guided exploration has been associated with higher levels of strategic knowledge, it is expected that individuals who utilized this active learning technique will have a greater increase in strategic self-evaluative activity than those exposed to proceduralized learning.

> Hypothesis 1a: Compared to proceduralized learning, guided exploration will lead to higher initial levels of self-evaluative activity focused on strategic task elements following an increase in task complexity.
>
> Hypothesis 1b: Compared to proceduralized learning, guided exploration will lead to a greater increase in self-evaluation activity focused on strategic task elements following an increase in task complexity.

Mechanisms of the Process: Strategic Self-evaluative Activity Yielding Strategic Information Gathering, Strategic Effort, and Performance

As discussed above, *strategic self-evaluative activity* is attention devoted to aspects of the feedback that reflect a deep understanding of the task. As previous research suggests, individuals who have a deeper understanding of the task domain are able to more rapidly identify the change and interpret how the change is impacting their performance (McDaniel & Schlager, 1990). However, identification of the source of the change does not presume that the information needed to address the change is known. Rather, self-evaluative activity will inform the information that is gathered from outside resources (e.g., a manual). Information will be gathered based on what feedback was evaluated; therefore, if strategic feedback is perused, strategic information will be gathered.

Information gathering is defined as the cognitive effort directed toward gathering information on the accuracy of behaviors that are designed to achieve a specific goal, which is a construct similar to feedback-seeking (Ashford, 1986). In the current task paradigm, information gathering is a behavior that attempts to reduce any gaps in knowledge that were identified by the feedback. Similar to self-evaluative activity, information gathering behaviors can be strategic or basic. Bell and Kozlowski (2008) investigated how information gathering behavior was involved in the self-regulatory process and discovered that exploratory learning led to an increase in information gathering activity (although they refer to the construct as cognitive effort) which positively influenced adaptive performance through strategic knowledge. However, these researchers did not investigate how information gathering behaviors change over time nor did they differentiate between basic and strategic information gathering behaviors.

As discussed above, fluctuation in the focus of self-evaluative activity (i.e., basic versus strategic) is expected to be associated with fluctuations in focus information gathering behaviors (i.e., basic versus strategic). In other words, the focus of attentional resources devoted to feedback will reflect attentional resources devoted to gathering information. One way in which this relationship can be explained is through understanding Feedback Intervention Theory proposed by Kluger and DeNisi (1996). An underlying principle of this theory is that one way individuals can achieve their goals is to gain information about what is causing that feedback-standard gap which is driven by a discrepancy between one's current and desired state. For instance, if individuals recognize a gap between their performance and goal, they will devote cognitive resources to the feedback they believe is driving this discrepancy and information they believe will close that gap. Therefore, as more resources are devoted to the strategic aspects of the feedback (or the strategic self-evaluative activity) more resources are expected to be devoted to strategic aspects of information gathering (i.e., through examining the manual).

Hypothesis 2: The amount of strategic self-evaluative activity will be positively related to the change in strategic information gathering following an increase in task complexity.

Another self-regulatory mechanism involved in the cognitive appraisal of a change is cognitive effort. *Effort* is defined in this study as behaviors that are directed at completing the task. Previous research investigated the positive impact of effort on performance both through self-report questionnaires (e.g., "How much effort have you invested in this task up to this point"; Yeo & Neal, 2004) and behavioral indicators (e.g., Bell, 2002; Bell & Kozlowski, 2008). Similar to the other two self-regulatory mechanisms involved in the cognitive pathway, effort can be directed towards the basic functions of the task (e.g., the identification of cues, the decision rules, and other basic operating features), or the strategic aspects of the task (e.g., prioritization of actions, and balancing multiple goals). Therefore, individuals will display their adaptive expertise through increasing strategic effort after a change occurs, thus demonstrating that appropriate cognitive self-regulatory mechanisms are at work.

Bell (2002) began the investigation of the relationship between information gathering and strategic performance, and discovered that there was a positive relationship between the two. However, Bell (2002) did not directly include effort in his model, but instead differentiated strategic versus basic performance; furthermore, only one measurement of adaptive performance was gathered, restricting understanding of how effort and performance changes over time. This study extends the work conducted on effort in the adaptation literature to suggest that type of information gathering behavior (basic or strategic) will be related to the type of effort that is allocated at subsequent points in time. In other words, if information is sought on the strategic aspects of the task, behavior will be devoted to actions that are related to the information that was just gathered.

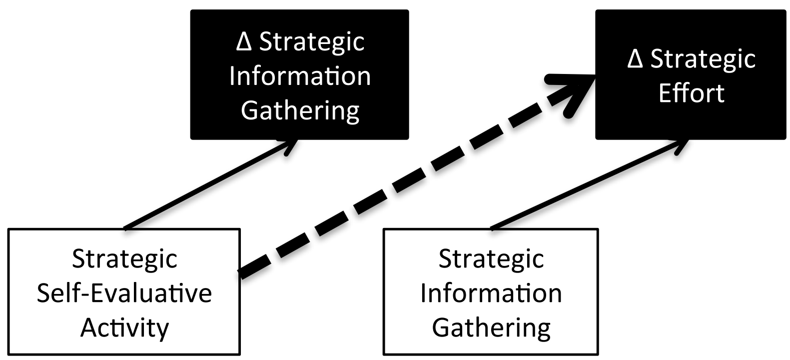
Hypothesis 3: The amount of strategic information gathering will be positively related to the change in strategic effort following an increase in task complexity.

However, as exposure to a changed task lengthens, less information will need to be gathered as the change will have been identified and diagnosed. As Jundt (2009) states "diagnosis can be defined as ascertaining the cause or nature of change in the given task" (p. 29). This process of diagnosis suggests that individuals have had the opportunity to experience a learning process after the change was introduced and have incorporated the information they needed in order to adapt to the situation. Earlier, it was hypothesized that strategic self-evaluative activity will be related to strategic information gathering behavior which will be associated with strategic effort, suggesting that information gathering serves as a mediator. However, as Jundt's research found, as an individual diagnoses the change (through self-evaluative activity) and incorporates new information into a working knowledge of the task, less information gathering behaviors will be employed. Instead, the self-evaluative activity will have a direct impact on where effort is allocated. Therefore, the mediating role of information gathering will become weaker over time and strategic self-evaluative activity will have a direct effect on strategic effort. The direct effect is expected to strengthen as self-evaluative activity (i.e., attentional resources devoted to the strategic aspects of the feedback) serves as a means of understanding whether strategic effort is having the desired effect on performance. See Figure 1 for a depiction of this relationship.

Hypothesis 4: Initially, following an increase in task complexity, the amount of self-evaluative activity focused on strategic task elements will be positively related to the change in strategic effort through the amount of strategic information gathered; however, over time there will be a stronger direct effect of strategic self-evaluative activity on changes in strategic effort.

Figure 1

The Relationship Between the Cognitive Self-regulatory Mechanisms



Note: There is a time lag reflected between the intercept and change variables

Motivational Pathway

In order to adapt and self-regulate, research suggests that there must be a motivational component that energizes an individual to act upon any discrepancy between performance and goals that they identified (Bandura, 1991). That is, without motivation, effort will not be devoted to changing behavior in response to an adaptive change, regardless of whether or not the change was correctly detected and diagnosed. Research suggests that error framing impacts the regulatory mechanisms involved in this pathway (Keith & Frese, 2005; Bell & Kozlowski, 2008); therefore, I will describe how error encouragement framing will activate self-efficacy, goals, effort, and performance over time, after a change is introduced.

Error Encouragement Versus Error Avoidance Yielding Self-efficacy

Errors are commonly thought of as something to be avoided; however, research suggests that framing errors in an acceptable and even encouraging manner during training increases adaptive performance (Keith & Frese, 2008). Error encouragement framing posits that errors are a crucial part of the learning process and therefore should be considered positive, whereas error avoidance framing suggests that errors are hindrances for the learning process and therefore should be avoided (Bell, 2002; Bell & Kozlowski, 2008).

Error encouragement framing has been found to have a greater positive impact on adaptive performance than error avoidance framing through the mediation of self-regulatory mechanisms (Bell & Kozlowski, 2008; Keith & Frese, 2005, 2008). Self-efficacy is one such mechanism that mediates the impact of error encouragement framing on adaptive performance (Bell & Kozlowski, 2008). *Self-efficacy* has been described by Bandura (1991) as a central mechanism to self-regulatory process as it is a belief in one's ability to control goals, effort levels, and performance. Given the research discussed earlier (e.g., Bell & Kozlowski, 2008), it is expected that error encouragement framing will lead to higher levels of self-efficacy initially after a change, as compared to error avoidance framing.

Additionally, error encouragement has been found to increase persistence in the face of poor performance (Dweck, 1986). Dweck posits that errors encourage the attainment of challenging goals and a mindset of persistence, which is an adaptive response; however errorless training promotes a maladaptive response, or ineffective goal striving and unreasonable goals.

Therefore, it is expected that error encouragement training will result in a faster growth in self-efficacy after a change is introduced as compared to error avoidance framing.

Hypothesis 5a: Compared to error avoidance framing, error encouragement framing will lead to higher initial levels of self-efficacy following an increase in task complexity.

Hypothesis 5b: Compared to error avoidance framing, error encouragement framing will lead to a greater increase in self-efficacy following an increase in task complexity.

Mechanisms of the Process: Self-efficacy Yielding Goals, Effort, and Performance

As described above, s*elf-efficacy* is a belief in one's ability to control goals, effort, and performance (Bandura, 1991). In addition to being activated by error framing, self-efficacy has been found to impact the difficulty of the goal set, the effort devoted to that goal, and the performance of the individual (Bandura, 1991; Latham & Locke, 1991). Latham and Locke (1991) state that self-efficacy not only has a direct effect on performance but also influences performance indirectly through increasing goal level and commitment. Some work has suggested that when controlling for previous performance, self-efficacy and goals have a non-significant (Kozlowski, Gully et al., 2001) or negative relationship with future performance (Vancouver, Thompson, & Williams, 2001). However, some researchers have argued that self-efficacy is more than a self-report of one's previous performance or knowledge basis, but rather is "a self-assessment of current and future capability that can influence motivational and regulatory processes during and after training" (Kozlowski, Gully et al., 2001, p. 24). Indeed, when Kozlowski and colleagues (2001) controlled for previous performance and knowledge, self-efficacy still had a significantly positive impact on adaptive performance.

Research investigating the within- individual effect of self-efficacy on various outcomes has been inconsistent. A recent meta-analysis of 35 empirical studies investigating the effect of self-efficacy on performance revealed several moderators that had a significant impact on the direction and strength of this relationship (Sitzmann & Yeo, 2012). In studies with a positive performance trend, the effect of self-efficacy and performance was positive and strong. Another moderator identified was the number of trials in the study, such that as the number of performance periods increased, the positive effect of self-efficacy and performance was strengthened. Sitzmann and Yeo (2012) suggested that this effect might be due to individuals having an increased opportunity to calibrate their level of self-efficacy over time. Other research has found that ambiguous situations serve as a boundary condition of the effect of self-efficacy on performance, suggesting that when the situation is highly ambiguous there is a negative relationship as individuals are unable to calibrate their self-efficacy (Schmidt & DeShon, 2010).

However, this study provides feedback after each performance period, which would reduce the ambiguity associated with the task and therefore ameliorate the negative effect of self-efficacy on performance (Schmidt & DeShon, 2010; Sitzmann & Yeo, 2012). Furthermore, a positive performance trend is expected after the change, as previous research suggests that individuals will eventually increase in their performance (e.g., LePine, 2003, 2005). Finally, as multiple adaptive trials will be investigated, it is expected that the effect of self-efficacy on performance will be positive as individuals will have the opportunity to calibrate their self-efficacy (Sitzmann & Yeo, 2012). Therefore, this study will adopt the perspective that self-efficacy has a positive impact on goals, effort, and performance (Latham & Locke, 1991).

Goal level has been conceptualized as a critical mechanism in the motivational pathway of the self-regulatory process as goals are related to previous performance in order to assess progress (Bandura, 1991; Karoly, 1993). As Latham and Locke (1991) suggest "[Goal setting theory] states that the simplest and most direct motivational explanation of why some people perform better than others is because they have different performance goals" (p.213). This suggests that goals have a positive relationship with performance. Multiple studies have established the positive relationship between self-efficacy and goals (Bandura, 1991; Latham & Locke, 1991; Bandura & Wood, 1989; Wood & Locke, 1987) such that when individuals are more efficacious they set higher goals due to their increased belief in their ability which results in higher motivation to get the job done. Contrarily, when an individual has low self-efficacy there is a decrease in motivation to accomplish the task resulting in the individual setting lower goals.

Self-efficacy has been suggested as having a positive relationship with goals when a task becomes more complex and adaptation is required due to increasing the resilience and persistence of individuals (Dweck, 1986; Gist & Mitchell, 1992). Work in the adaptation literature suggests that the positive effect of self-efficacy on performance is mediated by goal choice and goal striving activities (Chen et al., 2005). Furthermore, the positive relationship between self-efficacy and goals is supported by research over multiple points in time. Vancouver et al. (2001) investigated undergraduates performing a computer-based cognitive task and determined that within-person self-efficacy was positively related to goals over time. Similarly, in a study of graduate students from a business school participating in a simulated organization where individuals took on managerial positions, self-efficacy was positively related to goals over several points in time (Bandura & Wood, 1989). In a lab study of individuals performing a word completion task, Tolli and Schmidt (2008) found the change in self-efficacy positively predicted the change in goal level over two points of time. The authors also noted that self-efficacy had a stronger positive relationship with post-feedback goals as opposed to initial goals, which suggests that this positive relationship will be evident throughout the performance trials after the change. Therefore, it is expected that fluctuations in self-efficacy will be related to fluctuations in the level of goals set.

Hypothesis 6: The level of self-efficacy will be positively related to the change in goal level following an increase in task complexity.

As goal levels are simply a desired outcome, effort needs to be allocated in order for the goals to be translated to performance. *Effort*, defined in this paradigm, constitutes behaviors directed toward completing the task. Various self-regulation theories have conceptualized effort as a key motivational mechanism that positively impacts performance as effortful behaviors are what drive an individual toward a goal (e.g., Latham & Locke, 1991; Yeo & Neal, 2004). Bandura and Cervone (1983) investigated the impact of goals, effort, and performance in a lab environment over several points of time. They measured effort as the physical amount of effort devoted to the task. They demonstrated that the goals set by an individual predicted the effort expended over multiple trials. Therefore, changes in goals are expected to positively relate to changes in the total amount of effort devoted to the completion of the task.

Hypothesis 7: The level of goals will be positively related to the change in the total amount of effort employed following an increase in task complexity.

Not only is effort a result of goals, but effort has been found to predict performance over time (Bandura & Cervone, 1983). In a study of individuals performing 30 trials of a computer-based air traffic control simulation, Yeo and Neal (2004) found that changes in effort predicted changes in performance. The authors suggested that an increase in effort reflected an increase in motivation to work harder to reach the desired performance level. Yeo and Neal (2008) expanded on this finding with two studies, replicating the effect that effort positively predicted performance over time through self-report ratings of effort. However, this positive effect was only found when the task was perceived as difficult. Given that the need for adaptation is due to the environment increasing in complexity, this research expects that changes in effort will have a positive relationship on changes in performance after an event that requires adaptation is introduced.

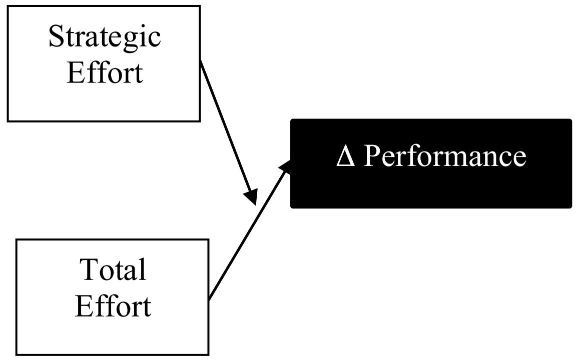
> Hypothesis 8: The total amount of effort employed will be positively related to the change in performance following an increase in task complexity.

However, effort can be allocated to different aspects of the task, as discussed earlier. It can be devoted to just working harder (basic effort) versus working smarter (strategic effort). Working smarter, or putting forth strategic effort, is one way of stating that adaptive expertise is developing. Therefore, it is hypothesized that the relationship between the total amount of effort and performance will be enhanced based on the proportion of total effort that is strategic. See Figure 2 for an illustration of this relationship.

> Hypothesis 9: The amount of strategic effort will moderate the relationship between the amount of total effort and the change in performance such that, following an increase in task complexity, when the amount of strategic effort behavior is high, the relationship between effort and change in performance will be greater as compared to when the amount of strategic effort is low.

Figure 2

The Interaction Between Effort and Performance



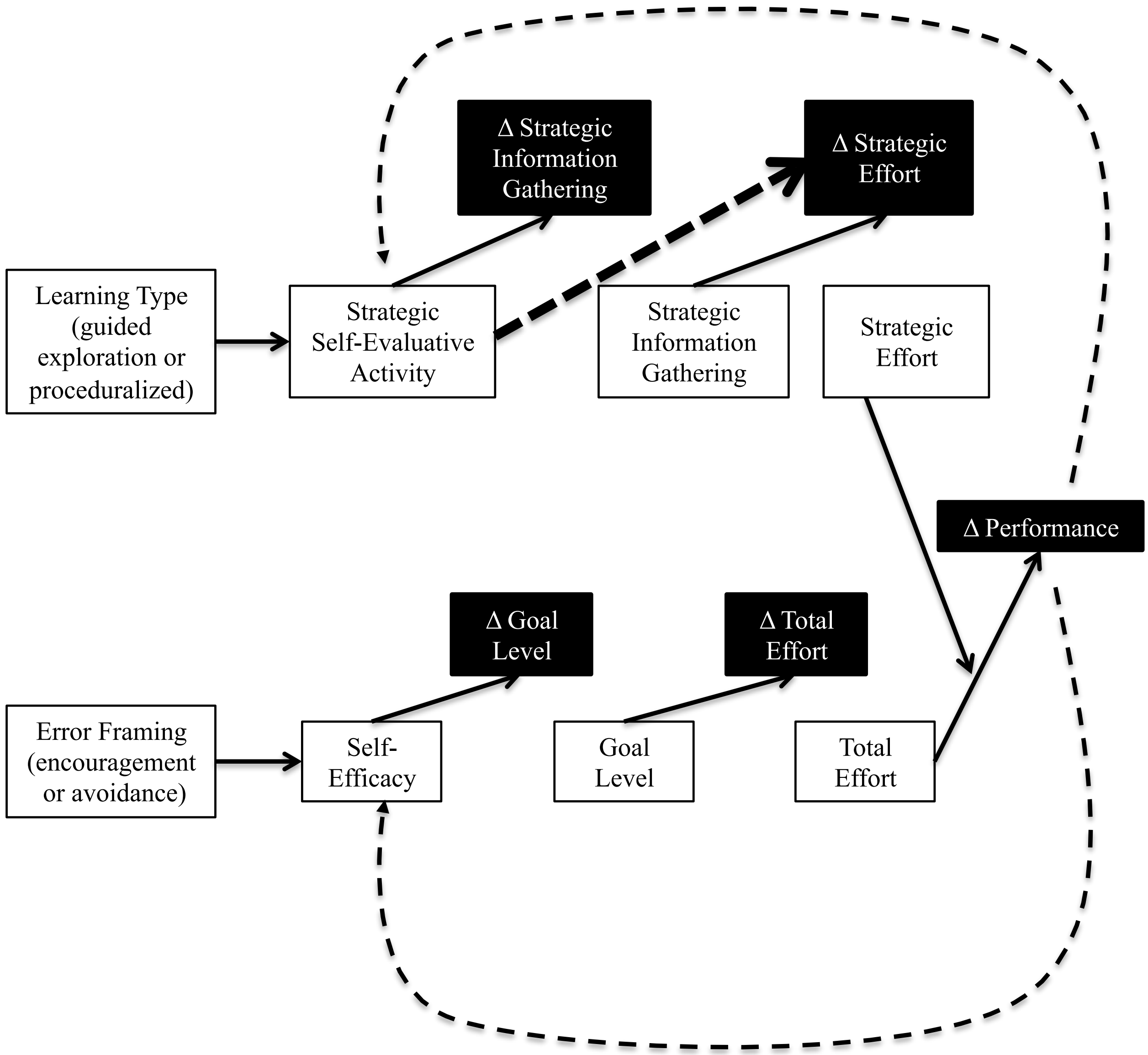
Note: There is a time lag reflected between the intercept and change variables

Summary

In summary, this research is attempting to unpack the process of adaptation through investigating how self-regulatory mechanisms drive fluctuations in behavior after a change in complexity is introduced into the task. This adaptive process can be understood through two regulatory pathways: cognitive and motivational. Furthermore, this process is impacted by instructional trainings and error framing. The model below (Figure 3) comprehensively illustrates the relationships between the training inductions, self-regulatory mechanisms, and performance (after a change) that are being investigated. Although the model appears similar to the extant research that focused primarily on adaptive performance change, as opposed to the adaptive process (e.g., Bell & Kozlowski, 2008), this figure is designed to visually represent the relationships described in the longitudinal hypotheses developed above in order to improve clarity and provide a comprehensive view of the process being examined.

