THE PROCESS OF ADAPTATION

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Psychology – Doctor of Philosophy

2015

ABSTRACT

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It is no surprise why there is resurgence in research on adaptation – we engage in work environments characterized by change. However, do we, as researchers and practitioners in organizational science, truly understand how individuals deal with these changes? In other words, do we understand how individuals adapt? For the last several decades, it appears the answer would be: not sufficiently. This research endeavor was developed to push the boundaries of the adaptation literature by theorizing a dynamic process of adaptation, examining the embedded cognitive and motivational self-regulatory mechanisms, and specifying the first and second order dynamics involved (i.e., trajectory and relationship changes). Through empirically examining both the post-change adaptation process and subsequent routine performance process, the findings reveal that these two processes are distinct. Two types of adaptive changes were investigated, and the results show similar trajectories and relationships across these change types, providing initial evidence of the generalizability of the adaptation process. Furthermore, the patterns of the cognitive and motivational cycles presented an interesting picture of the inner workings of the adaptation process in correcting performance decreases after a change. Through using discontinuous growth curve analyses, and a partially crossed, partially time-varying, cross-lag panel regression model, a clear distinction was evident in the utility of these dynamic techniques. Although the more standard trajectory analyses offered a straightforward picture of how variables increase or decrease over time, the more sophisticated cross-lag

analysis provided a unique perspective, as that model accounts for many sources of variance in the estimation of relationships. This research provides a first step into what could be a very fruitful path investigating the dynamics of the adaptation process.

This work is dedicated to my wonderful husband, William C. Perry, and to my loving parents, Paul and Veronica Baard.

ACKNOWLEDGEMENTS

I would like to sincerely thank my advisor, Dr. Steve Kozlowski, who provided me with invaluable guidance and direction in my graduate career and superb intellectual training so I could effectively reach my goals. He not only assisted me in the expansion of my knowledge of conducting behavioral research, but also was instrumental in my growth in theory development and writing prowess.

A special thank you is also due to my committee members, Dr. Georgia Chao, Dr. Rick DeShon, and Dr. Kevin Ford for their excellent advice and generous dedication of time and effort on my behalf. It has been an honor to work with them and see how their insights have not only assisted in the betterment of this dissertation, but also in my educational development and clarity of my thinking.

I also owe immense gratitude to my ever-supportive husband, William Perry, who has been a consistently positive presence, keeping my perspective in check through each step of this process. I would also like to share my deepest appreciation to my parents, Paul and Veronica Baard, who have provided incredible support and encouragement for me to not only complete this dissertation but also to pursue education throughout my entire life, and to my God, Jesus Christ, by whose strength I could accomplish this and to whom I will always give thanks.

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INTRODUCTION

Changing, *dynamic*, *unstable*, and *unpredictable* are words typically used to characterize the present workplace. It is less than surprising then that adaptation has become a frequently used term. Although companies consistently say they need individuals who can quickly adapt to changes, little is truly understood about the process of adaptation. However, the process – or a reoccurring set of behaviors – is what leads to the desirable outcomes (i.e., high performance) organizations seek when new situations arise (Burke, Stagl, Salas, Pierce & Kendall, 2006; Kozlowski, Gully, Salas & Cannon-Bowers, 1996).

One may ask: why is it necessary to understand how individuals change as long as they do so effectively? I offer two reasons why researchers should be interested in the means as well as the ends: 1) through identifying and understanding the process, we can learn to manipulate it through training in order to make individuals more effective at adapting to changes, and 2) since adaptation is an inherently longitudinal and dynamic phenomenon, a process framework allows the opportunity to discuss how the mechanisms dynamically adjust to the demands presented by different environments over time.

While the term adaptability or adaptation has been in the organizational literature since the early-to-mid-1900s (e.g., Ghiselli, 1951; Terreberry, 1968; Tiffin & Lawshe, 1942; Trites, Kubala, & Cobb, 1959), the majority of thorough, scientifically-driven approaches to the study of adaptation has only emerged over the past few decades, as researchers have responded to the need to investigate the increasingly dynamic organizational environments. Particularly in reference to the process approach to the study of adaptation, research has fallen short of addressing the two key reasons of why investigating dynamic processes is so vital in three ways. First, investigations need to be conducted at the individual level of analysis since individuals are the ones who adapt to changes within teams and organizations; however, the vast majority of the theoretical frameworks of the adaptation process are at the team level (see Baard, Rench & Kozlowski, 2014 for a review). Second, longitudinal and empirical studies are also needed to investigate a process; however, the current set of articles on the adaptation process is exclusively theoretical (Baard et al., 2014). Third, and of critical importance for this research endeavor, new dynamic analyses are needed to capture the cyclical nature of a process (i.e., through cross-lag and autoregressive analyses as opposed to latent growth curve analyses); however, not only is this difficult because of the complexity of the data analysis skills needed, but the programs for such analyses are only beginning to be established in the literature.

This research endeavor will address all three of these gaps. I will first provide an overview of several types of change, describe the main perspectives in the adaptation literature, and identify where this research endeavor fits as well as where it will advance the field. Then I will describe how self-regulation, learning and control theories assist in understanding how individuals engage in the adaptation process when a change is introduced. Following this overall description of the adaptation process, I will specify the dynamics of the mechanisms involved by describing two orders of change (Carver & Scheier, 1982; Powers, 1973): the trajectories of the variables and the relationships between them. "Trajectory" changes describe how the variables adjust in level over time while "Relationship" changes present the dynamics of the direction and strength between variables as individuals engage in the adaptation process. Finally, I will explicate the way in which this theory will be empirically investigated through the application of a newer analysis that can capture the reciprocal relationships inherent in the adaptation process.

ADAPTATION – THE PROCESS OF RESPONDING TO CHANGES

What is Change?

Before beginning the discussion of how adaptation is defined in the literature and how I will specifically investigate it, it is necessary to take a step back and consider what triggers the need for adaptation – namely, change. In the organizational literature, many types of changes have been identified, though these are conceptualized at the system level as opposed to the reactions of individuals when facing a change. It appears that one trend in the change literature is to bifurcate change into two extremes and compare them. Using a systems oriented perspective on change, Nasim and Sushil (2011) discuss four sets of change types. Table 1 summarizes these perspectives from their review.

Of particular interest in this research endeavor is the difference between incremental and revolutionary changes. They present these two types as having roots in many historical debates. To be more specific about these two types, incremental change (or first-order change, as some call it) is described as engaging in small variations in behaviors or strategies to continue on the same desired trajectory (Nadler & Tushman, 1995), but it "lacks creativity to discover new strategic ideas" (Atlas, 2007; p. 258). The other end of the spectrum is known by many names, including revolutionary, metamorphic, discontinuous, and transformational. They are grouped together here for the sake of showing how these types are often discussed – as the antithesis of incremental change – but there are differences. Both metamorphic (Tushman & Romanelli, 1985) and transformative (Dibella, 2007) change types are described as large recreations or reorientations, whereby organizations shift their core values and beliefs. However, Nadler and Tushman (1995) take a slightly less extreme perspective with their definition of discontinuous change, which is described as something that occurs at multiple periods of time where a new configuration (e.g., a new strategy or organizational structure) is needed. They describe this period as being very turbulent, but that it results in stabilization. This definition is more in line with an adaptive event that individuals or teams may deal with given that it would be highly unlikely for individuals to be asked to change their core values or beliefs in order to effectively adapt to a change. For example, individuals in an organization will not be required to shift from being an accountant to a human resources manager, but the way in which some authors describe this metamorphic change suggests that organizations may need to "re-create" themselves if faced with a serious enough shift in their environment.

Some authors break from the dichotomous conversation of change types to discuss a mid-level type of change. Atlas (2007) specified that a second-order change is a request for

Table 1

Types of System Level Change in the Organizational Literature

Type of change	**Definition**	**Example**
Planned vs. Emergent	**Planned** - change is due to a series of pre-planned steps organizations create and follow **Emergent** - nonlinear movement between stages based on the environment's uncertainty and complexity	Lewin's (1958) unfreezing, change, refreezing model
Static (or episodic) vs. Dynamic	**Static** - similar to the planned change; change is linear movement from one state to another **Dynamic** - based off of the emergent approach; focuses on the discontinuous nature of organizations and their work environments	Senge's (1990) complex dynamic systems of learning
Piecemeal vs. Holistic	**Piecemeal** - dealing with change is focusing on one aspect of the change at a time (e.g., a process, context, or outcome) **Holistic** – dealing with change is simultaneously considering all the factors that contribute to effective change	Beer, Eisenstat & Spector (1990) six steps to organizational change
Incremental vs. Revolutionary	**Incremental** - a series of more routine modifications that are made to maintain the pursuit of a particular goal or outcome **Revolutionary** - large changes that are needed to overcome the inertia that the organization has in order to remain the same as it had been.	Quinn's (1978) theory of logical incrementalism Tushman & Romanelli's (1995) punctuated equilibrium

innovation. The author suggests there are two key aspects to be dealt with: transformational (or the strategy, mission, and culture of the organization) and transactional (or the "psychological and organizational variables that predict and control the motivational and performance outcomes", p. 258). Both of these types will be of interest in the discussion of adaptation, and the concept of a mid-range type of change will be a focus of attention. Similarly, Reger (1994) described "tectonic" change as something larger than incremental change, but not as substantial as transformational change. Instead, tectonic changes require significant action on the part of the organization, but it builds upon existing aspects of the identity of the organization, rather than requiring a re-creation of values or beliefs. This concept of a change being larger than incremental but smaller than revolutionary will be key to how the present study will be investigating adaptation.

In addition to the consideration of mid-range changes, some authors discuss change types using a continuum framework. Nadler and colleagues expanded on the ideas proposed by Tushman and Romanelli (1985) and developed a taxonomy describing a gradient of change types (Nadler, 1988; Nadler & Rushman, 1995). These authors proposed that, in addition to incremental and discontinuous changes, there are anticipatory and reactive changes. With anticipatory changes organizations pre-plan their change, which can either be a small step in the pursuit of a goal, or a dramatic one. On the other hand, reactive changes are not expected by the organization and require immediate action. Nadler and Tushman (1995) present a 2x2 framework of incremental and discontinuous change paired with either anticipatory or reactive change to make a gradient of four paired types of change (e.g., incremental and anticipatory). With these four factors the authors suggest that discontinuous changes that are also reactive have the highest severity of impact on an organization, followed by discontinuous changes that are anticipatory. Following these in severity of impact are incremental changes, with those that are reactive having a stronger impact than those that are anticipatory. This taxonomy presents an initial framework that attempts to determine which types of changes are more difficult to deal with than others, but these authors, like many others in the organizational change literature, have chosen to remain with the mentality that there are two key types of change in any given framework, and have not begun the process of unpacking what elements of change many make the scaling more granular. This concept will be key for understanding how this study investigates adaptation in the context of the change literature. However, before going into much depth on that issue, it is necessary to first delve into understanding the breadth of the adaptation literature and how it will be discussed in this study.

Overview of the Adaptation Literature

For many decades, researchers have added to our understanding of the phenomenon broadly labeled “adaptation” through investigating how individuals, teams and organizations adjust behaviors in light of a new or changed environment (e.g., Caldwell & O’Reilly, 1982; Kozlowski, Gully, Nason & Smith, 1999; Pulakos, Arad, Donovan & Plamondon, 2000; Rosen, Bedwell, Wildman, Fritzsche, Salas, & Burke, 2011). This concept of adaptation, though focused on performance in this research, has been discussed broadly in different literatures; asking questions about socialization, expatriate adjustment, stress and coping. Given the great interest in this phenomenon, there has been divergence in the conceptualization and study of performance adaptation. Therefore, prior to describing the importance and dynamics of the self-regulatory mechanisms involved in the adaptation process as it is presented in this research endeavor, it is critical to determine which parts of the adaptation literature are relevant to this discussion.

In a recent effort to organize, synthesize, and direct future efforts at understanding adaptation, Baard and colleagues (2014) created a taxonomy to organize the diverse definitions that have been proposed over the years, using a bottom-up approach to review the extant literature. They bifurcated the literature into domain general (a situation-spanning approach where the adaptive capability of individuals and the instantiation of adaptation in environments are generalizable across settings) and domain specific conceptualizations (a situation-specific perspective where adaptation requires knowledge, skills and abilities inherent to that environment). Of the domain general perspectives, two streams of research were identified: adaptation as a performance construct (e.g., the eight-dimension framework presented by Pulakos, et al., 2000) and adaptation as an individual difference construct (e.g., the I-ADAPT measure presented by Ployhart & Bliese, 2006). As both of these perspectives view adaptation as a construct versus a process, as this framework does, the research from these two approaches will be drawn upon rarely in the description of the adaptation process.

Domain specific research efforts (i.e., the performance change and process approaches), however, oftentimes discuss the role of self-regulatory mechanisms in adaptive performance. The performance change perspective is primarily concerned with the change in performance that is evident when individuals shift from a routine task environment to an adaptive one. Research in this line of adaptation research is split into three streams: a simple input-output change (e.g., Dormann & Frese, 1994; Frese, Broadbeck, Heinbokel, Mooser, Schleiffenbaum, & Thiemann, 1991), a change influenced by the self-regulatory learning process (e.g., Bell & Kozlowski, 2002b, 2008; Chen, Thomas, & Wallace, 2005), and a difference in the trajectory of performance between routine and adaptive scenarios (e.g., LePine, 2003, 2005). Research investigating the learning process involved prior to adaptation will be scrutinized in depth as these works provide critical insights into the self-regulatory mechanisms involved, with some of these researchers suggesting that the pre-adaptation learning process mirrors the adaptation process (Kozlowski, Toney, Mullins, Weissbein, Brown & Bell, 2001). Given the importance of understanding the dynamics involved in adaptation, the literature examining the performance trajectories in adaptation (e.g., Lang & Bliese, 2009; LePine, 2003, 2005) will also be impactful as the adaptation process is examined. The second domain-specific approach, the process perspective, will also be examined in depth. This stream in the adaptation literature typically uses self-regulatory mechanisms to specifically describe the adaptation process (e.g., Burke, et al., 2006; Kozlowski, Watola, Jensen, Kim & Botero, 2009; Rosen, et al., 2011). These theories come as close to a dynamic understanding of the self-regulatory process of adaptation as is currently available in the literature.

A key goal of this research is to present a model that combines the efforts of these theory and research streams in the adaptation literature. Similar to Chen and colleagues (2005), I extend the work of Kozlowski and colleagues (Bell & Kozlowski, 2008; Kozlowski, Gully, Brown, Salas, Smith & Nason, 2001) to empirically examine the self-regulatory mechanisms that occur after training. However, I go beyond Chen et al. (2005) in that the self-regulatory mechanisms will be investigated not only after training, but after an adaptive event is initiated. I also extend the work of the researchers investigating performance change after an adaptive event (e.g., Lang & Bliese, 2009; LePine, 2003, 2005), as I will be examining the changes of the adaptive process mechanisms over time as well. Finally, I will be extending the process approach to the study of adaptation (which has focused on theoretical frameworks at the team level) in two ways: through presenting a theory of individual level adaptation and by examining the process empirically over time. Therefore, as my primary focus is on the longitudinal and dynamic process of adaptation, I use the research efforts of the performance change approach to extend our understanding of the adaptation as I attempt to fill several large gaps in the performance adaptation literature (see Baard et al., 2014).

The Process of Adaptation

Adaptation is defined in this research as the set of "cognitive, affective, motivational, and behavioral modifications made in response to the demands of a new or changing environment, or situational demands" (Baard et al., 2014; p. 46). This definition identifies two essential elements of adaptation: 1) it is a dynamic process of responding to changes in the environment, and 2) there are several components, or sub-cycles (i.e., cognitions, motivations and behaviors), that require modifications when such changes are introduced. In order to address these two elements of the adaptation process, I will first describe the demands of the different environments in which individuals work as well as present the relevance of other dynamic theories (i.e., learning and self-regulation) in the conceptualization of the process individuals engage in while performing tasks in these environments. Then I will address the second element of the definition above by using research from the adaptation, learning, and self-regulation literatures in discussing the unique but interrelated components of the adaptation process.

Part 1: The Dynamic Nature of the Process

The Changing Task Environments. Processes are dynamic in nature and performance adaptation is no exception, as it is described as the dynamic process of responding to environmental demands. Individuals typically perform tasks in routine performance environments where there is a clear understanding of the impact of certain actions on outcomes of interest. However, when a change occurs, there is a shift in environments – now an adaptive environment is present with a new set of demands. Individuals must now engage in the adaptation process in order to adjust their cognitions and behaviors, given the new requirements of the environment. Once these modifications have been made, individuals re-enter a performance environment where there is again a clear understanding of the relationship between behaviors and outcomes (although these relationships might be different than they were in the performance environment prior to the change). Changes activate the adaptation process as individuals must detect that a change occurred, diagnose the source, determine what an appropriate response is, act based on that strategic understanding, and regulate motivations to devote effort to address the change (Burke et al., 2006; Jundt, 2009; Kozlowski, et al., 1999; Rosen et al., 2011). Although this may seem to be a sequential set of actions, these cognitive and motivational behaviors inform each other, forming a cycle where the testing of one's strategies will inform where effort is placed and the outcomes of behavior inform the extent of the need for more strategic actions.

The speed with which individuals shift from an adaptive environment to a routinized environment will likely depend on the type of change they encounter. Wood (1986) suggests that there are three types of complexity: component, coordinative and dynamic. Component complexity is a change in the number of distinct actions that must be executed or the number of distinct pieces of information that must be processed. This is the simplest form of complexity change and typically requires individuals to increase their effort as they perform more acts within a similar period of time (e.g., taking on your colleague's job if he/she suddenly becomes incapacitated). Coordinative complexity is a change in the relationship between an input and an outcome through a shift in the strength, structure, or sequence of information, actions or outcomes. This is a more challenging form of complexity change and is typically evident in a change in the timing of the task, the frequency of information or communication that is required, or the way in which the task is conducted through underlying rule changes (e.g., adjusting to the priorities of a new boss). The third and most complex type of change is called dynamic, where the change is non-stationary over time. Wood (1986) describes that this type can occur from a sudden intense change in component or coordinative complexity that has implications for some time (e.g., an organizational merger is a one-time change that has implications over the course of several months or years), or as a continuous shift (e.g., having an information technology job that requires a consistent monitoring and learning of new products on the market), which can be controllable or non-controllable.

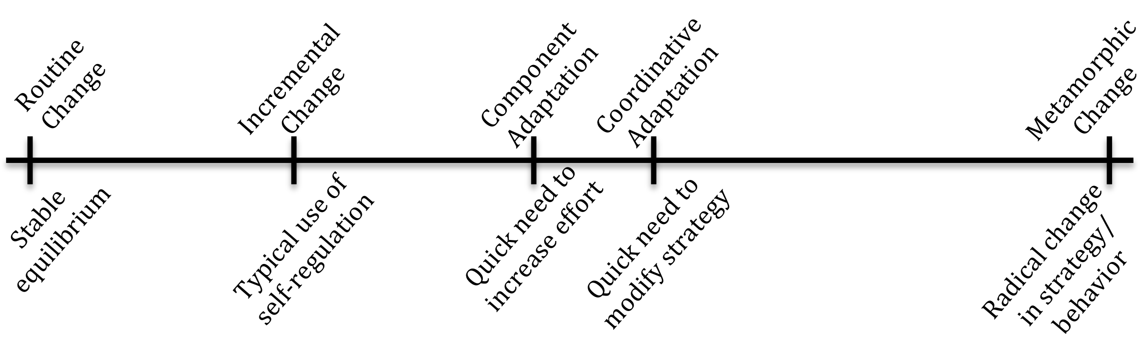
Mapping Complexity Change Onto the Larger Literature on Change. As discussed earlier, there are many types of change. Most popularly discussed is the dichotomy between incremental and metamorphic change (Tushman & Romanelli, 1985). However, these two ends of the spectrum do not seem to capture the kind of complexity change to which Wood (1986) refers. Incremental change appears too basic, since it is described as a way of engaging with the environment to make minor changes that result in the maintenance of a particular trajectory. As an aside, there is a distinction between a routine performance environment and incremental change. The former is a situation where individuals have a stable equilibrium that they are maintaining, with no desire to increase performance or goals; whereas, incremental change is where individuals are more likely to be pursuing a higher goal, but this goal pursuit does not require any change in strategy but rather the continuation of engagement in self-regulatory practices.

The typical incremental and metamorphic change types do not appear to be appropriate categories for the current perspective of adaptation. Adaptive change differs from incremental change in that the latter does not require urgency of action, and it is not necessarily based on external pressure, although it could be (e.g., an organization increases performance goals for next year which requires more effort, but is not strategy altering). However, adaptive changes are usually triggered by an external event that forces individuals to alter their strategy and do so immediately. Individuals do not typically know what specifically changed or how, or whether, they will be able to re-calibrate their knowledge, skills, and abilities to effectively deal with the change. On the other hand, the idea of metamorphic change appears to be too extreme, in that this type of change is described as a shift in values or beliefs, but it is highly unlikely that an individual would be required to do such a thing in a typical work situation.

Therefore, it is anticipated that the types of change that are associated with this investigation of the adaptation process fall in the middle of a continuum between incremental and metamorphic change types. Figure 1 below presents a general framework for the distinction between the two types of adaptive changes that will be examined, as well as presenting a small definition of what these changes incorporate. Given that Wood (1986) specified that component complexity change is a less extreme form of change, this type of adaptive change is located closer to incremental change than coordinative complexity. However, there is a large gap between the two adaptation change types and metamorphic change to represent the difference in the definitions, specifically with metamorphic change being consistently described as a value- or belief-altering change, which is not the focus of this research effort.

Figure 1

Heuristic of a Continuum of Change Types



Adaptation, Learning, and Self-Regulation as Dynamic Processes. The concept of the adaptation process as being a series of re-occurring phases or cycles has roots in some of the early conceptualizations of team adaptation. Kozlowski and colleagues (1996) proposed that teams go through several phases as they mature, developing adaptive capabilities, which then result in the team's ability to self-regulate in response to incremental and novel changes. Burke and associates (2006) also use a phase framework to describe team adaptation with the first phase being situation assessment when a change is recognized through the constant monitoring of the environment. The second phase involves setting a strategy (i.e., creating goals, assigning roles) to adapt to the change, while the third phase comprises of executing that plan and monitoring the performance outcomes based on those initial goals. Finally, the last phase is the reflection on the adaptive response made in order to understand why the change occurred and to determine the effectiveness of the team's response.

These theoretical frameworks of the team adaptation process and the empirical works of investigating adaptive performance change indicate that the conceptual roots of the adaptation process are evident in the learning and self-regulation literatures. Theoretical and empirical evidence from these fields have specified that the cognitive, motivational, affective and behavioral process mechanisms impact how individuals set goals, monitor their progress toward them, and adjust their behaviors in light of any discrepancies (Bandura, 1986, 1991; Blau, 1993; Flavell, 1979; Klein, 1989; Latham & Locke, 1991). Bell and Kozlowski (2008) provided a link between self-regulation, adaptation and learning through their use of a self-regulatory perspective when they describe the learning process that occurred prior to adaptation.

Learning and self-regulation processes are, in and of themselves, dynamic phenomena. Zimmerman (1989) presented a triadic model of self-regulation where self-efficacy, goals and cognitions drove the changes in individuals' internal motivation and external behaviors as they pursued various outcomes of interest. Zimmerman suggests that the person, behavior, and environment are dynamically and reciprocally related to each other. The regulatory actions are dependent on the internal state of the individuals, which impact their behaviors and influence how they operate in the environment, and the environment subsequently impacts those internal processes and external behaviors. The

Adaptive Character of Thought (ACT-R) is a theory of learning that suggests there is a dynamic process that occurs between developing declarative and procedural knowledge (Anderson, 1983). Anderson states that this transition process is knowledge creation. This creation of new procedural knowledge structures may be critical when individuals are faced with learning or adaptive situations. In this framework, the novel (or unique) components of the environment are driving the need to develop new or modified knowledge structures, but procedural knowledge will eventually become automated behaviors as the knowledge is utilized over and over. This theory provides conceptual evidence that there is a dynamic change in the formation and utilization of knowledge structures.