Figure 3

A Heuristic of the Relationships Between Self-regulatory Mechanisms After a Change and the Influence of Learning Type and Error Framing



Note: There is a time lag reflected between the intercept and change variables

METHOD

Participants

The sample consisted of 268 undergraduate students from a large Midwestern university. Individuals were recruited from the Psychology subject pool and were compensated with course credit. Sixty percent of the participants were male and 96% were between 18 and 22 years old.

Task

The task that will be used is a computer-based radar-tracking simulation, TANDEM, which is a decision making experimental platform that has been used in prior research in the adaptation literature (Kozlowski, Gully et al., 2001; Bell, 2002; Bell & Kozlowski, 2002a, 2002b; Bell & Kozlowski, 2008). As TANDEM is a complex decision-making task, it serves as a platform with high psychological fidelity to other complex tasks that require decision-making and information processing. This experimental task allows for the experimenter to control almost every element in the task. One can manipulate the number of contacts present, the placement of the contacts, the length of the trial, the information available before and after the trial, and the point allocations.

In order to perform well in this task, participants must make a series of decisions about the contacts before making a final decision (clear or shoot). The decision rules are based on three characteristics: type (air, surface, or submarine), class (civilian or military), and intent (peaceful or hostile). This information is sought after a contact is selected, or “hooked”. In addition to this set of decisions, the participants must not allow the contacts to penetrate the inner or outer perimeters. In order to do this, individuals must utilize the zoom function, and prioritize the contacts. Points are gained for correctly making the four decisions described above, and points are lost for incorrectly making those decisions and for allowing contacts to cross the perimeters.

Design

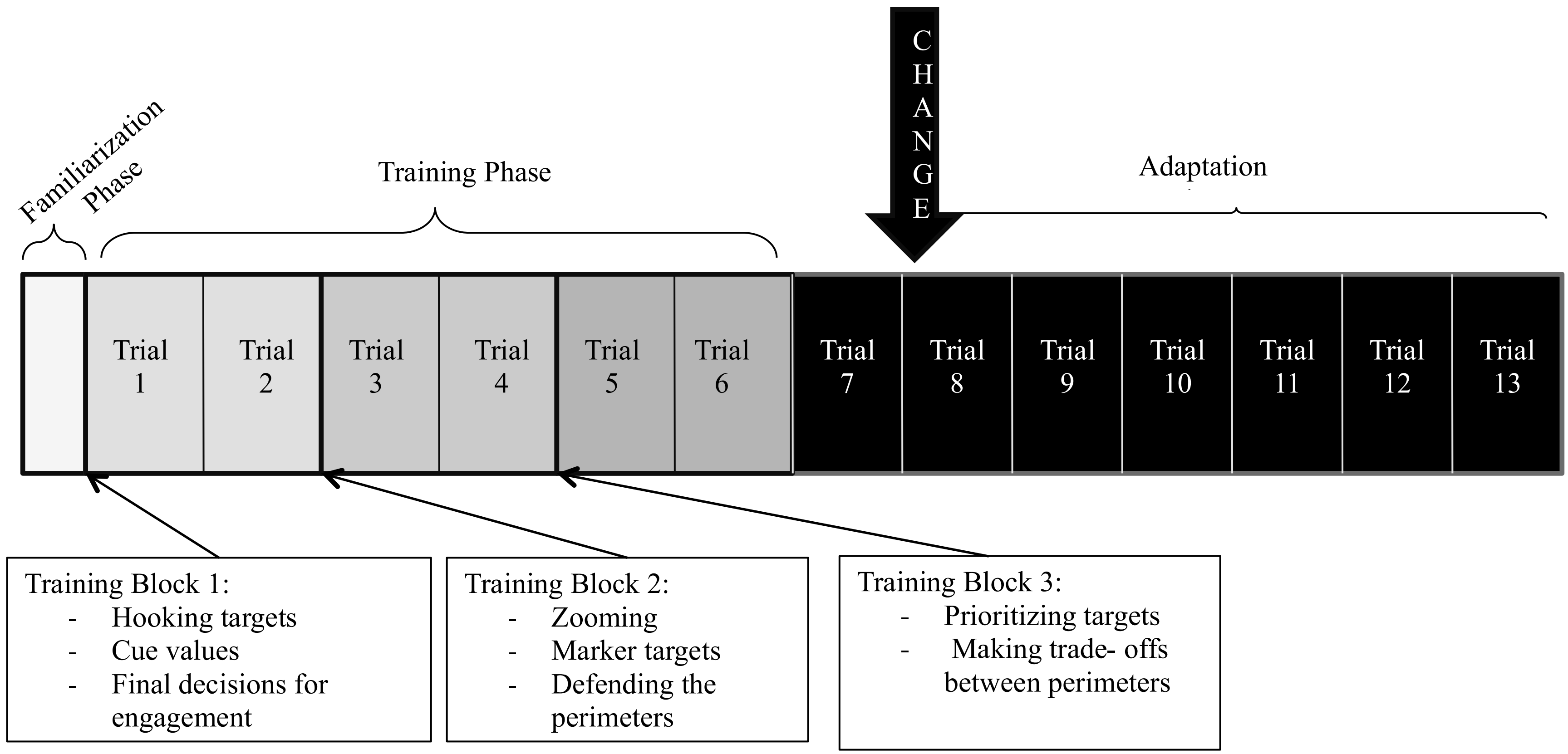
This experiment was a 2 (guided exploration vs. proceduralized instruction) x 2 (error-encouragement vs. error-avoidance) fully crossed between-subjects design using repeated measures. Participants will be randomly placed into one of the four conditions. There were three phases to this experiment: 1) the familiarization phase where individuals were introduced to the TANDEM task and requirements and performance is not recorded, 2) the training phase where individuals were given the training inductions (according to their condition) and performed six training trials and one performance trial similar to the training, and 3) the adaptation phase where the task increased substantially in complexity which required individuals to recognize and adapt to the change over six trials. Figure 4 is a visual representation about the flow of the experiment; however, Appendix A has a complete overview of the flow of the experiment including details about when measures were administered.

Procedure

Familiarization Phase

Upon entering the lab, participants were asked to complete an informed consent. Once obtained, a demographics questionnaire was completed. After all participants were finished, the experimenter gave a demonstration of the task through a PowerPoint presentation discussing the following topics: how to hook contacts, zoom, and the sequence in which you make a decision.

Figure 4
A Visual Representation of the Flow of the Experiment



After the demonstration, participants had 3 minutes to study the manual followed by a 1 minute familiarization trial (from which they did not receive any feedback). The purpose of that short trial was to expose the individuals to the task prior to beginning the training.

Training Phase

After the familiarization phase, participants were given instructions about what they should be learning during the next few trials. Instructions varied based on the condition but the learning objectives (see Appendix B) were consistent. The instructions were taken from Bell (2002) where learning type (see Appendices C and D) and error framing (see Appendix E) were manipulated. The manipulation was given through written instructions in three blocks with two trials in each block (see the below section for more detail on the training inductions). After reading the information, individuals engaged in the trials. First, participants had an opportunity to look at the manual (2 minutes); second, they engaged in a trial (4 minutes); and finally, they received feedback on their performance (1 minute). This continued until all six training trials were completed. At that time participants filled out another set of measures containing basic and strategic knowledge, and state goal orientation. After these measures were completed, individuals completed one performance trial that mirrored the training trials.

Adaptation Phase

Once completed with the measures from the training phase, individuals began the adaptation phase where they are told something has changed in their environment. These scenarios were more complex, contained more contacts, had different point values for high and low priority contacts, and had larger penalties for perimeter crossings. This increase in component complexity (through an increase in the number of contacts) and dynamic complexity (through a shift in the importance of certain actions) maps onto Wood's taxonomy of task complexity (1986), and is evidence that adaptation was required.

Participants engaged in six adaptation trials with steps similar to the training phase: look at the manual (2 minutes), perform the trial (4 minutes), receive feedback (1 minutes), and respond to a set of measures (i.e., self-efficacy and goal level; 2 minutes).

After all the trials have been completed, individuals were fully debriefed, thanked, and dismissed from the experiment.

Training Inductions

As noted above, the manipulations were given during the training phase. There were two types of manipulations, resulting in four different combinations. The manipulations were presented through written instructions in three blocks as referred to above. The materials that constitute these trainings were used in previous research by Bell and Kozlowski (2002b, 2008) and are found in Appendices B, C, D, and E.

Individuals received three sets of information at the beginning of each block: training topics (which will be the same for each individual regardless of conditions), task instructions (where the learning type will be manipulated), and error instructions (where error framing will be manipulated). In the first block, individuals were instructed to investigate how to correctly make the four decisions about a contact (type, class, intent, and prosecution) and how to navigate the task environment. The second block directed participants to focus on how to prevent contacts from crossing the borders through instruction on how to use the zoom function, how to identify marker contacts, and how to be prepared for pop-up contacts that suddenly appear on the screen.

Finally, the third block instructed individuals in prioritizing contacts and in making tradeoffs between protecting the inner and outer perimeters.

Learning Type

Guided exploration. Active learning techniques were employed in the guided exploration condition. As mentioned above, all individuals received the same training topics, but little guidance beyond that were provided. Instead, the participants were instructed to experiment with and explore the task environment in order to discover what the best strategy was (McDaniel & Schlager, 1990; Bell & Kozlowski, 2008). This active learning technique emphasized individual exploration and strategy development, which have been associated with a deeper understanding of the task domain after training (e.g., Bell, 2002). However, as past research has shown that some guidance is needed to focus cognitive and motivational resources, individuals will be given a short reminder that they should focus on exploring the task, specifically trying to understand the training topics (see Appendix C for the written instructions).

Proceduralized instruction. Participants who received proceduralized instruction were given explicit instruction about what actions to perform within the training scenarios. Individuals within this condition were given the same list of training topics, but instead of being told to explore the task, they were provided with step-by-step instructions that walked them through a specific set of behaviors that they should engage in throughout the trials. See Appendix D for the specific instructions that follow previous research in this paradigm (Bell & Kozlowski, 2008).

Error Framing

Error-encouragement. For each of the three blocks during the training phase, **i**ndividuals were given a list of the possible errors they could make during the task. These errors were associated with the training topics they were informed to focus on. Individuals needed to be informed of the possible errors before any error framing manipulation could be given (Bell, 2002). After reading what errors were possible, those in the error-encouragement condition were instructed that they are encouraged to make the listed errors because errors enhance the learning process (Gully et al., 2002; Bell & Kozlowski, 2008). Appendix E lists each block with the possible errors and both of the error framing manipulation statements.

Error-avoidance. Individuals in the error-avoidance condition received the same set of possible errors at the beginning of each training block, but they were informed that they should avoid making these errors as errors are detrimental to the learning process and would decrease their understanding of the task (Bell &Kozlowski, 2008).

Measures

Measures were collected at three distinct time points: once participants entered the lab (cognitive ability, demographics, trait goal orientation), once participants finished the training phase (basic and strategic knowledge, state goal orientation), and throughout the adaptive phase (self-evaluative activity, information gathering, self-efficacy, goal level, effort, performance). The self-report measures are listed in Appendix F, G and H and will be described below in order of when they appeared in the experiment.

Before the familiarization phase

Cognitive ability. Cognitive ability was gathered immediately upon individuals entering the lab. Previous research has suggested that the SAT and ACT are acceptable measurements of cognitive ability (e.g., Phillips & Gully, 1997). Furthermore, they are known to be highly reliable (e.g., KR-20 = .96 for the ACT composite score; American College Testing Program, 1989). GPA will be gathered to provide additional insight into an individual’s ability. Participants were ensured that their scores would remain confidential and only be used for research purposes. Self-reported cognitive ability scores have been found to have high correlations with official scores and are therefore considered an acceptable option for gathering this information (.95; Gully, Payne, Koles & Whiteman, 2002).

Demographics. This measure was also collected immediately upon individuals entering the lab and contained other individual difference items such as year in school, undergraduate major, gender and age.

Trait goal orientation. Trait goal orientation was measured using a modified version of the 13-item measure developed by VandeWalle (1997) as individuals enter the lab. This measure used a 6-point Likert-type scale with the range of "strongly disagree" (1) to "strongly disagree" (6). The measure has three subscales with the following reliabilities: mastery orientation (α = .85), performance-prove (α = .84), and performance-avoid (α = .83; VandeWalle, 1997).

After the training phase

Basic and strategic knowledge. Once the training phase was completed, declarative and procedural knowledge pertaining to the TANDEM task domain was assessed. This provided a baseline of how well an individual understood the rules of the task as well as the objective or overall goal. Basic knowledge was measured through the assessment of the basic operating features of the task (e.g., the identification of cues, the decision rules, and other basic operating features). Strategic knowledge measured the individual's procedural understanding of the task (e.g., prioritization of actions, marker contacts, zooming function). Bell and Kozlowski (2002b) found that basic and strategic knowledge loaded on two separate factors and the two factor representation of knowledge was a better fit to the data than a one factor model. This suggests that they are two distinct knowledge domains.

State goal orientation. State goal orientation identifies learning and performance orientations with regard to the specific task. This state was measured after the training phase in order to more accurately obtain an estimate of an individual's goal orientation during the TANDEM task. Bell and Kozlowski (2008) use an adapted measure of Horvath, Scheu, and DeShon (2001) to form the state mastery orientation measure. As the former work was conducted using the same paradigm with an alphas ranging from .79 to .90, this measure will be adopted in this study. The measure consisted of 15 items, and has three subscales (learning, performance prove and performance avoidance) using a 5-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5).

Throughout the adaptation phase

Self-efficacy. Self-efficacy was measured after each scenario with four items adapted from Ford, Smith, Weissbein, Gully and Salas (1998). They developed an 8-item self-report measure specifically for this task paradigm with an internal consistency of .90. This measure will use a five point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5). The reliability of this scale was high for all time points measured: .927. .930, .963, .971, .974, .974. Metric invariance of this measure will be described in the results section.

Goal level. Goal level was measured as the self reported level of performance the individual sought to obtain on the next trial and was measured throughout the adaptation phase. These items required the creation of both specific goals (e.g., identifying contacts correctly and eliminating threats) and overall performance goals (e.g., total score for the next trial).

Total effort. Total effort was a behavioral indicator measured throughout the trials in the adaptive phase. This measured the total amount of effort exerted by the individual (i.e., how hard an individual is working) through the number of contacts queried, contacts hooked, zooms, and prosecutions. There are two components of total effort: strategic effort consisting of behaviors devoted to the aspects of the task that changed (e.g., zooms and speed queries) and basic effort consisting of behaviors devoted to the basic principles of the task (e.g., hooking and executing contacts).

Self-evaluative activity. Self-evaluative activity was a behavioral indicator collected during each of the trials during the adaptive phase. This measure was intended to be a proportion variable of the amount of time spent viewing feedback that is related to the strategic aspects of the task over the total amount of time they spent reviewing feedback, but a count of strategic behaviors was used. Strategic elements are considered the number of speed queries, the number of times a marker contact is hooked, and the number of time zoomed in or out. More reflection on the strategic elements of the task would reflect an understanding of where the change occurred. It would be difficult to adapt without an increase in strategic self-evaluative activity.

Information gathering. Similar to self-evaluative activity, information gathering was a behavioral indicator that will be tracked through what information is being sought from the manual after an adaptive scenario. Furthermore, this variable was also intended to be a proportion of the amount of time spent viewing strategic information over the total amount of time spent reviewing the manual; however, the amount of strategic information sought was used.

Strategic effort. Strategic effort was another behavioral indicator assessed during the trials of the adaptive phase. This measure was a component of the total effort but focused on how *well* an individual is working, as opposed to simply how *hard* an individual is working. These strategic effort behaviors included the number of: speed queries, marker contacts hooked, zoom in or out, and correctly engaged high priority contacts (fast moving contacts that are close to a perimeter). Without an increase in strategic effort, it would be difficult for individuals to adapt to the environment.

Performance. Performance in TANDEM is dependent on an individual's ability to complete several actions: identify contacts within the radar area, make decisions about the type of contact, and protect the home base by not allowing contacts to cross either the inner or outer defensive perimeters. Performance was measured in the same manner previous research using this paradigm has measured it (e.g., Bell & Kozlowski, 2008). During the training phase, performance was computed by adding 100 points when all four decisions (type, class, intent, prosecution) are made correctly and 100 points will be subtracted if any one of those decisions were incorrect. Furthermore, 10 points was subtracted if a contact crosses the inner or outer defensive perimeter. During the adaptive phase there were more contacts, more pop-up contacts (contacts that appear suddenly and usually close to a perimeter), more outer perimeter intrusions, and a shift in the importance of perimeters crossings (175 points for visible inner perimeter intrusions and 125 for invisible outer perimeter intrusions). This increase in complexity was replicated from previous research using this task paradigm in the field of adaptation. Wood's (1986) typology of task complexity suggests that the increases in complexity described above create a novel environment that an individual must adapt to in order to perform well (Bell & Kozlowski, 2008).

Statistical models

Bivariate latent difference score models were used to examine the dynamic nature of the relationship between the variables over the course of the adaptation phase (see McArdle, 2001 for more details on the mathematics underlying the model). Below is the general equation for the latent changes of variables x and y as seen in Figure 5:

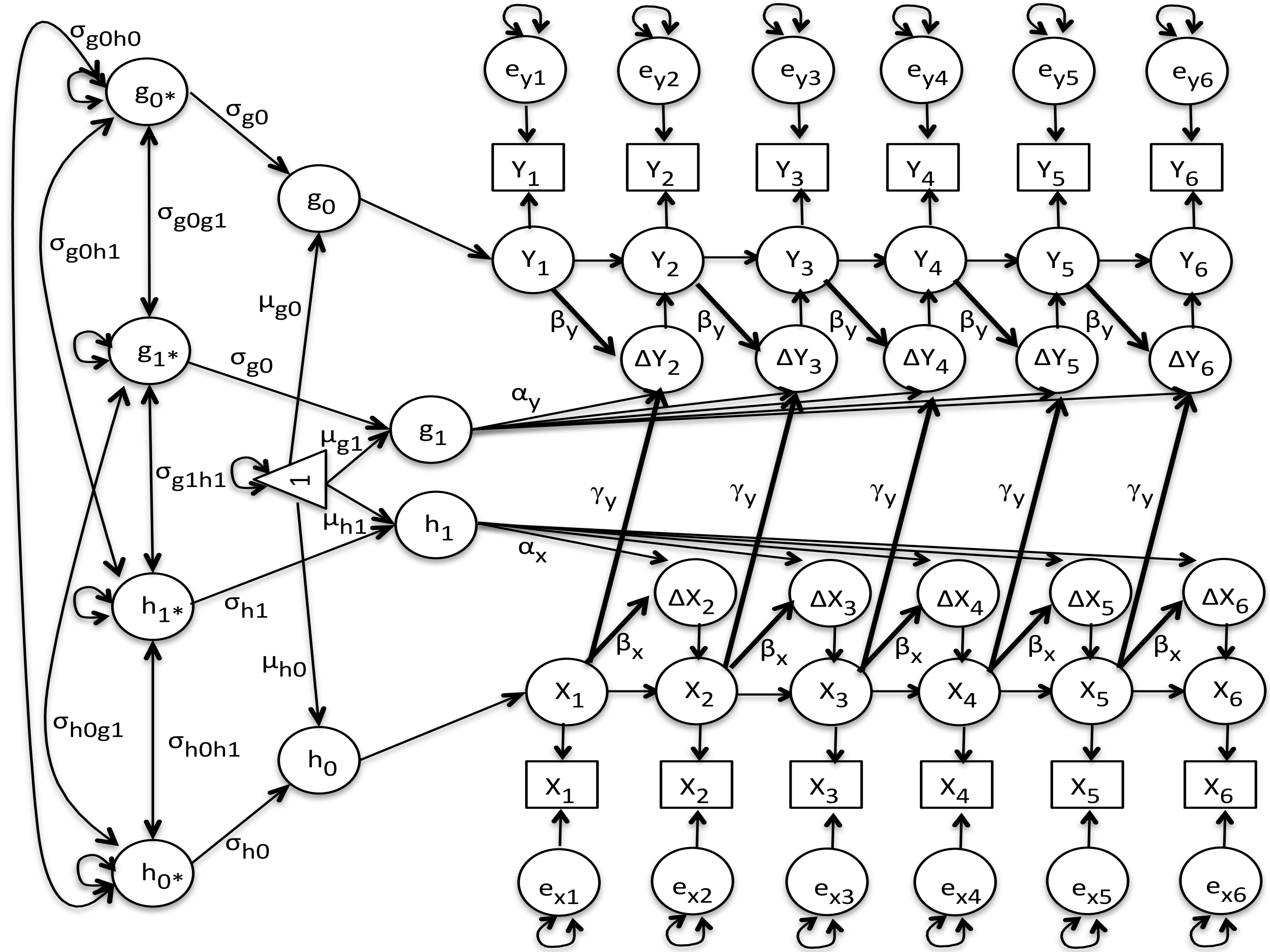
$$\Delta y[t]_t = \alpha_y * g_{yn} + \beta_y * y[t-1]_n + \gamma_y * x[t-1]_n + \zeta_y[t]_n$$

$$\Delta x[t]_n = \alpha_x * h_{xn} + \beta_x * x[t-1]_n + \gamma_x * y[t-1]_n + \zeta_x[t]_n$$

where α is the coefficient of the slope (g or h) of the change of x and y; β is the autoregressive parameter representing the influence of that variable at the last time point on change in the variable at the current time point (also referred to as proportional change); γ is the coupling parameter referring to the influence of another variable's previous state (e.g., Y at time 2) on changes in the focal variable (e.g., change in X at time 3); and ζ is the unexplained portion (error). Therefore, there are four sources of change for each variable: (1) the difference score, Δx or Δy, (2) the slope of the change, α_x or α_y, (3) the proportional change or autoregressive effect, β_x or β_y, and (4) the coupling effect where the level of one variable at the previous time point influences changes in another variable at the next time point, γ (Ferrer, Shaywitz, Holahan, Marchione & Shaywitz, 2010).

Bivariate latent difference score modeling is particularly beneficial in longitudinal analyses where the relationship between variables is hypothesized to change over time. Other analyses, such as latent growth curve analysis, do not allow for such flexibility, nor do they allow for the prediction of one variable from another but rather estimates a correlation between the slopes of the trajectories. Bivariate latent difference score models estimates four sources of change in a variable of interest: (1) a latent difference score, which is a direct measure of change in the variable between two adjacent time points, (2) a proportional chance (or autoregressive change), which takes into account the previous state of that variable and how much impact the previous level has on the change in that variable, (3) the slope of the change, which is a typically

Figure 5
Bivariate Latent Difference Score Model with X-Y Coupling Only



a linear growth curve of the difference scores (or changes) in the variable of interest (e.g., if the slope is large this indicates that the variable changes more as time continues; if the slope is zero it indicates that the amount of change in the variable is the same across time), and (4) the coupling effect, which is the impact of the previous state of another variable on the change in the variable of interest. Figure 5 shows a graphical depiction of self-efficacy (variable x) and goal level (variable y).

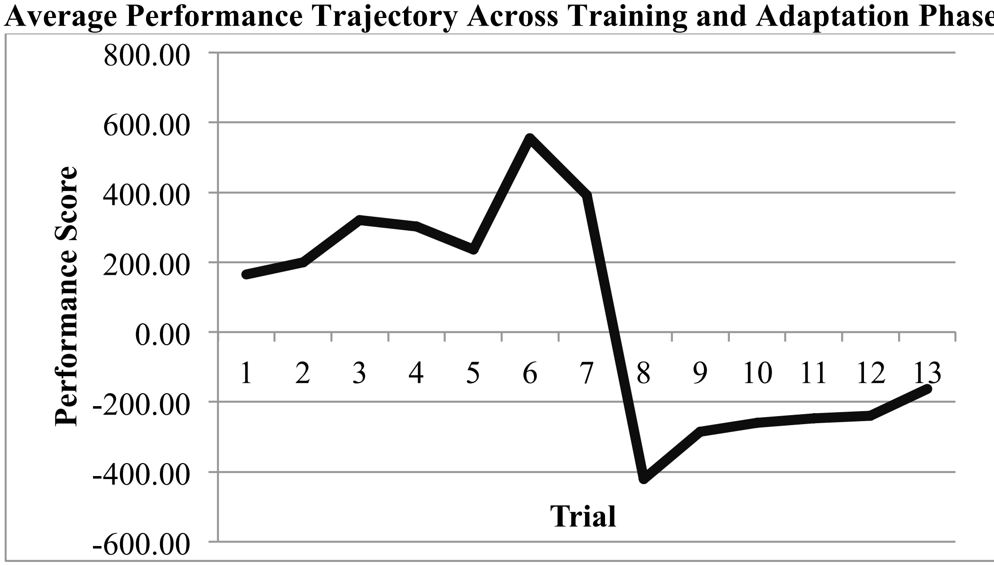
Other related analyses that will be presented are: a univariate latent difference score model and a multigroup latent difference score model. The univariate latent difference score model uses the same principles as the bivariate described above but without covariances between the latent growth curves and without a coupling effect (i.e., the influence of the previous state of X on the change in Y). This would be as if we only investigated X in Figure 5, without Y in the picture. The univariate latent difference score allows the researcher to investigate the structure of change within one variable across time without including other variables as possible predictors of the change. A multigroup model estimates multiple univariate latent difference score models for the different groups under investigation and parameters are relaxed until the change in the model fit shows no significant misfit. The comparison of these models allows for conclusions to be drawn on which parameters are significantly different from each other. When parameters are relaxed across the groups and there is decreased misfit, it is concluded that these parameters are significantly different from each other. Contrarily, when parameters are relaxed and the model shows no significant change in fit, the parameters are concluded to be not significantly different from each other.

RESULTS

Variable Description

In the following analysis, the focus will be placed on the adaptation phase (trials 8-13). However, Figure 6 shows that there was a drop in performance after the change occurred as compared to the previous trial, providing evidence that individuals were required to adapt their strategies in order to increase subsequent performance. As a note, all strategic variables are at the behavioral level, not as a proportion of strategic behavior over total behavior. Therefore, strategic feedback (e.g., the number of targets that crossed a perimeter in the last trial) and information seeking behaviors (e.g., the information regarding how to make trade-offs) were measured in the number of seconds spent on pages deemed strategic, strategic effort was the number of behaviors devoted to the aspects of the task that changed (e.g., the number of times the speed of targets was investigated), goal level was a single item (i.e., how many targets do you plan to prosecute correctly), and self-efficacy was measured as four items that were considered a single measure. The descriptive statistics and correlation of the key variables used in the analyses are found in Table 1 and show each variable over the six adaptation trials.

Figure 6
Average Performance Trajectory Across Training and Adaptation Phases



As self-efficacy was the only multiple indicator measure used in these analyses, it was necessary to show evidence of strong metric invariance. Therefore, a series of models were estimated to investigate whether the measure of self-efficacy remained the same over time (see Table 2). The configural invariance model revealed the pattern of factor loadings to be the same across time (X^2(df)= 353.534 (177), p<.001; RMSEA=.061; CFI=.981; SRMR=.023). The weak metric invariance model constrained loadings to be the same across time in order to test whether there is a common unit over time and the model did not reveal significantly worse misfit (ΔX^2(Δdf) =17.816(15), p=.272). Finally, to state that the measure is the same across time, strong metric invariance was tested to establish that there is a common origin. Although this model revealed significantly worse misfit (ΔX^2(Δdf) =27.875(15), p=.022), the RMSEA, CFI and SRMR were all within acceptable standards (Hu & Bentler, 1999) and therefore the four items of self-efficacy were combined to form the measure of self-efficacy for further analyses (X^2(df)=399.229(207), p<.001; RMSEA=.059; CFI=.980; SRMR=.03).

Next, in order to run bivariate latent difference score models, the univariate models had to first be estimated for each variable independently. Table 3 shows the univariate results for each of the key variables that will be used in hypothesis testing. For strategic feedback seeking behavior, strategic information gathering behavior, efficacy, goal level, and performance, the best fitting model was one that allowed the autoregressive component to be different across time. This suggests that previous levels of the variables had differential effects on the change in that variable at the next time point. Specifically, the higher the level of the variable, the less that variable changed at the next time point. For strategic and total effort behaviors, the proportional effect did not differ across time. This suggests that the influence of the last time point remained constant over the adaptive phase. These univariate models were used in the following bivariate

Table 1
Means, Standard Deviations, and Correlations of Key Variables

	Mean	S.D.	Learning Manip.	Error Manip.	Perf.8	Perf.9	Perf.10	Perf.11	Perf.12	Perf.13
LearningManipulation	0.49	0.50								
ErrorManipulation	0.51	0.50	-.022							
Performance.8	-421.07	481.48	.030	.135*						
Performance.9	-284.59	539.21	-.013	.129*	.726*					
Performance.10	-260.51	520.89	.062	.148*	.724*	.746*				
Performance.11	-246.76	572.67	.071	.141*	.684*	.716*	.779*			
Performance.12	-238.93	590.73	.070	.114	.651*	.698*	.761*	.779*		
Performance.13	-163.27	565.67	.007	.088	.612*	.666*	.722*	.738*	.785*	
TotalEffort.8	113.82	29.37	.027	.134*	.513*	.476*	.515*	.486*	.455*	.429*
TotalEffort.9	113.77	31.61	-.015	.095	.515*	.541*	.520*	.501*	.489*	.457*
TotalEffort.10	114.64	31.29	.002	.119	.523*	.518*	.550*	.507*	.497*	.459*
TotalEffort.11	115.12	32.25	-.009	.127*	.519*	.540*	.550*	.582*	.516*	.523*
TotalEffort.12	114.39	35.50	.040	.067	.422*	.492*	.463*	.490*	.552*	.524*
TotalEffort.13	115.25	35.18	.017	.112	.467*	.496*	.492*	.505*	.542*	.545*
StrategicEffort.8	25.19	11.51	.015	.103	.281*	.312*	.284*	.326*	.296*	.266*
StrategicEffort.9	26.81	13.40	.057	.100	.263*	.336*	.282*	.332*	.295*	.282*
StrategicEffort.10	26.58	13.55	-.032	.123*	.225*	.272*	.209*	.251*	.225*	.195*
StrategicEffort.11	26.97	13.67	-.001	.147*	.263*	.279*	.275*	.246*	.239*	.209*
StrategicEffort.12	26.26	14.51	.012	.141*	.193*	.282*	.192*	.217*	.249*	.182*
StrategicEffort.13	26.43	14.46	-.009	.100	.199*	.274*	.214*	.194*	.219*	.188*
StrategicManual.8	21.14	34.90	.083	.133*	.052	.071	.089	.065	.042	.013
StrategicManual.9	17.16	35.32	-.027	.025	.176*	.148*	.152*	.141*	.121*	.038
StrategicManual.10	16.02	34.82	-.079	.203*	.094	.051	.096	.037	.019	.115
StrategicManual.11	8.15	25.89	-.090	.085	.127*	.065	.112	.111	.125*	.060
StrategicManual.12	4.37	19.06	.128*	.019	.006	-.017	.026	.045	.007	.000
StrategicManual.13	3.14	16.20	.013	-.031	-.010	-.028	-.050	-.030	-.015	-.047
StrategicFeedback.8	12.83	7.32	-.094	.045	.324*	.248*	.244*	.305*	.296*	.325*
StrategicFeedback.9	10.45	8.03	-.122	.070	.199*	.241*	.177*	.265*	.201*	.243*
StrategicFeedback.10	8.44	6.57	-.068	.108	.164*	.167*	.172*	.190*	.184*	.189*

Note: * indicates p<.05

Table 1 (cont'd)

	Mean	S.D.	Learning Manip.	Error Manip.	Perf.8	Perf.9	Perf.10	Perf.11	Perf.12	Perf.13
StrategicFeedback.11	7.62	7.06	-.077	.181*	.175*	.182*	.117	.242*	.166*	.152*
StrategicFeedback.12	6.40	6.51	-.139	.082	.240*	.218*	.212*	.244*	.242*	.279*
StrategicFeedback.13	5.07	3.70	-.163	.058	.207*	.260*	.151*	.217*	.210*	.324*
Efficacy.8	3.63	0.73	.115	.047	.245*	.177*	.204*	.240*	.269*	.222*
Efficacy.9	2.98	0.88	.001	.051	.317*	.203*	.253*	.246*	.270*	.173*
Efficacy.10	2.80	0.98	.022	.060	.334*	.392*	.335*	.341*	.402*	.310*
Efficacy.11	2.85	1.05	.010	.063	.299*	.320*	.437*	.387*	.447*	.355*
Efficacy.12	2.74	1.10	.031	.072	.279*	.328*	.374*	.456*	.434*	.319*
Efficacy.13	2.76	1.16	-.014	.096	.278*	.347*	.383*	.438*	.493*	.378*
Goal.8	6.49	4.02	.169*	.041	-.047	-.053	-.081	-.006	-.039	-.049
Goal.9	5.73	3.94	.151*	.073	.056	.007	.007	.053	.028	-.015
Goal.10	5.24	3.61	.178*	.037	.070	.099	.060	.115	.116	.074
Goal.11	5.22	3.83	.183*	.006	.084	.037	.170*	.165*	.153*	.112
Goal.12	5.07	3.72	.163*	-.004	.094	.126*	.120*	.225*	.177*	.108
Goal.13	4.97	3.80	.120*	.011	.126*	.166*	.132*	.220*	.211*	.180*

Note: * indicates p<.05

Table 1 (cont'd)

	Total Effort.8	Total Effort.9	Total Effort. 10	Total Effort. 11	Total Effort. 12	Total Effort. 13	Strategic Effort. 8	Strategic Effort. 9	Strategic Effort. 10	Strategic Effort. 11	Strategic Effort. 12	Strategic Effort. 13
TEffort.9	.914*											
TEffort.10	.901*	.925*										
TEffort.11	.837*	.878*	.890*									
TEffort.12	.718*	.792*	.796*	.837*								
TEffort.13	.755*	.800*	.787*	.853*	.857*							
StrEffort.8	.487*	.464*	.500*	.494*	.472*	.463*						
StrEffort.9	.491*	.571*	.543*	.533*	.512*	.499*	.769*					
StrEffort.10	.408*	.470*	.523*	.489*	.475*	.448*	.771*	.827*				
StrEffort.11	.376*	.432*	.447*	.508*	.435*	.449*	.693*	.759*	.798*			
StrEffort.12	.359*	.419*	.433*	.441*	.552*	.469*	.702*	.742*	.806*	.786*		
StrEffort.13	.363*	.401*	.423*	.441*	.457*	.552*	.658*	.710*	.762*	.769*	.818*	
StrManual.8	.100	.068	.085	.113	.112	.081	.200*	.114	.137*	.093	.169*	.127*
StrManual.9	.183*	.175*	.178*	.172*	.164*	.160*	.077	.193*	.166*	.132*	.151*	.123*
StrManual.10	.044	.035	.048	.081	.108	.117	.141*	.150*	.206*	.159*	.149*	.147*
StrManual.11	.068	.078	.075	.081	.102	.111	.091	.087	.151*	.136*	.140*	.071
StrManual.12	.027	.010	.028	.052	.052	.056	.158*	.082	.088	.068	.060	.085
StrManual.13	-.060	-.040	-.038	-.035	-.044	-.023	.104	.097	.119	.115	.112	.097
StrFdbk.8	.179*	.185*	.188*	.234*	.238*	.264*	.234*	.253*	.199*	.257*	.194*	.212*
StrFdbk.9	.080	.079	.136*	.198*	.201*	.180*	.199*	.175*	.159*	.206*	.165*	.243*
StrFdbk.10	.108	.123*	.157*	.166*	.157*	.134*	.240*	.230*	.289*	.317*	.300*	.299*
StrFdbk.11	.162*	.176*	.198*	.217*	.220*	.175*	.303*	.244*	.333*	.294*	.315*	.228*
StrFdbk.12	.124*	.140*	.176*	.215*	.220*	.216*	.286*	.211*	.228*	.290*	.261*	.207*
StrFdbk.13	.165*	.191*	.199*	.257*	.265*	.220*	.305*	.333*	.312*	.298*	.319*	.305*

Note: * indicates p<.05

Table 1 (cont'd)

	Total Effort.8	Total Effort.9	Total Effort. 10	Total Effort. 11	Total Effort. 12	Total Effort. 13	Strategic Effort. 8	Strategic Effort. 9	Strategic Effort. 10	Strategic Effort. 11	Strategic Effort. 12	Strategic Effort. 13
efficacy.8	.160*	.174*	.193*	.198*	.207*	.237*	.126*	.139*	.115	.085	.115	.140*
efficacy.9	.078	.091	.135*	.099	.105	.130*	-.035	-.022	.018	-.004	.023	.054
efficacy.10	.153*	.178*	.215*	.178*	.188*	.197*	.028	.070	.056	.020	.049	.073
efficacy.11	.111	.137*	.169*	.152*	.173*	.176*	-.006	.041	.000	.054	.056	.077
efficacy.12	.085	.137*	.144*	.148*	.193*	.197*	.009	.037	.012	.037	.077	.060
efficacy.13	.125*	.185*	.180*	.183*	.216*	.237*	.014	.004	-.010	.018	.036	.025
goal.8	.024	.041	-.007	.001	.003	.053	-.033	.018	-.001	-.018	-.005	.009
goal.9	.045	.073	.046	.075	.043	.102	-.031	-.013	-.025	-.028	-.043	-.019
goal.10	.065	.118	.080	.116	.118	.149*	.036	.052	.020	.019	-.001	.022
goal.11	.045	.043	.071	.084	.026	.051	.015	-.005	-.016	.001	-.051	-.035
goal.12	.070	.124*	.082	.153*	.134*	.148*	.031	.045	.027	.037	.014	-.002
goal.13	.059	.110	.063	.136*	.121*	.169*	-.028	-.036	-.043	-.043	-.060	-.046

Note: * indicates $p<.05$

Table 1 (cont'd)

	Str Manual. 8	Str Manual . 9	Str Manual. 10	Str Manual. 11	Str Manual. 12	Str Manual. 13	Str Fdbk. 8	Str Fdbk. 9	Str Fdbk. 10	Str Fdbk. 11	Str Fdbk. 12	Str Fdbk. 13
StrManual.9	.239*											
StrManual.10	.288*	.327*										
StrManual.11	.224*	.276*	.304*									
StrManual.12	.221*	.168*	.291*	.202*								
StrManual.13	.221*	.138*	.074	.367*	.033							
StrFdbk.8	-.021	.045	.182*	.083	.059	.055						
StrFdbk.9	.088	-.012	.125*	.059	.103	.105	.539*					
StrFdbk.10	.094	-.007	.102	.102	.064	-.010	.415*	.440*				
StrFdbk.11	.099	.005	.283*	.091	.080	.025	.428*	.376*	.428*			
StrFdbk.12	.129*	-.047	.183*	.052	-.022	-.012	.350*	.346*	.263*	.505*		
StrFdbk.13	.112	.051	.170*	.007	-.023	.058	.359*	.411*	.424*	.427*	.362*	
efficacy.8	.032	.021	-.011	-.029	-.031	-.051	.171*	.093	.167*	.053	.093	.050
efficacy.9	-.071	-.066	.015	-.009	-.019	-.042	.160*	.049	.028	.021	.022	-.027
efficacy.10	-.038	-.019	.000	.024	-.046	-.055	.100	.099	.091	.045	.086	.108
efficacy.11	-.055	-.029	.022	.068	.002	-.039	.091	.109	.146*	.036	.117	.080
efficacy.12	-.043	-.016	.022	.073	.026	-.057	.111	.102	.122*	.102	.115	.032
efficacy.13	-.054	-.076	-.012	.090	-.029	-.050	.095	.049	.085	.077	.095	.044
goal.8	-.022	-.118	-.087	.025	-.025	.025	-.037	-.097	-.021	-.085	-.041	-.091
goal.9	.016	-.104	-.045	.000	.028	-.054	.019	-.091	-.059	-.116	-.054	-.073
goal.10	.040	-.121	.005	.055	.011	.026	.016	-.050	-.085	-.103	-.033	-.011
goal.11	.085	-.078	.008	.064	.079	.090	.013	-.063	-.013	-.103	-.011	-.008
goal.12	.062	-.044	-.009	.099	.072	.081	.004	-.030	-.012	-.087	-.024	-.021
goal.13	.057	-.061	-.002	.054	.002	.049	.029	-.015	-.014	-.085	-.039	.036

Note: * indicates p<.05

Table 1 (cont'd)

	efficacy.8	efficacy.9	efficacy.10	efficacy.11	efficacy.12	efficacy.13	goal.8	goal.9	goal.10	goal.11	goal.12
efficacy.9	.602*										
efficacy.10	.477*	.748*									
efficacy.11	.448*	.688*	.801*								
efficacy.12	.400*	.637*	.704*	.802*							
efficacy.13	.381*	.587*	.700*	.777*	.848*						
goal.8	.203*	.172*	.090	.107	.114	.102					
goal.9	.219*	.270*	.212*	.177*	.187*	.186*	.760*				
goal.10	.193*	.230*	.264*	.229*	.255*	.237*	.664*	.829*			
goal.11	.239*	.291*	.264*	.315*	.253*	.257*	.584*	.729*	.797*		
goal.12	.235*	.259*	.286*	.280*	.352*	.324*	.567*	.681*	.710*	.724*	
goal.13	.229*	.222*	.283*	.255*	.320*	.397*	.524*	.597*	.639*	.665*	.794*

Note: * indicates $p<.05$

Table 2
Metric Invariance of self-efficacy

Step	X^2	df	ΔX^2	Δdf	RMSEA	CFI	SRMR
Configural	353.534	177	---	---	.061	.981	.023
Weak	371.354	192	17.82$^{(n.s.)}$	15	.059	.981	.033
Strong	***399.229***	***207***	***27.875****	***15***	***.059***	***.980***	***.036***
Strict	508.822	227	109.593***	20	.069	.970	.043

Note. P-values are indicated as follows: * <.05; ** <.01; *** <.001.