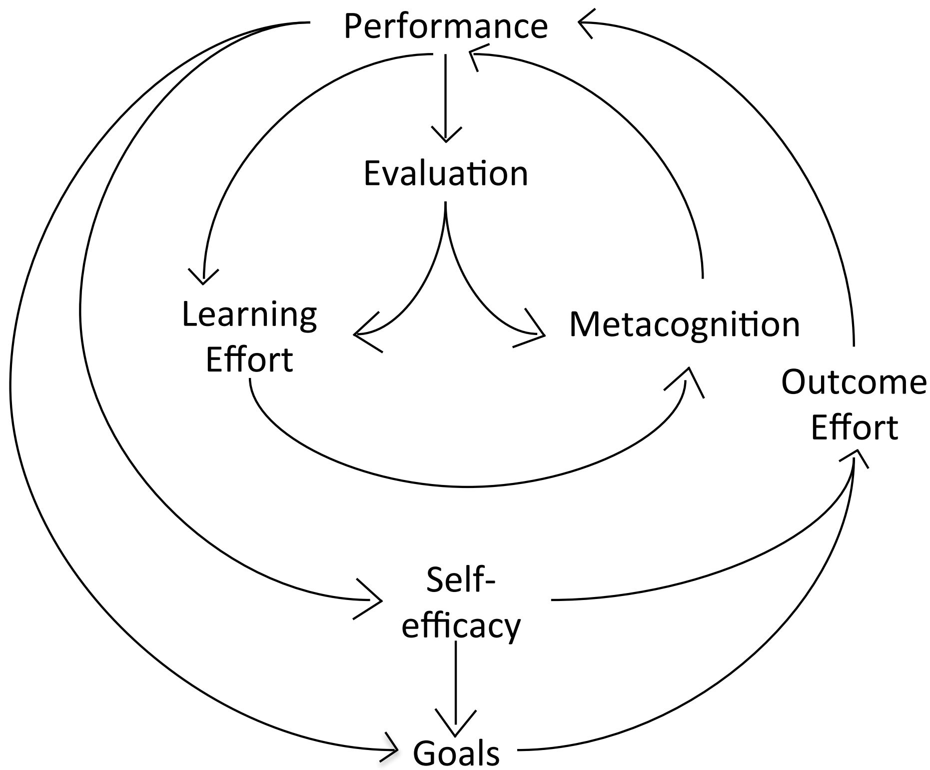
Some have suggested that learning and adaptation are the same phenomenon (e.g., Edmondson, 1999; Staddon, 1975), and I agree that there are similarities between learning and adaptation (e.g., their use of self-regulatory strategies in modifying behaviors in light of a need to learn new information). However, the main distinction I see between learning and adaptation is in the need to revise current knowledge structures to meet the demands of the environment, when engaging in adaptation, versus having to create new structures, as in Anderson's explication of learning. As Burke and colleagues aptly stated, "Learning is an essential but insufficient condition for team adaptation" (Burke et al., 2006, p. 1190).

Anderson (1983) discusses learning (i.e., knowledge creation) as the precursor to routinized behavior. Therefore, I consider learning as a state that occurs before performance is stabilized. In this learning environment, individuals are obtaining an understanding about the relationships that exist between their behaviors and outcomes. Once these links are created, a routine performance environment is established. This typical environment serves a critical role for individuals. It allows them to identify a pattern of behavior that is effective and a reference point for future performance. Without this calibration, individuals will be unable to comprehend whether the lack of performance stability is due to a lack of understanding of the task or a novel change that requires adaptation. However, after learning occurs and routinization is evident, when a change occurs individuals can adjust their behaviors to revise or relearn how their actions are influencing the outcomes.

Self-regulation theory provides a link between all the environments in which individuals engage. Whether it is learning, routine performance, adaptation, or re-stabilizing performance, self-regulation appears to be key. Regardless of what environment individuals are in, regulating cognitions, motivations, and behaviors is essential in understanding new information, revising current knowledge structures, or simply performing a task that is currently understood. Therefore, I consider adaptation as embedded in an ongoing self-regulation process and suggest that self-regulation is the theoretical driver of the adaptation process, similar to previous work in the adaptation literature (e.g., Kozlowski et al., 2009; Tsui & Ashford, 1994).

As suggested by this discussion, the dynamics of the adaptation process are a critical component of this theory. Adaptation is not a static phenomenon. It does not occur at one singular moment, but is a regulatory process individuals engage in when they are exposed to a change. Figure 2 presents a graphical representation of this heuristic, which I will explain in more depth presently. Although the theory is represented in a static model for the purpose of clarity, the theory suggests that individuals move through this process many times as they engage in work environments.

Figure 2
Heuristic Representation of the Adaptation Process



Part 2: The Sub-Cycles

The second critical element of the definition of adaptation adopted in this research is the existence of multiple components. Specifically, I suggest that the behaviors of individuals are modified through engaging in two interwoven cycles: cognitive (the understanding of the environment and the impact of the adaptive change on behaviors and outcomes) and motivational (the pursuit of regaining pre-change performance level). The concept of a two-fold subsystem underlying a single process is not a new innovation (see Karoly, 1993; Klein, 1989; Pintrich, 2000; Zimmerman, 1989 for examples). The adaptation literature has been using the cognitive, motivational, and, at times, affective cycles described in the self-regulation theory to describe a pre-adaptation learning process for many years (e.g., Bell, 2002; Bell & Kozlowski, 2008; Kozlowski et al., 1999). However, as the affective cycle has not received support in empirical investigations (e.g., Bell & Kozlowski, 2008), this pathway will not be discussed in more detail in this study. Bell and Kozlowski (2008) specify that the cognitive cycle (or pathway, as the authors describe it) includes the self-regulatory mechanisms of metacognition, evaluation, and knowledge, while the motivation element involves goal orientation, self-efficacy and intrinsic motivation. This multiple pathway framework is also supported by some of the early theoretical conceptualizations of the self-regulation process. In his description of the triadic model of self-regulation, Zimmerman (1989) discussed the role of cognitions and motivations in the context of how individuals modify their behaviors in task environments. He states that cognitive components are critical in the evaluation of strategies and motivational elements are essential in the drive to perform behaviors. Other researchers also suggest that there are cognitive and motivational components in the self-regulatory process involved in controlling behavior such that individuals must cognitively develop goals and compare the current state to the desired state as well as be motivated to resolve any discrepancies found in the comparison (Carver & Scheier, 1982; Klein, 1989).

Therefore, I describe the cognitive cycle of the adaptation process as those elements that assist individuals in understanding the impact changes (or environmental elements) have on current or previous behaviors. Cognitive mechanisms include strategy development, metacognitive behaviors, and feedback evaluation behaviors (Bell & Kozlowski, 2008). Thus, after a change is introduced, individuals must examine performance feedback, diagnose feedback, devote effort toward learning new information to resolve any issues identified in the feedback, create new strategies, and analyze the effectiveness of strategies employed (engaging in the cognitive cycle of the adaptation process). These elements are most critical when an adaptive change is introduced, as the reason for the change in outcomes must be identified and resolved. In a routine performance environment there is less of a need for evaluating performance and strategizing behaviors since the relationship between behaviors and outcomes is clear and understood. However, when a novel situation arises, there is a need to re-evaluate the effectiveness of the strategies and possibly learn new information to develop better methods to adapt to the change. Therefore, the cognitive cycle of the adaptation process is critical in novel environments.

The motivational cycle of the adaptation process, on the other hand, incorporates elements that capture overall desire to continue in or change behaviors to address the cognitive strategy one is pursuing. In other words, it is insufficient to simply have a plan for action; individuals must also be motivated to devote time and energy to achieve the desired outcome. For this reason, goals, self-efficacy, and effort are key for this aspect of self-regulation (Bell & Kozlowski, 2008). Therefore, after a change, individuals must set goals to drive behavior, have a certain level of confidence associated with that goal, and devote behavioral effort toward achieving that goal (engaging in the motivational cycle of the adaptation process). Motivational mechanisms are also critical in the adaptation process as it is necessary for individuals to be motivated to devote effort toward changing cognitions and behaviors in order to adapt effectively. The motivational cycle is even more important in performance environments where a change is not present but there is a need to continue to maintain performance despite the possible monotony a routine environment may bring. In the following sections I describe, in more depth, the specific dynamics of these cycles.

The Cognitive Cycle. The cognitive component of adaptation process suggests that individuals must learn the impact of a change and how to cope with it. In the adaptation literature, researchers have consistently described learning and adaptation as self-regulation processes containing cognitive elements such as on task cognition (Bell & Kozlowski, 2002b), cognitive flexibility (Griffin & Hesketh, 2003; Mumford, Baughman, Threlfall, Uhlman & Costanza, 1993), information sharing (Johnson, Hollenbeck, Humphrey, Ilgen, Jundt & Meyer, 2006), job experience and knowledge breadth (Niessen, Swarowsky & Leiz, 2010; Spiro & Weitz, 1990), resource allocation (Porter, Webb & Gogus, 2010), openness to change (Pulakos, Schmitt, Dorsey, Arad, Borman & Hadge, 2002), mental model similarity and accuracy (Randall, Resick, & DeChurch, 2011), error use (Woltz, Gardner & Gyll, 2000), and metacognition (e.g., Bell & Kozlowski, 2008; Ivancic & Hesketh, 2000). Clearly, cognitive mechanisms are critical for the self-regulation of behavior and, although there have been a variety of constructs investigated, it is evident that strategy-focused mechanisms are particularly important for studies considering the regulation process prior to and during adaptation. Specifically, I assert that there are three key mechanisms involved in the cognitive cycle of the adaptation process: metacognition, feedback evaluation, and learning-oriented effort. The inner cycle of Figure 2 shows a graphical representation of the interdependence of these mechanisms.

Although metacognition has been defined and investigated many ways, Flavell, one of the leading thinkers on the topic of metacognition, proposed that this phenomenon has several elements: knowledge, experiences, goals/tasks, and actions/strategies (Flavell, 1979). In this definition, metacognition could entail all of a cognitive self-regulatory process, but in this study, this overall metacognitive process is being separated into the components in order to more specifically investigate the impact of cognitive variables (i.e., evaluation, learning effort, and strategy development) on performance behavior. Many researchers describe metacognition as monitoring one's cognitions and behaviors associated with those ideas, and re-evaluating whether these behaviors are in line with one's strategy (Bell & Kozlowski, 2008; Cannon-Bowers, Rhodenizer, Salas & Bowers, 1998; Flavell, 1979). Researchers have suggested that metacognition allows for a more rapid assessment of the environment, understanding of the core elements and better success in learning (Ford, Smith, Weissbein, Gully & Salas, 1998; Ivancic & Hesketh, 1999). Therefore, in this paper, metacognition refers to the actions individuals take to understand the effectiveness and impact of their strategies on the pursuit of their goals.

Evaluation behaviors are actions devoted to analyzing performance feedback. They can be as simple as viewing a general performance score from a task simulation or as complex as seeking 360-degree evaluations within an organization. There are several ways in which evaluation behaviors are operationalized in the adaptation literature. Some researchers label it behavioral adaptation, referring to monitoring behaviors that are conducted as individuals perform (or after a performance period) and these behaviors are directed toward understanding the impact of a change on performance outcomes (e.g., LePine, 2003, 2005). Other researchers in the adaptation literature operationalize evaluation activity as time spent viewing performance feedback. Still others consider evaluation to be a behavioral manifestation of metacognition in that the focus of the performance evaluation behaviors (i.e., which parts of the performance information are being analyzed) presents insight into which strategies are being scrutinized (e.g., Bell & Kozlowski, 2008; Ford et al., 1998). However, in all of them, the focus is on the cognitive understanding of the impact of behaviors on performance outcomes.

Finally, learning-oriented effort is a component of effort that is devoted toward understanding the environment by testing strategies and attaining additional information. Adaptation researchers state that "effort alone is often not enough to perform well on difficult and complex tasks. Individuals must also focus their effort on relevant aspects of the task" (Bell & Kozlowski, 2002a; p. 278). Fisher and Ford (1998) also proposed that effort can be operationalized as the number of behaviors devoted to a task, but can *also* be thought of as the complexity of the cognitive involvement of the individuals (i.e., the amount of cognitive effort is dependent on the type of process chosen: encoding, organization, or retrieval). Together, these researchers suggest that effort is more than the sum of behavioral output; effort also has a cognitive component. Some label this form of effort in adaptive contexts as strategic effort as they differentiated the behaviors in the task in order to capture effort devoted to aspects of the task that changed (i.e., strategic effort) versus aspects that did not (i.e., basic effort; see Bell & Kozlowski, 2008; Kozlowski et al., 2001). However, there is one challenge in approaching the cognitively focused effort in such a manner: "strategic" behaviors conducted in an adaptive environment (where this is an unknown change) can become "basic" behaviors in a performance environment (where individuals understand the change and are optimizing a strategy). Therefore, I specifically label cognitively focused and strategizing behaviors as "learning-oriented effort" as both entail obtaining additional understanding and information from the environment. Given this conceptualization, neither the definition nor the operationalization of this type of effort will depend on the kind of environment in which individuals are engaged.

The Motivational Cycle. It is conceptually insufficient to only theorize about the cognitive elements involved in self-regulation, regardless of whether the discussion is on the process occurring before or after a change. Simply investigating the cognitive components of adaptation without giving pause to consider the impact of motivation on seeking out information for strategy development or behaviors directed at enhancing performance would be to only examine one side of a coin and would present an incomplete picture of the phenomenon. In essence, this follows from the logic that an unmotivated individual, although perhaps having a brilliant strategy of how to excel in an adaptive environment, stills need to be motivated and devote effort toward the strategy. Without such motivated and directed effort, individuals will not effectively adapt to the change. It is not suggested here that motivational mechanisms serve as moderators of the cognitive mechanisms, but rather that each must be considered as distinct but integrated parts of the self-regulatory process.

Several motivational and behavioral mechanisms have been identified and studied in the adaptation literature, including effort (DeRue, Hollenbeck, Johnson, Ilgen & Jundt, 2008), emotional stability or reactions (Driskell, Goodwin, Salas & O'Shea, 2006; Kozlowski, et al., 2001; Rosen et al., 2011; Keith & Frese, 2005), intrinsic motivation (e.g., Bell & Kozlowski, 2008, 2010), interpersonal processes (LePine, 2005), willingness to adapt (Bröder & Schiffer, 2006), internal locus of control (Mumford et al., 1993; Spiro & Weitz, 1990), self-efficacy (e.g., Griffin & Hesketh, 2003, 2004, 2005; Bell & Kozlowski, 2002a, 2002b, 2008, 2010), and goals (e.g., Burke et al., 2006; Chen et al., 2005). As self-efficacy, goals, and effort have been consistently identified as essential mechanisms in the self-regulation process, I expect that these three mechanisms are the key motivational mechanisms involved in the adaptation process. See the outer cycle of Figure 2 for a representation of the interrelationships between these mechanisms.

Goals are critical for regulatory behavior as they set the standard for subsequent comparisons (Bandura, 1991; Karoly, 1993). They provide a reference point from which discrepancies can be detected, evaluated, and corrected. 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).

Self-efficacy is the well-studied self-regulatory mechanism, which is defined as a belief in one's ability to control goals, effort, and performance (Bandura, 1991). It has been found to impact the difficulty of the goal level set, the commitment and effort devoted to that goal, the performance of individuals during learning and the performance of individuals after an adaptive event (Bandura, 1991; Bell & Kozlowski, 2008; Kozlowski, Gully, et al., 2001; Latham & Locke, 1991) and can therefore be considered a vital component of a motivational self-regulatory cycle.

Effort is broadly defined as behaviors directed at completing a task (Blau, 1993). Effort has been operationalized through the amount of time spent on task (e.g., Fisher & Ford, 1998), objective assessments of behavioral effort (e.g., Bell & Kozlowski, 2008), and self-reports of effort (e.g., "How hard were you trying just before the screen froze?" p. 263; Yeo & Neal, 2004). However, effort has several components as discussed above. One component of effort focuses on *how well* or *how smart* an individual is working (i.e., learning-oriented effort), whereas the other component is on *how hard* an individual is working (i.e., what I label "outcome-oriented effort"). Outcome-oriented effort is therefore a description of the effort individuals specifically devote to achieving a desired performance level. Cognitive, learning-oriented effort may impact the specific behaviors of the outcome-oriented effort. For instance, certain effort behaviors may be more strategic in nature in an adaptation environment when strategies are being tested (i.e., labeled "strategic effort" in previous adaptation research; Bell & Kozlowski, 2008), but if these behaviors are determined to be effective, they will continue to be executed in performance environments even though they are no longer strategic in nature. In order to maintain consistency in the meaning of effort across environments, I label the effort devoted to performance outcomes, whether strategic or not, "outcome-oriented" effort. Although this distinction may seem nuanced, since I theorize that the adaptation process is cyclic and dynamic over time, it is necessary that the definitions of the mechanisms involved are not dependent on the type of environment.

Behavioral Mechanisms. As is evident in the discussions above, behaviors play a unique role in self-regulation as they provide external observational insights into the internal regulatory process of individuals (e.g., changes in cognition or motivation that would otherwise remain hidden phenomena). Thus, behavioral mechanisms are inherently tied to the cognitive and motivational cycles of adaptation. Specifically, with regard to cognition, the emphasis is: *how well* did the individuals perform? The behavioral manifestation of this is in feedback evaluation and effort devoted to understanding the effectiveness of strategies used. This emphasis contrasts with the foci of the motivational pathways behaviors, which is: *how much* did individuals do? One way of distinguishing these paths is by differentiating the meaning of effort within both of these paths. Overall, whereas the motivational path is concerned with working harder, the cognitive path is focused on working smarter.

Two Orders of Change

The following sections of this paper will specify the dynamics of the adaptation process. Both Powers (1973) and Carver and Scheier (1982) suggest that dynamics can be investigated through examining change in two ways. They state that first order changes are evident in the changing trajectories of each variable. Trajectories allow for insight into how the levels of the variables are impacted by the environment and by time. Therefore, the discussion of the dynamics of the adaptation process will begin at this level. Powers (1973) and Carver and Scheier (1982) also state that second order changes are observed through changes in the bivariate relationships of the variables. Thus, once first order change trajectories are discussed, the second order relationship changes will be explicated, specifically describing the direction and strength of the relationships of the adaptation process mechanisms as seen in Figure 2.

FIRST ORDER CHANGES: TRAJECTORIES

Since level, or trajectory, changes in variables are considered first order changes (Powers, 1973), I will begin my explication of the adaptation processes with a description of the expected level and slopes of the variables in these processes as determined by the environment in which they are engaged. Examining the trajectories allows for developing an understanding of how the variables change. From this knowledge, one can then ask why the variables change in the manner they do and what determines the trajectory changes. The 'why' is the second order change; I will come back to this thought in the following section.

Prior to specifying the trajectory changes of each mechanism within the two cycles of the adaptation process, it is first necessary to investigate the demands of the environments that the process must adjust to. As referred to earlier, I suggest that individuals face two types of environments: adaptive (i.e., novel) and performance (i.e., typical or routine) environments. For example, an individual working on his job is typically performing his tasks with high levels of routine and performance is very stable – this is the first situation where a performance environment is evident. Then, for instance, this individual is given the work of a coworker who went on vacation and so his workload has doubled. This change has presented the employee with an adaptive environment where performance is, at least temporarily, very unstable as the ramifications of such an increase in workload may require him to re-prioritize and re-strategize his other projects. Finally, once he obtains an understanding of how he should adapt to this change and performance begins to increase, the individual will re-enter a performance environment where performance levels begin to stabilize again. To summarize, individuals begin in a stable performance environment, shift to an unstable adaptive environment when a change occurs, and then transition into a second performance environment where performance is re-stabilizing. Since the dynamics of the first performance environment are not expected to be as interesting as those in the second performance environment (given the lack of variability likely to exist in the first stable situation) I will devote my attention to the re-stabilizing performance environment that occurs after adaptation.

The Trajectory of Performance

Based on the above description, performance change is a key indicator of a shift in to and out of an adaptive environment. The adaptation literature has oftentimes defined adaptation as the change in performance from a routine to a changed setting (e.g., Kozlowski et al., 1999; LePine, 2003). Adaptive individuals are those who did not have as large of a decrease in performance when faced with a change. Researchers in the adaptation literature assert that individuals likely engage in a process of regulating behavior in order to effectively adapt, but they have not examined that process after a change is introduced. However, simply because the empirical research has not yet advanced to that point, it does not mean that currently existing theories are not capable of informing the situation.

Control theory suggests that changes are detected through the recognition of a large gap between desired performance level and actual performance level. Carver and Scheier (1982) link control theory to self-regulatory theory in their extension of Wiener's (1948) cybernetic framework. The key principle of control theory is the influence of negative feedback loops in controlling behaviors. Carver and Scheier (1982) suggest that when individuals are faced with a large goal-feedback gap, they engage in cognitively focused behaviors that are devoted to "discrepancy reduction". In this cognitive cycle, as in my model (see Figure 2), individuals are focused on examining feedback in order to evaluate the source of the change, to obtain more information about the environment, and finally to develop and test new strategies to cope with the change. Carver and Scheier (1982) also propose that there is a motivational component involved in that individuals must determine the "expectancy-assessment" of behaviors, which is the extent to which individuals expect their behaviors to be able to correct the discrepancy in performance. Therefore, a motivational process is also activated by a performance change, similar to the theorized model of this research endeavor (see Figure 2).

In addition to defining effective adaptation as higher performance at one time point after a change, researchers have also investigated the longitudinal effects of change through examining performance trajectories before and after a change. Through this line of research, they have established that performance not only significantly decreases with a change, but more adaptive individuals will increase their performance more rapidly in an adaptive environment (e.g., Lang & Bliese, 2009; LePine, 2003, 2005). Therefore, it is expected that after a change is introduced, individuals will initially have very low performance, but this will rapidly increase as they engage in the adaptation process (which I will describe in more detail below). Figure 3 presents a graphical representation of the expected trajectories of performance and all process mechanisms in both the adaptation and performance environments.