Table 3
Univariate Difference Score Models for Key Variables

	Strategic Feedback Seeking	Strategic Information Seeking	Strategic Effort Behaviors	Self-efficacy	Goal Level	Total Effort Behaviors	Performance
Fit Indices							
X^2/df	28.712(11)***	32.013(11)***	34.469(15)**	71.153(11)***	59.43(11)***	61.293(15)***	12.539(11)
RMSEA	0.078	0.084	0.07	0.143	0.128	0.108	0.023
CFI	0.958	0.875	0.987	0.952	0.963	0.979	0.999
SRMR	0.054	0.052	0.033	0.043	0.079	0.057	0.024
Parameter Estimates							
Intercept	12.828***	21.288***	25.394***	3.63***	6.154*	113.916***	-416.91**
Slope	5.544***	4.863	12.005**	1.1***	-2.426	-27.906^{+}	-60.12*
Proportional Change							
β1 (Δtrial8-9)	-0.612***	-0.433*	-0.447**	-0.481***	0.339	0.246^{+}	-0.409***
β2 (Δtrial9-10)	-0.733***	-0.358	-0.447**	-0.427***	0.33	0.246^{+}	-0.354***
β3 (Δtrial10-11)	-0.72***	-0.756***	-0.447**	-0.375***	0.461	0.246^{+}	-0.307**
β4 (Δtrial11-12)	-0.88***	1.08***	-0.447**	-0.425***	0.419	0.246^{+}	-0.327**
β5 (Δtrial12-13)	-1.091***	-1.434**	-0.447**	-0.394***	0.438	0.246^{+}	-0.472***

Note. P-values are indicated as follows: * <.05; ** <.01; *** <.001.

analyses. Attention will now be placed on the cross-lagged effects (or the couplings), which describe the impacts of levels of variable X on the change in variable Y. These strength, direction, and change in these couplings over time will be the tests of the hypotheses. It should be noted that the following analyses reveal between person relationships.

Hypothesis Testing

Beginning with the hypotheses associated with the cognitive path, hypothesis 1 stated that the exploratory learning condition would lead to greater strategic feedback seeking right after the adaptive change (H1a) as well as an increase in the behavior over time (H1b) as compared to the procedural learning condition. A series of multigroup univariate latent difference score models were conducted in order to establish the difference in the parameter estimates between the procedural and guided exploration learning conditions. The final model shows some misfit (X^2(df)=59.299(22), $p<.001$; RMSEA=.112; CFI=.916; SRMR=.073); however, it has significantly less misfit than more constrained models (see table for all model comparisons). Therefore, the fully unconstrained model was retained. See Table 4 for a comparison of the models.

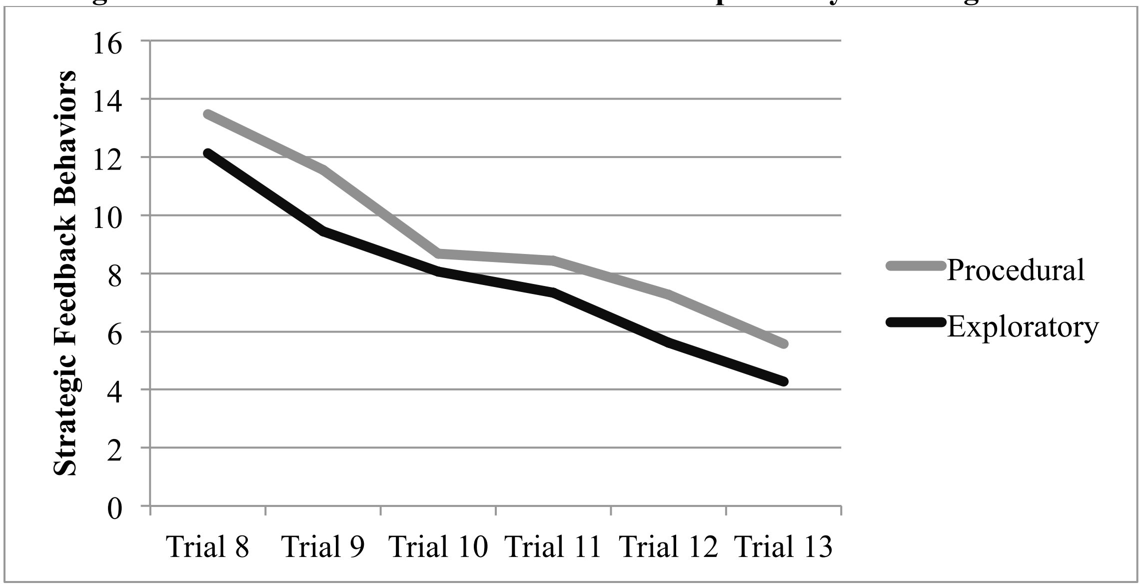
Results suggest that individuals in the guided exploration condition had slightly lower initial levels of strategic feedback seeking but changed more rapidly than those in the procedural learning condition. However, the proportional change aspect of the model suggests that the more feedback investigated at the last time point, the less was sought at the next time point resulting in a slower rate of change across time. This indicates that, taken together, individuals in the exploratory learning condition investigated less strategic feedback than the procedural learning condition as time went on. Therefore, both H1a and H1b were not. See Figure 7 for a depiction of strategic feedback seeking behaviors of both groups over the course of the adaptation phase.

Table 4
Multigroup Difference Score Models Comparing Learning Conditions on Strategic Feedback Seeking Behaviors

	Fully Constrained		Unconstrained (except proportional effect)		***Fully Unconstrained***	
Fit Indices						
X^2/df	90.141(36)***		77.664(30)***		***59.299(22)****	
RMSEA	0.106		0.109		***0.112***	
CFI	0.878		0.892		***0.916***	
SRMR	0.103		0.086		***0.073***	
Parameter Estimates	**Procedural**	**Exploratory**	**Procedural**	**Exploratory**	***Procedural***	***Exploratory***
Intercept	12.666***	12.666***	13.412***	11.904***	***13.48****	***12.131****
Slope	-0.156	-0.156	0.045	-0.357	***3.952***$^{+}$	***5.631***
Proportional Change	**Procedural**	**Exploratory**	**Procedural**	**Exploratory**	***Procedural***	***Exploratory***
β1 (Δtrial8-9)	-0.149**	-0.149**	-0.162**	-0.134^{+}	***-0.436***	***-0.686****
β2 (Δtrial9-10)	-0.149**	-0.149**	-0.162**	-0.134^{+}	***-0.592***	***-0.747***
β3 (Δtrial10-11)	-0.149**	-0.149**	-0.162**	-0.134^{+}	***-0.482****	***-0.788***
β4 (Δtrial11-12)	-0.149**	-0.149**	-0.162**	-0.134^{+}	***-0.607****	***-1.002****
β5 (Δtrial12-13)	-0.149**	-0.149**	-0.162**	-0.134^{+}	***-0.777***	***-1.241***

Note. P-values are indicated as follows: $^{+}$<.10; * <.05; ** <.01; *** <.001.

Figure 7
Strategic Feedback Behaviors of Procedural and Exploratory Learning Conditions



Hypothesis 2 stated that increases in strategic feedback seeking would be related to change in strategic information seeking. A fully unconstrained bivariate latent difference score model between strategic feedback seeking and strategic information seeking behavior was estimated and revealed acceptable fit (X^2(df)=95.231(43), p<.001; RMSEA=.067; CFI=.915; SRMR=.054). In order to obtain the most parsimonious description of the coupling effect, the cross-lagged relationships were constrained to be equal, yielding a model with not significantly worse misfit (X^2(df)=99.549(47), p<.001; RMSEA=.065; CFI=.915; SRMR=.056). Finally, the coupling was constrained to be equal, resulting in no further misfit (X^2(df)=99.762(48), p<.001; RMSEA=.063; CFI=.916; SRMR=.056). Therefore, the coupling constrained to be zero model was retained. See Table 5 for a comparison of the models.

The model suggests that the slope of change in time spent on both seeking strategic feedback and seeking strategic information increased over time. However, the proportional (or autoregressive) effect showed that the more strategic feedback sought at the previous time point, the less the amount feedback investigated at the next time point. A similar effect was found for

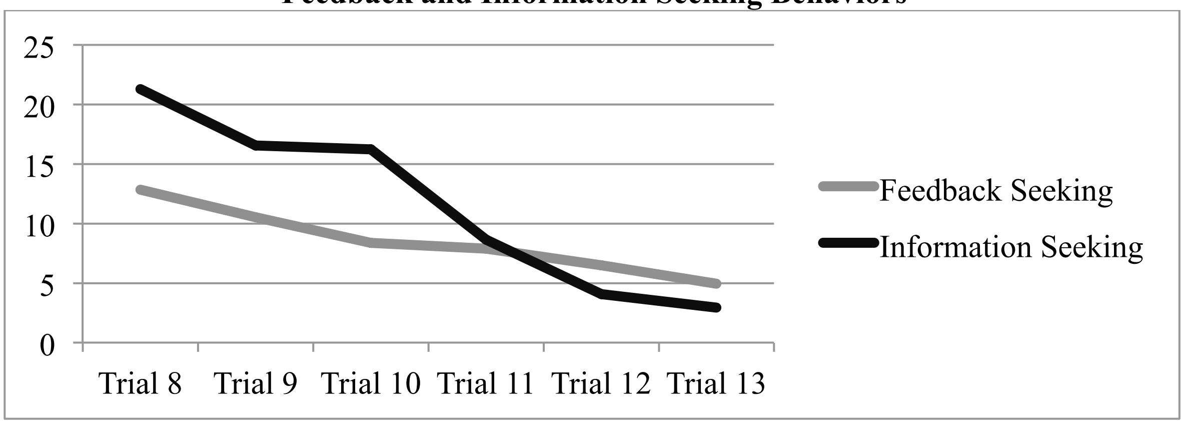
Table 5
Bivariate Latent Difference Score Model of
Strategic Feedback and Information Seeking Behaviors

	Cross Lagged Effect Unconstrained		Cross Lagged Effect Constrained Over Time		***Cross Lagged Effect Constrained to be Zero***	
Fit Indices						
X^2/df	95.231(43)***		99.549(47)***		***99.762(48)****	
RMSEA	0.067		0.065		***0.063***	
CFI	0.915		0.915		***0.916***	
SRMR	0.054		0.056		***0.056***	
Parameter Estimates	**Feedback Seeking**	**Information Seeking**	**Feedback Seeking**	**Information Seeking**	***Feedback Seeking***	***Information Seeking***
Intercept	12.813***	21.320***	12.829***	21.284***	***12.823****	***21.271****
Slope	4.872***	11.604	5.784**	3.402	***5.298****	***4.183***
Proportional Change	**Feedback Seeking**	**Information Seeking**	**Feedback Seeking**	**Information Seeking**	***Feedback Seeking***	***Information Seeking***
β1 (Δtrial8-9)	-0.557***	-0.281	-0.632***	-0.580*	***-0.593****	***-0.417***
β2 (Δtrial9-10)	-0.672***	-0.415	-0.756***	-0.441	***-0.708****	***-0.273***
β3 (Δtrial10-11)	-0.639***	-0.483	-0.748***	-0.850***	***-0.691****	***-0.724****
β4 (Δtrial11-12)	-0.797***	-0.983*	-0.910***	-1.214**	***-0.849****	***-1.010****
β5 (Δtrial12-13)	-0.990***	-1.062	1-.129***	-1.646*	***-1.054****	***-1.309****
Coupling Effect						
ϒ1 (X_{T8}- β1)	-0.842		0.334		***0***	
ϒ2 (X_{T9}- β2)	-0.338		0.334		***0***	
ϒ3 (X_{T10}- β3)	-1.520		0.334		***0***	
ϒ4 (X_{T11}- β4)	-0.936		0.334		***0***	
ϒ5 (X_{T12}- β5)	-1.307		0.334		***0***	

Note. P-values are indicated as follows: * <.05; 0.334** <.01; *** <.001.

strategic information seeking behaviors. Furthermore, as the coupling effect was estimated to be zero, strategic feedback seeking was not found to directly influence change in strategic information seeking behaviors. Therefore, Hypothesis 2 was not supported. See Figure 8 for a depiction of the change in strategic feedback and information seeking over the course of the adaptation phase.

Figure 8
Feedback and Information Seeking Behaviors



Hypothesis 3 suggested that increases in strategic information seeking would be related to greater change in strategic effort. A fully unconstrained bivariate latent difference score model between strategic information seeking and strategic effort behavior was estimated and revealed good fit ($X^2(df)=70.121(47)$, p=.016; RMSEA=.043; CFI=.986; SRMR=.046). In order to obtain the most parsimonious description of the coupling effect, the cross-lagged relationships were constrained to be equal, yielding a model with not significantly worse misfit ($X^2(df)=77.325(51)$, p=.010; RMSEA=.044; CFI=.985; SRMR=.042). When constraining the coupling to be zero, there was a significant increase in misfit of the model ($\Delta X^2(\Delta df)=6.055(1)$, p=.013). Therefore, the constrained but non-zero couplings model was retained. See Table 6 for a comparison.

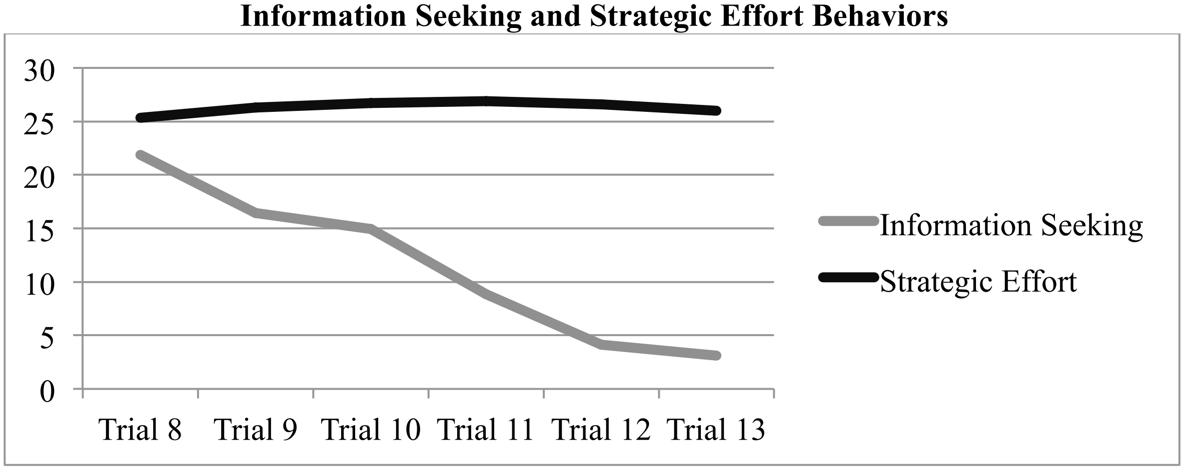
Table 6
Bivariate Latent Difference Score Model of
Strategic Information Seeking and Strategic Effort Behaviors

	Cross Lagged Effect Unconstrained		***Cross Lagged Effect Constrained Over Time***		Cross Lagged Effect Constrained to be Zero	
Fit Indices						
X^2/df	70.121 (47)*		***77.325 (51)****		83.380 (52)**	
RMSEA	0.043		***0.044***		0.047	
CFI	0.986		***0.985***		0.982	
SRMR	0.046		***0.042***		0.037	
Parameter Estimates	**Information Seeking**	**Strategic Effort**	***Information Seeking***	***Strategic Effort***	**Information Seeking**	**Strategic Effort**
Intercept	18.472***	25.015***	***21.882****	***25.329****	21.627***	25.337***
Slope	15.392**	-23.899	***4.833***$^+$	***4.289***	4.12$^+$	12.904**
Proportional Change	**Information Seeking**	**Strategic Effort**	***Information Seeking***	***Strategic Effort***	**Information Seeking**	**Strategic Effort**
β1 (Δtrial8-9)	-0.957***	0.009	***-0.470****	***-0.195***	-0.419**	-0.481**
β2 (Δtrial9-10)	-0.941**	0.009	***-0.383****	***-0.195***	-0.313$^+$	-0.481**
β3 (Δtrial10-11)	-1.345***	0.009	***-0.730****	***-0.195***	-0.708***	-0.481**
β4 (Δtrial11-12)	-2.039***	0.009	***-1.077****	***-0.195***	-1.007***	-0.481**
β5 (Δtrial12-13)	-3.212**	0.009	***-1.419****	***-0.195***	-1.300**	-0.481**
Coupling Effect						
ϒ1 (X_{T8}- β1)	1.371		***0.075****		0	
ϒ2 (X_{T9}- β2)	1.472		***0.075****		0	
ϒ3 (X_{T10}- β3)	1.432		***0.075****		0	
ϒ4 (X_{T11}- β4)	2.417		***0.075****		0	
ϒ5 (X_{T12}- β5)	4.428		***0.075****		0	

Note. P-values are indicated as follows: $^+$<.10; * <.05; ** <.01; *** <.001.

The slope of change of both strategic information seeking and effort behaviors suggests that the change would be getting larger over time if it were not for the proportional effect of previous time points of the variables. This latter effect indicates that the more information that was sought (or strategic effort performed) at the previous time point, the less was sought at the next time point. The coupling effect also suggests that previous levels of strategic information seeking behavior had a significantly positive influence on subsequent change in strategic effort behaviors, such that the more information sought about the aspects of the task that changed (the strategic component), the more effort was devoted to those aspects that changed. This supported hypothesis 3. Although the trajectories of both variables were negative, the coupling effect suggests that, across individuals, if the negative proportional effect of strategic effort were not so strong, seeking more strategic information would significantly increase strategic effort over time. See Figure 9 for a depiction of the trajectories of information seeking and strategic effort (note that feedback and information seeking behaviors are measured in number of seconds and strategic effort is measured in the number of behaviors).

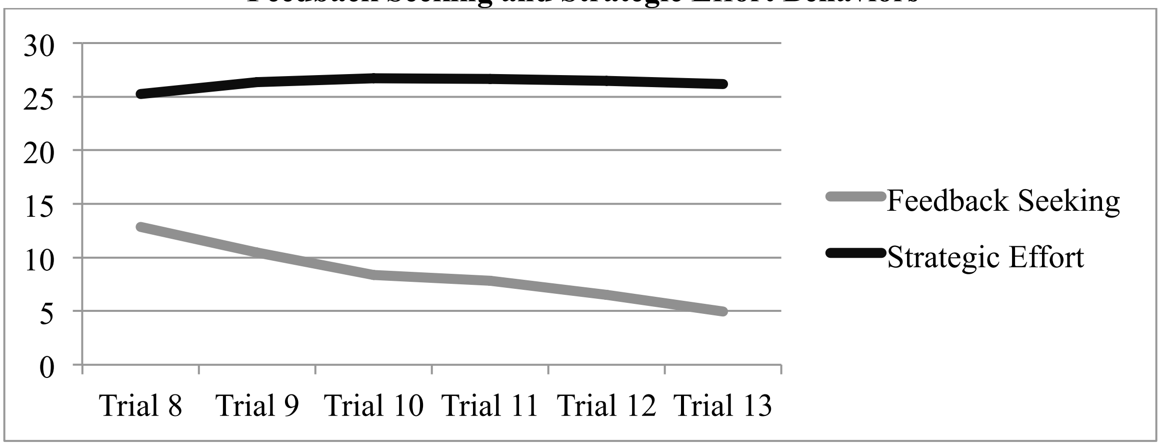
Figure 9
Information Seeking and Strategic Effort Behaviors



Hypothesis 4 indicated that as time went by, the relationship between feedback and information seeking would diminish and the relationship between feedback and strategic effort would increase. Although the previously discussed model of the coupling between strategic feedback and information seeking suggested that the relationship did not diminish over time (as it was found to be zero), in order to test whether strategic feedback seeking influenced strategic effort behaviors, a fully unconstrained bivariate latent difference score model was estimated and revealed acceptable fit ($X^2(df)=103.775(47)$, $p<.001$; RMSEA=.067; CFI=.972; SRMR=.046). Any constraint on the couplings revealed significantly worse misfit ($\Delta X^2(\Delta df)=10.79(1)$, $p=.029$). See Table 7 for a comparison of the models.

The positive slopes of the changes in both strategic feedback seeking and strategic effort suggest that the change was larger as time continued. The proportional effect of feedback indicated that the more feedback sought in the previous trial, the less that was typically obtained in the next. However, increased strategic effort in the last trial resulted in increased change in strategic effort in the next. The coupling effect indicated that, across individuals, the fewer strategic aspects of the feedback investigated, the more behaviors were allocated toward the elements of the task that addressed the change (strategic effort). The dynamic aspect of this relationship was found in the changing significance of the coupling effect where the relationship between strategic feedback and strategic effort was not significant early in the adaptation trial, it increased in strength over the course of the adaptive trials. This indicates that perhaps individuals gathered enough feedback information to correctly identify the change and were allocating effort toward addressing it and therefore did not need to consistently check feedback information. Instead, the less strategic feedback was sought, the more strategic effort was allocated. Therefore, hypothesis 4 was partially supported. See Figure 10 for a representation of the trajectories of these variables (note that information seeking behaviors are measured in number of seconds and strategic effort is measured in the number of behaviors).