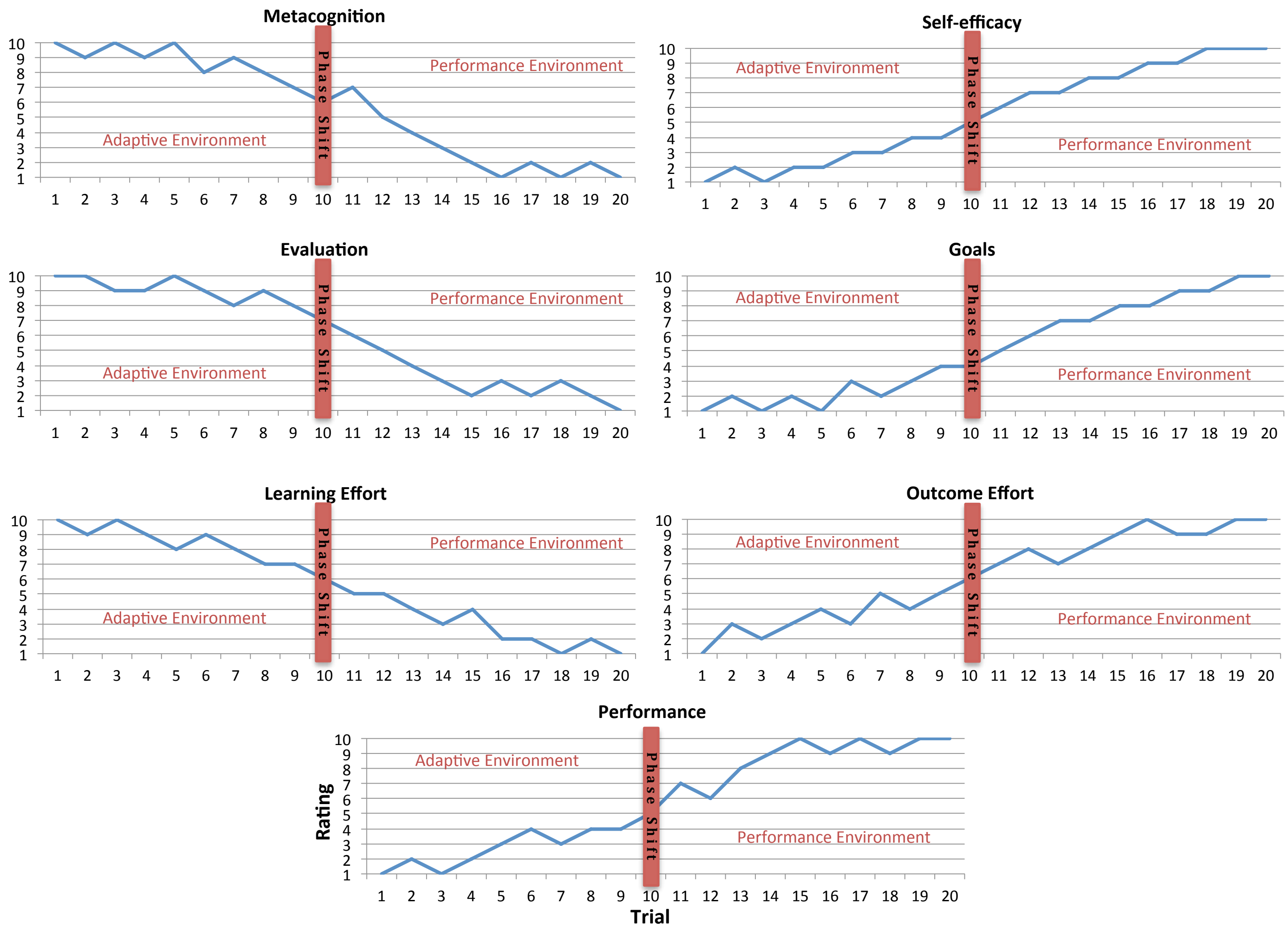
> **Hypothesis 1a:** In the adaptation environment, performance will have a low intercept and a strong positive slope.

Performance environments, on the other hand, are characterized by efficiency, productivity and, eventually, automaticity (Anderson, 1983; March, 1991). Individuals transition into this type of environment when they begin to see improvements in performance, and their behaviors begin to stabilize. Unlike in adaptive environments, individuals will not be as confused about what behaviors lead to what outcomes. Extending control theory to describe the rationale of why this is the case, some original work by Carver and Scheier (1982) would suggest that once the reason behind a discrepancy between a goal and performance feedback is understood, the focus shifts to performing the behaviors that will correct this change. This point is determined by either the dissipation of the gap or when the rate at which it is decreasing is at an acceptable pace so that the individual is confident that further adaptation is no longer required. For this reason, it is expected that when individuals shift to a performance environment, performance will be at a moderately high level and will increase as more focus is devoted to executing the new strategy rather than continuing to strategize and determine how to adapt. This increase is based on self-regulation and learning theories, which suggest that individuals increase in performance as they practice (Bröder & Shiffer, 2006; Kozlowski, et al., 2001). However, given that it is unreasonable for individuals to consistently increase in performance levels indefinitely, the rate of growth will slow, until they reach a plateau, or a point where performance will remain relatively stable as they engage in the performance environment.

Hypothesis 1b: In the performance environment, performance will have a high intercept and a weak positive slope.

Figure 3

Example Trajectories of Key Mechanisms Across the Adaptation and Performance Environment



The Driver of Performance Trajectory Changes

As mentioned earlier, control theory suggests that understanding the source and impact of a change is vital to adaptation. Theorists suggest that adaptation is needed where there is a large discrepancy between the original goals made and the performance feedback received. When such a situation arises, a discrepancy-reduction process is initiated (here, it is called an adaptation process) where individuals engage in evaluation, re-strategizing, and testing strategies in order to determine an effective solution. A failure to engage in an adaptation process would likely result in optimizing an ineffective strategy, resulting in decreased performance. This is consistent with claims made by March (1991) when he discussed the need for organizations to engage in learning and strategy behaviors when faced with a change rather than immediately choosing a solution and exploiting it. However, in both theories it is clear that once individuals choose a strategy and begin to exploit it, they transition from an adaptation-focused environment to a performance-execution environment.

> **Hypothesis 2:** Individuals shift from an adaptive to a performance environment when a strategy is chosen.

The speed at which individuals are able to identify the source of the change, develop a strategy to deal with it, and execute that strategy will be different based on the type of complexity introduced, given the differences Wood (1986) describes in his theory. This will impact the rate that individuals switch from an adaptive environment to a performance environment. Since dynamic complexity change is a complex combination and extension of component and coordinative change, this type will not be a focus of this research endeavor.

As component complexity is the simplest type of change Wood discusses, it is expected that individuals will more rapidly identify the source of the change and a plausible solution for it (Wood, 1986). This would result in a faster shift from an adaptive environment, where individuals are searching to understand the impact of their behaviors in the new situation, to a performance environment, where individuals are executing behaviors based on the strategy they chose to deal with the change. Coordinative complexity change, on the other hand, is not only more difficult to detect, but it is also more challenging to understand what an effective new strategy would be, given the more nuanced nature of this type of change (Wood, 1986). This would result in a slower shift from an adaptive environment to a performance environment.

> **Hypothesis 3:** Individuals exposed to a component complexity change will shift from an adaptive environment to a performance environment faster than individuals exposed to a coordinative complexity change.

The Trajectories of the Process Mechanisms

Given that individuals engage in self-regulatory behaviors in both adaptation and performance environments, the sections below will specify the expected trajectories of the cognitive and motivational mechanisms in both settings. As discussed earlier, the mechanisms involved in the cognitive cycle of the adaptation process (metacognition, feedback evaluation, and learning-oriented effort) are primarily concerned with understanding the reason for the change and devoting effort toward the best solution. Therefore, these mechanisms are the primary ones activated in an adaptation environment. However, once individuals transition to a performance environment, where a strategy has been chosen to handle the change, the motivational cycle (self-efficacy, goals, and outcome-oriented effort) will be the source of most influential process mechanisms. Both cycles are critical in both environments, but the trajectories they follow will differ based on the environment in which the individuals are engaged. The following sections will specify how.

Longitudinal research on self-regulatory mechanisms has both historically and recently adopted one of the following two characteristics (see DeShon, 2012 for a recent discussion of dynamic research in organizational science). Researchers tend to use three to five measurement time points to capture the phenomenon of interest, and/or they will separate the measurement of processes and outcomes between the time points in order to present a case for mediation (e.g., Converse, Piccone, Lockamy, Miloslavic, Mysiak, & Pathak, 2014; Cron, Slocum, VandeWalle & Fu, 2005; Thomas & Mathieu, 1994). Thus, there are few instances of the process variables being repeatedly measured (see Vancouver, Thompson, Tischner & Putka, 2002 for an example of an exception). The lack of empirical investigations of the changes in self-regulatory variables makes it difficult to ascertain the specifics of the trajectories of the mechanisms of the adaptation process over time. However, there is considerable work devoted to the theoretical understanding of the impact of cognitions and motivations in both the adaptation and self-regulation literatures. The following discussion of the trajectory changes of the adaptation process will therefore be based on the empirical evidence available as well as extrapolations of the dynamics inherent in some of the theoretical works.

The Cognitive Cycle

Adaptive Environment. The cognitive aspects of the adaptation process are all focused on evaluating the change that occurred, determining the source of it, examining the result of current behaviors, and analyzing what strategy would result in the best adaptive performance. McGrath (2001) also states, “in highly novel settings, groups should follow the variety-generating approach. This is because, absent a base of cause-and-effect understanding, experimentation generates information that cannot be obtained any other way” (p.118). Research in that adaptation literature suggests that employing a learning focus prior to a novel change results in increased performance in such an environment as a deeper understanding of the task is developed (Bell & Kozlowski, 2008). Through this deeper understanding, individuals can more quickly identify the source of the change and adjust subsequent behaviors accordingly. Given that they are all very interrelated in achieving these objectives, it is expected that they would all follow similar trajectories in an adaptive environment. Specifically, the initial levels of these variables will be high, as it is necessary to engage in these behaviors in order to effectively adapt. As individuals continue to perform in an adaptation environment, the behaviors will decrease slightly as the objectives are slowly met. Another way of thinking of the reason for the decrease in levels is based on the fact that individuals have limited resources that they can devote toward a task. Initially, individuals need to allocate more resources toward cognitively understanding the environment, but this resource allocation must eventually shift to motivational behaviors as a strategy is chosen and tested (and as they transition to a performance environment). See Figure 3 for a representation of these trajectories.

Research in the adaptation literature has not yet advanced to empirically examining how process mechanisms change over time. However, several studies have suggested that metacognition is related to increased adaptive performance immediately after a change (Bell & Kozlowski, 2008; Ivancic & Hesketh, 2000; Keith & Frese, 2005). This supports the statement that metacognitive behaviors will be initially elevated when a change occurs. Authors have also intimated that metacognitive behaviors will decrease over time. Some researchers describe metacognition as a central component to self-regulating cognition during a task through monitoring the environment and revising strategies so that changes are more quickly recognized, understood and addressed (Bell & Kozlowski, 2008; Ivancic & Hesketh, 2000; Keith & Frese, 2005). Therefore, it is expected that as individuals engage in high levels of metacognition, the change will be understood more rapidly, reducing the need to continue performing these behaviors, resulting in their decrease over time in an adaptation environment.

Feedback evaluation behaviors have a purpose similar to metacognition. Performance outcomes are able to serve as a comparator between the initial goal and the result of actions (e.g., effort) directed toward that goal. Evaluation is the behavioral manifestation of that comparison, which informs future goal formation and strategizing (i.e., metacognition; Bell & Kozlowski, 2008; Ford et al., 1998). Those new goals and strategies then form a new comparator against which future performance outcomes will be evaluated. Thus, evaluation behaviors are essential for effectively engaging in the cognitive cycle of adaptation (i.e., goals leading to behavior, resulting in performance and evaluation, leading to revised goals and behaviors). Using a problem-solving framework as a means of understanding the adaptation process, Zaccaro, Banks, Kiechel-Koles, Kemp and Bader (2009) described performance evaluation as "affirming the realignment between the unit (organization or team) and its environment" (p. 7). This suggests that high levels of evaluation activity allow the team to identify whether a strategy is effective in light of an adaptive change, which then leads to more effective performance behaviors. In addition to the positive impact of evaluation behaviors on performance outcomes, researchers have also suggested that higher levels of evaluation behaviors have resulted in a deeper understanding of the task (Bell & Kozlowski, 2008; Ford et al., 1998; Kozlowski & Bell, 2006). As individuals develop an understanding of how behaviors impact performance outcomes, fewer evaluation behaviors are needed over time. Therefore, it is expected the evaluation will decrease as individuals continue to engage in adaptation environments.

The third mechanism involved in the cognitive cycle of adaptation is learning-oriented effort. Similar to the others, this form of effort is focused on gathering information about the environment, the change, and an appropriate response to it. Research in the adaptation literature typically does not investigate cognitive effort itself, but rather the impact of different goals or strategies on effort behaviors. However, few have provided insight on how these effort behaviors may change over time. Yeo and Neal (2004) examined the relationship between effort and practice and found that it is increased during the early stages of a novel task. This provides initial evidence that cognitive effort will likely be high as individuals are exposed to a change that is not understood. Research has also suggested that the relationship between effort and performance weakens with practice (Kanfer & Ackerman, 1989). Yeo and Neal (2004) also propose that the relationship between effort and performance is established early in the task such that if individuals do not devote effort immediately after a change, an appropriate strategy will not be established and thus increasing effort will not show increased performance. These findings support the assertions made by Bell and Kozlowski (2002a, 2008) that effort not only has a motivational component but also a cognitive one – individuals must recognize that a new strategy is required in addition to maintaining or increasing motivation in order to deal with the change. Therefore, it is expected that although learning-oriented effort will be high initially after the change, these behaviors will slowly decrease as individuals engage in the adaptation environment.

> **Hypothesis 4a:** In the adaptation environment, metacognition will have a high intercept and a weak negative slope.
>
> **Hypothesis 4b:** In the adaptation environment, evaluation will have a high intercept and a weak negative slope.
>
> **Hypothesis 4c:** In the adaptation environment, learning-oriented effort will have a high intercept and a weak negative slope.

Performance Environment. As individuals move out of an adaptation-focused environment and transition to a performance environment, where the focus is on executing a strategy, the impact of cognitive mechanisms changes. Since the cognitive mechanisms are primarily centered on understanding the environment, once individuals enter a performance environment, continuing to engage in such behaviors is less necessary and could possibly be harmful to performance, as the goal is now to execute behaviors rather than continuing to reflect on strategies (Kluger & DeNisi, 1996). Considering that research has not yet examined the trajectories of the process mechanisms during adaptation, it is not surprising that research has not yet moved toward understanding the re-stabilization of these regulatory variables after a change is addressed. However, through extending adaptation and self-regulation research, it is expected that these cognitive mechanisms will decrease in importance in a performance environment. Therefore, it is expected that these cognitive mechanisms will initially be at a moderate level, but will decrease rapidly as individuals continue to recognize that the strategies chosen is a viable solution to deal with the change in the environment.

Metacognition is discussed as regulation of strategy effectiveness (Bell & Kozlowski, 2008). Individuals engage in this activity when developing an understanding of the environment or the impact of their behaviors. Initially upon transitioning to a performance environment, it is possible that metacognition would remain slightly elevated as individuals continue to test whether the strategy is effective. However, when the environment is understood, it is logical to hypothesize that metacognitive activity would decrease significantly as it would no longer be necessary to re-strategize in order to maintain effective performance. In fact, some suggest that a failure to reduce metacognitive activity would result in a lack of available resources that could be devoted to executing the task since cognitive and motivational resources can be in competition (e.g., March, 1991).

Feedback evaluation is a critical element in adjusting behaviors when a goal is not met according to control theory (Carver & Scheier, 1982). However, when the goal-performance gap is acceptable, it is no longer necessary to engage in as many feedback evaluation behaviors in order to be effective in that environment. In other words, once individuals transition to a performance environment, evaluation behaviors may be initially elevated as the strategy being used is still being checked for accuracy, but feedback seeking will quickly diminish as performance continues to increase as expected.

Learning-oriented effort will also be less critical in performance environments. This form of effort is dedicated to understanding the environment. However, when individuals transition to a performance environment, they have chosen a strategy to deal with the change and, therefore, are no longer in need of additional information to inform that decision. Given this, it is expected that learning-oriented effort, similar to metacognition and evaluation behaviors, will initially be slightly elevated but will rapidly increase as individuals engage in the performance environment.

Hypothesis 5a: In the performance environment, metacognition will have a mid-level intercept and a strong negative slope.

Hypothesis 5b: In the performance environment, evaluation will have a mid-level intercept and a strong negative slope.

Hypothesis 5c: In the performance environment, learning-oriented effort will have a mid-level intercept and a strong negative slope.

The Motivational Cycle

Adaptive Environment. Having a cognitive understanding of an environment is essential but insufficient for effective performance. Individuals must also be motivated to change their behaviors in the face of a change, as well as to maintain or increase effort levels, when transitioning to a more typical performance environment. Each of the three mechanisms involved in the motivational cycle of the adaptation process (goals, self-efficacy, outcome-oriented effort) are expected to follow a similar trajectory as they are all focused on achieving a common outcome: the calibration of effort to achieve effective performance. In a novel environment, the likelihood of previous goals and behaviors being an effective performance strategy is extremely low. This will impact not only initial goal levels, but also efficacy and effort allocation behaviors. Specifically, it is expected that individuals will initially have low levels of these mechanisms as they determine how their behaviors are calibrated to the outcomes. However, as individuals continue to engage in the adaptation environment, it is expected that the trajectories of these motivational mechanisms will be weakly positive as individuals gain more confidence, set higher goals, and put more effort toward the task. See Figure 3 for a representation of these trajectories.

Similar to the research on the cognitive cycle, the adaptation literature has not yet advanced to empirically investigating the trajectories of these mechanisms. However, researchers have taken steps to examine how goals are part of the learning process and have theoretically applied the results to the adaptation process after a change is initiated as well. In a multilevel study, Chen and colleagues (2005) found that both individual and team regulatory goal processes fully-mediated the relationship between self-efficacy (and collective efficacy) and individual (and team) adaptive performance (respectively). At the individual level, goal choice (defined as the selection of a goal) positively and significantly predicted goal striving (defined as the effort devoted toward achieving that goal), which in turn predicted adaptive performance after the change. This research suggests that goals are a critical part of a regulation process that influences adaptive performance. However, what is unclear is the relative level of the goals made *after* a change, as compared to goals made before a change. In other words, Chen et al. (2005) show that goals created before a change are related to performance after a change, but they did not provide insight on whether the goals vary based on whether they are made before or after a change is introduced. I extend their research by suggesting that although goals will increase with performance levels over time as individuals engage in the adaptive environment, goals (like performance) will be initially low. Ilies (2003) supports this claim through examining the impact of performance on goal levels over multiple trials in a task. He found that when individuals experienced negative feedback, goals were decreased, as would be expected initially after a change is introduced; however, goals were increased following positive feedback, which would be likely once individuals start to increase their performance in the adaptation environment.

Researchers have consistently described the utility of self-efficacy in self-regulation (e.g., Bandura, 1991; Bell & Kozlowski, 2008; Zimmerman, 1989). Although the specific variables involved in the self-regulatory process described by these researchers changes slightly between studies, self-efficacy is consistently conceptualized as a motivational mechanism (along with intrinsic motivation and goal orientation) that works in concert with cognitive (e.g., knowledge acquisition, metacognitive activity) and behavioral elements (e.g., effort, self-evaluation activity; Bell & Kozlowski, 2008, 2010). Research has shown that self-efficacy has a unique, positive, and significant impact on adaptive performance (e.g., Kozlowski, Gully et al., 2001; Bell & Kozlowski, 2002a, 2002b, 2008). Using a cyclical and longitudinal framework, this would suggest that changes in self-efficacy result in changes in performance, and vice versa. Therefore, when a change is introduced, it is expected that both performance and self-efficacy will be low. Other studies also provide initial evidence that practicing a different version of a task during training results in increased self-efficacy in an adaptive situation (Holladay & Quiñones, 2003). Extending this finding to variations being presented in the adaptive environment itself, it may be that efficacy will increase as individuals are continually exposed to such changes.

The third motivational mechanism, outcome-oriented effort, is the key driver of performance behavior. The self-regulation literature suggests that individuals who are committed to their goals are more likely to regulate their behaviors to achieve those goals. They do this by comparing their current performance state to the previous one and determining if there is a discrepancy between the effort they are devoting to the task and the outcomes of those behaviors (Bandura, 1993). In the words of Bandura, "[individuals] seek self-satisfaction from fulfilling valued goals and are prompted to intensify their efforts by discontent with substandard performances" (p. 130). When performance is drastically increased (i.e., when a change that requires adaptation is introduced), although individuals may be motivated to increase performance, a lack of understanding about the reason for the performance discrepancy may result in low outcome-oriented effort behaviors initially. For this reason, I delineate two elements of effort: a learning-oriented component (which will be increased in the face of a change) and an outcome-oriented component (which will be low initially, as there is limited understanding of the impact of effort behaviors). Support for this concept can be found in some initial research in the adaptation literature. Ford et al. (1998) determined that influencing the type of goals set by individuals led to different levels of effort devoted to the learning process. Those with mastery goals were more motivated during learning and therefore devoted more effort to the task at hand. This suggests that more effective individuals are those who devote more learning-oriented effort as opposed to outcome-oriented effort when exposed to an adaptive change. However, in other research, behavioral effort (as described by the amount of behavior devoted to the task, i.e., outcome-oriented effort) was related to enhanced performance in an adaptive scenario (e.g., Bell & Kozlowski, 2008; Kozlowski, et al., 1999). Therefore, it is likely that as individuals continue to engage in an adaptive environment, both effort and performance will increase.

> **Hypothesis 6a:** In the adaptation environment, goals will have a low intercept and a weak positive slope.

Hypothesis 6b: In the adaptation environment, self-efficacy will have a low intercept and a weak positive slope.

Hypothesis 6c: In the adaptation environment, outcome-oriented effort will have a low intercept and a weak positive slope.

Performance Environment. As was true with the cognitive cycle, the trajectories of the mechanisms involved in the motivational cycle change once individuals shift from an adaptive to a performance environment and resources must be re-allocated. Unlike the cognitive elements, which become less critical, the motivational mechanisms take on a new level of importance. In a performance environment, a cognitively driven strategy is chosen that has shown initial evidence of increasing performance. However, an effective strategy is only as effective as the behaviors devoted toward the strategy. Therefore, the mechanisms of the motivational cycle, as seen in setting goals, feeling efficacious and behaviorally devoting effort toward performance outcomes, will start relatively low, but rapidly increase as the need for maintaining motivation in performance becomes all the more critical for effectiveness.

Research in the goal setting literature has long suggested that goals are critical for maintaining and increasing performance (e.g., Brown, 2005; Latham & Locke, 1991). In a performance environment where change is no longer the driving force behind behaviors, it is critical to set difficult and specific goals in order for performance to continue to increase and not remain the same or decrease due to fatigue. As goals will only just be starting to be calibrated initially upon transitioning to a performance environment, it is expected that they will be at only a moderate level. However, as performance continues to increase and goals are met, these goals are expected to increase.

Similarly, self-regulation literature suggests that as individuals practice a task more, they develop more expertise, which results in higher levels of self-efficacy (e.g., Holladay & Quiñones, 2003). As discussed earlier, when a novel change is introduced, efficacy will be negatively impacted. However, as individuals transition to a performance environment, confidence in their ability to continue performing the task will likely be re-established and increasing. Therefore, it is expected that the trajectory of this mechanism will also be positive throughout the performance environment as individuals gain more expertise in the task and have opportunity to show their capabilities in it.

Finally, outcome-oriented effort, or effort directed at completing a task (Blau, 1993), is essential in a performance environment. While cognitive behaviors are the critical components in adaptive environments, when the situation has stabilized and the change is understood, individuals need to re-allocate resources to devote behavioral effort toward achieving the highest level of performance as possible. Yeo and Neal (2008) examined the intra-individual dynamics of the relationship between effort and performance and 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. In the second study they manipulated the difficulty of the task at the midway point. They found that the relationship between effort and performance did not replicate in the more difficult scenario perhaps due to the situation being too difficult to handle simply by increasing effort. Taken together, I suggest that the initial level of effort may only be at a moderate level as individuals are only beginning to transition to a more stable performance environment; however, it is expected that outcome-oriented effort will increase as individuals engage in a performance environment and continue to optimize on the strategy they have chosen to adapt to the change previously introduced into their task.

Hypothesis 7a: In the performance environment, goals will have a mid-level intercept and a strong positive slope.

Hypothesis 7b: In the performance environment, self-efficacy will have a mid-level intercept and a strong positive slope.

Hypothesis 7c: In the performance environment, outcome-oriented effort will have a mid-level intercept and a strong positive slope.

SECOND ORDER CHANGES: RELATIONSHIPS

Considering that the mechanisms of the adaptation process (i.e., goals, metacognition, self-efficacy, effort, and evaluation) will clearly change over time, it is now necessary to discuss the causes of the trajectories. A process perspective implies dynamic and cyclical changes. However, the current longitudinal analyses employed in the adaptation and self-regulation literature typically investigate solely the level changes in the variables involved in the process (e.g., latent growth curves), or SEM frameworks are employed when investigating the process at one or two points in time. Level, or trajectory, changes in the process of adaptation only tell part of the story of this dynamic phenomenon. The first order changes provide insight into *how* variables change, but not into *why* they change. The reason *why* certain trajectories are seen is based on the *relationships* a variable has with previous levels of itself (an autoregressive component) and with previous levels of other related variables (a cross-variable lagged component). Therefore, detailed theoretical descriptions of these relationships, as well as analyses (e.g., vector autoregression, longitudinal cross-lag panel regression), that can capture cyclical relationships are needed.