Figure 10
Feedback Seeking and Strategic Effort Behaviors



Moving to hypotheses related to the motivational pathway, hypothesis 5 stated that error encouragement would lead to higher initial levels of self-efficacy directly after an adaptive change (H5a) and would increase more than error avoidance would over the course of the adaptive phase (H5b). A series of multigroup univariate latent difference score models were conducted in order to establish the difference in the parameter estimates between the error avoidance and error encouragement conditions. The final model shows some misfit (X^2(df)= 92.473(22), p<.001; RMSEA=.155; CFI=.944; SRMR=.056); however, it has significantly less misfit than more constrained models (see table for all model comparisons). Therefore, the fully unconstrained model was retained. See Table 8 for a comparison of the models.

The unconstrained model shows that individuals in the error encouragement condition had slightly higher initial levels of self-efficacy, although not significantly, and changed slightly more rapidly than those in the error avoidance condition, although in the opposite direction. Therefore, H5a was supported and H5b was not. The autoregressive component reveals that,

Table 7
Bivariate Latent Difference Score Model of
Strategic Feedback Seeking and Strategic Effort Behaviors

	Cross Lagged Effect Unconstrained		Cross Lagged Effect Constrained Over Time		Cross Lagged Effect Constrained to be Zero	
Fit Indices						
X^2/df	***103.775 (47)****		114.565 (51)***		119.665 (52)***	
RMSEA	***0.067***		0.068		0.070	
CFI	***0.972***		0.968		0.966	
SRMR	***0.046***		0.043		0.042	
Parameter Estimates	***Feedback Seeking***	***Strategic Effort***	**Feedback Seeking**	**Strategic Effort**	**Feedback Seeking**	**Strategic Effort**
Intercept	***12.722****	***25.332****	12.846***	25.257***	12.795***	25.366***
Slope	***4.688****	***5.486***	5.427***	8.296*	5.403***	11.906**
Proportional Change	***Feedback Seeking***	***Strategic Effort***	**Feedback Seeking**	**Strategic Effort**	**Feedback Seeking**	**Strategic Effort**
β1 (Δtrial8-9)	***-0.536****	***0.274***	-0.606***	-0.361**	-0.600***	-0.455**
β2 (Δtrial9-10)	***-0.652****	***0.274***	-0.719***	-0.361**	-0.720***	-0.455**
β3 (Δtrial10-11)	***-0.612****	***0.274***	-0.709***	-0.361**	-0.702***	-0.455**
β4 (Δtrial11-12)	***-0.771****	***0.274***	-0.863***	-0.361**	-0.860***	-0.455**
β5 (Δtrial12-13)	***-0.957****	***0.274***	-1.072***	-0.361**	-1.067***	-0.455**
Coupling Effect						
ϒ1 (X_{T8}- β1)	***-0.872***$^{+}$		-.151*		0	
ϒ2 (X_{T9}- β2)	***-1.230****		-.151*		0	
ϒ3 (X_{T10}- β3)	***-1.471***$^{+}$		-.151*		0	
ϒ4 (X_{T11}- β4)	***-1.687****		-.151*		0	
ϒ5 (X_{T12}- β5)	***-1.946****		-.151*		0	

Note. P-values are indicated as follows: $^{+}$<.10; * <.05; ** <.01; *** <.001.

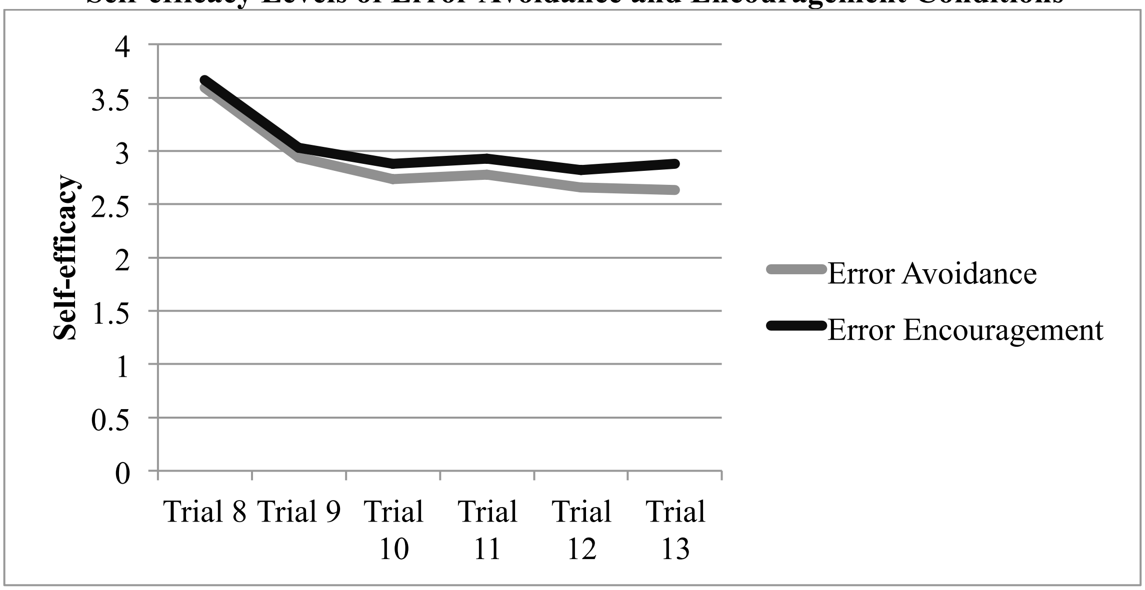
Table 8
Multigroup Difference Score Models:
Comparing Error Conditions on Self-efficacy Levels

	Fully Constrained		Unconstrained (except proportional effect)		***Fully Unconstrained***	
Fit Indices						
X^2/df	132.01(36)***		127.338(30)***		***92.473(22)****	
RMSEA	0.144		0.156		***0.155***	
CFI	0.923		0.923		***0.944***	
SRMR	0.112		0.071		***0.056***	
Parameter Estimates	**Avoid**	**Encourage**	**Avoid**	**Encourage**	***Avoid***	***Encourage***
Intercept	3.633***	3.633***	3.588***	3.674***	***3.596***	***3.664****
Slope	1.742***	1.742***	1.58***	1.951***	***1.057****	***1.168****
Proportional Change	**Avoid**	**Encourage**	**Avoid**	**Encourage**	***Avoid***	***Encourage***
β1 (Δtrial8-9)	-0.636***	-0.636***	-0.600***	-0.687***	***-0.476****	***-0.492****
β2 (Δtrial9-10)	-0.636***	-0.636***	-0.600***	-0.687***	***-0.429****	***-0.435****
β3 (Δtrial10-11)	-0.636***	-0.636***	-0.600***	-0.687***	***-0.372****	***-0.388****
β4 (Δtrial11-12)	-0.636***	-0.636***	-0.600***	-0.687***	***-0.423****	***-0.436****
β5 (Δtrial12-13)	-0.636***	-0.636***	-0.600***	-0.687***	***-0.407****	***-0.393****

Note. P-values are indicated as follows: * <.05; ** <.01; *** <.001.

contrary to expectations, levels of efficacy decreased over time as previous levels of self-efficacy related to lower levels of subsequent self-efficacy in both groups. However, those in the error encouragement condition plateaued more rapidly and self-efficacy did not diminish as much as those in the error avoidance condition. See Figure 11 for a depiction of self-efficacy level.

Figure 11
Self-efficacy Levels of Error Avoidance and Encouragement Conditions



Hypothesis 6 stated that increases in efficacy would lead to increases in the change in goal level. A fully unconstrained bivariate latent difference score model between self-efficacy and goal level revealed acceptable fit (X^2(df)=129.512(44), p<.001; RMSEA=.085; CFI=.968; SRMR=.028). In order to obtain the most parsimonious description of the coupling effect, the cross-lagged relationships were constrained to be equal, yielding a model with not significantly worse misfit (X^2(df)=137.215(47), p<.001; RMSEA=.085; CFI=.966; SRMR=.034). Constraining the couplings to be zero resulted in significant misfit ($\Delta X^2(\Delta df)$= 24.218(1), p<.001) and was not retained. See Table 9 for a comparison of the models.

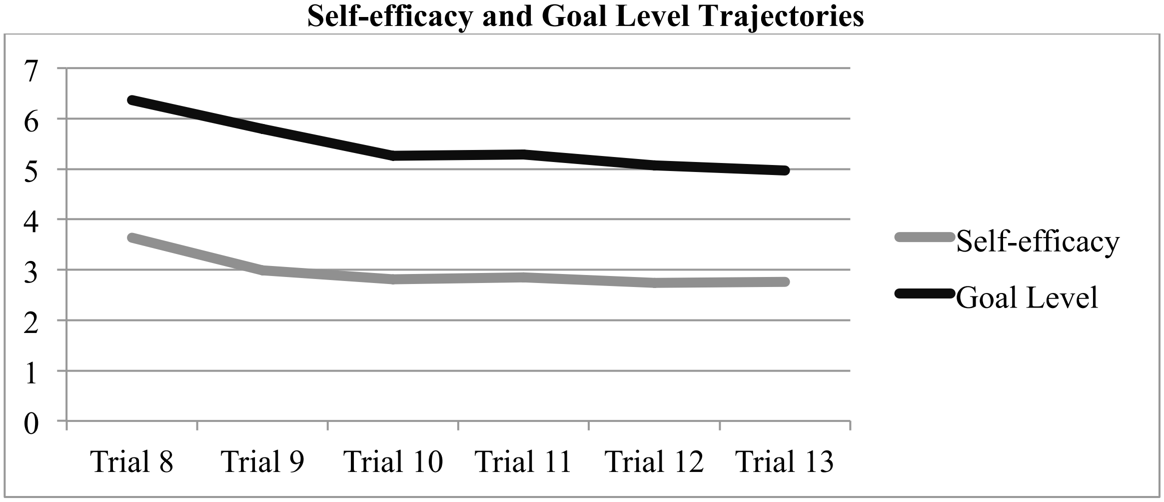
Table 9
Bivariate Latent Difference Score Model of Self-efficacy and Goal Level

	Cross Lagged Effect Unconstrained		*Cross Lagged Effect Constrained Over Time*		Cross Lagged Effect Constrained to be Zero	
Fit Indices						
X^2/df	129.512 (44)***		137.215 (47)***		161.433 (48)***	
RMSEA	0.085		0.085		0.094	
CFI	0.968		0.966		0.958	
SRMR	0.028		0.034		0.054	
Parameter Estimates	**Self-efficacy**	**Goal Level**	***Self-efficacy***	***Goal Level***	**Self-efficacy**	**Goal Level**
Intercept	3.63***	6.496***	3.635***	6.363***	3.623***	6.167***
Slope	1.112***	0.858	1.130***	1.093	1.014***	-1.306
Proportional Change	**Self-efficacy**	**Goal Level**	***Self-efficacy***	***Goal Level***	**Self-efficacy**	**Goal Level**
β1 (Δtrial8-9)	-0.484***	0.573*	-0.489***	0.702^{+}	-0.454***	0.157
β2 (Δtrial9-10)	-0.431***	0.249	-0.438***	0.588	-0.398***	0.136
β3 (Δtrial10-11)	-0.379***	0.371	-0.386***	0.698^{+}	-0.344***	0.251
β4 (Δtrial11-12)	-0.430***	0.322	-0.436***	0.655^{+}	-0.396***	0.206
β5 (Δtrial12-13)	-0.398***	0.323	-0.405***	0.673^{+}	-0.366***	0.212
Coupling Effect						
ϒ1 (X_{T8}- β1)	-1.468***		-1.686**		0	
ϒ2 (X_{T9}- β2)	-0.935*		-1.686**		0	
ϒ3 (X_{T10}- β3)	-0.987*		-1.686**		0	
ϒ4 (X_{T11}- β4)	-0.958*		-1.686**		0	
ϒ5 (X_{T12}- β5)	-0.958*		-1.686**		0	

Note. P-values are indicated as follows: * <.05; ** <.01; *** <.001.

Changes in self-efficacy and goal level were found to increase over time, suggesting that both variables changed more rapidly as time continued. The autoregressive effects revealed that previous levels of self-efficacy resulted in significantly lower change self-efficacy at the next time point. The proportional effect of goal level suggests that goal levels would have increased over the course of the adaptation phase *if* the cross lagged effect of self-efficacy did not have such a strong limiting effect. Instead, as self-efficacy decreased, goal levels increased. Therefore, the negative relationship between self-efficacy and goal level did not support hypothesis 6. See Figure 12 for a representation of the trajectories of these variables (note that self-efficacy was measured on a five point scale and goal level was measured in the number of targets predicted to be correctly executed).

Figure 12
Self-efficacy and Goal Level Trajectories



Hypothesis 7 indicated that increases in goal level would lead to increases in the change in total effort. A fully unconstrained bivariate latent difference score model between goal level and the total amount of effort behaviors was estimated and revealed less than preferable fit (X^2(df)=170.938(47), p<.001; RMSEA=.099; CFI=.965; SRMR=.057). However, in order to obtain the most parsimonious description of the coupling effect, the cross-lagged relationships were constrained to be equal, yielding a model with not significantly worse misfit (X^2(df)= 177.551(51), p<.001; RMSEA=.096; CFI=.964; SRMR=.057). Finally, the coupling was constrained to be equal, resulting in no further misfit (X^2(df)=178.421(52), p<.001; RMSEA=.095; CFI=.964; SRMR=.058). Therefore, the coupling constrained to be zero model was retained. See Table 10 for a comparison of models.

The slopes of the change in both goal level and total effort were found to be negative suggesting that as the adaptation phase continued, the change in these variables diminished. The proportional change revealed that higher levels of goals at the previous time point resulted in higher goals set at the next time point, although this effect was not statistically significant. Previous effort behaviors were also found to have a positive impact on subsequent effort behaviors. The null coupling effect suggests that goal level was not directly related to changes in effort behaviors, not supporting hypothesis 7. See Figure 13 for a depiction of the trajectory in effort behaviors over the course of the adaptation phase.

Figure 13
Total Effort Behaviors Trajectory

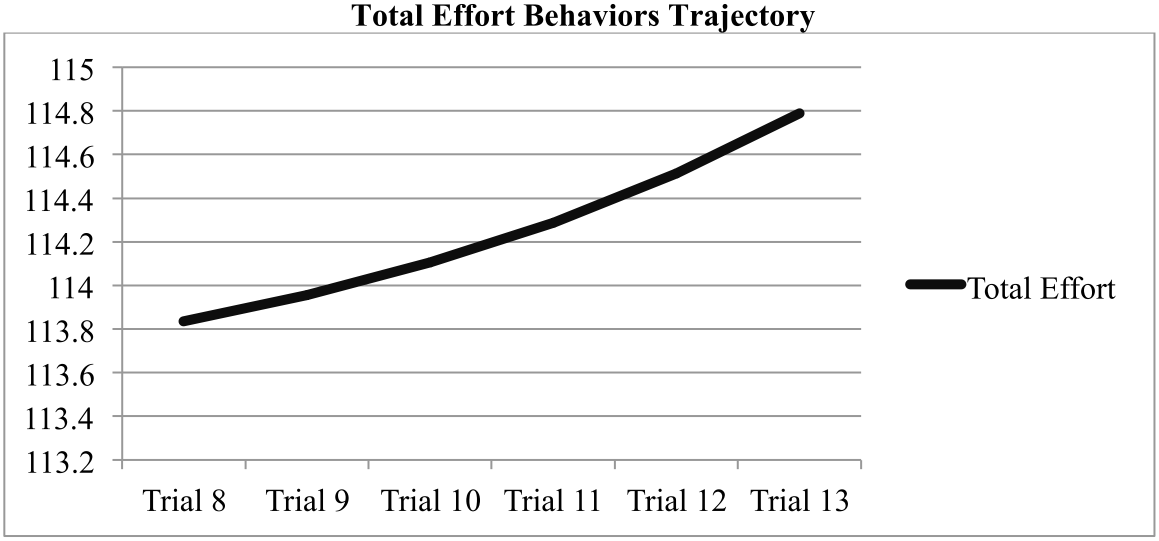


Table 10
Bivariate Latent Difference Score Model of Goal Level and Total Effort Behaviors

	Cross Lagged Effect Unconstrained		Cross Lagged Effect Constrained Over Time		***Cross Lagged Effect Constrained to be Zero***	
Fit Indices						
X^2/df	170.938 (47)***		177.551 (51)***		***178.421 (52)****	
RMSEA	0.099		0.096		***0.095***	
CFI	0.965		0.964		***0.964***	
SRMR	0.057		0.057		***0.058***	
Parameter Estimates	**Goal Level**	**Total Effort**	**Goal Level**	**Total effort**	***Goal Level***	***Total Effort***
Intercept	6.152***	113.585***	6.149***	114.111***	***6.158****	***113.835****
Slope	-2.243$^+$	-24.360	-2.426	-23.222	***-3.835***	***-25.719***$^+$
Proportional Change	**Goal Level**	**Total Effort**	**Goal Level**	**Total effort**	***Goal Level***	***Total Effort***
β1 (Δtrial8-9)	0.309	0.335*	0.339	0.235$^+$	***0.453***	***0.227***$^+$
β2 (Δtrial9-10)	0.300	0.335*	0.332	0.235$^+$	***0.454***	***0.227***$^+$
β3 (Δtrial10-11)	0.427$^+$	0.335*	0.460	0.235$^+$	***0.593***	***0.227***$^+$
β4 (Δtrial11-12)	0.385	0.335*	0.420	0.235$^+$	***0.555***	***0.227***$^+$
β5 (Δtrial12-13)	0.402	0.335*	0.437	0.235$^+$	***0.577***	***0.227***$^+$
Coupling Effect						
ϒ1 (X_{T8}- β1)	-2.140*		-0.612		***0***	
ϒ2 (X_{T9}- β2)	-2.380*		-0.612		***0***	
ϒ3 (X_{T10}- β3)	-2.520*		-0.612		***0***	
ϒ4 (X_{T11}- β4)	-2.805*		-0.612		***0***	
ϒ5 (X_{T12}- β5)	-2.526*		-0.612		***0***	

Note. P-values are indicated as follows: $^+$<.10; * <.05; ** <.01; *** <.001.

A follow-up analysis was conducted to see if self-efficacy had a direct impact on changes in total effort. A fully unconstrained bivariate latent difference score model between self efficacy and the total amount of effort behaviors was estimated and revealed acceptable fit (X^2(df)= 135.201 (43), p<.001; RMSEA=.090; CFI=.973; SRMR=.031). Constraining the cross-lagged to be equal, yielding a significantly worse fitting model (ΔX^2 (Δdf)=8.928(4), p=.063). Therefore, the couplings were allowed to differ over time. See Table 11 for the model comparisons.

The result of this additional analysis revealed that self-efficacy only had a significant impact on total effort initially such that when self-efficacy as low, total effort increased, but this effect did not persist over time. It is possible that this indicated a motivational compensation technique as individuals attempted to boost their efficacy by simply doing more even though they did not feel as if they knew exactly what to do. Although the direct relationship between self-efficacy and effort was not hypothesized, it may provide insight into why goals did not have an impact on total effort. Individuals may not have accurately understood how their effort related to performance initially and therefore increased motivation (efficacy) was not positively related to increased action (effort).

Hypothesis 8 claimed that increases in total effort would lead to increased changes in performance. A fully unconstrained bivariate latent difference score model between the total amount of effort behaviors and performance was estimated and revealed poor fit (X^2(df)= 325.039 (47), p<.001; RMSEA=.14; CFI=.927; SRMR=.062). When constraining the coupling effect to be constant over time, the model fit was significantly increased (X^2 (df)= 182.255(56), p<.001; RMSEA=.092; CFI=.966; SRMR=.046). However, if the coupling was constrained to be equal, the model resulted in a significant increase in misfit (ΔX^2(Δdf)= 8.969(1), p=.002). The couplings were constrained to be the same across time but not equal to zero. See Table 12.

Table 11
Bivariate Latent Difference Score Model of Self-efficacy and Total Effort Behaviors

	Cross Lagged Effect Unconstrained		Cross Lagged Effect Constrained Over Time		Cross Lagged Effect Constrained to be Zero	
Fit Indices						
X^2/df	***135.201 (43)****		144.129 (47)***		149.921 (48)***	
RMSEA	***0.090***		0.088		0.089	
CFI	***0.973***		0.972		0.971	
SRMR	***0.031***		0.038		0.042	
Parameter Estimates	***Efficacy***	***Total Effort***	**Efficacy**	**Total effort**	**Efficacy**	**Total Effort**
Intercept	***3.632****	***113.794****	3.634***	113.531***	3.631***	113.433***
Slope	***1.169****	***-18.375***	1.158***	-25.391	1.135***	-29.614^{+}
Proportional Change	***Efficacy***	***Total Effort***	**Efficacy**	**Total effort**	**Efficacy**	**Total Effort**
β1 (Δtrial8-9)	***-0.501****	***0.362****	-0.498***	0.338*	-0.491***	0.267^{+}
β2 (Δtrial9-10)	***-0.450****	***0.225***$^{+}$	-0.446***	0.317*	-0.438***	0.265^{+}
β3 (Δtrial10-11)	***-0.399****	***0.255***$^{+}$	-0.446***	0.307*	-0.387***	0.260^{+}
β4 (Δtrial11-12)	***-0.449****	***0.220***$^{+}$	-0.396***	0.302*	-0.437***	0.253^{+}
β5 (Δtrial12-13)	***-0.418****	***0.228***$^{+}$	-0.415***	0.310*	-0.407***	0.264^{+}
Coupling Effect						
ϒ1 (X_{T8}- β1)	***-6.239****		-3.431*		0	
ϒ2 (X_{T9}- β2)	***-2.208***		-3.431*		0	
ϒ3 (X_{T10}- β3)	***-3.810****		-3.431*		0	
ϒ4 (X_{T11}- β4)	***-2.571***		-3.431*		0	
ϒ5 (X_{T12}- β5)	***-2.543***		-3.431*		0	

Note. P-values are indicated as follows: $^{+}$<.10; * <.05; ** <.01; *** <.001.