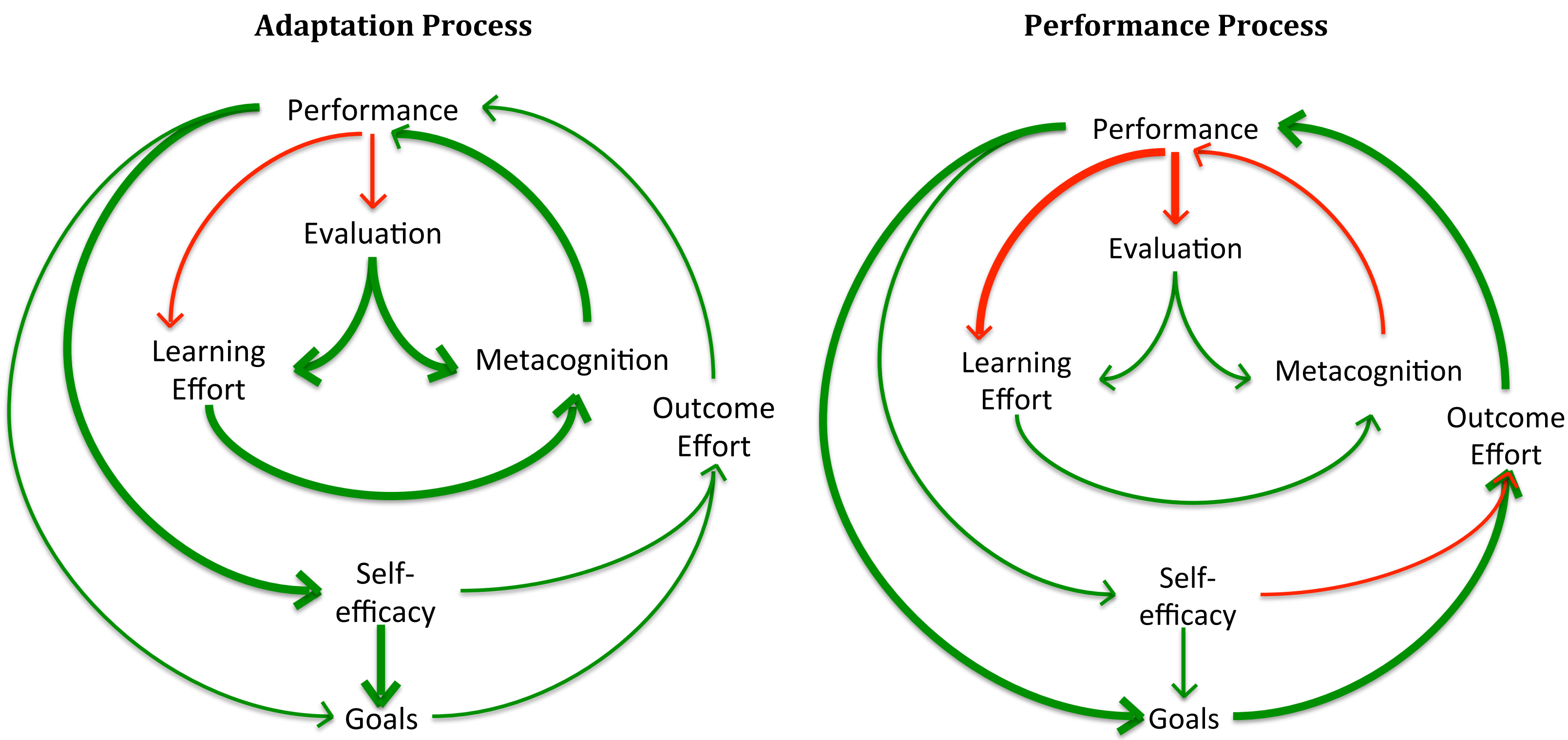
Processes are sometimes referred to as a “black box” as they are not only difficult to theorize but very difficult to test. I argue that both the trajectories and relationships of the variables involved in a process need to be investigated longitudinally in order to understand the phenomenon. Therefore, I turn my attention to the relationships involved within each process, describing the overall relationships of the mechanisms involved in the cognitive and motivational cycles, as well as specifying the changes in the bivariate relationship embedded in the cycle, in order to define the expected dynamics of the process. I will begin my discussion with the dynamics of the mechanisms in the cognitive cycle (containing evaluation, learning-oriented effort, and metacognition) both in the adaptation and performance processes, as seen in the inner circle of Figures 3 and 4, respectively. Then I will move to present the dynamics of the motivational cycle (containing goals, self-efficacy, and outcome-oriented effort) in these processes, as depicted in the outer circles of Figure 4.

The Cognitive Cycle

As described earlier, the cognitive cycle has three key mechanisms: evaluation, metacognition, and learning-oriented effort behaviors. Evaluation is primarily described as seeking feedback information about performance in order to determine the source and impact of the change based on performance change. Metacognition is an examination of the effectiveness of a strategy used in a performance situation. Learning-oriented effort is the component of effort that is not directly relevant to performance that is devoted to understanding the source and impact of the change. These mechanisms dynamically interact with each other, where performance impacts learning-oriented effort, which then impacts metacognitive behaviors, finally impacting subsequent performance. In a new environment, individuals are faced with a decrease in performance. This large goal-performance discrepancy results in the need for effort to be devoted to understanding the "why" behind the change. Based on control theory, this suggests that individuals are required to increase in their reflection on the strategies employed in order to correct performance decreases in order to re-attain the desired goal level. Evaluation behaviors are also a critical component of the cognitive cycle in its impact on both learning-oriented

Figure 4

Heuristic Representations of the Relationships in the Adaptation and Performance Processes



effort and metacognitive behaviors as it is necessary to reflect on performance levels in order to determine that there is a need for learning and strategy revision. The following sections specify the bivariate relationships involved in the dynamic cognitive process occurring in both adaptation and routine performance processes (see Figure 4), based on the trajectory changes previously discussed (see Figure 3). Bivariate relationships (as opposed to multivariate) are described in order to present the theoretical workings of the dynamic adaptation process as clearly as possible. First, I will describe the cycle where performance impacts learning-oriented effort, which then influences metacognition, which cycles back to effect performance. Then, I will present how evaluation behaviors are intertwined in this cycle (in that performance influences evaluation), which then impacts effort and metacognitive behaviors.

Performance and Learning-Oriented Effort

One challenge associated with dynamic theory is the inherent lagged relationship between variables. In this case, the first link in the cognitive cycle is that performance will influence subsequent effort behaviors, but static research typically only investigates the opposite direction of this relationship. Yeo and Neal (2008) found that the amount of cognitive effort individuals devoted to a task fluctuated with respect to performance, expertise, difficulty, and practice. Less cognitive effort was associated with more practice and more expertise, but more cognitive effort was associated with more difficult environments. The results of their study suggest that cognitive effort and performance had a strong positive correlation between people but only a weak positive one within the person. Given that the situation will become more complex after the adaptive change, it is expected that, initially, individuals will need high levels of cognitive effort (supported by Yeo & Neal, 2008), as performance will be negatively impacted. Therefore, it is expected that there will be a weak negative relationship between performance and cognitive effort such that as performance begins to increase, less cognitive effort (which can be considered learning-oriented effort) will be needed.

> **Hypothesis 8a:** In the adaptation process, performance will have a weak and negative impact on subsequent learning-oriented effort behaviors.

However, as individuals understand the source of the change and choose a new strategy, individuals will transition to a performance process where effort and performance will be more strongly related. In this environment, higher performance will lead to less effort devoted toward learning since additional strategizing and information gathering will not be as necessary. This is supported by Yeo and Neal (2008) in their finding that more practice and decreased difficulty resulted in less cognitive effort devoted to the task. This is likely due to the individual understanding the source of the change, recognizing the strategy that needed to be employed, and realizing that any additional resources devoted to re-strategizing would be wasted effort that should instead be devoted to executing the task (March, 1991).

> **Hypothesis 8b:** In the performance process, performance will have a strong and negative impact on subsequent learning-oriented effort behaviors.

Learning-Oriented Effort and Metacognition

Continuing in the cognitive cycle, when individuals are faced with a change, not only does performance changes cue the need for additional information and understanding, but individuals who devote more effort to these behaviors will also likely engage in more effective strategizing. This suggests that learning-oriented effort and metacognitive activity will both be devoted toward obtaining more information about what strategy would be most effective. If effort is not devoted to learning, it is likely that the individual is not analyzing the strategy, resulting in less metacognitive activity. Zimmerman (1989) indirectly discussed this relationship in the triadic model of self-regulation where cognitive behaviors are thought to provide the strategic links among the internal regulatory process (of goal formation and motivation), the external behaviors employed, and feedback that is required to test the strategy. Empirically, Clause, Delbridge, Schmitt, Chan, and Jennings (2001) investigated the relationship between motivational factors, metacognition, effort and performance in police officer candidates applying for a position. Results from this study suggest that the more metacognitive activity the applicant engaged in, the more effort they devoted to engaging in the task and the higher the performance they achieved. These studies support the relationship seen in Figure 4, where the relationship between effort devoted to learning and metacognitive behaviors is expected to be positive given that as individuals engage in strategic thinking about the task, they are likely to devote effort to determine the effectiveness of their strategy through engaging in metacognitive activity.

> **Hypothesis 9a:** In the adaptation process, learning-oriented effort will have a strong and positive impact on subsequent metacognition behaviors.

However, as individuals are exposed to the changed environment for longer periods, performance will increase, resulting in a decreased need for learning-oriented effort and metacognitive activity (see Figure 3 for a reminder of the expected trajectory changes). Given that learning and metacognition are consistently related to each other in the development of knowledge and strategies, and that their relationship spans across domains (Veenman, Van Hout-Wolters & Afflerbach, 2006), it is expected that this relationship would remain positive regardless of whether an individual is initially learning a task, re-strategizing based on a change, or monitoring the effectiveness of established strategies. A recent meta-analysis reported that the relationship between metacognition and learning strategies was one of the strongest effects among self-regulatory variables ($\rho = .83$, $k = 39$, $N = 9{,}529$; Sitzmann & Ely, 2011), suggesting that devoting effort toward learning presents a natural inclination for individuals to test and evaluate that information through metacognitive behavior. Therefore, in the performance environment, it is anticipated that there will be a weaker, though still positive, relationship between effort and metacognition (see Figure 4), since a certain level of learning will remain as individuals must maintain their understanding of the environment and monitor the effectiveness of strategies.

> **Hypothesis 9b:** In the performance process, learning-oriented effort will have a weak and positive impact on subsequent metacognitive behaviors.

Metacognition and Performance

Unlike some of the research on the other relationships in the cognitive cycle described above, work on metacognition typically incorporates some complex situation where individuals or groups need to re-strategize in order to improve their performance. While some of this work is in the education literature, examining the impact of metacognition and intelligence on performance (e.g., Landine & Stewart, 1998; Pintrich &

DeGroot, 1990), some work has also been done in the adaptation literature. In an investigation of the team adaptation process, Zaccaro and colleagues (2009) proposed that effective strategies and performance are involved in a problem solving process where the strategy is assessed as performance occurs, suggesting that this metacognitive activity is critical for effective team adaptive performance. Researchers have also indirectly determined that there is a positive relationship between metacognition and performance in both field and laboratory settings where complexity increased through investigating the impact of metacognition on learning knowledge outcomes, which then were found to be positively associated with adaptive performance (e.g., Bell & Kozlowski, 2008; Keith & Frese, 2005; White, Mueller-Hanson, Dorsey, Pulakos, Wisecarver, Deagle & Medini, 2005). Thus, given the increasing levels of metacognition and performance (see Figure 2), it is hypothesized that metacognition will have a strong and positive impact on performance in adaptive environments (see Figure 4).

> **Hypothesis 10a:** In the adaptation process, metacognition will have a strong and positive impact on subsequent performance.

However, once a strategy is chosen and individuals shift to a performance process, metacognitive activity will no longer be needed in order to continue to improve performance. In organizational theory, March (1991) and McGrath (2001) both suggested that extensive and unneeded exploration (or learning-oriented) behaviors result in wasted time and resources when those cognitive and motivational efforts could be devoted to exploiting the strategy that is being effective. Therefore, it is expected that increases in metacognitive activity would lead to decreases in performance as resources that should be devoted to performance execution is instead being devoted to unneeded strategy contemplation. This will result in a weakly negative relationship between metacognition and performance in the performance process (see Figure 4).

> **Hypothesis 10b:** In the performance process, metacognition will have a weak and negative impact on subsequent performance.

Performance and Evaluation

Transitioning to focusing on the role of evaluation behaviors in the cognitive cycle, research in the feedback seeking literature suggests that the more feedback that is evaluated, the better performance will be in the future (Kluger & DeNisi, 1996). Similar to the issue described with the relationship between effort and performance, the direction of the relationship posed in the larger literature is typically the inverse of what is expected in the present theory. Investigating the impact of performance on evaluation behaviors requires a cyclical and longitudinal approach, which is largely not the focus of investigations. Unlike some of the relationships involved in the adaptation process, research in the extent literature has empirically investigated the relationship between evaluation and performance. In a series of articles by Kozlowski and colleagues, evaluative activity (measured as time spent on investigating performance feedback) has been positively related to increased knowledge and performance after an adaptive event is introduced. They attributed this to a desire to develop a deeper understanding of the task that one attains from evaluating feedback (Bell & Kozlowski, 2008; Ford et al., 1998; Kozlowski & Bell, 2006). These findings suggest that evaluative activity is useful to the extent that it impacts metacognitive activity and strategy development, but it also suggests that there is a relationship between evaluation activity and performance level. Evaluation activities are needed to determine why performance decreased and how to respond.

Given that these studies did not look at multiple iterations of performance in the adaptive environment, it is unknown what the cyclical relationship between evaluation and performance would be. However, given their findings, it is expected that when individuals are faced with an unacceptable goal-performance gap (i.e., when a novel change occurs and adaptation is required), they will seek feedback in order to diagnose the change and the new strategy that should be employed. As individuals continue to perform and develop an understanding of the environment, less evaluation activity will be needed, resulting in a negative relationship between evaluation and performance in adaptive environments. This is based on the general principle of a negative feedback loop as discussed in control theory (Klein, 1989).

> **Hypothesis 11a:** In the adaptation process, performance will have a weak and negative impact on subsequent evaluation behaviors.

The negative feedback loop, as described by control theory, will continue to result in a negative relationship between performance and evaluation behaviors in a performance process because individuals will continue to reduce their feedback seeking behaviors once their performance begins to stabilize. Researchers have suggested that feedback seeking behavior is only useful when there is a need or an uncertainty to which the individual is responding (Ashford & Cummings, 1983). Therefore, in non-adaptive environments, increases in performance will trigger decreases in evaluation behaviors, as the level of performance will inform individuals on the effectiveness of their behaviors. Therefore, they will not need to continue searching for the underlying meaning of performance changes through evaluating feedback. If this evaluation behavior continues, then it is likely that this is due to continuing low performance.

> **Hypothesis 11b:** In the performance process, performance will have a strong and negative impact on subsequent evaluation behaviors.

Evaluation and Learning-Oriented Effort

Evaluation is the examining of feedback, and this investigation of performance is expected to impact strategizing in two ways. The first way evaluation impacts the cognitive cycle is by influencing the cognitive effort devoted to filling in any gaps in knowledge. Both evaluation and effort are behavioral mechanisms that have been discussed as critical components in understanding performance (Jundt, 2009). Evaluating feedback without devoting effort based on that information is a waste of cognitive resources, which, in adaptive environments, is just as critical as the behavioral resources used to adapt to a change. In self-regulatory research, the feedback and strategic goals were experimentally shown to be associated with the effort devoted by individuals. Both goals and evaluation were needed in order for performance to increase due to effort (Bandura & Cervone, 1983). Therefore, these researchers not only show the critical link of the relationship between evaluation and strategic effort behaviors, but it also supports the importance of the dynamics of the cognitive cycle of which this relationship is a part. Therefore, it is expected that, in an adaptive environment, increases in evaluation behaviors (see Figure 2) will be strongly and positively associated with effort devoted to understanding the reason behind the performance feedback (see Figure 4).

Hypothesis 12a: In the adaptation process, evaluation behaviors will have a strong and positive impact on subsequent learning-oriented effort behaviors.

However, over time, as individuals are exposed to the environment, develop a strategy, and experience performance increases, evaluation and effort behaviors would both decrease as cognitive resources are not as central a need in the performance environment. Hattie and Timperly (2007) describe the importance of evaluation behaviors in determining the extent to which further understanding and learning are needed. Ashford and Cummings (1983) also state that one of the most critical reasons why feedback is sought is to reduce uncertainty about goal-performance discrepancies. In addition to learning from performance feedback, individuals must also learn by obtaining more information from the environment. Therefore, to the extent that evaluation behaviors are engaged in (see Figure 2), learning-oriented effort will follow; however, given that fewer of these behaviors will be performed, there would be a weaker, but still positive, relationship between these mechanisms (see Figure 4).

Hypothesis 12b: In the performance process, evaluation behaviors will have a weak and positive impact on subsequent learning-oriented effort behaviors.

Evaluation and Metacognition

The second way evaluation impacts the cognitive cycle is by impacting the development and testing of strategies through enhancing metacognition. Both feedback evaluation and metacognitive behaviors are concerned with understanding the underlying strategy of the task, although one is a direct investigation of performance feedback while the other is an analysis of the strategy used to attain that performance. Therefore, it is logical that they would be positively associated with each other. This is supported by early self-regulatory research, where the relationship between evaluation behaviors and metacognition were indirectly discussed in the triadic model of self-regulation (Zimmerman, 1989). Strategy development and testing (i.e., metacognition) provided an important link between the internal process Zimmerman described (containing goal formation and motivation) and the external process (of behaviors and feedback). This was supported by Ertmer and Newby (1996) in their inclusion of evaluation activities within an overall discussion of metacognitive behaviors. The authors suggest that without having re-evaluated the strategy employed, when evaluating feedback information, the feedback is less useful. More specifically associated with adaptation, Ford, Bell, Kozlowski and colleagues conducted a series of studies where evaluation behaviors were related to increased strategic knowledge and adaptive performance. They further claimed that this strategic knowledge and adaptive performance was reflective of a deeper processing of the task (Bell & Kozlowski, 2008; Ford et al., 1998; Kozlowski & Bell, 2006). The positive relationship between evaluation and metacognition also appears in team-level theories of the adaptation process where strategies currently being employed are analyzed through performance information, which then informs subsequent strategy development (Rosen et al., 2011; Zaccaro et al., 2009). Therefore, individuals who engage in evaluation behaviors will engage in more strategic thinking (i.e., metacognitive activity) about the change that occurred, resulting in a strong positive relationship. Similarly, individuals who choose not to evaluate their performance would likely not think about their strategy as they likely did not recognize any discrepancies in the feedback.

> **Hypothesis 13a:** In the adaptation process, evaluation behaviors will have a strong and positive impact on subsequent metacognition behaviors.

Even once a strategy is chosen and individuals shift to a performance process, the extent to which individuals devote energy and effort to evaluating performance feedback will be reflected in the extent to which they engage in metacognitive activity. Hattie and Timperly (2007) discuss the positive impact of evaluation behaviors in the engagement in metacognitive activity. They describe one of the key benefits of evaluating performance feedback as being able to detect errors, which provides the opportunity for individuals to seek out better strategies and problem solve more effectively. Given that both evaluation and metacognitive activity should not be as required in a performance process, there will be a lack of variance in both of these variables, resulting in a weaker, though still positive, relationship.

> **Hypothesis 13b:** In the performance process, evaluation behaviors will have a weak and positive impact on subsequent metacognition behaviors.

The Motivational Cycle

The motivational cycle has three key mechanisms, as discussed earlier: goals, self-efficacy, and outcome-oriented effort behaviors. Goals are used to calibrate motivation through setting a particular outcome to achieve. Self-efficacy is the confidence an individual has in achieving a goal. Outcome-oriented effort is another component of effort that is directly relevant to performance by focusing on executing behaviors to complete the task.

These mechanisms dynamically interact with each other where performance influences the subsequent goal that is set, which drives behaviors directed toward achieving that goal, resulting in performance based on those behaviors. Self-efficacy is also a critical component of this process as the level of confidence associated with performance impacts both the level of the goal and the behavior that is devoted to achieving it. In a new environment, goals may not initially be set at a high level considering the unknown nature of the environment; however, as confidence increases, the amount of effort devoted to achieving the outcome will be enhanced. Similar to the discussion of the cognitive cycle, the following sections specify the bivariate relationships involved in the dynamic motivational process occurring in both adaptation and routine performance processes (Figure 4). The bivariate relationships are based on the logic discussed earlier in the overall description of the process as well as the expected trajectories of the mechanisms involved (see Figure 3). First I begin my discussion of the motivational cycle with the description of how performance impacts goals, which then influences the outcome-oriented effort devoted to the task, which finally cycles back to effect performance. Then, I will explicate how self-efficacy is intertwined in this motivational cycle through describing how performance impacts individuals' confidence in their abilities, which then influences subsequent goal levels and effort behaviors.

Performance and Goals

Beginning with the well-examined relationship between performance and goals, researchers have, for many decades, supported the positive impact of goals on performance. Work in the goal-setting literature, in particular, suggests that individuals calibrate their performance to their goals (Bandura, 1991; Latham & Locke, 1991). However, it is also possible that performance impacts goals as well. Carver and Scheier (1998) suggest that goals may initially fluctuate in response to an increase in complexity as individuals attempt to identify how to respond. Evaluating performance changes is critical in order to understand how to create effective and reasonable goals. Therefore, it is likely that in novel environments, there would initially be a weak relationship between performance and goals. Research in the adaptation literature also shows that goals are positively related to adaptive performance measured in a variety of settings incorporating changes in component, coordinative and dynamic complexity (Bell & Kozlowski, 2008; Drach-Zahavy & Somech, 1999; Washburn, Smith & Taglialatela, 2005). At the team level, LePine (2005) found that goals, by themselves, did not effectively predict initial levels of team performance adaptation. However, LePine did find that when difficult goals were set, only teams of individuals low in performance orientation were able to adapt effectively, and easy goals were equally ineffective for both goal orientation types. This was also true in his examination of the moderation of goal orientation with respect to transition and action processes. Although research typically focuses on the impact of goals on performance, there is initial evidence that performance will also impact subsequent goals, with this relationship being weak when an individual is initially faced with the adaptive change (see Figure 4). This weak relationship is due to individuals having insufficient information about the source of, or the appropriate strategy to deal with, the adaptive change, resulting in goals that may not be feasible.

> **Hypothesis 14a:** In the adaptation process, performance will have a weak and positive impact on subsequent goals.

However, as individuals shift to a performance process where performance is more stable and a strategy is chosen, the relationship between performance and goals will become stronger. In this environment, individuals can gain more confidence in their performance, resulting in higher goals. Although some researchers suggest that there is a negative relationship between goals and performance (e.g., Vancouver, Thompson, & Williams, 2001), others suggest that this is not the case in highly complex environments where feedback is provided (Schmidt & DeShon, 2010; Sitzmann & Yeo, 2013). Furthermore, given that the direction of the relationship is from performance onto goals, it is expected that even in a performance environment, the relationship will remain positive and strong (see Figure 4).

> **Hypothesis 14b:** In the performance process, performance will have a strong and positive impact on subsequent goals.

Goals and Outcome-Oriented Effort

Not only does the literature support the impact of performance on goals, but goals also impact the effort individuals devote to a task. Self-regulation theories describe goals as a key motivational mechanism that impacts how much effort individuals allocate in a task (e.g., Latham & Locke, 1991; Yeo & Neal, 2004). Bandura and Cervone (1983) experimentally and behaviorally examined the effort individuals devoted to a task and found that when individuals increased goals, they also increased their effort in the subsequent trial of the task. Converse and colleagues (2014) also examined the relationship over time and found a within-person positive relationship where previous goal level influenced subsequent effort levels. In the adaptation process that occurs right after a novel change is introduced, it is expected that goals and effort will have a weak but positive relationship since the reason for the change will be initially unknown and goals may not be calibrated appropriately.