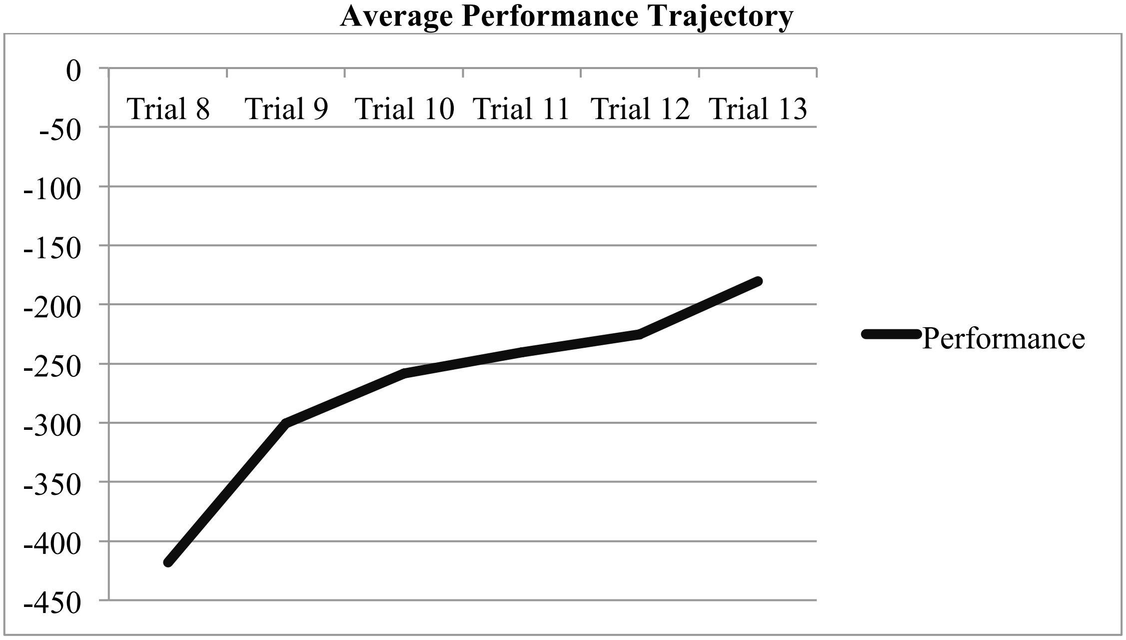
Table 12
Bivariate Latent Difference Score Model of Total Effort and Performance

	Cross Lagged Effect Unconstrained		***Cross Lagged Effect Constrained Over Time***		Cross Lagged Effect Constrained to be Zero	
Fit Indices						
X^2/df	325.039 (52)***		***182.255 (56)****		191.224 (57)***	
RMSEA	0.140		***0.092***		0.094	
CFI	0.927		***0.966***		0.964	
SRMR	0.062		***0.046***		0.046	
Parameter Estimates	**Total Effort**	**Performance**	***Total Effort***	***Performance***	**Total Effort**	**Performance**
Intercept	114.196***	-418.904***	***113.894****	***-418.278****	113.841***	-415.188
Slope	193.164***	389.724	***-22.633****	***-743.970****	-17.632*	-48.155^{+}
Proportional Change	**Total Effort**	**Performance**	***Total Effort***	***Performance***	**Total Effort**	**Performance**
β1 (Δtrial8-9)	-1.689***	-0.318^{+}	***0.200****	***-0.485****	0.156*	-0.377*
β2 (Δtrial9-10)	-1.689***	-0.357*	***0.200****	***-0.421****	0.156*	-0.298*
β3 (Δtrial10-11)	-1.689***	-0.289^{+}	***0.200****	***-0.392****	0.156*	-0.268*
β4 (Δtrial11-12)	-1.689***	-0.311^{+}	***0.200****	***-0.404****	0.156*	-0.277*
β5 (Δtrial12-13)	-1.689***	-0.440**	***0.200****	***-0.557****	0.156*	-0.426*
Coupling Effect						
ϒ1 (X_{T8}- β1)	-3.359		***5.785****		0	
ϒ2 (X_{T9}- β2)	-4.094		***5.785****		0	
ϒ3 (X_{T10}- β3)	-3.965		***5.785****		0	
ϒ4 (X_{T11}- β4)	-3.987		***5.785****		0	
ϒ5 (X_{T12}- β5)	-3.697		***5.785****		0	

Note. P-values are indicated as follows: $^{+}$<.10; * <.05; ** <.01; *** <.001.

The slope of the changes in both total effort and performance shows that there was a decline in the amount change in both variables over time such that as time continued, individuals changed less in these variables. The proportional effect of effort indicates that more effort shown in the previous trials led to significantly more effort in the subsequent trial. The proportional effect of performance indicated that higher performance in the last trial resulted in significantly lower performance in the next trial, contrary to most research findings. However, the coupling effect of effort on performance showed that higher levels of effort in the last trial led to significantly higher positive change in performance in the next trial, supporting hypothesis 8. The negative influence of performance on itself is contrary to typical findings but may suggest that effort had a very strong relationship with performance such that if effort did not increase, individuals may have been showing fatigue or lack of focus on the task. In other words, simply having good performance in the last trial was not sufficient motivation to have increased performance in the next trial. See Figure 14 for a graph of the trajectory of average performance over the adaptation phase.

Figure 14
Average Performance Trajectory



Finally, hypothesis 9 suggested that strategic effort would moderate the relationship between total effort and performance. In order to test this, a multigroup bivariate latent difference score model was estimated for two groups: one group of individuals who demonstrated high strategic behaviors (above the mean of strategic effort behaviors across the trials of the adaptation phase) and the other group of individuals who performed few strategic effort behaviors. Since the two groups were split based on strategic effort (which is a part of total effort), the baseline model was one where the groups were fully constrained to be the same, except for the initial means of total effort. This model revealed some misfit but was acceptable (X^2(df)= 402.941(149), p<.001; RMSEA=.113; CFI=.927; SRMR=.113). Allowing the cross lagged effect between total effort and performance to be difference between the two groups increased the model fit, but only approached significance ($\Delta X^2(\Delta df)$ = 2.585(1), p=.108). Although the freed coupling model did not have significant reduction of misfit, the model statistics were similar to the baseline model and will therefore be retained for interpretation (X^2(df)= 400.356(148), p<.001; RMSEA=.113; CFI=.927; SRMR=.113). See Table 13 for a comparison of the two models.

In order to understand this multigroup model, Figures 15 and 16 provide a graphical depiction of the trajectories of both total effort and performance over the adaptation trials. These figures reveal that individuals who performed less strategic behaviors also performed fewer total amounts of behaviors (this is no surprise as strategic effort was a part of total effort), and their effort decreased over time. Individuals in the high strategic effort group had increased adaptive performance as compared to the low strategic effort group, especially later in the adaptation phase. This may show more resilience, motivation or engagement with the task. The coupling of the multigroup model shows a different component about the two groups. Individuals who performed fewer strategic behaviors had a stronger relationship with performance than those who had higher strategic efforts. This is contrary to hypothesis 9, but may reveal an interesting effect.

Figure 15
Total Effort Trajectories of Strategic Effort Groups

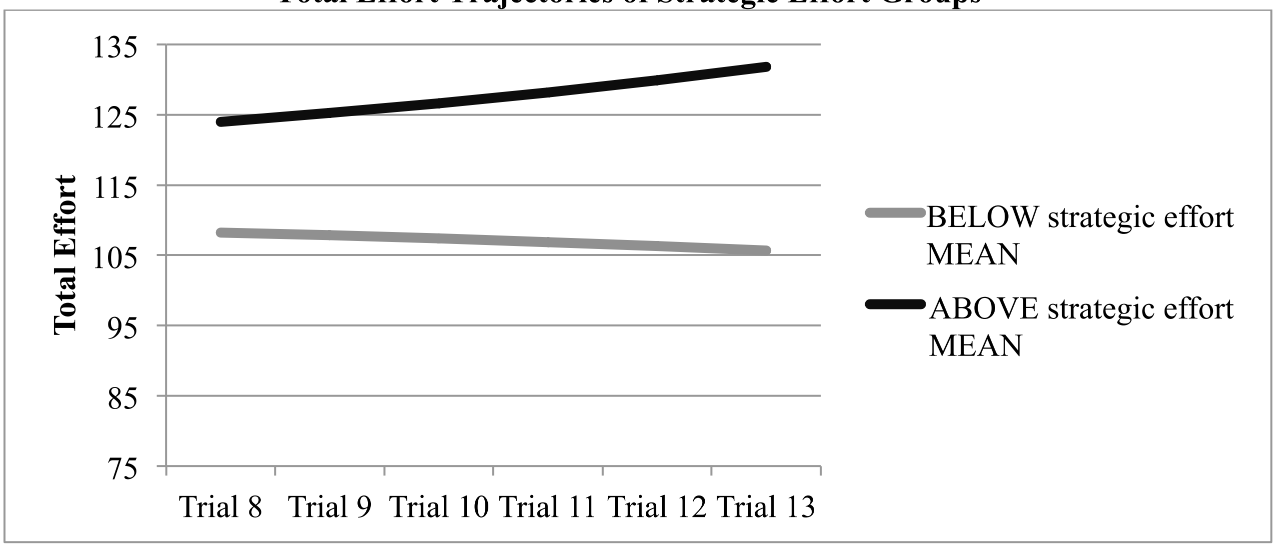


Figure 16
Performance Trajectories of Strategic Effort Groups

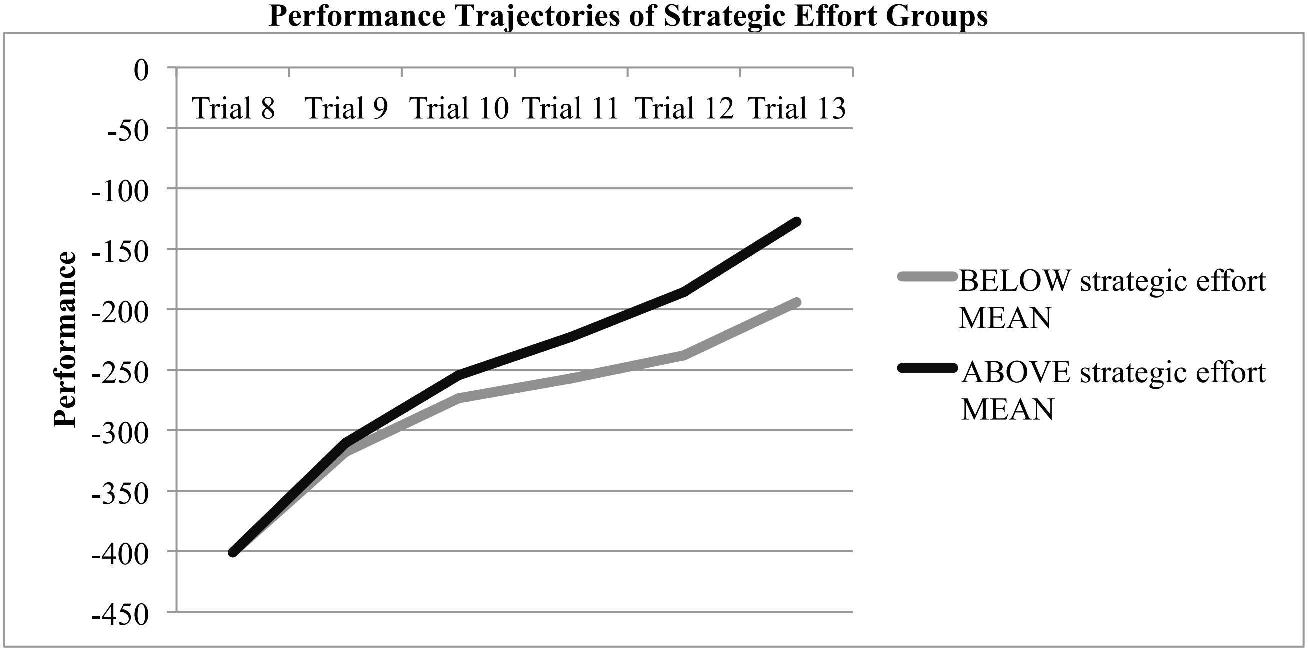


Table 13
Multigroup Bivariate Latent Difference Score Model of Total Effort and Performance: Below or Above the Mean of Strategic Effort

	Constrained Across Groups (Except Intercept Means)				*Intercept Means and Cross Lagged Relationships Unconstrained*			
Fit Indices								
X^2/df	402.941 (149)***				400.356 (148)***			
RMSEA	0.113				0.113			
CFI	0.927				0.927			
SRMR	0.113				0.113			
	BELOW Strategic Effort mean		ABOVE Strategic Effort mean		*BELOW Strategic Effort mean*		*ABOVE Strategic Effort mean*	
Parameter Estimates	**Total Effort**	**Performance**	**Total Effort**	**Performance**	***Total Effort***	***Performance***	***Total Effort***	***Performance***
Intercept	108.123***	-399.818***	124.079***	-399.818***	108.256***	-401.002***	123.960***	-401.002***
Slope	-112.109***	-226.996***	-12.109***	-226.966***	-12.109***	-451.108***	-12.109**	-451.108***
Proportional Change	**Total Effort**	**Perform-ance**	**Total Effort**	**Perform-ance**	***Total Effort***	***Perform-ance***	***Total Effort***	***Perform-ance***
β1 (Δtrial8-9)	.108***	-.292***	.108***	-.292***	.107***	-.312***	.107***	-.312***
β2 (Δtrial9-10)	.108***	-.254**	.108***	-.254**	.107***	-.277**	.107***	-.277**
β3 (Δtrial10-11)	.108***	-.202*	.108***	-.202*	.107***	-.225*	.107***	-.225*
β4 (Δtrial11-12)	.108***	-.233**	.108***	-.233**	.107***	-.258**	.107***	-.258**
β5 (Δtrial12-13)	.108***	-.362***	.108***	-.362***	.107***	-.391***	.107***	-.391***
Coupling Effect								
ϒ1 (X_{T8}- β1)	1.704*		1.704*		3.779*		3.361*	
ϒ2 (X_{T9}- β2)	1.704*		1.704*		3.779*		3.361*	
ϒ3 (X_{T10}- β3)	1.704*		1.704*		3.779*		3.361*	
ϒ4 (X_{T11}- β4)	1.704*		1.704*		3.779*		3.361*	
ϒ5 (X_{T12}- β5)	1.704*		1.704*		3.779*		3.361*	

Note. P-values are indicated as follows: * <.05; ** <.01; *** <.001.

Of individuals who did not act on the strategic aspects of the task, total effort had a stronger, direct impact on performance; however, the relationship was not as strong for individuals who performed higher amounts of strategic effort behaviors. In other words, it may be that individuals who were not being strategic about their effort allocation had to rely on increasing their total amount of effort in order to positively influence performance, whereas individuals who were smart about where they allocated their effort did not have such a heavy reliance on simply increasing effort in order for their performance to increase.

Post Hoc Analysis

In order to examine how the four conditions performed across the adaptive trials, a multigroup univariate latent difference score model was conducted to establish the difference in the parameter estimates between the four conditions. The final model shows excellent fit (X^2(df)=44.323 (44), p=.458; RMSEA=.01; CFI=1.000; SRMR=.0390). See Table 14 for the final model and Figure 17 for a graphical depiction of the performance trajectories.

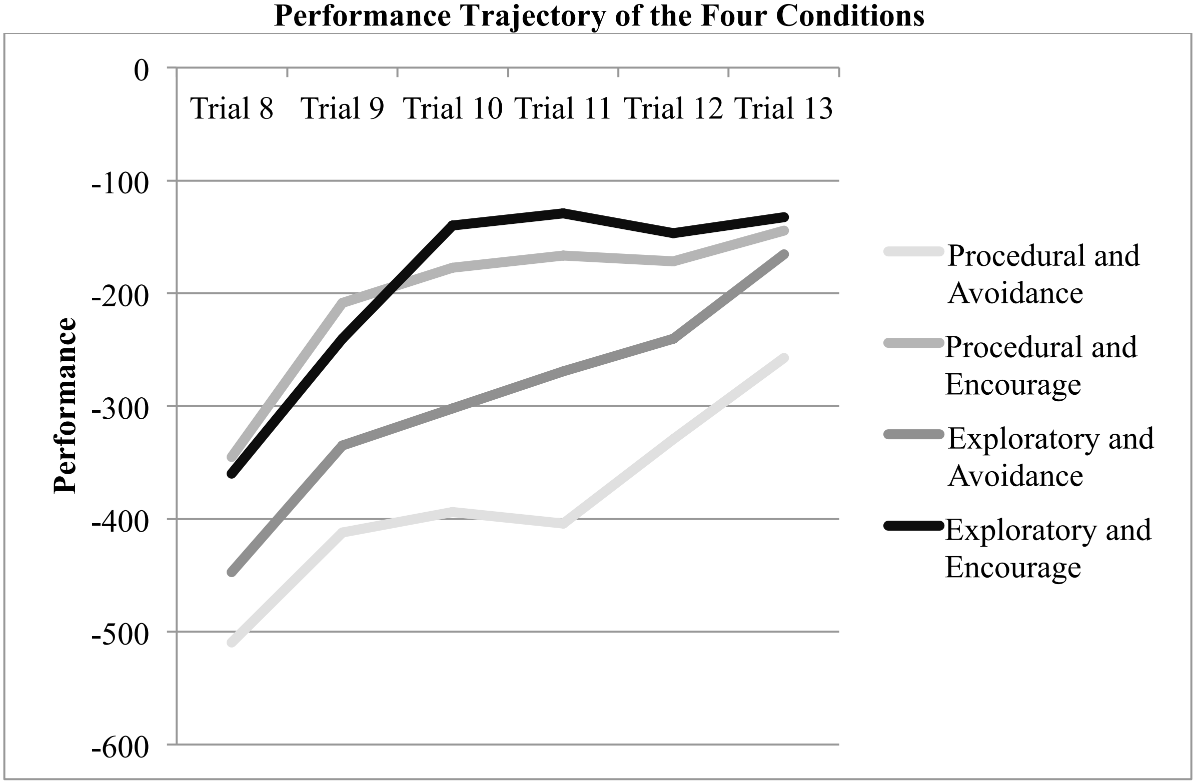
This model reveals that individuals in the exploratory learning/error encouragement condition increased the most in and maintained the highest level of performance. Procedural learning/error encouragement condition performed the next highest. Performing around the middle was the exploratory learning/error avoidance condition. Finally, the procedural learning/ error avoidance condition performed the most poorly and grew the slowest of all the groups. These results are somewhat similar to the findings of Bell and Kozlowski (2008), which will be revisited in the discussion. It should be noted that three of the four conditions were performing at about the same level by the end of the adaptation phase, while the procedural learning/error avoidance condition remained lower.

Table 14
Fully Unconstrained Multigroup Difference Score Model Comparing the Four Experimental Conditions on Performance Trajectories

Fit Indices				
X^2/df		44.323(44)		
RMSEA		0.045		
CFI		0.995		
SRMR		0.030		
Parameter Estimates	**Procedural and Avoid**	**Procedural and Encourage**	**Exploratory and Avoid**	**Exploratory and Encourage**
Intercept	-509.687***	-345.174***	-447.36***	-360.15***
Slope	-18.352	-101.514	18.307	-100.34$^+$
Proportional Change	**Procedural and Avoid**	**Procedural and Encourage**	**Exploratory and Avoid**	**Exploratory and Encourage**
β1 (Δtrial8-9)	-0.228	-0.690**	-0.210$^+$	-0.612**
β2 (Δtrial9-10)	-0.088	-0.634*	-0.044	-0.835***
β3 (Δtrial10-11)	-0.021	-0.634*	-0.049	-0.794***
β4 (Δtrial11-12)	-0.231	-0.579*	-0.039	-0.642**
β5 (Δtrial12-13)	-0.274	-0.751**	-0.234$^+$	-0.780***

Note. P-values are indicated as follows: $^+$<.10; * <.05; ** <.01; *** <.001.

Figure 17
Performance Trajectory of the Four Conditions



DISCUSSION

General Discussion

With regard to the motivational pathway of the adaptation process, it was expected that, generally, self-efficacy would increase over time. However, the data show that, across individuals, self-efficacy decreased over the course of the task. This may have been due to the average performance of all individuals remaining below zero. Although the trajectory of performance was positive, suggesting that individuals were increasing in their abilities as time went on, the fact that performance remained below zero might have skewed any positive perceptions. However, the impact of overall effort on performance reveals that increases in the total amount of effort was related to increases in the change in performance, suggesting that increased motivation had a positive impact on the adaptation of individuals.