> **Hypothesis 15a:** In the adaptation process, goals will have a weak and positive impact on subsequent outcome-oriented effort behaviors.

However, as individuals have more exposure to the environment and shift to a performance process where performance is increasing, goals will be more effectively set and will likely be a better estimate of what the individual can realistically accomplish, resulting in a stronger positive relationship with effort devoted to those goals. This is supported by the model discussed by Kluger and DeNisi (1996) that suggests that individuals engage in different behaviors based on their response to the feedback-standard discrepancy. This claim was supported by self-regulation researchers who state that individuals will devote the effort that is needed to goals that they are committed to and pursuing (Bandura & Locke, 2003; Sitzmann & Ely, 2011). DeShon, Kozlowski, Schmidt, Milner & Wiechmann (2004) experimentally investigated the impact of goals on subsequent effort in a computer simulation task over multiple trials and determined that goals were positively related to subsequent self-focused effort (or effort that was related to performing the task). This effort was then related to increases in performance levels. Therefore, it is expected that when there is an increase in performance, there would be a positive relationship between goals and effort such that goals would increase, resulting in more effort devoted to that desired outcome level.

> **Hypothesis 15b:** In the performance process, goals will have a strong and positive impact on subsequent outcome-oriented effort behaviors.

Outcome-Oriented Effort and Performance

The final relationship in the motivational cycle is the impact effort has on performance (see Figures 3 and 4). Self-regulatory research has found strong support for the relationship between effort and performance. Schmidt, Dolis & Tolli (2009) found that individuals were more likely to devote time and energy toward goals that were influenced by an unpredicted event. Yeo and Neal (2004) also found that the relationship between effort and performance increased initially in a novel task. Other researchers suggest the relationship becomes weaker over time (e.g., Kanfer & Ackerman, 1989), but Yeo and Neal suggest that this is due to the lack of effective strategy or the lack of strategic effort, not the raw effort devoted to performing the task. Good and Michel (2013) investigated the impact of outcome-oriented effort among undergraduate students performing a decision-making task in an adaptive environment. They found that the effort had a weak positive relationship with adaptive performance, although their measurement of this type of effort was through an individual difference (i.e., the amount to which individuals are prone to be focused in their attention). These studies suggest that, when individuals are faced with an unexpected change, they will put forth more effort to achieve their previous level of performance (see Figure 2), but this effort may not be well-calibrated, as the reason for performance changes may not be initially clear. Therefore, it is expected that effort and performance will have a weak and positive relationship in adaptive environments.

> **Hypothesis 16a:** In the adaptation process, outcome-oriented effort behaviors will have a weak and positive impact on subsequent performance.

The studies discussed above have shown that effort and performance have an inherently positive relationship, even in the face of a novel change. This is also based on some of Campbell's original work describing performance as being impacted by the motivation of the individual (Campbell, 1990). In this work, he presented a framework where the motivation of the individual was based on the goal choice, the level of effort, and the persistence of effort. These factors then impacted the performance level the individuals were able to achieve. This principle was reiterated in more recent work summarizing the relationship between effort and performance, with Campbell specifically stating that effort is so inherently tied to performance that the two should not be separated (Campbell, 2012). Instead, he proposes that effort, as a distinct entity, should be discussed as persistence or extra effort that is devoted to a task. This strong positive relationship between effort behaviors and performance outcomes is supported by empirical evidence that suggests that increasing effort behaviors will increase performance (Baard, 2013; DeShon et al., 2004). Given the strong relationship between effort and performance in the literature, it is expected that once individuals understand the source of the change and choose a new strategy, they will transition to a performance process where effort and performance will be more strongly related, given that the impact of effort is more clearly understood.

> **Hypothesis 16b:** In the performance process, outcome-oriented effort behaviors will have a strong and positive impact on subsequent performance.

Performance and Self-efficacy

It would be conceptually incomplete to neglect a discussion of the impact self-efficacy has on the motivational cycle. The literature on self-efficacy and performance reflects a very complex relationship. The classic between-person theory suggests that increases in self-efficacy lead to increased performance (Bandura, 1991). However, within-person empirical findings suggests that there is a negative within-person effect (Vancouver et al., 2001; Yeo & Neal, 2008) such that increases in self-efficacy result in lower performance due to individuals having a sense of overconfidence in their ability and devoting less effort toward their goals. More recent within-person research suggests that this effect is true only when the environment is highly ambiguous. However, there is a positive relationship between self-efficacy and performance when feedback information is provided (Schmidt & DeShon, 2010). Other researchers have also suggested that self-efficacy impacts performance through calibrating their goals and that performance serves as a way to calibrate subsequent self-efficacy (Sitzmann & Yeo, 2013; Tolli & Schmidt, 2008). This is also supported by within-individual analyses (e.g., Seo & Ilies, 2009). In the adaptation literature, Chen et al. (2005), using an adaptation performance scenario, found that self-efficacy was related to adaptive performance through impacting goal choice and goal striving activities such that more efficacious individuals set more challenging goals and pursued them with more effort. Several studies have shown that self-efficacy also positively impacts adaptive performance directly (e.g., Bell & Kozlowski, 2008; Kozlowski, Gully, Brown, Salas, Smith & Nason, 2001). Some measure self-efficacy as a confidence in their ability to perform in an adaptive setting and found that it does predict adaptive performance (Pulakos et al., 2002; Griffin & Hesketh, 2005; White et al., 2005). As evidenced in the literature above, it is more typical for self-efficacy to be predictive of performance, rather than performance on self-efficacy. However, it may also be that performance impacts self-efficacy such that as performance increases, it will inform the individuals about their ability levels and therefore their self-efficacy will directly reflect fluctuations in performance. Given that the research by Schmidt and DeShon (2010) suggest that this positive association is possible in highly complex situations, it is expected that this would hold true in adaptive settings.

> **Hypothesis 17a:** In the adaptation process, performance will have a strong and positive impact on subsequent self-efficacy.

It is expected that once individuals start to increase performance and determine an effective strategy for adaptation, they will shift into a performance environment. A recent meta-analysis examining the within-person relationship between self-efficacy and performance shows that although the impact of self-efficacy on subsequent performance is very small, the influence of performance on subsequent self-efficacy remained at a moderate level ($r=.4$; Sitzmann & Yeo, 2013). Furthermore, Vancouver and Kendall (2006) used a cyclical framework to investigate the impact of self-efficacy on performance, and performance on self-efficacy, and determined that although self-efficacy had a negative impact on future performance, performance had a positive impact on subsequent self-efficacy. Therefore, it is expected that the relationship between performance and self-efficacy will remain positive during the performance process.

> **Hypothesis 17b:** In the performance process, performance will have a weak and positive impact on subsequent self-efficacy.

Self-efficacy and Goals

Self-efficacy is the confidence individuals have in their ability to perform a task. This confidence impacts motivation in two important ways; the first is through impacting goals.

The self-regulation literature has revealed a complex relationship between self-efficacy and goals. Bandura (1991) and Zimmerman (1989) suggest that there is a positive association between these variables as they are a part of a cyclical and internal regulatory system. However, Vancouver and colleagues (2001) suggest that there is a negative relationship between these mechanisms over time as individuals become overconfident in their abilities and set less challenging goals. However, Schmidt and DeShon (2010) suggest that there is a positive relationship in complex environments where feedback information is given in a timely manner. Furthermore, in the adaptation literature, Chen et al. (2005) found that the relationship between self-efficacy and performance is mediated by goal choice and goal striving activities both at the individual and team levels. Therefore, it is expected that when individuals are faced with a novel change, self-efficacy and goals will both be negatively impacted (see Figure 2). However, as individuals engage with the task, they will use their reflection on their efficacy to determine what they deem to be appropriate goals. Thus, self-efficacy and goals will be strongly and positively related to each other during adaptation (see Figure 4).

> **Hypothesis 18a:** In the adaptation process, self-efficacy will have a strong and positive impact on subsequent goals.

However, as individuals continue to increase in their performance, both self-efficacy and goals will reach a point where they will not be fluctuating as much due to individuals understanding when they have reached their maximum or optimal performance level. As self-regulation researchers have indicated, achieving the desired performance levels increases self-efficacy, which then results in creating even higher goals to pursue (Bandura

& Cervone, 1983; Bandura & Locke, 2003; Sitzmann & Ely, 2011). Given that the present theory adopts a longitudinal lens where self-efficacy and goals will not be able to increase continually, it is expected that, although self-efficacy and goals will remain positively related, they will be so less strongly because they will both likely plateau (see Figure 4).

> **Hypothesis 18b:** In the performance process, self-efficacy will have a weak and positive impact on subsequent goals.

Self-efficacy and Outcome-Oriented Effort

The second way self-efficacy influences motivation is through impacting the effort individuals devote to a task. The relationship between self-efficacy and effort can be thought of in two ways: a) individuals are motivated to devote effort toward tasks in which they are efficacious, or b) individuals become overconfident in tasks in which they feel confident in their abilities and therefore devote less effort toward them. In early research, Bandura (1993) suggested that perceptions of high self-efficacy are theoretically associated with increased motivation to pursue higher goals and putting forth effort to achieve those goals. This is supported by recent research by Komarraju and Nadler (2013) where undergraduate students were asked to self-report their self-efficacy, effort, and GPA, and a positive relationship between self-efficacy and GPA was found with effort serving as the mediator. Carver & Scheier (1998) also provide some insight into the theoretical dynamics involved in that they describe effort in the form of behaviors that are performed during a task. Those behaviors then inform the internal self-regulatory process of the individual (i.e., the level of motivation and confidence the individual has), which then informs future effort behaviors. These studies support the concept that these self-regulatory variables are positively related to each other. Therefore, it is expected that, in the adaption process, there will be a positive relationship between self-efficacy and effort.

> **Hypothesis 19a:** In the adaptation process, self-efficacy will have a weak and positive impact on subsequent outcome-oriented effort behaviors

The second view of self-efficacy and effort comes into play once individuals have transitioned to a performance environment. Here, it is expected that the relationship between these mechanisms would become negative, as individuals are more stagnant in their efficacy level and possibly overconfident. This is also based on the work of Vancouver et al. (2001) who found that self-efficacy and performance were negatively related at the within-person level. He suggests that this is due to individuals being overconfident in their ability level, resulting in less effort devoted to the goal. Thus, it is expected that higher self-efficacy would lower effort levels, but lower self-efficacy would result in more effort in a performance environment (i.e., when no novel changes are present).

> **Hypothesis 19b:** In the performance process, self-efficacy will have a weak and negative impact on subsequent outcome-oriented effort behaviors

METHOD

Participants

The sample consisted of 605[1] undergraduate students from a large midwestern university. Individuals were recruited from the Psychology Department's subject pool and were compensated with credit in their course and the possibility of a reward based on their performance level. Additional information regarding the reward is provided below. Sixty-three of these individuals did not return for the second part of the experiment, so they were eliminated from the final dataset. Eighteen participants were also removed from the analyses due to their non-compliance. This was seen in either a) the experimenter reported them as being visibly distracted during the second day of the study (e.g., listening to music on headphones while engaging in the task), or b) they did not perform any behaviors during 20% or more of the adaptation trials on Day 2 (i.e., they did not click on a single target or piece of information). This 20% cutoff was determined based on a clear difference in the data from individuals who randomly had one trial of nonresponse versus the other individuals who fell into the 20% category who had multiple nonresponse trials within a short period of time. Therefore, the final sample consisted of 509 individuals and 16,279 trials. The final sample was comprised of 60% males, and spanned the ages of 18 to 24.

A two-part series of simulations was conducted for the longitudinal cross-lag panel regression model that determined this sample size was appropriate to capture the effects, given the number of time points in the adaptation and performance environments, and the anticipated error rates and effect sizes (see Appendix A for a description of the method and more detailed results from the simulations).

[1] An additional 112 individuals participated in a pilot test and the code checked for errors. Once the task was finalized, data collection began.

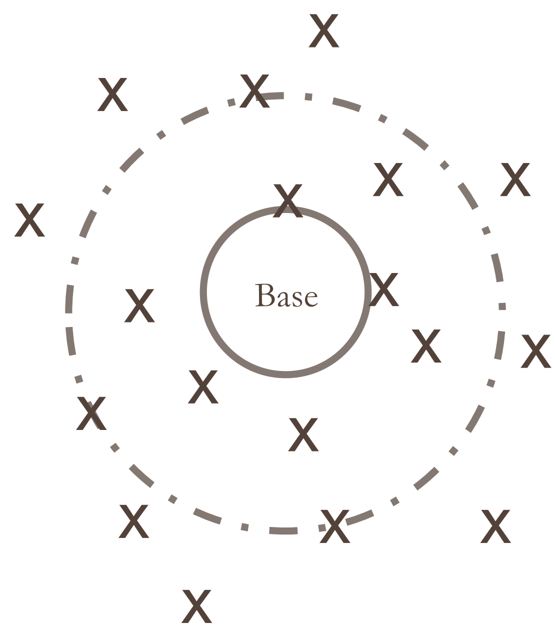
Task

The task used was a computer-based radar-tracking simulation, TANDEM, which is a decision-making experimental platform that had been utilized in prior research in the adaptation literature (Kozlowski, Gully et al., 2001; Bell, 2002; Bell & Kozlowski, 2002a, 2002b; Bell & Kozlowski, 2008). Participants are required to view a radar area, detect targets, identify them as friendly or hostile, and take appropriate actions to protect their base. As TANDEM is a complex decision-making task, it serves as a platform with high psychological fidelity to other complex tasks that require information processing. This experimental task allows 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.

Figure 5 shows a representation of this environment. In order to perform well in this task, participants had to make a series of decisions about the contacts (denoted in Figure 5 by the X markings) before making a final decision (i.e., clear or shoot). The decision rules were based on three characteristics: type (i.e., air, surface, or submarine), class (i.e., civilian or military), and intent (i.e., peaceful or hostile). This information was sought after a contact was selected, or "hooked". In addition to this set of decisions, the participants were not allowed to let the contacts penetrate the inner or outer perimeters (in Figure 5, the inner perimeter is indicated with a solid line surrounding the base, while the invisible outer perimeter is denoted by the dotted line). In order to do this, individuals utilized the zoom function and prioritized the contacts. Points were gained for correctly making the four decisions described above, and points were lost for incorrectly making those decisions and for allowing contacts to cross the perimeters.

Figure 5

Representation of the TANDEM Task Environment



Design

This experiment was a three-condition between-person design using repeated measures. Individuals were randomly distributed between the control condition (where no adaptive change was introduced), a component change condition (one type of adaptive change), or a coordinative change condition (another type of adaptive change). The study spanned two days. See Appendix B for an overall picture of the flow of the experiment.

Day 1: Training

On Day 1, individuals were trained on TANDEM over nine trials. This was done to ensure that participants in all conditions were trained to proficiency prior to the introduction of any task changes. The training focused on exploratory learning (with general principles guiding learning during the trials) and encouraged errors during the training period. Given that previous research has consistently shown that these trainings best prepare individuals to perform effectively when an adaptive change is introduced (see Bell & Kozlowski, 2002; Baard, 2013), the training remained the same across conditions.

Familiarization Phase. Upon entering the lab, participants were asked to complete an informed consent form. 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, engage the zoom function, and determine the sequence in which one makes a decision. After the demonstration, participants had three minutes to study the manual followed by a one-minute familiarization trial (from which they would not receive any feedback). The purpose of that short trial was to expose individuals to the task prior to beginning training.

Training Phase. After the familiarization phase, participants were given instructions about what they should be learning during the next few trials. This was based on the work by Bell and Kozlowski (2008) and the same learning objectives and instructions they established for the TANDEM environment were used (see Appendix C). The training was given through written direction, separating the nine trials into three three-trial blocks. In the first block, individuals were instructed to investigate how to correctly make the four decisions about a contact (type, class, intent, and execution) and how to navigate the task environment. The second block directed participants to focus on how to prevent contacts from crossing the perimeters 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. Within each block of three trials, individuals were given two minutes to read the instructions, then look at the manual (one minute), engage in a trial (four minutes), and investigate feedback (one minute). This cycle continued until all nine training trials were completed. At that time participants completed another set of measures containing basic and strategic knowledge, and state goal orientation. Once those measures were completed, individuals were dismissed from the experiment for the day. This part of the experiment took two hours and individuals received course credit for their participation.

Day 2: Performance

On Day 2, there was a period for re-learning, followed by five routine performance trials that were similar to the initial training trials, but the participants were informed that these were performance trials. After the completion of the routine performance trials, a series of 15 "adaptive" trials was introduced. Individuals in the component or coordinative complexity change conditions were told that "something changed" in their environment and they would have the remainder of the trials to determine what to do, but the specifics of the change were not delineated. Individuals in the control condition were told that they were "entering the second phase of the study" in order to mirror the communication mid-study, as in the component and coordinative complexity conditions. At this transition point, individuals were reminded about the reward opportunity for high performance. In between each trial, both before and after the change, a series of measures was given. Therefore, for each trial, individuals first had an opportunity to investigate the manual (for a maximum of one minute), perform the trial (for four minutes), receive feedback on their performance (for a maximum of one minute), and respond to the self-report questionnaires of self-efficacy, goals, effort, and metacognition (for a maximum of two minutes). This was the cycle for all 20 trials that the individuals engaged in on Day 2.

In the ***component complexity change condition**,* when the “adaptive event” occurred during Trial 19, individuals were informed that the task environment changed and that their goal was to understand the change in order to recover and exceed their pre-change performance level by the end of the study. These adaptive trials doubled the number of targets in the scenario. All other features of the task remained constant between the routine and adaptive trials.

In the ***coordinative complexity change condition**,* when the “adaptive event” occurred during Trial 19, individuals were also informed that the task environment changed and that their goal was to understand the change in order to recover and exceed their pre-change performance level by the end of the study. In the adaptive trials, individuals were exposed to a new set of point allocations. The outer perimeter increased in point value and the number of targets threatening to cross that perimeter increased (however, the number of targets remained the same).

In the ***control condition***, although no adaptive change was introduced, during Trial 19, individuals were informed that they are entering the final phase of the study (serving as a placebo set of instructions). All the trials remained the same as the training environment.

Day 2 took a total of three hours. Individuals received course credit for their participation and they had an opportunity to win a cash prize for the highest average performance across all the trials on Day 2. As each condition had different trials, the division of top performers was distributed based on the number of individuals in the condition. As the number of individuals assigned to the control condition was half of those of the other two conditions, the number of individuals receiving prizes was also half of those in the other two conditions. Thus, the top 10 individuals (top two of the control condition, top four of the component condition, and top four of the coordinative condition) received $50, the following 15 individuals (three in control, six in component and six in coordinative) received $20 and the next 20 individuals (four in control, eight in component and eight in coordinative) received $10. This was intended to provide additional motivation to remain focused throughout the study.

Measures

The measures used for each of the key variables involved in the adaptation process, as well as performance and individual differences, are detailed below. The specific items can be found in Appendix D, along with additional measures that were used for identifying when the shift between the adaptation and performance environments occurred.

Metacognition was measured after each performance trial. This measure was modified from previous research in the TANDEM environment by Bell (2002), which was adapted from a measure created by Ford et al. (1998). This four-item questionnaire asked about the strategies used by, and the focus of, individuals in the last scenario. They responded to the question on a five-point Likert-type scale with 1 being “never’” and 5 being “constantly”. Cronbach’s alpha shows that this measure was reliable over the trials as they ranged from .864 to .960.

Evaluation was measured as a behavioral indicator collected during each of the trials during the performance trials. This measure assessed the amount of time spent viewing feedback about their performance in the last trial.

Learning-oriented effort was measured as a behavioral indicator. It was based on the effort devoted toward seeking additional information about the task, outside of the trial itself, through investigating the task manual information available to them.

Self-efficacy was measured after each performance trial with four items adapted from Ford, et al. (1998). They developed an eight-item self-report measure specifically for this task paradigm. This measure used a five-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5). Cronbach's alpha shows that this measure was reliable over the trials as they ranged from .924 to .970.

Goals were measured by obtaining information regarding the participants' expected number of points in the next trial. This was based on previous research in the TANDEM environment (see Baard, 2013; Bell & Kozlowski, 2008).

Outcome-oriented effort was captured through the behavioral indicator of the total amount of effort exerted by the individual (i.e., how hard an individual is working) through the number of targets engaged, contacts queried, contacts hooked, zooms, and executions. There are two components of outcome-oriented effort: strategic effort consisting of behaviors devoted to the aspects of the task that are relevant to prioritization and resource allocation (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). The sum of these behaviors constituted the overall outcome-oriented effort measure.

Performance in TANDEM was 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 as in previous research using this paradigm (e.g., Bell & Kozlowski, 2008). During training and routine performance trials, there were 30 targets, and performance was computed by adding 100 points when all four decisions (type, class, intent, final decision) were made correctly, and by subtracting 100 points if any one of those decisions was incorrect. Furthermore, 10 points were subtracted if a contact crossed the inner or outer defensive perimeter. During the adaptive trials of the ***control condition***, the details remained the same as the routine trials. For the ***component complexity change condition*****,** there were 60 (as opposed to 30) targets with four threatening to cross the inner perimeter and four the outer, but all the point distributions remained the same. For the ***coordinative complexity change condition***, there were 30 targets, but more targets crossed the perimeters and there was a shift in the importance of perimeter crossings (175 points for visible inner perimeter intrusions and 125 points 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). Table 2 displays the specifics of the manipulations for each condition.

TANDEM knowledge tests were given to individuals once the training phase was completed on Day 1. The declarative and procedural knowledge pertaining to the TANDEM task domain was assessed in order to determine individuals' baseline understandings of the rules of the task, as well as their objectives or overall goals. 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 individuals' understanding of the resource allocation aspects 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 there are two distinct knowledge domains that need to be evaluated in this test of knowledge acquisition.

Demographics and individual differences information was collected immediately upon individuals' entering the lab on Day 1, and contained other individual difference items such as year in school, undergraduate major, gender, age, cognitive ability, individual adaptability, and trait and state goal orientation. These data were gathered in the event that the measures could provide insight into any odd findings or provide insight into significant differences between groups; however, as this did not occur, these measures were not used in the data analyses, but the measurement origins and statistics can be found at the end of Appendix D.

Statistical Models

In order to test the hypotheses, I used a variety of analyses. For Hypotheses 1, 2, and 3, which focused on determining the transition point of the adaptation and performance phases that occurred after the change was introduced, I employed discontinuous growth curve models. This model has been used in adaptation research in the investigation of differences in performance trajectories in pre- and post-change environments (Lang & Bliese, 2009). As the utility of this model is in its ability to provide empirical specification of the differences in trajectories in two environments, the extension of this model to the adaptation and post-change performance environment seems to be within the bounds of the previous use of this analysis.

Each trajectory specified in Hypotheses 4, 5, 6, and 7, which focus on the trajectory change in the self-regulatory variables between the post-change adaptation and performance environments, was tested with separate latent growth curve models. There are two key aspects of latent growth curve modeling: the intercept and the slope. The intercept indicates the level of the initial score of the average individual on the variable being tested (e.g., self-efficacy). The slope indicates the average growth of the average of individuals from the start to the end of that period of time (e.g., a growth curve will be estimated for all trials in the adaptation environment separately from those in the performance environment).

Hypotheses 8 through 19 focused on the relationships between the self-regulatory variables in the adaptation and performance processes, and were tested with one longitudinal cross-lag panel regression model. Cross-lag models allow for the investigation of reciprocal relationships and the specification of different relationships over time. Therefore, this analysis provides the most complete model for investigating a longitudinal process as is available in our literature. Cross-lag models have also been referred to as multivariate autoregressive models, autoregressive cross-lag models, and cross-lagged panel models (Selig & Little, 2012). Below is the general equation for a two variable model:

$$X_{t,n} = \beta_{11}X_{t-1,n} \ \gamma_{12}Y_{t-1,n} + \varepsilon_{xt,n}$$

$$Y_{t,n} = \beta_{22}Y_{t-1,n} \ \gamma_{21}X_{t-1,n} + \varepsilon_{yt,n}$$

Figure 6 shows the base cross-lag model with two variables over two time points. This model specifies an autoregressive effect of the variable on itself over time, and a cross-lag relationship of X on Y as well as Y on X. This reciprocal relationship estimation is critical for investigating processes over time. Figure 7 presents part of the model that was used to test this set of hypotheses. The first few trials in the figure represent the adaptation trials and the final trials representing the performance trials; note the slight change in the thickness of the lines connecting the trials, indicating these relationships will be allowed to differ in their estimations across the adaptation and performance processes.

Table 2

Specific Adaptive Manipulations for Each Experimental Condition

		Total # Targets	**# Cross Inner/Outer Perimeters**	**Points: Perimeter Crosses**	**Points: Target Decisions**
Training	All	30	2 inner 2 outer	-10 inner -10 outer	+100 correct -100 incorrect
Routine Performance	All	30	2 inner 2 outer	-10 inner -10 outer	+100 correct -100 incorrect
	Control	30	2 inner 2 outer	-10 inner -10 outer	+100 correct -100 incorrect
Adaptive Performance	**Component Change**	**60**	**4 inner** **4 outer**	-10 inner -10 outer	+100 correct -100 incorrect
	Coordinative Change	30	***2 inner*** ***6 outer***	***-175 inner*** ***-125 outer***	+100 correct -100 incorrect

Figure 6
Example of a Fully Crossed Longitudinal Cross-Lag Panel Model With Two Variables

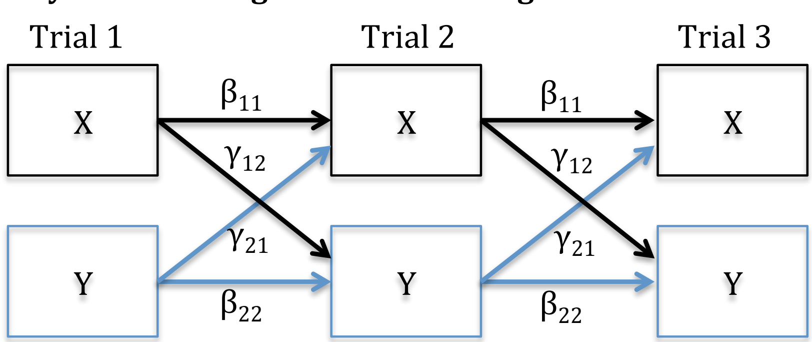
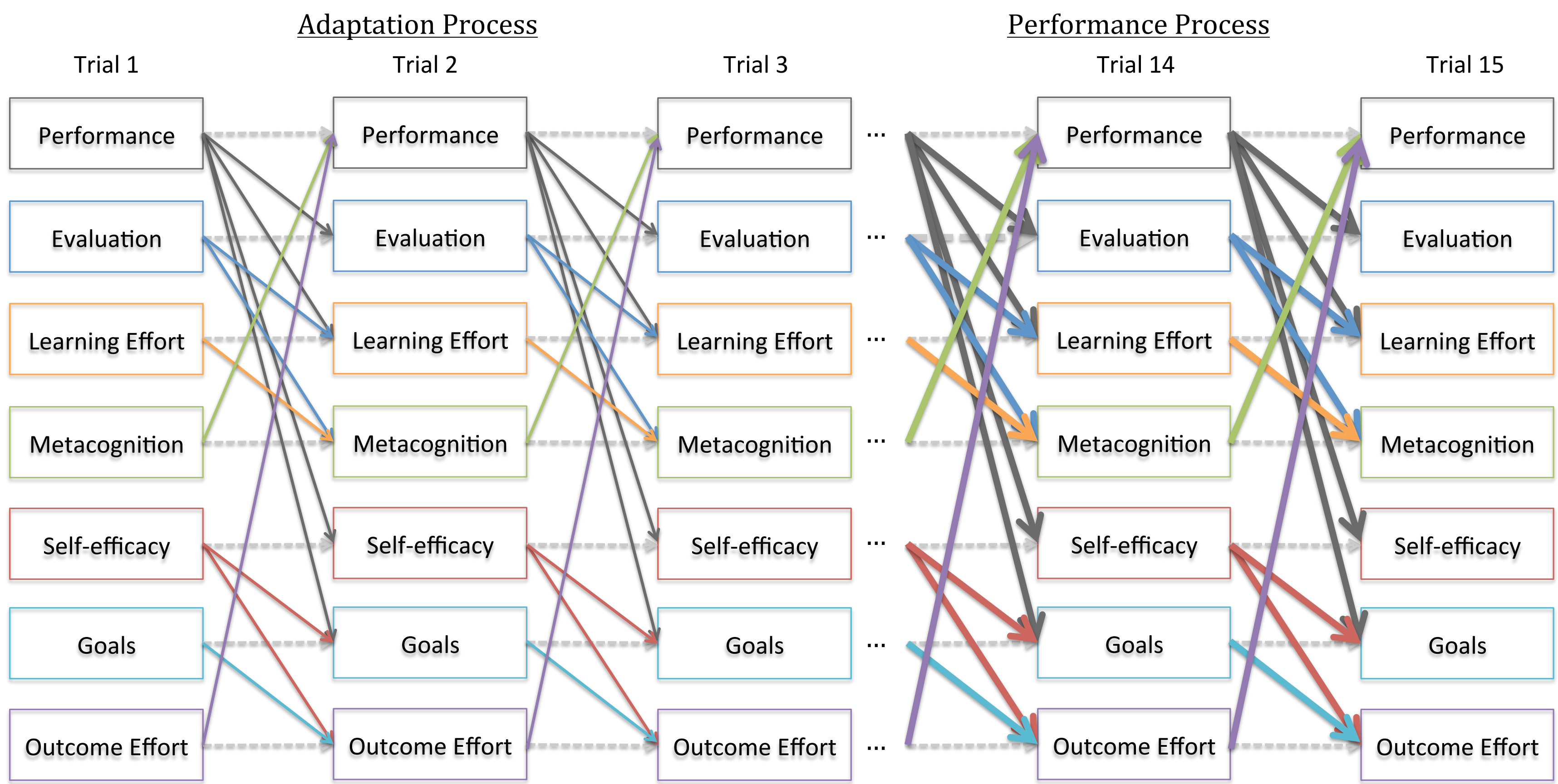


Figure 7

Example of the Hypothesized Relationships in the Longitudinal Cross-Lag Panel Regression Model



RESULTS

Pre-Hypothesis Testing

Variable Information and Data Cleaning

As many of the variables in this dataset were collected 20 to 32 times, presenting a correlation matrix in the body of this paper is not feasible. However, as the cross-lag models are primarily based on the differences between two processes occurring after a change was introduced in the component and coordinative complexity conditions; therefore, the means, standard deviations, and correlations are provided based on the average of the trials in these two processes (see Tables 3 and 4). Only one variable had an outlier situation based on non-compliance on the part of the participant. This occurred in the goal variable where four individuals reported impossible goals for a total of five trials that were far outside the range of the other responses (i.e., “1000000”, “10000000” and “2147483647”). Given that it was not my intention to remove this information (and therefore lose their entire trial data) or substitute it to zero (thereby suggesting that they had no goal when they reported a very high one), I replaced their responses with the highest response below one million (i.e., 40,000). This procedure removed the very small number of outliers while maintaining the integrity of the data suggesting these four individuals were pursuing a high goal in those five trials.

Metric invariance tests were also conducted on the self-report measures of self-efficacy and metacognition, given that these measures were collected after every trial of the study. Therefore, it was necessary to show that the measure did not change over the course of the 22 trials. These longitudinal metric invariance tests indicated that self-efficacy and metacognition did not change over the course of the study.

Table 3
Descriptives and Correlations: Adaptation Environment

		Performance	Learning-Oriented Effort	Metacognition	Evaluation	Goals	Outcome-Oriented Effort	Self-efficacy
Means		344.433	11.938	3.269	20.506	754.322	93.605	3.798
Standard Deviations		427.623	13.654	.897	7.945	767.743	29.924	.726
Performance	Correlation	1	.011	-.029	.099*	.343**	.523**	.245**
	Sig.		.821	.555	.045	.000	.000	.000
	N	413	413	413	413	413	413	413
Learning-Oriented Effort	Correlation	.011	1	.139**	.217**	-.053	.152**	-.026
	Sig.	.821		.005	.000	.283	.002	.592
	N	413	413	413	413	413	413	413
Metacognition	Correlation	-.029	.139**	1	.105*	.044	-.031	.423**
	Sig.	.555	.005		.034	.373	.525	.000
	N	413	413	413	413	413	413	413
Evaluation	Correlation	.099*	.217**	.105*	1	.005	.127**	.043
	Sig.	.045	.000	.034		.913	.010	.383
	N	413	413	413	413	413	413	413
Goals	Correlation	.343**	-.053	.044	.005	1	.199**	.227**
	Sig.	.000	.283	.373	.913		.000	.000
	N	413	413	413	413	413	413	413
Outcome-Oriented Effort	Correlation	.523**	.152**	-.031	.127**	.199**	1	.199**
	Sig.	.000	.002	.525	.010	.000		.000
	N	413	413	413	413	413	413	413
Self-efficacy	Correlation	.245**	-.026	.423**	.043	.227**	.199**	1
	Sig.	.000	.592	.000	.383	.000	.000	
	N	413	413	413	413	413	413	413

Table 4
Descriptives and Correlations: Performance Environment

		Performance	Learning-Oriented Effort	Metacognition	Evaluation	Goals	Outcome-Oriented Effort	Self-efficacy
Means		426.424	4.382	3.095	13.567	684.312	90.141	4.609
Standard Deviations		470.365	8.955	1.032	4.922	808.400	32.869	.855
Performance	Correlation	1	.115*	.041	.131**	.324**	.629**	.322**
	Sig.		.020	.409	.008	.000	.000	.000
	N	413	413	413	413	413	413	413
Learning-Oriented Effort	Correlation	.115*	1	.086	.251**	.012	.223**	.083
	Sig.	.020		.080	.000	.802	.000	.093
	N	413	413	413	413	413	413	413
Metacognition	Correlation	.041	.086	1	.050	.126*	-.007	.491**
	Sig.	.409	.080		.311	.010	.879	.000
	N	413	413	413	413	413	413	413
Evaluation	Correlation	.131**	.251**	.050	1	.013	.115*	.063
	Sig.	.008	.000	.311		.790	.019	.201
	N	413	413	413	413	413	413	413
Goals	Correlation	.324**	.012	.126*	.013	1	.186**	.217**
	Sig.	.000	.802	.010	.790		.000	.000
	N	413	413	413	413	413	413	413
Outcome-Oriented Effort	Correlation	.629**	.223**	-.007	.115*	.186**	1	.257**
	Sig.	.000	.000	.879	.019	.000		.000
	N	413	413	413	413	413	413	413
Self-efficacy	Correlation	.322**	.083	.491**	.063	.217**	.257**	1
	Sig.	.000	.093	.000	.201	.000	.000	
	N	413	413	413	413	413	413	413

First, while investigating configural invariance, tests indicated that the pattern loadings of both measures remained the same across time (self efficacy: $\chi^2(2829)$ = 6209.839, p<.000, RMSEA = .048, CFI = .950, SRMR = .025; metacognition: $\chi^2(2829)$ = 5378.830, p<.000, RMSEA = .042, CFI = .960, SRMR = .034). Next, weak invariance was tested and although the chi-square difference tests revealed significantly more misfit, the fit statistics were within acceptable parameters according to Hu and Bentler (1999), thus it was concluded that the measures have the same unit over time ($\chi^2(2895)$ = 6331.698, p<.000, RMSEA = .048, CFI = .950, SRMR = .031; metacognition: $\chi^2(2895)$ = 5467.934, p<.000, RMSEA = .041, CFI = .959, SRMR = .033). Strong metric invariance also showed significantly more misfit with the chi-square different tests; however, the fit statics remained adequate and so the measures were considered to have the same origins over time (self-efficacy: $\chi^2(2895)$ = 5467.934, p<.000, RMSEA = .041, CFI = .959, SRMR = .033; metacognition: $\chi^2(2983)$ = 5787.318, p<.000, RMSEA = .043, CFI = .956, SRMR = .038). Finally, the test of strict invariance, investigating whether the measures had the same variance over time, was also considered as having significantly more misfit but still within acceptable parameters (self-efficacy: $\chi^2(3071)$ = 7205.827, p<.000, RMSEA = .051, CFI = .939, SRMR = .044; metacognition: $\chi^2(3071)$ = 6292.876, p<.000, RMSEA = .045, CFI = .949, SRMR = .044).

These tests show support that a single latent factor of both self-efficacy and metacognition can be used to examine the relationships between these variables and others over the course of the study. Therefore, the average of the items of these scales will be used for the remainder of the analyses.

Test of Training Effectiveness

As described in the methodology, training and initial performance were administered on Day 1, while performance in the adaptive environment occurred on Day 2. This research design was chosen, as the length of the study would be such that participants would not have been likely to remain engaged for the duration of the study had both days been combined. However, this separation merits a brief investigation of 1) whether there was any decay of knowledge between the two days (there was a 48-hour period of separation between the two parts of the experiment), and 2) whether performance plateaued before individuals were faced with the change.

In addressing the first concern, mean differences were examined to see if knowledge on Day 2 was different from Day 1. All three conditions were combined for these analyses given that training and initial performance trials were identical. Knowledge actually increased from Day 1 to Day 2 ($t = -4.504$; $df = 1016$; $p <. 000$; mean score Day 1 = 14.130; mean score Day 2 = 15.183). This suggests that, although there may have been a test-retest effect, they remembered the information they learned during training. Therefore, I concluded that the training from Day 1 was valid on Day 2.

To investigate the second concern regarding the plateauing of performance prior to the adaptive change on Day 2, a discontinuous growth curve model was fitted to the data, separating Day 1 training and performance trials from Day 2 non-adaptive performance trials. The results of this model show that there was a significantly positive growth curve during Day 1 training and performance ($t(8317)=37.882$, $p<.000$; see Table 5 for the specific parameter estimates), while there was a significant decrease in performance on Day 2 ($t(8317)=-3.130$, $p=.002$). This latter trajectory is slightly confusing as it was not

Table 5
Discontinuous Growth Curve Analysis of Training and Performance

Condition	Day 1 Training	Transition to Day 2	Day 2 Routine Performance
ALL conditions	Value: 42.132 Std.error: 1.112 DF: 8137 t-value: 37.882 p-value: .000	Value: 13.694 Std.error: 13.704 DF: 8137 t-value: .872 p-value: .382	Value: -13.617 Std.error: 4.250 DF: 8137 t-value: -3.130 p-value: .002
ONLY Control	Value: 42.712 Std.error: 2.602 DF: 1533 t-value: .072 p-value: .000	Value: 2.654 Std.error: 36.750 DF: 1533 t-value: .072 p-value: .942	Value: -8.972 Std.error: 10.178 DF: 1533 t-value: -.881 p-value: .3782
ONLY Component Complexity	Value: 45. 920 Std.error: 1.670 DF: 3468 t-value: 27.398 p-value: .000	Value: 3.124 Std.error: 23.670 DF: 3468 t-value: .132 p-value: .895	Value: -19.924 Std.error: 6.555 DF: 3468 t-value: -3.040 p-value: .002
ONLY Coordinative Complexity	Value: 37.648 Std.error: 1.808 DF: 3130 t-value: 20.824 p-value: .000	Value: 30.845 Std.error: 25.518 DF: 3130 t-value: 1.209 p-value: .227	Value: -8.897 Std.error: 7.072 DF: 3130 t-value: -1.258 p-value: .208

expected to decrease over the second day; however, when investigating the differences between the conditions, it was found that the control and coordinative complexity conditions had non-significant slopes (Control: $t(1533)=-.881$, $p=.378$; Coordinative: $t(3130)=-1.258$, $p=.208$), while the component complexity condition had a significantly negative slope ($t(3468)=-3.040$, $p=.002$). Although this is not ideal, it still provides support that individuals completed the learning process and reached asymptote in performance prior to the adaptive change being introduced. This is supported by all three conditions reaching similar levels both directly after training on Day 1 ($F(1,506)= 2.039$, $p=.154$), at the end of performance on Day 1 ($F(1,506)= .336$, $p=.563$), at the beginning of Day 2 ($F(1,507)= 1.216$, $p=.271$), and just before the change was introduced on Day 2 ($F(1,507)=$

1.477, p=.225). Thus, all conditions appeared to follow the same pattern of learning and performance, and asymptoting prior to any change being introduced.

Hypothesis Testing

Identifying the Transition Point

In order to test Hypothesis 1, I examined several methodologies before settling on conducting a series of discontinuous growth curve models to detect a shift in performance after the change was introduced. The pattern described in the presentation of the theory suggested that there would be a strong positive increase in performance during the initial adaptation process, followed by a weak (or non-significant) slope in the performance process. First, I attempted to determine this through the self-report questionnaire that asked individuals to indicate when they comprehended what changed in the environment. Unfortunately, this question was not helpful as it was consistently misinterpreted as indicate what changed in the environment since the last trial (rather than from when the only change was introduced). I then investigated whether the correlations or mean difference tests between the trials would be insightful; however, they too were uninformative as all the results were significant. Therefore, as discontinuous growth curve models can empirically test differences in trajectories, this method was chosen as the best alternative to determine when a shift occurred from the adaptive to the performance process, based on the pattern described in the theory. I systematically went through a series of discontinuous growth curve analyses, modifying only which trial was the transition trial. As it was expected that the two conditions would have different transition points (Hypothesis 3), the component and complexity conditions were tested separately.

Based on the expected pattern described in the theory, in the component complexity condition individuals transitioned from the adaptation process to the performance process at Trial 25. This was based on the first time the following pattern was observed: there was a positive and significant slope for the trials directly after the change (Trials 19 through 24; $t(3032)=3.776$, $p<.000$), then a non-significant slope for the remaining trials (Trials 25 through 33; $t(3032)=-1.734$, $p=.083$), with a non-significant transition trial (Trial 25; $t(3032)=1.624$, $p=.105$). A significant transition trial would indicate that during this trial there was either a significant event or a significant reaction that resulted in a large increase or decrease in the variable of interest at that specific point. For example, in Lang and Bliese (2009) they labeled the transition trial as the moment an adaptive change was introduced so that the pre-change performance trajectory was compared to the post-change performance trajectory. Here, however, a non-significant transition trial was desirable given that there was no reason any particular trial should have significant meaning, since both of the growth curves being estimated occurred after the change was introduced. The slopes before and after should show the pattern of significantly positive to non-significant, revealing that performance plateaued, reaching a somewhat stable equilibrium. Therefore, both the intercepts and slopes for Hypothesis 1a and 1b were supported by the component complexity condition (see Figure 8 for a depiction of the slope changes and Table 6 for the specific parameter estimates).

The coordinative complexity condition, however, did not follow the expected pattern of performance change and instead showed consistently low performance followed by a lagged increase in performance. Therefore, in order to appropriately detect the transition point between the adaptation and performance processes, I applied the same logic of a significant slope at one point with a non-significant transition trial and a non-significant slope at the other point. In the component complexity condition the pattern was such that the significantly increasing slope was first (in the adaptation environment); however, the coordinative complexity condition showed that the significantly increasing slope was in the second environment (i.e., the performance environment; $t(2739)=2.757$, $p=.006$), while the non-significant slope was in the adaptation environment ($t(2739)=-1.325$, $p=.185$). Similar to the component complexity condition, the coordinative complexity condition also had a non-significant transition trial ($t(2739)=-.359$, $p=.720$). The analysis also revealed that the transition between these two processes occurred one trial later than the component complexity condition (see Table 6 and Figure 8). Therefore, although the intercepts of the trajectories for Hypothesis 1a and 1b were supported for the coordinative complexity condition, the slopes were not. Given the difference in transition points between the two conditions (component at Trial 25, coordinative at Trial 26), Hypothesis 3 was supported.

This led to a question of whether the coordinative complexity condition had a lagged adaptation process in which case the performance process would not have been measured. In order to determine this, an additional discontinuous growth model was fitted with self-reported focus of the type of goal being pursued as the variable of interest. It is logical that, when individuals shift their focus from learning as much as they could about the task to determining what changed and how to deal with it (i.e., exploration behaviors) to focusing on executing as much as possible to increase performance effectiveness (i.e., exploitation behaviors), we then can conclude that there was a transition from the adaptation process to the performance process, given the theory discussed earlier. In both conditions (with

Table 6

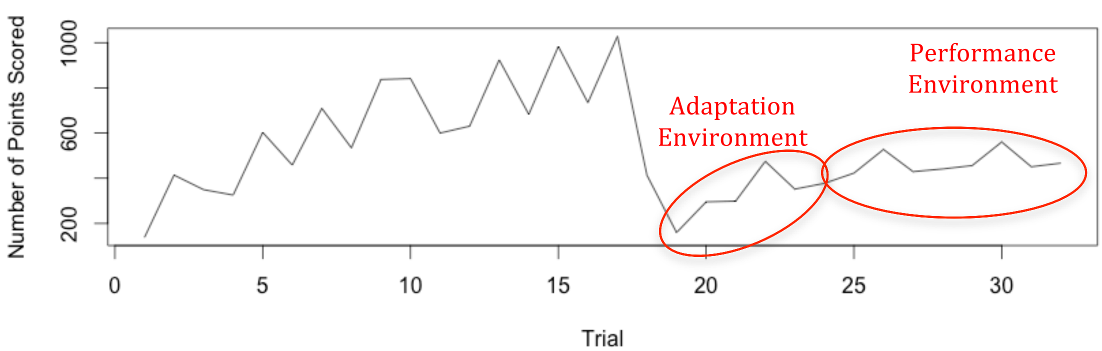
Results of Discontinuous Growth Curve Analyses for Performance

Condition	Adaptation Process	Transition Trial	Performance Process
Component Complexity Performance	Parameter: 18.857 Std.error: 4.993 DF: 3032 t-value: 3.776 p-value: .000	Parameter: 34.828 Std.error: 21.451 DF: 3032 t-value: 1.624 p-value: .105	Parameter: -9.844 Std.error: 5.676 DF: 3032 t-value: -1.734 p-value: .083
Coordinative Complexity Performance	Parameter: -5.938 Std.error: 4.483 DF: 2739 t-value: -1.325 p-value: .185	Parameter: -8.818 Std.error: 24.556 DF: 2739 t-value: -.359 p-value: .720	Parameter: 15.965 Std.error: 5.790 DF: 2739 t-value: 2.757 p-value: .006