With regard to the cognitive pathway of the adaptation process, it was expected that, generally, there would be an increase in the strategic cognitive behaviors relative to non-strategic behaviors during the adaptation trials. However, proportion variables could not be used in the analyses; therefore, both basic and strategic behaviors decreased over time. Individuals may have already identified the important feedback information and needed less time spent reviewing all feedback or they knew all the relevant aspects of the task and required less time investigating information. The moderation of strategic effort on the relationship between total effort and performance suggests of the individuals who performed many strategic effort behaviors, were able to increase their performance with less total effort because they were working smarter. However, of those individuals who did not perform as many strategic effort behaviors, total effort behaviors had a stronger relationship with changes in performance as they had to work harder in order to improve in the task. It also was clear that across all individuals, increased total effort (which included strategic effort) was related to increased performance, suggesting that the differences in performance between individuals was not a result of performing more strategic behaviors, but rather that after they performed the necessary strategic behaviors, individuals who executed more of the contacts were able to perform more effectively

The following section will summarize the findings for each hypothesis, providing an explanation of why the particular result described previously occurred. It should be noted that the analyses were between person and therefore conclusions are held to the between subject level.

Discussion of Hypothesis Testing

With regard to training, the learning condition (exploratory or procedural) differentially impacted the amount of time spent investigating strategic feedback such that those in the exploratory learning condition had slightly lower initial levels of feedback seeking, but the slope indicated that those individuals changed more than the procedural learning condition. The autoregressive impact indicated that the change was negative – those in the exploratory learning condition spent less time investigating strategic aspects of the feedback. It is possible that individuals in the exploratory learning condition had lower overall feedback seeking behaviors due to their ability to more rapidly identify the feedback that was relevant and required less time to investigate the information than those in the procedural learning condition. Therefore, over time, these individuals did not need to dwell on the feedback information in order to maintain effective performance.

The error framing training (encourage or avoid) differentially influenced self-efficacy over time, as anticipated. Initially, individuals in the error encouragement condition reported higher levels of self-efficacy and increased more rapidly over time than those in the error avoidance condition. However, previous levels of efficacy had a diminishing impact on subsequent self-efficacy. Self-efficacy was not expected to decrease over time, but may have been due to fatigue or lack of interest in the task over the course of the adaptation phase.

When looking at the cognitive process variables under investigation, the null effect of the direct influence of strategic feedback seeking on strategic information seeking behavior was likely due to the lengthy training period. During that time individuals were given considerable opportunity to access all relevant information that was needed for adapting effectively. Once the adaptation trials ensued, individuals (in general) may have been familiar enough with the information that they did not need to access it in order to address the change. Therefore, there were higher initial levels of strategic feedback and information seeking behavior (as they identified the source of the change), but those behaviors decreased over time (as that information was no longer needed to continue increasing their performance).

Furthermore, strategic information seeking had a positive influence on the strategic effort of an individual; however, the model suggested that the more strategic effort that was performed in the last trial, the less was done in the next (though not significantly less). The steep decline in strategic information seeking behaviors was likely due to having enough access to the information prior to the adaptation trials and therefore the relationship between information seeking and strategic effort was lessened. This may also explain why there was not much change in strategic effort behaviors over the course of the adaptation phase – it is possible that most individuals already understood what behaviors were necessary for adaptation given the extensive training phase. Therefore, there was greater initial change in strategic behaviors, but less change as time continued.

Finally, the dynamic relationship between strategic feedback seeking behavior and strategic effort suggest that, initially, more strategic feedback was not related to increased strategic effort behaviors; however, later on in the adaptation phase, decreased strategic feedback seeking resulted in increased strategic effort behaviors. Although this was contrary to the expected relationship, it is possible that, across individuals, the source of the adaptive change was identified early on, resulting in the need for less feedback in order to devote effort toward the strategic parts of the task. Thus, as individuals located the source of the adaptive change in the feedback, they did not need to reference this information in order to maintain their level of strategic effort.

Directing attention toward the motivational processes investigated, self-efficacy had a limiting effect on goal level. It is likely that individuals decreased in self-efficacy over time due to fatigue or reduced motivation. Alternatively, as the average performance trajectory of all individuals remained below zero, self-efficacy may have been low due to a slower increase in performance.

Given that individuals decreased in their goal levels over time, they were likely underestimating their capabilities. However, even though their goals decreased, effort increased. This finding is not consistent with most of the social cognitive theories and could be a result of individuals not setting an accurate goal or the measure being insufficient to capture variance.

Total effort had a significantly positive impact on performance over time. This suggests that increased effort, even in small amounts, led to enhanced performance. However, if effort did not increase, performance was decreased, perhaps due to a lack of motivation or desire to continue with the task. The result of the moderation of strategic effort revealed that the individuals who had higher strategic effort behaviors did not have to rely as heavily on putting in more total effort to see enhanced performance compared to the low strategic performance group. This suggests that individuals could adapt better and smarter if effort was differentially allocated;

however, if individuals did not understand the nature of the change, increased motivation (as seen in overall effort behaviors) yielded enhanced performance. Another reason why the overall effect for total effort on performance was found is that once individuals located the nature of the adaptive change and began to devote strategic effort to those aspects, further increases in performance were due to increases in overall effort behaviors (e.g., executing more targets). It seems as if this was likely the case given that Figure 15 shows that those who were high in strategic effort behaviors increased in their total amount of effort over time while individuals who were low in strategic effort saw a decline in overall effort. Therefore, the increase in non-strategic behaviors (e.g., executing more targets in addition to those that were most threatening) was accounting for additional increased performance later in the adaptive phase.

Finally, the multigroup model of the four conditions and performance suggest that encouraging errors provided individuals with a considerable advantage over those who were told to avoid errors. This indicates that individuals were better able to identify which errors led to certain effects, possibly contributing to individuals locating and addressing the elements of the task that changed in the beginning of the adaptive phase more rapidly. This result mirrors the findings of Bell and Kozlowski (2008), although they did not investigate performance over multiple trials after the change. The impact of exploratory learning was limited by the effect of the error condition such that only when mistakes were discouraged was exploratory learning found to be more beneficial for performance than procedural learning. This suggests that individuals who were forced to follow a set of instructions without making mistakes had significantly decreased performance when informed of exactly how to go about learning the task. Although Bell and Kozlowski (2008) found that exploratory learning led to increased adaptive performance regardless of error condition, the results of the current study indicates that the impact of exploratory learning may be particularly salient in the trajectory of adaptive performance. As Figure17 shows, all conditions *but* the proceduralized learning/error avoidance condition had similarly high levels of performance by the end of the adaptation phase. This may indicate that individuals who are discouraged from making errors and are told exactly what to do (e.g., lower level employees or possibly enlisted military personnel) may be at considerable risk when presented with an adaptive change and may not be able to reach the same level of performance as others.

Limitations and Extensions

This next section will discuss limitations to the experimental design and associated next steps for future research. They key limitations are: the forced feedback and information seeking, the inability to use proportional variables, the limitations of the analysis and the use of a laboratory setting.

The radar simulation was a novel task for all individuals, unlike a typical job where individuals already have a relevant set of expertise upon starting the job. Therefore, individuals had to engage in a lengthy training phase. This required participants to access information on the task many times, possibly resulting in overlearning or boredom with looking at the same information over the course of the experiment. This likely influenced how individuals would normally go about adapting to a change (i.e., there may not have been as great a need for gathering new information given the ample opportunity to do so during the training phase). Alternatively, as all individuals were given a forced period of time for gathering feedback and information before each trial of both the learning and adaptation phases, it is likely that there was reduced variability in these behaviors which may have resulted in less predictive power. Also, individuals may not have been always looking at the information on the pages, as it was a forced time period unless they clicked out of the system. It is therefore possible that some of the strategic behaviors captured were an artifact of individuals spending a small amount of time reading the information and then becoming distracted but remaining on the page. Future research should: (1) allow for more control over when and whether an individual accesses information, (2) remove time constraints so that information does not need to be accessed if not desired, (3) encourage individuals to not linger on information without being actively reading it (e.g., distracted thoughts), and/or (4) implement a means of tracking distracted behavior (e.g., eye trackers). This would allow researchers to more accurately examine how individuals might regulate these resources during the adaptation process without experimental constraints

Related to the above, strategic behaviors were coded as those efforts devoted to understanding the aspects of the task that changed. Since the overall pattern of the data revealed that less information was gathered, a proportion of strategic behaviors over the total amount of behaviors may have provided more insight into how individuals were behaving. However, models using proportional variables did not converge, suggesting that there needs to be further research conducted in order to determine whether the misfit was due to these particular data or due to the proportion variables. As proportional variables are not typically investigated in behavioral research, future research questions may include whether the distribution of behaviors provide unique insight into a phenomenon beyond the actual behaviors.

Regarding the analysis employed, bivariate latent difference score models has the limitation of only being able to investigate two process variables at a time. Although this study was still able to draw conclusions about the relationships between the self-regulatory processes, future research should use an analysis that allows for all variables to be dynamically investigated within a single analysis in order to examine whether these self-regulatory process variables act as a single entity forming an adaptive process. Furthermore, the analyses were between-person, suggesting that there might be additional insight gained if a process model could be analyzed within-person. A within-person process model would allow for the discussion of how an individual adapts. In this study, I could only hypothesize about what an individual might be doing from the average relationship between two variables across all individuals. Future research should investigate whether the relationships found between individuals are similar when examined within individuals.

The final limitation is that as this was an experiment in a controlled, laboratory environment there was an excellent amount of control over the environment and access to information and cues. However, as discussed above, there were still ways in which behavioral indicators may not be a completely accurate depiction of what is going on inside an individual during adaptation. Additionally, it is likely that individuals were not as motivated to engage in the task than if their job or career or promotion depended on their performance after a change occurred. Given the decrease in almost all self-regulation variables and from observations of the participants, individuals lost interest in the experiment as time continued. It would be interesting to examine whether the reward structure associated with performance influence how quickly and effectively an individual adapts or whether the process of adaptation remains the same. Perhaps a quasi-field setting would be possible to investigate this phenomenon (e.g., an undergraduate classroom). Although more challenging, a field setting would allow for individuals to have a vested interest in performing effectively for another purpose than experimental credits. This may result in an increase in the psychological fidelity of the process identified.

Implications

This research confirms that training not only impacts performance directly after a change, but also how individuals increased in their performance, suggesting that training may influence the process of adaptation. In particular, training that encouraged errors yielded the best results in adaptive performance both initially after the change and the speed with which they adapted over the course of the following trials. The implication of this finding for practice is that individuals who are given the opportunity to make errors and are encouraged to do so are able to adjust their behaviors in light of a change in their task. Although making errors can be very deleterious in most occupations, providing a realistic simulation for training may allow for individuals to see the negative impacts of various errors, which would allow them to mitigate the effects of a change and permit them to adapt more quickly. Furthermore, the results revealed that when errors were not encouraged, individuals who were instructed to explore their environment in order to learn the task were able to adapt more quickly when a change was introduced. Therefore, in jobs where errors are not able to be encouraged, it would be beneficial to developing an individual's adaptive capacity in order to allow them to learn by experimenting with their task as opposed to strict training where they are walked through the task step-by-step. Organizations would be wise to allow individuals to engage in active learning to increase their ability to adapt.

There is still a need to investigate which self-regulatory processes can be informative in the study of the adaptation process. We do see that increased effort in light of a change is useful for increasing performance, indicating that motivated individuals may be more prepared to deal with an adaptive change. Furthermore, the results suggest that understanding the relevant information that addresses the change is critical in order for performance to be enhanced. This indicates that individuals need to have access to support (e.g., written information or feedback) to identify the source of the change in the environment. Without insight into what the change was and how it impacts performance it would be very difficult, if not impossible, to adapt.

Conclusion

This research is an extension of previous work in the performance adaptation literature investigating the effect of self-regulatory variables on an individual's adaptation. One key contribution of this study is in the investigation of these regulatory variables throughout the adaptation phase as opposed to during training in an attempt to understand whether these processes are also relevant in explaining the adaptation process as well as an individual's learning process. A simulated laboratory task was used to gain insight into this phenomenon. The training manipulations indicated that encouraging errors during training allowed individuals to understand the change more rapidly and they increased in performance faster. When individuals were not informed to avoid errors but were given an opportunity to learn the task through exploration, they were more capable of adapting than if they were given step-by-step instructions. The results of the cognitive self-regulatory processes revealed that individuals who were able to identify the origin of the change in the task and sought feedback and information that aligned with that change required less of that information over time. This suggests that these individuals were able to adapt more quickly than those who were not able to do so. The motivational pathway of self-regulation was less clear. Self-efficacy was found to decrease over time, unlike expectations; however, individuals increased in their total amount of effort over time, which was related to an increase in performance. This leads to the conclusion that increased motivation may be beneficial in the adaptation process. Although this study takes the next step of looking at the self-regulatory processes *during* adaptation, future research should investigate how these processes, taken together, create cycles of self-regulatory processes that influence the adaptation of individuals.

APPENDICES

APPENDIX A
Overall Flow of Experiment

Familiarization Phase:
Informed Consent, Demographics and trait goal orientation measure (15 min)
Demo program by experimenter (10 min)
Familiarization Trial (5 min)
TOTAL FAMILIARIZATION TIME: 30 min

Training Phase:
Block 1 instructions (5 min)
  Look at manual (2 min)
Scenario 1 (4 min)
  Feedback (1 min)
Look at manual (2 min)
Scenario 2 (4 min)
  Feedback (1 min)
Block 2 instructions (5 min)
  Look at manual (2 min)
Scenario 3 (4 min)
  Feedback (1 min)
Look at manual (2 min)
Scenario 4 (4 min)
  Feedback (1 min)
Block 3 instructions (5 min)
  Look at manual (2 min)
Scenario 5 (4 min)
  Feedback (1 min)
Look at manual (2 min)
Scenario 6 (4 min)
  Feedback (1 min)
Measures: basic and strategic knowledge, state goal orientation (10 min)
TOTAL TRAINING TIME: 67 min

Adaptation Phase (repeat 7 times):
  Measures (2 min)
  Look at manual (2 min)
  Scenario (4 min)
  Feedback (1 min)
TOTAL ADAPTATION TIME: 63 min

Debrief (15 min)

TOTAL EXPERIMENT TIME: 3 hours

APPENDIX B
Practice Topics

Training Topics for Training Block 1

In this first block of two trials, the major focus of training is getting familiar with the simulation and making contact decisions. You should focus on the following training topics:

1. Using the mouse and other equipment to operate the simulation.
2. Hooking contacts and accessing the pull down menus.
3. Making TYPE contact decisions.
4. Making CLASS contact decisions.
5. Making INTENT contact decisions.
6. Making FINAL ENGAGEMENT contact decisions.
7. Viewing right button feedback after making contact decisions.

Training Topics for Training Block 2

In this second block of two trials, the major focus of training is preventing contacts from crossing the defensive perimeters. You should focus on the following training topics:

1. Using the zoom function to view the “big picture” and monitoring the inner and outer perimeters.
2. Using marker contacts to locate the outer defensive perimeter.
3. Watching for pop-up contacts that appear suddenly on your screen.

Training Topics for Block 3

In this last block of two trials, the major focus of training is being able to apply strategies that are used to better prevent contacts from crossing the defensive perimeters. You should focus on the following training topics:

1. Prioritizing contacts located on the radar screen to determine high and low priority contacts and the order in which contacts should be prosecuted.
2. Making trade-offs between contacts that are approaching your inner and outer defensive perimeters.

APPENDIX C
Exploratory Learning Instructions

Task Instructions – Block 1

An effective method for learning the skills just discussed is to explore the task and develop your own understanding of it. As you practice the scenarios, explore the task to understand what is occurring in the scenario, and discover the best strategy to deal with the situation. Also, experiment with different strategies and methods as you explore the task and learn important task skills. Remember, your task is to learn the basic features of the simulation, hook the contacts and use the pull-down menus, make contact decisions, and view right-button feedback following contact decisions.

Task Instructions – Block 2

An effective method for learning the skills just discussed is to explore the task and develop your own understanding of it. As you practice the scenarios, explore the task to understand what is occurring in the scenario, and discover the best strategy to deal with the situation. Also, experiment with different strategies and methods as you explore the task and learn important task skills. Remember, your task is to learn how to prevent contacts from crossing your perimeters. To do this effectively, you will need to learn how to use the zoom function, how to use marker contacts to locate the outer defensive perimeter, and how to watch for pop-up contacts that appear suddenly on your screen.

Task Instructions – Block 3

An effective method for learning the skills just discussed is to explore the task and develop your own understanding of it. As you practice the scenarios, explore the task to understand what is occurring in the scenario, and discover the best strategy to deal with the situation. Also, experiment with different strategies and methods as you explore the task and learn important task skills. Remember, your task is to learn how to prioritize contacts and make tradeoffs between contacts that are approaching your inner and outer perimeters.

APPENDIX D
Proceduralized Learning Instructions

Task Instructions – Block 1

During each of the first two trials, there will be 22 contacts on the radar screen. When you start each trial, you will see a number of these contacts on the screen. Since your focus in on learning basic features of the task and making contact decisions, you should focus on these contacts for now. After the experimenter instructs you to start the scenario and the timer begins to count down, you will focus on hooking contacts, making decisions about the contacts, and viewing feedback about your decisions. You should follow the instructions below for Trials 1 & 2. During these trials, you should follow the following steps:

1. Hook a contact of your choice.
   a. Using the mouse, place the arrow on a contact and click the left mouse button.
   b. When the contact is properly hooked, it will turn green and the Hooked Track # in the lower right corner of your radar screen changes to correspond to the contact number.
   c. When you gather information from your chip's sensors, that information will be given for the contact you currently have hooked.
2. Make TYPE, CLASS, INTENT sub-decisions for hooked contacts.
   a. After the contact is hooked, place the arrow on the TYPE menu button located in the top right of your radar screen. Click on the right mouse button to display the menu options.
   b. Move your arrow to the button that says "Speed" and click and hold the right mouse button to view the contact's speed. Use the chart on the next page to see what type of contact is indicated by the speed information. After viewing contact speed, do the same for "Altitude/Depth" and "Communication Time." Once again, use the chart on the next page to see what type of contact is indicated by the cue values. Note that one value you gathered may be inconsistent with the other two; if this is the case choose the option indicated by the majority (2 out of 3) of the values.
   c. After viewing the three pieces of information, you are ready to make the TYPE decision. Choose "ID_Air/Sub/Surface" from the bottom of the TYPE menu.
   d. A list of choices appears in a menu on the lower right corner of your radar screen. Choose the option that was indicated by the majority of the cues you collected by clicking your right mouse button on the option.
   e. Perform steps a through d for the CLASS decision and the INTENT decision.
3. Make FINAL ENGAGEMENT decision.
   a. After you have made the TYPE, CLASS, and INTENT decisions for a contact, you can then make the FINAL ENGAGEMENT decision.
   b. Move your arrow to the OPER menu and click the right mouse button.
   c. Move your arrow to the menu option that says "Engage_Shoot/Clear" and click the right mouse button. A list of choice appears in the lower right corner of your radar screen.
   d. If the INTENT of the contact was peaceful you should click your right mouse button on the "clear" option, but if the INTENT of the contact was Hostile you should click your right mouse button on the "shoot" option. See next steps before doing this.
   e. When you click your right mouse button on either "clear" or "shoot" you can hold it down to receive information on whether you have engaged the contact correctly.
4. REPEAT
   a. After you make the final engagement decision, the contact will disappear and you should repeat steps 1 – 3 for another contact.

b. If you eliminate all contacts in your viewing range, place your arrow on the OPER menu and click the right mouse button. Then place the arrow on the "Zoom-Out" option and click your right mouse button. When you do this, more contacts should appear and you can continue.

Contact Cue Values

Listed below are the cue values for different type of contacts. Remember, as you make TYPE, CLASS, and INTENT decisions you want to select the option indicated by the MAJORITY of the cue values. Note: you will not be able to use this sheet in the final two trials.

CONTACT TYPE

AIR	Speed > 35 knots
	Altitude/Depth > 0 feet
	Communication Time = 0 – 40 s
SURFACE	Speed = 25 – 35 knots
	Altitude/Depth = 0 feet
	Communication Time = 41 – 80 s
SUB	Speed = 0 – 24 knots
	Altitude/Depth < 0 feet
	Communication Time = 81 – 120 s

CONTACT CLASS

CIVILIAN	Intelligence = Private
	Direction of Origin = Blue Lagoon
	Maneuvering Pattern = Code Foxtrot
UNKNOWN	Intelligence = Unavailable
	Direction of Origin = Unknown
	Maneuvering Pattern = Code Echo
MILITARY	Intelligence = Platform
	Direction of Origin = Red Sea
	Maneuvering Pattern = Code Delta

CONTACT INTENT

PEACEFUL	Countermeasures = None
	Threat Level = 1
	Response = Given
UNKNOWN	Countermeasures = Unknown
	Threat Level = 2
	Response = Inaudible
HOSTILE	Countermeasures = Jamming
	Threat Level = 3
	Response = No Response

FINAL ENGAGEMENT DECISION

CLEAR	If INTENT = Peaceful
SHOOT	If INTENT = Hostile

APPENDIX E
Error Instructions

Errors – Block 1

For each of the training topics listed above, there is the potential for a number of errors. Some of the mistakes that can be made in these areas are listed below:

1. Clicking on the wrong mouse button (left/right) to hook a contact or access a menu.

2. Not properly evaluating contact information and making incorrect contact sub-decisions (TYPE, CLASS, INTENT) and decisions (FINAL ENGAGEMENT).