Figure 8

Discontinuous Growth Curves for Performance

Trial Performance Component Complexity



Trial Performance Coordinative Complexity

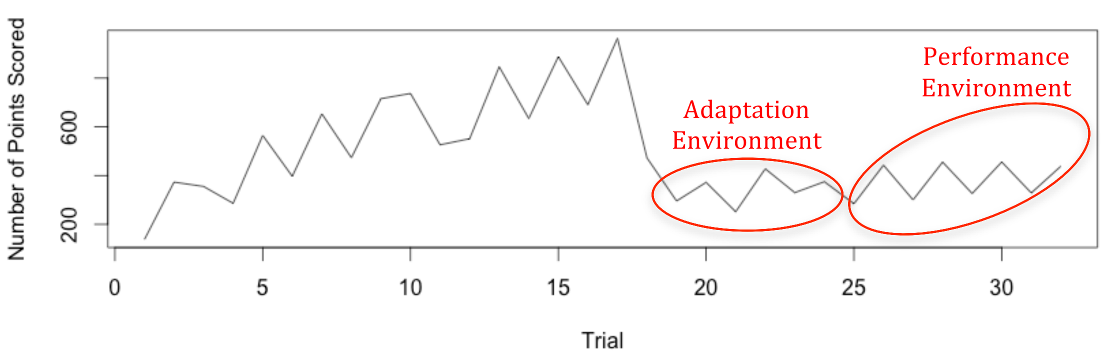


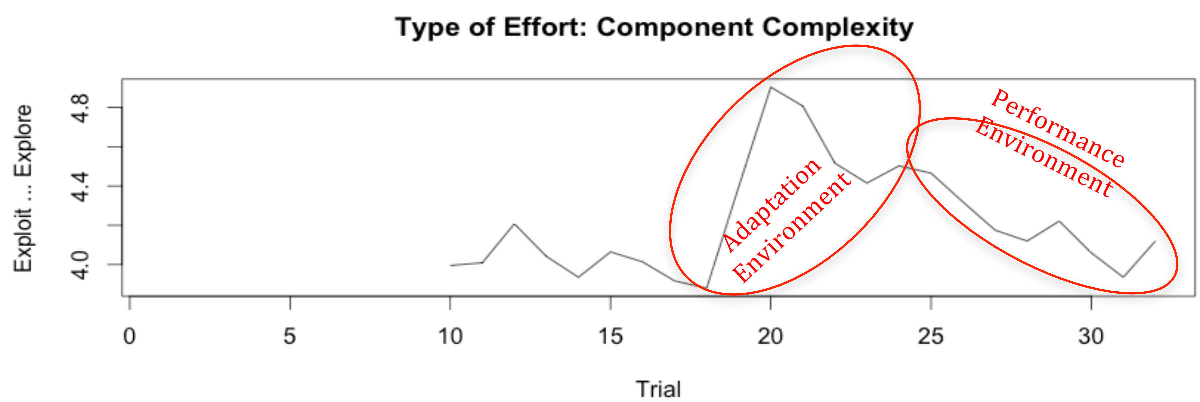
Table 7

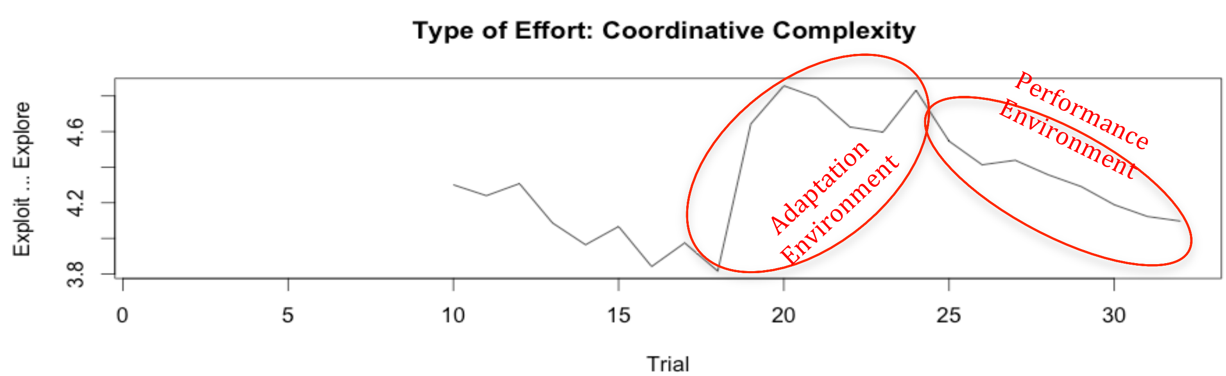
Results of Discontinuous Growth Curve Analyses for Type of Effort

Condition	Adaptation Process	Transition Trial	Performance Process
Component Complexity Learning Effort	Parameter: .081 Std.error: .030 DF: 3032 t-value: 2.673 p-value: .008	Parameter: -.184 Std.error: .131 DF: 3032 t-value: -1.403 p-value: .161	Parameter: -.141 Std.error: .035 DF: 3032 t-value: -4.051 p-value: .000
Coordinative Complexity Learning Effort	Parameter .097 Std.error: .0241 DF: 2739 t-value: 4.028 p-value: .000	Parameter -.290 Std.error: .132 DF: 2739 t-value: -2.192 p-value: .028	Parameter -.161 Std.error: .031 DF: 2739 t-value: -5.177 p-value: .000

Figure 9

Discontinuous Growth Curves for Type of Effort





their respective transition points, see Figure 9 and Table 7), individuals focused significantly more on exploration behaviors to learn about the task (the upper end of the scale) over the course of the adaptation process (component complexity: $t(3032)=2.673$, $p=.008$; coordinative complexity: $t(2739)=4.028$, $p<.000$), and then shifted focus onto exploitation behaviors (the lower end of the scale) to maximize performance output in the performance process (component complexity: $t(3032)=-4.051$, $p<.000$; coordinative complexity: $t(2739)=-5.177$, $p<.000$). This change in strategy, which supports Hypothesis 2, also supports the conclusion that both the component and coordinative complexity conditions first engaged in an adaptation process (even though performance trajectories appeared slightly different), and then they transitioned to a performance process. Therefore, for the remainder of the analyses, the two conditions will be combined, removing Trial 25 in order to maintain the consistency of the transition points.

Examining Trajectory Changes

In order to test Hypotheses 4 through 7, which focused on the trajectories of the self-regulatory variables in the adaptation and performance environments, twelve latent growth curve analyses were conducted to determine the significance of the levels and slopes of the variables. Both the component and coordinative complexity conditions showed very similar trajectories and, therefore, the analyses reported are from the combined data. All significant differences are noted below. Figures 10 and 11 display the trajectories of the combined, component complexity and coordinative complexity conditions data separately in order to further show the similarities between these conditions in the self-regulatory variables. Note that the trial numbers refer only to the post-change trials; therefore, the transition between the adaptation and performance environments occurred at Trial 7 in the component condition and at Trial 8 in the coordinative condition. Table 8 provides a summary of the hypotheses, analyses used for testing and conclusions based on the results. These conclusions were based the following standards. Predicted high and mid-level intercepts were considered supported if they were significantly different from zero. Low-level intercepts were supported by non-significant intercept estimates. Similarly, predicted strong slopes were supported by significant estimates; predicted weak slopes were supported by non-significant estimates.

With regard to the cognitive variables in the adaptation environment, metacognition was elevated after the change was introduced and did not significantly decrease throughout the adaptation environment, supporting Hypothesis 4a with a high intercept and a non-significantly negative slope (see Table 9 for the specific estimates and significance levels for all cognitive variables). Evaluation and learning-oriented effort both were initially elevated, but significantly decreased over the adaptation environment. It should be noted that the decrease was non-significant in the component complexity condition. Therefore, Hypotheses 4b and 4c were not supported, however, the intercepts were high (as expected) but the slopes were in the expected direction (i.e., negative), though they were significant as opposed to the predicted non-significant slopes, thus, the results suggest that the finding is in the appropriate direction. This finding may indicate that individuals did not feel the need to engage in as much metacognitive or learning-oriented behaviors in the adaptation environment.

Table 8

Summary of Trajectory Hypotheses, Analyses, and Results

Description	#	Hypothesis	Environment	Analysis	Summary of Results
Performance Trajectory	*1a*	*Performance: Low Intercept,* ***Strong + Slope***	*Adaptation*	Discontinuous Growth Curve (2 models)	Component Complexity: Supported Coordinative Complexity: Not Supported
	1b	Performance: High *Intercept*, Weak + Slope	Performance		Component Complexity: Supported Coordinative Complexity: Not Supported
Reason for Shift in Environments	2	The environment shift occurs when a strategy is chosen			Supported
	3	Component complexity condition will shift more quickly			Supported
Trajectory Changes of Cognitive Cycle Mechanisms	*4a*	*Metacognition: High Intercept Weak - Slope*	*Adaptation*	Latent Growth Curve (12 models)	Intercept: Supported Slope: Supported
	4b	*Evaluation: High Intercept Weak – Slope*	*Adaptation*		Intercept: Supported Slope: Not Supported
	4c	*Learning Effort: High Intercept, Weak - Slope*	*Adaptation*		Intercept: Supported Slope: Not Supported
	5a	Metacognition: Mid *Intercept*, **Strong - Slope**	Performance		Intercept: Supported Slope: Supported
	5b	Evaluation: Mid *Intercept*, **Strong - Slope**	Performance		Intercept: Supported Slope: Supported
	5c	Learning Effort: Mid *Intercept*, **Strong -Slope**	Performance		Intercept: Supported Slope: Supported
Trajectory Changes of Motivational Cycle Mechanisms	*6a*	*Goals: Low Intercept, Weak + Slope*	*Adaptation*		Intercept: Not Supported Slope: Not Supported
	6b	*Self-efficacy: Low Intercept, Weak + Slope*	*Adaptation*		Intercept: Not Supported Slope: Not Supported
	6c	*Outcome Effort: Low Intercept, Weak + Slope*	*Adaptation*		Intercept: Not Supported Slope: Not Supported
	7a	Goals: Mid *Intercept*, **Strong + Slope**	Performance		Intercept: Supported Slope: Not Supported
	7b	Self-efficacy: Mid *Intercept*, **Strong + Slope**	Performance		Intercept: Supported Slope: Not Supported
	7c	Outcome Effort: Mid *Intercept*, **Strong +Slope**	Performance		Intercept: Supported Slope: Not Supported

Shifting to the performance environment, all cognitive variables (i.e., metacognition, evaluation, and learning-oriented effort behaviors) performed as expected. They each had significantly high initial intercepts, and the trajectories significantly decreased over time. These findings were consistent across the two conditions and fully support Hypotheses 5a, 5b, and 5c (see Table 9 and Figure 10).

With regard to the motivation variables, the trajectories in both environments were not as expected. Instead of the variables being very low, directly after the change (i.e., having an intercept not significantly different from zero), individuals had elevated levels of self-efficacy and goals (see Table 10 for the specific estimates and significance levels for all motivational variables). This was unexpected as it was anticipated that, when faced with a change, self-efficacy would be low, as confusion and lack of confidence in one's ability would set in and goals would follow suit. However, instead of an abrupt drop (as was seen in performance), there was a significantly negative decrease in these variables throughout the adaptation environment. Although positive slopes were predicted for self-efficacy and goals, given the elevated initial levels, significantly negative slopes were reasonable. Therefore, although Hypotheses 6a and 6b were not supported, it appears that this may have been due to initial overconfidence in their ability to adapt, which subsequently resulted in inflated goals. Outcome-oriented effort behaviors also followed an odd trajectory in the adaptation environment as they also started significantly elevated, suggesting that individuals did not pause to learn how to adapt but continued to work hard despite their effort likely being incorrectly placed. It is possible that this was due to overconfidence in their ability. Furthermore, the slope of outcome-oriented effort behaviors in the adaptation environment decreased, not supporting Hypothesis 6c, which proposed that there would be a low intercept and positive slope, as was found with self-efficacy and goals. However, it should be noted that the component complexity condition did not have a significantly decreasing slope, showing that individuals in that condition (where the number of targets increased twofold) correctly assessed the situation and recognized that effort had to remain elevated.

Given the differences in the trajectories in the motivation variables in the adaptation environment, it is not surprising that they should be different in the performance environment as well. Hypotheses 7a, 7b, and 7c suggested that self-efficacy, goals, and outcome-oriented effort would all follow the pattern of a significantly high intercept with a significantly positive slope. Instead of self-efficacy, goals, and outcome-oriented effort strongly increasing over that period of time, they stabilized at a lower level for the duration of the performance environment (see Table 10 and Figure 11). This suggests that although individuals faced the adaptation trials with overconfidence, they eventually stabilized their self-efficacy, goals, and effort. Self-efficacy, goals, and effort had levels significantly higher than zero at the beginning of the performance environment, thereby not supporting Hypotheses 7a, 7b, and 7c, but providing some promise that the hypotheses may hold true in other experiments in that the intercept was as expected, while the slopes were not. It should be noted that self-efficacy and outcome-oriented effort behaviors in the coordinative complexity condition did significantly decrease in the performance environment, most likely due to the increased difficulty of the task, and participants being encouraged to work smarter, not harder. Thus, effort decreasing is not surprising, as in that condition (where the strategy was shifted) fewer, but more targeted behaviors, led to more effective outcomes, but these behaviors were more challenging to identify and execute.

Table 9
Latent Growth Curve Analyses of Cognitively Focused Variables

Environment	*Variable*	*Element*	*Parameter*	*Std. Er*	*DF*	*t-value*	*p-value*
	Metacognition	*Intercept*	*3.339*	*.161*	*2062*	*20.705*	*.000*
	(Hypothesis 4a)	*Slope*	*-.003*	*.008*	*2062*	*-.0427*	*.669*
	Evaluation	*Intercept*	*50.286*	*2.785*	*2062*	*18.059*	*.000*
Adaptation	*(Hypothesis 4b)*	*Slope*	*-1.385*	*.125*	*2062*	*-11.044*	*.000*
	Learning Effort	*Intercept*	*23.158*	*4.367*	*2062*	*5.302*	*.000*
	(Hypothesis 4c)	*Slope*	*-.522*	*.201*	*2062*	*-2.598*	*.010*
	Metacognition	Intercept	3.522	.164	2889	21.421	.000
	(Hypothesis 5a)	Slope	-.014	.006	2889	-2.617	.001
	Evaluation	Intercept	38.185	1.930	2889	19.789	.000
Performance	*(Hypothesis 5b)*	Slope	-.835	.062	2889	-13.493	.000
	Learning Effort	Intercept	30.303	3.446	2889	8.794	.000
	(Hypothesis 5c)	Slope	-.879	.108	2889	-8.139	.000

Figure 10
Trajectories of Cognitively Focused Variables

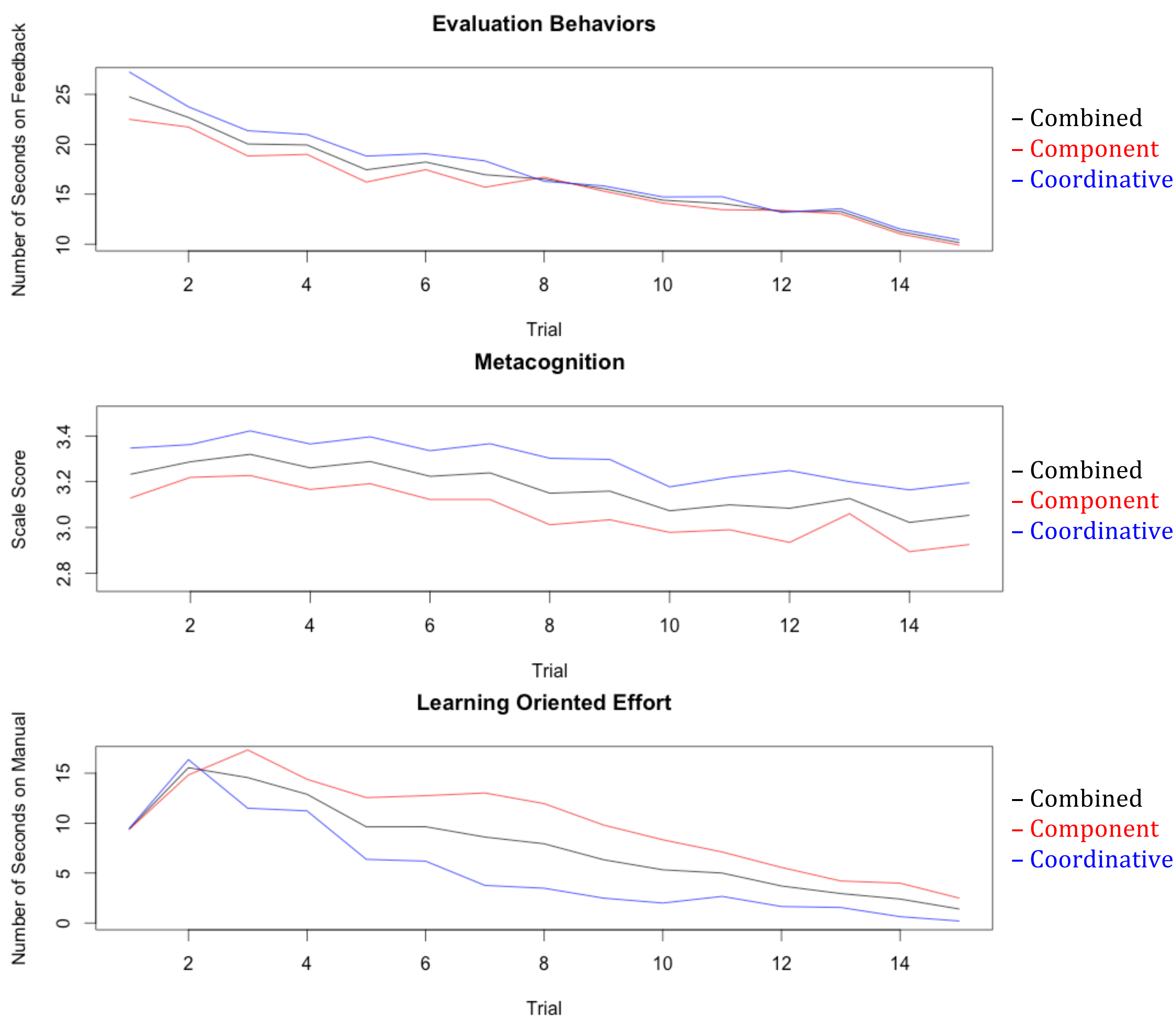
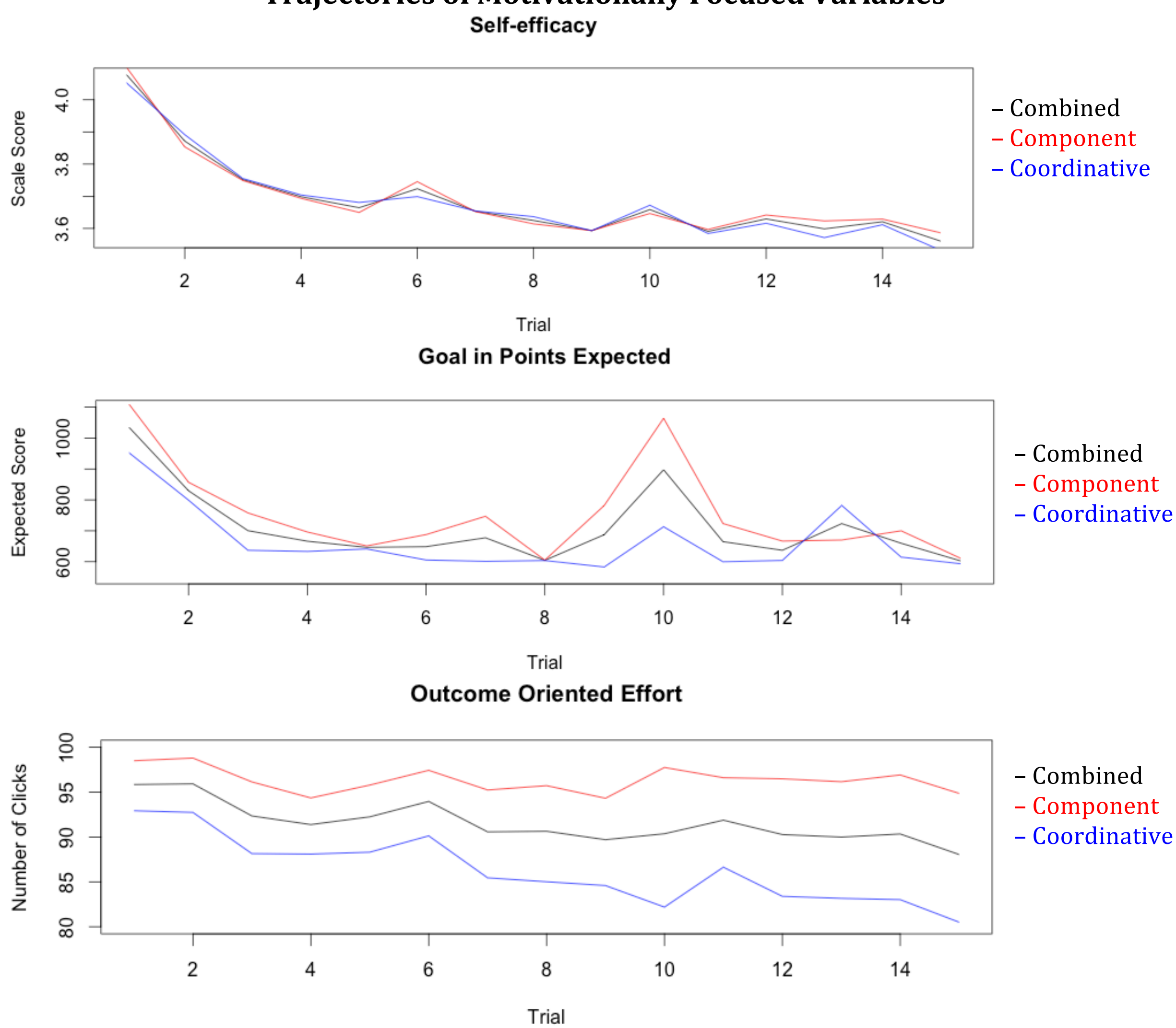


Table 10
Latent Growth Curve Analysis of Motivationally Focused Variables

Environment	*Variable*	*Element*	*Parameter*	*Std. Er*	*DF*	*t-value*	*p-value*
Adaptation	*Goals (Hypothesis 6a)*	*Intercept*	*2296.626*	*133.913*	*2062*	*17.150*	*.000*
		Slope	*-71.733*	*5.700*	*2062*	*-12.584*	*.000*
	Self-efficacy (Hypothesis 6b)	*Intercept*	*5.302*	*.134*	*2062*	*39.695*	*.000*
		Slope	*-.070*	*.007*	*2062*	*-10.573*	*.000*
	Outcome effort (Hypothesis 6c)	*Intercept*	*106.472*	*3.709*	*2062*	*28.708*	*.000*
		Slope	*-.598*	*.164*	*2062*	*-3.644*	*.000*
Performance	*Goals (Hypothesis 7a)*	*Intercept*	*931.561*	*365.522*	*2889*	*2.549*	*.011*
		Slope	*-8.376*	*11.870*	*2889*	*-.706*	*.481*
	Self-efficacy (Hypothesis 7b)	*Intercept*	*3.770*	*.153*	*2889*	*24.684*	*.000*
		Slope	*-.005*	*.005*	*2889*	*-1.079*	*.281*
	Outcome effort (Hypothesis 7c)	*Intercept*	*96.503*	*4.228*	*2889*	*22.825*	*.000*
		Slope	*-.216*	*.141*	*2889*	*-1.530*	*.126*

Figure 11
Trajectories of Motivationally Focused Variables



Understanding Relationship Changes

Hypotheses 8 through 19 focused on the relationships among the self-regulatory variables in the adaptation and performance processes. All relationships in both processes were tested in one partially crossed, partially time-varying, cross-lag panel regression model with seven variables. Just as the two adaptive conditions were combined in the trajectory analyses, so they were combined in this model, removing Trial 25 to ensure consistency of the two processes. This removal was due to the difference in the transition between the performance and adaptation environments (which put Trial 25 in the performance environment for the component condition but in adaptation for the coordinative condition). Therefore, for consistency in the description of the processes, this trial had to be removed from this analysis in order to combine the two conditions.

As the variables were of different scales (e.g., self-efficacy on a five-point Likert scale versus evaluation of feedback information measured in zero to 60 seconds versus performance ranging from about -2,000 to +2,000), in order for the maximum likelihood estimation to work properly, all variables were standardized. The model fit was not excellent, but will be retained for the purposes of analyzing the theoretical model as well as possible, particularly since research have not investigated what the norm of cross lag model fit statistics should be ($X^2(5408) = 19983.202$, $p<.000$, RMSEA = .081, CFI = .691).

Before continuing to the analysis of the hypothesized relationships in the adaptation and performance processes, I would like to discuss one important element of the cross-lag model: the autoregressive components. Although not hypothesized, the autoregressions were all expected to be significantly and positively related to each other, showing that previous levels of the variables were associated with subsequent levels of the variables.