3. Making contact sub-decisions based on a single cue value. For example, deciding a contact's TYPE based only on speed information.

4. Making contact decisions too quickly.

Errors – Block 2

For each of the training topics listed above, there is the potential for a number of errors. Some of the common mistakes in these areas are listed below

1. Focusing on only the inner perimeter rather than zooming out to see the "big picture" and to monitor the outer perimeter.

2. Hooking the wrong marker contacts or not using marker contacts to locate the outer perimeter.

3. Focusing only on stable contacts and ignoring contacts that pop-up suddenly on the screen. Often people do not monitor their screen for pop-up contacts.

4. Letting contacts cross the inner and outer defensive perimeters.

Errors – Block 3

For each of the training topics listed above, there is the potential for a number of errors. Some of the common mistakes in these areas are listed below:

1. Focusing on low priority rather than high priority contacts.

2. Not checking the speeds of contacts close to the perimeters.

3. Preventing all contacts from crossing one perimeter while ignoring the other perimeter.

Error-encouragement framing

During training, you are encouraged to make these errors. For training to be effective, you should make these errors. Errors are a positive part of the learning experience. As a result of making errors, you can learn from your mistakes and develop a better understanding of the simulation. The more errors you make the more you learn.

Error-avoidance framing

During training, you are encouraged to avoid these errors. For training to be effective, you should try not to make these errors. Errors are detrimental to the learning process and will hurt your understanding of the simulation. The more errors you avoid the more you learn.

APPENDIX F
Measures Before the Familiarization Phase

Demographics Questionnaire

Please provide as much of the following information as is applicable. It is important to understand that these scores will be kept confidential and used only for research purposes. If you do not remember your exam scores, please put a zero in that space.

Gender: _____(M / F)

Age: _____

Year in College: ____

Major: __________________

College GPA: _________

SAT score: ____________

ACT score: ____________

Trait Goal Orientation

For each of the following statements, please indicate how true it is for you on the scale provided below.

1	2	3	4	5	6
Strongly Disagree	Moderately Disagree	Slightly Disagree	Slightly Agree	Moderately Agree	Strongly Agree

Goal Orientation Learning

1. I am willing to take on challenges that I can learn a lot from.
2. I often look for opportunities to develop new skills and knowledge.
3. I enjoy challenging and difficult activities where I'll learn new skills.
4. For me, development of my abilities is important enough to take risks.

Goal Orientation Prove:

1. I prefer to do things that require a high level of ability and talent.
2. I'm concerned with showing that I can perform better than my peers.
3. I try to figure out what it takes to prove my ability to others.
4. I enjoy it when others are aware of how well I am doing.
5. I prefer to participate in things where I can prove my ability to others.

Goal Orientation Avoidance:

1. I would avoid taking on a new task if there was a chance that I would appear rather incompetent to others.
2. Avoiding a show of low ability is more important to me than learning a new skill.
3. I'm concerned about taking on a task if my performance would reveal that I had low ability.
4. I prefer to avoid situations where I might perform poorly.

APPENDIX G
Measures After the Training Phase

<u>Basic and Strategic Knowledge Test</u>

The following is a knowledge test about the simulation. Please select the response that best answers the question.

1. If a Response is Given, what is the likely Intent of the contact?
    a. Military
    b. Hostile
    c. Civilian
    d. Peaceful

2. A submarine may have which of the following characteristics?
    a. Speed 30 knots, Altitude/Depth -20, Communication time 85 seconds
    b. Speed 30 knots, Altitude/Depth 0, Communication time 30 seconds
    c. Speed 20 knots, Altitude/Depth 0, Communication time 80 seconds
    d. Speed 20 knots, Altitude/Depth -20, Communication time 90 seconds

3. A Maneuvering Pattern of Code Delta indicates the contact is which of the following?
    a. Air
    b. Military
    c. Surface
    d. Civilian

4. A Blue Lagoon Direction of Origin indicates the contact is which of the following?
    a. Unknown
    b. Sub
    c. Civilian
    d. Military

5. If a contact's Altitude/Depth is 10 feet, what is the Type of the contact?
    a. Air
    b. Surface
    c. Submarine
    d. Unknown
6. If a contact's Intelligence is Unavailable, what Class does this suggest for the contact?
    a. Air
    b. Civilian
    c. Military
    d. Unknown

7. If a contact's characteristics are Communication Time = 20 seconds and Speed = 50 knots, which of the following actions should you take?
    a. Choose Intent is Peaceful
    b. Choose Type is Surface
    c. Get another piece of information
    d. Choose Type is Air

8. A communication Time of 52 seconds indicates that the contact is likely:
    a. Air
    b. Surface
    c. Submarine
    d. Unknown

9. If a contact's characteristics are Intelligence is Private and Maneuvering Pattern is Code Foxtrot, which of the following actions should you take?
    a. Choose Class is Military
    b. Choose Intent is Peaceful
    c. Choose Class is Civilian
    d. Choose Intent is Unknown

10. If a contact's Maneuvering Pattern is Code Echo, this suggests that the contact falls into which category?
    a. Class is Unknown
    b. Class is Military
    c. Class is Hostile
    d. Class is Peaceful

11. If a contact's Speed is 40 knots, what does this suggest about the contact?
    a. The contact is Air
    b. The contact is Surface
    c. The contact is Civilian
    d. The contact is Military

12. You Outer Defensive Perimeter is located at:
    a. 64 nm
    b. 128 nm
    c. 256 nm
    d. 512 nm

13. If you've just noticed three contacts near your inner perimeter, which of the following should you do next?
    a. Engage the contact nearest the inner perimeter
    b. Engage the faster contact near the inner perimeter
    c. Zoom-Out to check the outer perimeter
    d. Zoom-In to check how close the contacts are to the inner perimeter

14. If you Zoom-Out to find three contacts around your Outer Perimeter, how would you determine which contact is the marker contact?
    a. Check to see which contact is closest to the outer perimeter
    b. Check the speeds of the contacts
    c. Check to see which contact is Civilian
    d. Check to see which contact is Hostile

15. What is the purpose of marker contacts?
    a. To determine which Contacts are Hostile and which are Peaceful
    b. To locate your Inner Defensive Perimeter
    c. To quickly determine the speeds of contacts near your perimeters
    d. To locate your Outer Defensive Perimeter

16. Which of the following pieces of information is NOT useful for prioritizing contacts?
    a. The distance of contacts from the Outer Defensive Perimeter
    b. Whether the contact is Peaceful or Hostile
    c. The distance of contacts from the Inner Defensive Perimeter
    d. The Speed of contacts near your Inner and Outer Defensive Perimeter

17. Which of the following functions is most useful for identifying marker contacts?
    a. Zoom-In
    b. Right-button feedback
    c. Engage Shoot or Clear
    d. Zoom-Out

18. If three contacts are about 10 miles outside your Outer Defensive Perimeter, which of the following should you do to prioritize the contacts?
    a. Engage the fastest contact
    b. Engage the hostile contact
    c. Engage the closest contact
    d. It makes no difference in what order you engage the contacts

19. On the average, approximately how many contacts pop-up during each practice trial?
    a. 1
    b. 3
    c. 6
    d. 9

20. Which of the following would be the most effective strategy for defending your Outer Defensive Perimeter?
    a. Zoom-Out to 128 nm, locate the Marker Contacts, and check the Speed of contacts near the Outer Perimeter
    b. Zoom-Out to 256 nm, locate the Marker Contacts, and check the Speed of contacts near the Outer Perimeter
    c. Zoom-Out to 128 nm, locate a Hostile Air Contact, and check the Speed of contacts near the Outer Perimeter
    d. Zoom-Out to 256 nm, locate a Hostile Air Contact, and check the Speed of contacts near the Outer Perimeter

21. If all penalty intrusions cost -100 points, which would be the most effective strategy?
    a. Do not allow any contacts to enter your Inner Defensive Perimeter, even if it means allowing contacts to cross your Outer Defensive Perimeter

b. Do not allow any contacts to enter your Outer Defensive Perimeter, even if it means allowing contacts to cross your Inner Defensive Perimeter
c. Defend both your Inner and Outer Defensive Perimeters
d. None of these are effective strategies

22. It is important to make trade-offs between contacts:
    a. That are Hostile and those that are Peaceful
    b. Approaching your Inner and Outer Perimeters
    c. That are Civilian and those that are Military
    d. That have already crossed your Inner Defensive Perimeter and those that are approaching your Outer Defensive Perimeter

State Mastery Orientation Measure

For each of the following statements, please indicate how true it is for you with regard to how your approach ***this task*** on the scale provided below.

1	2	3	4	5
Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree

Goal Orientation Learning
1. I prefer to work on aspects of this task that force me to learn new things.
2. I am willing to work on challenging aspects of this task that I can learn a lot from.
3. The opportunity to learn new things about this task is important to me.
4. The opportunity to work on challenging aspects of this task is important to me.
5. On this task, my goal is to learn the task as well as I can.

Goal Orientation Prove:
1. It is important to me to perform better than others in this task.
2. It is important to me to impress others by doing a good job on this task.
3. I was the experimenters and other students to recognize that I am one of the best on this task.
4. I want to show myself how good I am on this task.
5. On this task, my goal is to perform well.

Goal Orientation Avoidance:
1. On this task, I would like to hide from others that they are better than me.
2. On this task, I would like to avoid situations where I might demonstrate poor performance to myself.
3. On this task, I would like to avoid discovering that others are better than me.
4. I am reluctant to ask questions about this task because others may think I'm incompetent.
5. On this task, my goal is to avoid performing poorly.

APPENDIX H
Measures Throughout the Adaptation Phase

Self Efficacy

This set of questions asks you to describe how you feel about your capabilities for performing on **THE NEXT TRIAL** of the simulation.

1	2	3	4	5
Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree

1. I can meet the challenges of this simulation.
2. I am certain that I can manage the requirements of this task.
3. I believe I can develop methods to handle changing aspects of this task.
4. I am certain I can cope with the task components competing for my time.

Goal Level

Please indicate your desired level of performance **ON THE NEXT TRIAL.**

Number of contacts correctly identified ____
Number of threatening contacts eliminated ____
Total points ____

REFERENCES

REFERENCES

Ashford, S. J. (1986). Feedback-seeking in individual adaptation: A resource perspective. *Academy of Management Journal, 29*(3), 465-487.

Baard, S. K., Rench, T. A., & Kozlowski, S. W. J. (in press). Adaptation: A theoretical review and integration. *Journal of Management*.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*, 248-287.

Bandura, A. & Wood, R. (1989). Effect of perceived controllability and performance standards on self-regulation of complex decision making. *Journal of Personality and Social Psychology, 56*(5), 805-814.

Bandura, A. & Cervone, D. (1983). Self-evaluative and self-efficacy mechanisms governing the motivational effects of goal systems. *Journal of Personality and Social Psychology, 45*(5), 1017-1028.

Bell, B. S. (2002). An examination of the instructional, motivational, and emotional elements of error training. Ph.D. dissertation, Michigan State University, United States, MI. (Publication No. AAT 3064202).

Bell, B. S. & Kozlowski, S. W. J. (2002a). Goal orientation and ability: Interactive effects on self-efficacy, performance, and knowledge. *Journal of Applied Psychology, 87*(3), 497-505.

Bell, B. S. & Kozlowski, S. W. J. (2002b). Adaptive guidance: Enhancing self-regulation, knowledge, and performance in technology-based training. *Personnel Psychology, 55*, 267-306.

Bell, B. S. & Kozlowski, S. W. J. (2008). Active learning: Effects of core training design elements on self-regulatory processes, learning and adaptability. *Journal of Applied Psychology, 93*(2), 296-316.

Bell, B. S. & Kozlowski, S. W. J. (2010). Toward a theory of learner-centered training design: An integrative framework of active learning. In S. W. J. Kozlowski & E. Salas (Eds.), *Learning, Training and Development in Organizations* (pp. 263-300). New York, NY: Routledge Taylor & Francis Group.

Burke, C. S., Stagl, K. C., Salas, E., Pierce, L. & Kendall, D. (2006). Understanding team adaptation: A conceptual analysis and model. *Journal of Applied Psychology, 91*(6), 1189-1207.

Chan, D. (2000). Understanding adaptation to changes in the work environment: Integrating individual difference and learning perspectives. *Research in Personnel and Human Resources Management, 18*, 1-42.

Chen, G., Thomas, B. & Wallace, J. C. (2005). A multilevel examination of the relationships among training outcomes, mediating regulatory processes, and adaptive performance. *Journal of Applied Psychology, 90*(5), 827-841.

Debowski, S., Wood, R. E., & Bandura, A. (2001). Impact of guided exploration and enactive exploration on self-regulatory mechanisms and information acquisition through electronic search. *Journal of Applied Psychology, 86*(6), 1129-1141.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41*(10), 1040-1048.

Faul, F. Erdfelder, E., Land, A.-G. & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175-191.

Ferrer, E., Shaywitz, B. A., Holahan, J. N., Marchione, K. & Shaywitz, S. E. (2010). Uncoupling of reading and IQ over time: Empirical evidence for a definition of dyslexia. *Psychological Science, 21*, 93-101.

Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83*(2), 218-233.

Gist, M. E., & Mitchell, T. R. (1992). Self-efficacy: A theoretical analysis of its determinants and malleability. *Academy of Management Review, 17*(2), 183-211.

Griffin, B. & Hesketh, B. (2004). Are conscientious workers adaptable? *Australian Journal of Management, 30*(2), 245-259.

Gully, S. M., Payne, S. C., Koles, K. L. K., & Whiteman, J.-A. K. (2002). The impact of error training and individual differences on training outcomes: An attribute-treatment interaction perspective. *Journal of Applied Psychology, 87*(1), 143-155.

Hu, L.-H. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Ivancic, K. & Hesketh, B. (2000). Learning from errors in a driving simulation: Effects on driving skill and self-confidence. *Ergonomics, 43*(12), 1966-1984.

Jundt, D. (2009). Adaptability from a process perspective: Examining the effects of task change type and a metacognitive intervention on adaptive performance. Ph.D. dissertation, Michigan State University, United States, MI. (Publication No. ATT 3381265).

Karoly, P. (1993). Mechanisms of self-regulation: A systems review. *Annual Review of Psychology, 44*, 23-52.

Keith, N. & Frese, M. (2005). Self-regulation in error management training: Emotion control and metacognition as mediators of performance effects. *Journal of Applied Psychology, 90*, 677-691.

Keith, N. & Frese, M. (2008). Effectiveness of error management training: A meta-analysis. *Journal of Applied Psychology, 93*(1), 59-69.

Kluger, A. N. & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin, 119*, 254-284.

Kozlowski, S. W. J. & Bell, B.S. (2006). Disentangling achievement orientation and goal setting: Effects on self-regulatory processes. *Journal of Applied Psychology, 91*(4), 900-916.

Kozlowski, S. W. J., Gully, S. M., Nason, E. R. & Smith, E. M. (1999). Developing adaptive teams: A theory of compilation and performance across levels and time. In D. R. Ilgen, & E. D. Pulakos (Eds.). *The changing nature of performance: Implications for staffing, motivation, and development* (pp.240-292). San Francisco: Jossey-Bass Publishers.

Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes, 85*(1), 1-31.

Kozlowski, S. W. J., Gully, S. M., Salas, E., & Cannon-Bowers, J. A. (2010). Team leadership and development: Theory, principles, and guidelines for training leaders and teams. *Advances in Interdisciplinary Studies of Work Teams, 3*, 253-291.

Kozlowski, S. W. J., Watola, D. J., Jensen, J. M., Kim, B. H., & Botero, I. C. (2009). Developing adaptive teams: A theory of dynamic team leadership. In E. Salas, G. F. Goodwin, & C. S. Burke (Eds.), *Team Effectiveness in Complex Organizations: Cross-disciplinary Perspectives and Approaches* (pp. 113-155). New York, NY: Routledge Academic.

Kozlowski, S. W. J., Toney, R. J., Mullins, M. E., Weissbein, D. A., Brown, K. G., & Bell, B. S. (2001). Developing adaptability: A theory for the design of integrated-embedded training systems. In E. Salas (Ed.), *Advances in human performance and cognitive engineering research* (Vol. 1, pp. 59-123). Amsterdam: JAI/Elsevier Science.

Latham, G. P. & Locke, E. A. (1991). Self-regulation through goal setting. *Organizational Behavior and Human Decision Processes, 50*, 212-247.

LePine, J. A. (2003). Team adaptation and postchange performance: Effects of team composition in terms of members' cognitive ability and personality. *Journal of Applied Psychology, 88*(1), 27-39.

LePine, J. A. (2005). Adaptation of teams in response to unforeseen change: Effects of goal difficulty and team composition in terms of cognitive ability and goal orientation. *Journal of Applied Psychology, 90*(6), 1153-1167.

LePine, J. A., Colquitt, J. A. & Erez, A. (2000). Adaptability to changing task contexts: Effects of general cognitive ability, conscientiousness, and openness to experience. *Personnel Psychology, 53*, 563-593.

McArdle, J. J. (2001). A latent difference score approach to longitudinal dynamic structural analyses. In R. Cudeck, S. DuToit, & D. Sorbom (Eds.), *Structural Equation Modeling: Present and Future* (pp. 342-380). Lincolnwood, IL: SSI.

McDaniel, M. A. & Schlager, M. S. (1990). Discovery learning and transfer of problem-solving skills. *Cognition and Instruction, 7*(2), 129-159.

Phan, H. P. (2009). Relations between goals, self-efficacy, critical thinking and deep processing strategies: A path analysis. *Educational Psychology, 29*(7), 777-799.

Phillips, J. M. & Gully, S. M. (1997). Role of goal orientation, ability, need for achievement, and locus of control in the self-efficacy and goal-setting process. *Journal of Applied Psychology, 82*(5), 792-802.

Ployhart, R. E. & Bliese, P. D. (2006). Individual ADAPTability (I-ADAPT) Theory: Conceptualizing the antecedents, consequences, and measurement of individual differences in adaptability. In S. Burke, L. Pierce, & E. Salas (Eds.), *Understanding Adaptability: A Prerequisite for Effective Performance Within Complex Environments*. Elsevier Science.

Pulakos, E. D., Arad, S., Donovan, M. A. & Plamondon, K. E. (2000). Adaptability in the workplace: Development of a taxonomy of adaptive performance. *Journal of Applied Psychology, 85*(4), 612-624.

Pulakos, E. D., Schmitt, N., Dorsey, D. W., Arad, S., Borman, W. C. & Hedge, J. W. (2002). Predicting adaptive performance: Further tests of a model of adaptability. *Human Performance, 15*(4), 299-323.

Schmidt, A. M. & DeShon, R. P. (2010). The moderating effects of performance ambiguity on the relationship between self-efficacy and performance.

Smith, E. M., Ford, J. K. & Kozlowski, S. W. J. (1997). Building adaptive expertise: Implications for training design strategies. In M. A Quinones & A. Dudda (Eds.), *Training for a rapidly changing workplace: Applications of psychological research* (pp. 89-118). Washington, DC: APA Books.

Sitzmann, T. & Yeo, G. (April, 2012). *A Meta-Analysis of the Within-Person Effect of Self-Efficacy on Performance.* Symposium at the 27th Annual Conference of the Society for Industrial and Organizational Psychology (SIOP), San Diego, CA.

Tolli, A. P. & Schmidt, A. M. (2008). The role of feedback, causal attributions, and self-efficacy in goal revision. *Journal of Applied Psychology, 93*(3), 692-701.

Vancouver, J. B., Thompson, C. M. & Williams, A. A. (2001). The changing signs in the relationships among self-efficacy, personal goals, and performance. *Journal of Applied Psychology, 86*(4), 605-620.

VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement, 57*, 995-1015.

Wang, H., Law, K. S., Hackett, R. D., Wang, D. & Chen, Z. X. (2005). Leader-member exchange as a mediator of the relationship between transformational leadership and followers' performance and organizational citizenship behavior. *The Academy of Management Journal, 48*(3), 420-432.

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes, 37*, 60-82.

Wood, R. E. & Locke, E. A. (1987). The relation of self-efficacy and grade goals to academic performance. *Educational and Psychological Measurement, 47*, 1013-1024.

Yeo, G. B. & Neal, A. (2004). A multilevel analysis of effort, practice and performance: Effects of ability, conscientiousness, and goal orientation. *Journal of Applied Psychology, 89*(2), 231-247.

Yeo, G. & Neal, A. (2008). Subjective cognitive effort: A model of states, traits, and time. *Journal of Applied Psychology, 93*(3), 617-631.