The reason these relationships were not hypothesized is that it is understood that from one time point to the next, variables are more similar to each other than not (DeShon, 2012). The results of the cross-lag model show that, across both the adaptation and performance environments, the autoregressive estimates of performance and all the self-regulatory variables were positive and significant (see Table 11). The positive autoregression estimates are critical to consider, given that some of the findings among the relationships appear to be confusing based on their trajectory differences. However, when removing the variance due to the previous level of a variable, it opens up the possibility that other variables may have an opposite relationship, but that the positive relationship between the previous and subsequent levels of that variable was so strong that the trajectory continued in the same direction as earlier. For example, performance increased over time and the autoregressive component suggests that the level in the prior trial was strongly associated with an increase in the subsequent trial; contrarily, metacognitive behaviors decreased over time and the autoregressive component suggested that a decrease in the last trial led to a decrease in the next. When considering the predictive relationship between metacognition and performance, it is important to consider that previous performance as well as previous metacognition is being used to predict subsequent performance. Therefore, the relationship could be positive or negative, based on fluctuations in the variables between time points, as opposed to the overall trajectories of the variables.

The following paragraphs will take each hypothesis in the order it was initially presented, beginning with the cognitive cycle. See Table 12 for the parameter estimates, summary of the findings, and support for the hypotheses and Figure 12 for a visual representation of the theoretical and empirical models for both processes.

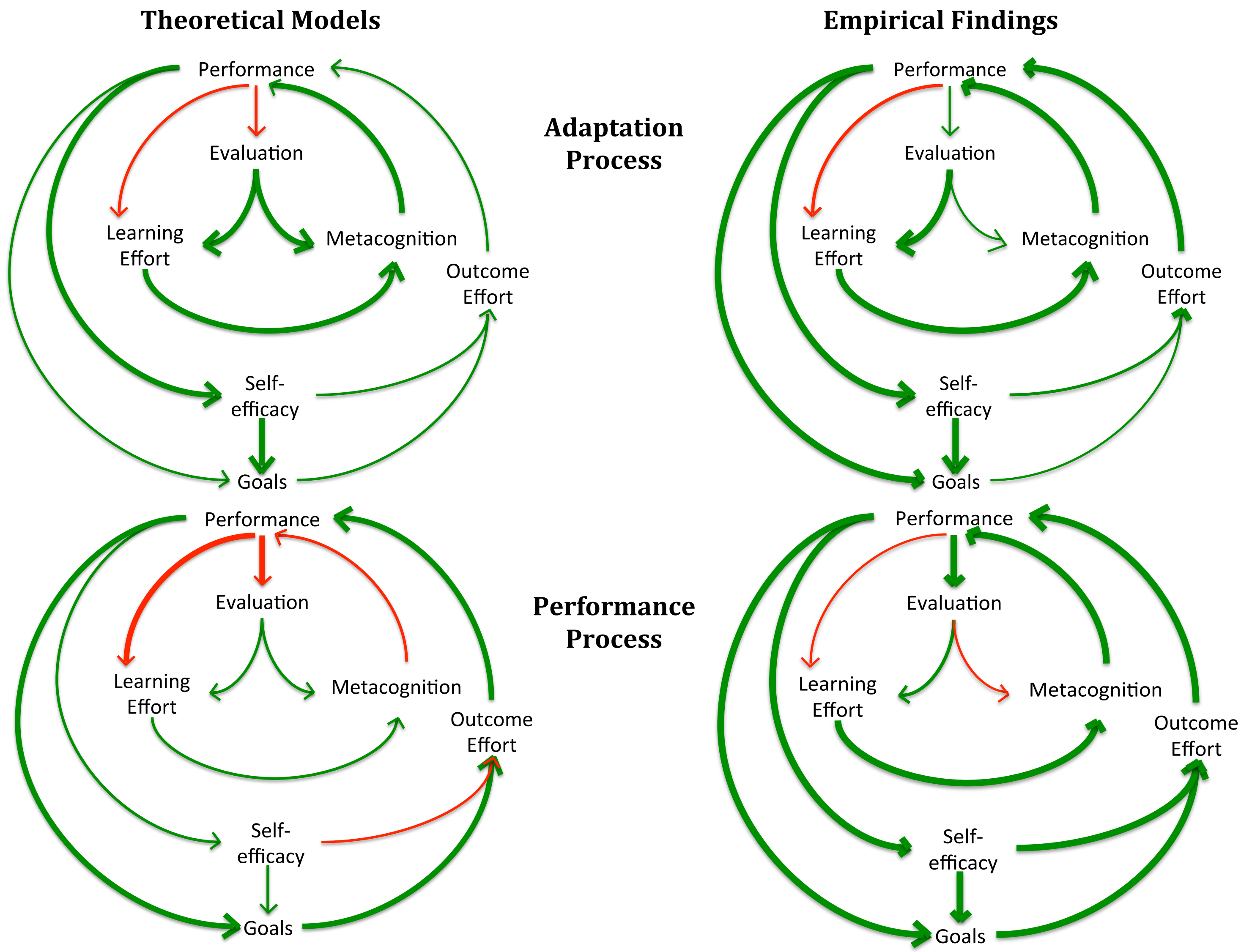
Table 11
Autoregressive Results from the Cross-Lag Model

Cognitive Variables				Motivation Variables			
Variable	**AR estimate**	**Std. Error**	**p-value**	**Variable**	**AR estimate**	**Std. Error**	**p-value**
Learning Effort	.424	.011	.000	Goals	.697	.004	.000
Metacognition	.847	.007	.000	Outcome Effort	.884	.006	.000
Evaluation	.313	.012	.000	Self-efficacy	.849	.007	.000
Performance	.556	.010	.000				

Table 12
Summary of Hypotheses and Results from the Cross-Lag Model

#	Hypothesis	Process	CL Estimate	Std. Error	p-value	Summary of Results
8a	*Performance→ Learning Effort: Weak -*	*Adaptation*	-.032	.022	.145	Supported
8b	Performance→ Learning Effort: **Strong** -	Performance	-.003	.010	.724	Not Supported
9a	*Learning Effort→ Metacognition: **Strong** +*	*Adaptation*	.039	.010	.000	Supported
9b	Learning Effort→ Metacognition: Weak +	Performance	.007	.011	538	Supported
10a	*Metacognition→ Performance: **Strong** +*	*Adaptation*	.040	.015	.007	Supported
10b	Metacognition→ Performance: Weak -	Performance	.054	.011	.000	Not Supported
11a	*Performance→ Evaluation: Weak -*	*Adaptation*	.041	.022	.063	Not Supported
11b	Performance→ Evaluation: **Strong** -	Performance	.051	.011	.000	Not Supported
12a	*Evaluation→ Learning Effort: **Strong** +*	*Adaptation*	.063	.020	.002	Supported
12b	Evaluation→Learning Effort: Weak +	Performance	.083	.013	.000	Not Supported
13a	*Evaluation→Metacognition: **Strong** +*	*Adaptation*	.014	.012	.256	Not Supported
13b	Evaluation→Metacognition: Weak +	Performance	-.008	.010	.444	Not Supported
14a	*Performance→ Goals: Weak +*	*Adaptation*	.083	.008	.000	Not Supported
14b	Performance→Goals: **Strong** +	Performance	.067	.006	.000	Supported
15a	*Goals→Outcome Effort: Weak +*	*Adaptation*	.016	.015	.284	Supported
15b	Goals→Outcome Effort: **Strong** +	Performance	.020	.006	.001	Supported
16a	*Outcome Effort→ Performance: Weak +*	*Adaptation*	.236	.017	.000	Not Supported
16b	Outcome Effort→ Performance: **Strong** +	Performance	.275	.012	.000	Supported
17a	*Performance→Self-efficacy: **Strong** +*	*Adaptation*	.087	.011	.000	Supported
17b	Performance→Self-efficacy: Weak +	Performance	.094	.009	.000	Not Supported
18a	*Self-efficacy→Goals: **Strong** +*	*Adaptation*	.049	.008	.000	Supported
18b	Self-efficacy→Goals: Weak +	Performance	.029	.006	.000	Not Supported
19a	*Self-efficacy→ Outcome Effort: Weak +*	*Adaptation*	.016	.010	.108	Supported
19b	Self-efficacy→ Outcome Effort: Weak -	Performance	.030	.008	.000	Not Supported

Figure 12
Comparison of the Theoretical Model and Empirical Findings



Results of the Cognitive Cycle. Hypothesis 8a suggested that performance would have a weak and negative cross-lag relationship during the adaptation process given that, initially, performance would be low but growing, while learning-oriented effort would be high and remain so. This finding was consistent with the hypothesis. As individuals shift to the performance process, Hypothesis 8b suggested that these variables would have a strong negative relationship; however, similar to the adaptation process, the variables had a weak negative cross-lag relationship, showing only partial support for the hypothesis. This suggests that when performance increased, less learning-oriented effort was required. The weakness of this relationship may be partially due to the relative stability of both performance and learning-oriented effort, causing a lack of variance from which strong predictions can be made.

Hypothesis 9a stated that learning-oriented effort would have a strong and positive impact on subsequent metacognition behaviors in the adaptation process as investigating information outside of the task would lead to the testing of new strategies during the task. The findings support this expectation. Unlike the strong positive relationship between learning-oriented effort and metacognition in adaptation, Hypothesis 9b suggested that this relationship would become weak after the shift to the performance process, given that both of these variables would decrease over time and the lack of variance would result in a non-significant relationship. This was also supported by the findings.

Hypothesis 10a presented the expectation that metacognition and performance would have a strong and positive cross-lagged relationship in the adaptation process, as it was posited that increased focus on strategy development during the prior trial would result in higher performance in the next. The results supported this hypothesis. However, Hypothesis 10b postulates that as individuals shift to the performance process, the relationship would become weak and negative, as it was anticipated that when more effort was devoted to strategy development and testing during a more routine environment, then less effort could be devoted to the execution of the task. The results did not support this expectation as it was found that these variables had a positive cross-lagged relationship, suggesting that despite the decrease in metacognitive behaviors over the course of the performance environment, metacognitive increases or decreases were associated with similar patterns in performance. This may have been due to the sawtooth pattern that both of these variables followed, resulting in a positive relationship despite differences in the trajectories. In other words, if both metacognition and performance followed the same pattern (i.e., increasing, then decreasing), then the consistent fluctuations, though small, can show a strong positive relationship. Although this finding was unexpected, it may speak to a critical difference between standard trajectory analyses and cross-lag analyses in their ability to detect such interesting nuances. This will be revisited in the discussion section.

In Hypothesis 11a, performance was expected to have a weak and negative impact on subsequent evaluation behaviors in the adaptation process, suggesting that when individuals had poor performance in one trial, there would be a greater need to perform evaluation activities in the subsequent trial. The results show partial support for this hypothesis in that the relationship was weak, though positive. Similarly, when transitioning the performance process, Hypothesis 11b suggested that the relationship between previous performance and evaluation behaviors would be negative and stronger, as it was expected that individuals would understand the change in the environment and thus not need to investigate feedback information to continue to perform effectively. However, the results did not support this hypothesis in that there was a strong positive relationship. The results of the test of these hypotheses (11a and 11b) may have been influenced by the sawtooth pattern of performance and evaluation, similar to the impact on metacognition and performance, as discussed in relation to Hypothesis 10b. In that case, these relationships pointed to an interesting outcome of conducting a cross-lag analysis rather than just showing trajectory changes. These results show that despite the trajectories of performance increasing and evaluation behaviors decreasing over time (Hypotheses 1a, 1b, 4b, and 5b), investigating the relationships between the variables presents a different look into the process. The positive relationship may suggest that as performance decreased, individuals became apathetic to the outcome, and therefore did not investigate feedback to attempt to determine why that was. On the other hand, it may suggest that when performance increased, after having decreased in the previous trial, subsequent feedback evaluation increased, possibly to ascertain what was done correctly in order to attempt to replicate those behaviors in the next trial.

Hypothesis 12a proposed that evaluation behaviors would have a strong positive relationship on subsequent learning-oriented effort behaviors. This finding was consistent with the hypothesis, showing that, if individuals increased in evaluation behaviors in the prior trial, they decreased in learning-oriented effort behaviors in the next trial. Similarly, Hypothesis 12b, suggested that the lagged relationship between evaluation and learning-oriented effort would also be positive, but would become weaker as individuals transitioned to the performance process, given that there was expected to be less variance available to be explained in these variables. This prediction was partially supported in that there was a positive relationship, but it was strong. This may have been due to the fact that, although both of these variables decreased over time, any fluctuations in these variables may have caused a strong positive prediction.

The last of the relationships in the cognitive cycle was that of evaluation and metacognition, and Hypothesis 13a explained that there should have been a strong positive relationship in the adaptation process, as increases in feedback seeking (i.e., evaluation) were expected to result in more metacognitive activities during the task. The results of the analysis partially supported this hypothesis, in that there was a positive relationship, albeit a weak one, when a strong positive relationship was predicted. This may have been due to evaluation following a sawtooth pattern but metacognition having a relatively stable trajectory during adaptation. Contrary to Hypothesis 13a, 13b suggested that the lagged relationship should become weak, though still positive, as individuals transitioned to the performance process, since the expected low levels of metacognition and evaluation were expected to result in less variance and, therefore, in a weaker relationship. This hypothesis was not supported by the data, in that the relationship was weak, but negative. It is possible that this negative relationship was due to the sawtooth trajectories of the variables. The negative relationship suggests that, as previous evaluation behaviors increased, metacognitive behaviors decreased. Given the interpretation of Hypothesis 11b regarding the positive relationship between previous performance and subsequent evaluation behaviors, it may have been the case that as individuals investigated their feedback following increased performance and determined what elements were correct, subsequently less metacognitive effort was required. Similarly, when fewer feedback behaviors were employed, individuals may have decided to devote their effort to changing metacognitive strategies instead. These series of interesting relationships among performance, evaluation, metacognition, and subsequent performance will be reviewed in more detail in the discussion section.

Results of the Motivational Cycle*.* As Hypothesis 14a stated, performance was expected to have a weak and positive lagged impact on goals in the adaptation process, given that performance would not likely be calibrated to goals initially, as the change was in the process of being understood. The results indicate a strong positive relationship, not supporting Hypothesis 14a, though it shows that performance maintained its positive impact on goals despite the differences in trajectories, likely due to the strong sawtooth pattern in performance and the weak one in goals. Hypothesis 14b suggested that, as individuals transitioned to the performance process, the relationship between performance and goals was expected to be even stronger, as goals were anticipated to be better calibrated as the change was understood. This hypothesis was supported by the data.

The next link in the motivational cycle was the relationship between goals and outcome-oriented effort. Hypothesis 15a predicted that there would be a weak positive cross-lag relationship, given that goals would not likely be well-calibrated during the adaptation process. Results support this prediction. Similar to the change in the relationship between performance and goals, Hypothesis 15b suggested that, in the performance process, the relationship between previous goals and subsequent outcome-oriented effort would transition from weak to strong, given that goals were expected to be better calibrated in this process. The finding supported the hypothesis.

Hypothesis 16a proposed that, in the adaptation process, outcome-oriented effort behaviors would have a weak and positive impact on subsequent performance, indicating, as more effort is devoted to the task, higher performance would result. However, this would be weakened by the fact that, in the adaptation phase, effort would not be well-calibrated to understand what aspects of the task had changed and how that impacted performance. Results show partial support for the hypothesis in that the relationship was positive but strong, instead of weak. This suggests that individuals were able to more quickly calibrate their effort to their performance, even directly after the change. This may have been due to the fact that, in the component condition in particular, increasing effort was related to better performance, thus, even slight increases in effort would result in better performance. When transitioning to the performance process, Hypothesis 16b suggested that, similar to the previous motivational relationships discussed, the lagged relationship between outcome-oriented effort and performance would transition to have a strong and positive relationship in the performance phase, as effort would be better-calibrated in this phase. The findings were consistent with this hypothesis.

Hypothesis 17a proposed that performance would have a strong and positive impact on subsequent self-efficacy in the adaptation phase, as increases in performance, despite the initial decline, would be associated with later increases in confidence in their ability to handle the new environment. The results show support for this hypothesis. Hypothesis 17b also proposed that the lagged relationship would be positive as individuals transitioned to the performance process, but would become weak, given the expectation that self-efficacy would stabilize, resulting in less variability for prediction. Results from the analysis showed partial support for the hypothesis in that the relationship was positive, but strong. This suggests that, even in the performance phase, performing well or poorly continued to impact self-efficacy, showing that individuals may have thought the task was continuing to change. This conclusion is partially based on the misinterpretation apparent in the responses to the self-report variable that asked participants to explicate what changed in the task itself, during the current trial (when the change was introduced), about which they instead reported what they thought changed from the last trial.

Hypothesis 18a anticipated that in the adaptation process, self-efficacy would have a strong and positive impact on subsequent goals, given that belief in ability has been shown to have a strong impact on goals created. This was supported by the results. However, when shifting to the performance process, it was expected that this positive relationship would have a weaker effect, given that both variables were expected to have less variability. Thus, the result of the analysis did not show support for Hypothesis 18b in that the relationship was positive; instead, the relationship was stronger than anticipated. This suggests that even small fluctuations in self-efficacy predicted fluctuations in goal levels.

For the final relationship of the motivational cycle, Hypothesis 19a stated that self-efficacy was expected to have a weak and positive impact on subsequent outcome-oriented effort behaviors, given that expectations of ability in a new environment were anticipated to help individuals persist in a difficult situation, despite the fact that individuals may not have their effort well-calibrated initially. Results show support for this hypothesis. Unlike in the adaptation process, Hypothesis 19b proposed that, in the performance process, self-efficacy was expected to have a weak and negative impact on subsequent outcome-oriented effort behaviors given that research suggests that overconfidence can lead to less effort being devoted to the task. Results did not support this hypothesis, instead showing that there continued to be a positive relationship, and a strong one at that. Given that self-efficacy stabilized at a relatively low level, this may have accounted for the maintenance of effort despite transitioning to the performance process.

DISCUSSION

The purpose of the study was to present a theory of the process of adaptation, specifying the dynamics involved, theoretically distinguishing adaptation from routine performance, and empirically presenting evidence for such a distinction. This research was necessary given that the literature has not yet empirically investigated adaptation as a process (Baard et al., 2014), and the self-regulatory processes, typically associated with the conceptualizations of the process, have not been examined longitudinally (e.g., Kozlowski et al., 1996; Burke et al., 2006). However, the workplace continues to require individuals, teams, and organizations to adapt to new situations. Given this need and the fact that many of the proposed hypotheses were supported, the present research has the ability to inform individuals and organizations in how they can better prepare for adaptive situations.

In this last section, I will structure my thoughts in the following way. First, I will discuss the interesting elements discovered concerning the trajectory changes in performance and the self-regulatory variables, presenting both what was expected and what was not. Then, I will move to describe the relationship changes in both the adaptation and performance processes, focusing mostly on what was not expected, since the results show support for many of the hypotheses. Therefore, an exhaustive discussion on them would be redundant to the theoretical framing previously presented. Next, I will summarize the findings of the overall process, as well as some higher-level observations about the results. Finally, I will move onto the practical implications, limitations, and opportunities for future research prior to my concluding remarks.

Discussion of the results

1st Order Changes: Transition and Trajectories

The first step in understanding when the adaptation process began and ended was through identifying the transition point that separated the adaptation and performance processes in the conditions. The results demonstrated that the coordinative complexity condition had a later transition point, suggesting that that type of change is more difficult to adapt to than a component complexity change, supporting Wood's (1986) conceptualization and the continuum of change types proposed in Figure 1 earlier. This finding extends the research by Lang and Bliese (2009) in applying the analysis of discontinuous growth curves to not only separate performance occurring after a change (rather than just the transition point to identify when adaptation began) but also in applying it to a non-performance variable (i.e., focus of effort) to provide additional support for the transition point. This suggests, even though the performance trajectories were slightly different between the conditions (i.e., the trajectory of performance in the coordinative condition was non-significant during the adaptation process and increased in the performance process, while the component complexity condition had the opposite finding), this analysis can be used to examine variables other than performance to understand changes over time. Furthermore, the results on the trajectory differences present an interesting situation. It would appear the coordinative complexity condition did not adapt *if* the adaptation environment was only defined by performance increasing and *if* the performance environment was only defined by performance stabilizing during this period. However, using the self-regulatory variable that measured the focus on learning versus execution allowed for the process to be the focus, not just performance. These results may suggest that although performance trajectories may look slightly different based on the level of difficulty of the change, the process duration may be more similar. In other words, more difficult changes will result in a lag in performance such that, even though the adaptation process is completed (i.e., individuals have all the information they need to understand what they need to do), performance will take longer to be corrected than if the change was easier to identify and understand. It would be interesting for a conversation to begin in the literature regarding whether performance should be the primary way in which adaptation is diagnosed (as is the favored approach in the current adaptation literature; e.g., Bell & Kozlowski, 2008; Dorman & Frese, 1994; Keith & Frese, 2005; Lang & Bliese, 2009; Mathieu et al., 2000), or whether this should be accomplished with some other factor (e.g., a focus on learning versus a focus on execution) that should drive our understanding of whether the adaptation process is complete or not.

The majority of the trajectory changes of the cognitive variables in both the adaptation and performance environments were as expected. This provides additional evidence to the literature that has long suggested that there is a high need to cognitively evaluate changes that occur in the environment and the ramifications of various possible actions.

The motivational variables, however, did not follow the expected trajectories. Instead of self-efficacy and goals dropping suddenly after the adaptive change was introduced, individuals appeared to have overinflated levels of these regulatory variables. This may have been caused by the artificial setting, with little at stake, but may also be attributable to individuals not being aware of their own ability to adapt, showing a lack of self-awareness. This speculation is supported by the positively skewed responses to the

IADAPT questionnaire in which individuals had higher responses than a normal distribution would dictate. The Shapiro-Wilk test for normality indicated that the IADAPT measure was non-normal ($W=.992$, $p=.006$). Further investigation indicated that this non-normality was positively valenced, with the mean of the adaptability measure being 3.642 and the standard deviation equaling .313 (while the scale only ranged from one to five). Furthermore, there was range restriction of this measure, with the minimum being 2.728; and the maximum, 4.8. This suggests that not only in this task, but in general, individuals are overconfident in their ability to deal with adaptive situations. There are pros and cons to this finding. On the positive side, maintaining high levels of self-efficacy and goals may show that individuals felt well-prepared to handle the challenge of the change. However, the quick decrease in self-efficacy and goals over the next few trials suggests that individuals lost that confidence as the task continued to be challenging and performance was not increasing rapidly. On the other hand, overconfidence has the ability to distort one's perspective on the task, resulting in less motivation, if performance does not immediately increase, or in a lack of adaptation, if the performance decrease is not taken seriously. Thus, it appears that the general overconfidence individuals have in their adaptability will likely have a negative impact on their ability to adapt. Perhaps more training on effective adaptive techniques (e.g., where to get information if a change should occur, or how to develop different strategies) may help individuals better align their self-efficacy and goals in adaptive situations.

Finally, the similarity in these trajectories across the two conditions (component and coordinative complexity changes) lends support to the conclusion that, although changes may be different in difficulty and type, individuals engage in the same adaptation process. This has large ramifications for both research and practice, as theories can be developed with multiple types of changes in mind, and organizations can implement trainings or learning initiatives that are not job specific but rather focused on the general principles presented in this study.

2^{nd} Order Changes: Relationships

Although the trajectory changes of the cognitive variables were as expected, not all of the relationship changes were. On the other hand, the motivational variables had very unexpected trajectories, yet their relationships were mostly as expected. This presents an interesting difference in the ways in which dynamics are investigated. Unlike single variable, single process growth curve analyses, the partially crossed, partially time varying cross-lag panel regression analysis incorporates all variables involved in the processes into one analysis, providing a very holistic approach to the examination of the changes in the processes. Furthermore, the cross-lag analysis estimates an autoregressive term which accounts for the variance associated with previous levels of that same variable, which appears to have had a large impact on the relationships estimated. This will be discussed in more detail as I focus on the cognitive and motivational sub-cycles.

Cognitive Cycle Observations. Of particular interest in this sub-cycle were the lagged relationships between initial performance, evaluation, metacognition, and subsequent performance. For one, all the paths in the adaptation process were positive although performance was increasing while metacognition was somewhat stable and evaluation was decreasing. The positive cross-lag relationship between performance and evaluation may have been due to individuals desiring the continuance of increasing performance by seeking more feedback, even when performance was increasing (rather than decreasing). This appeared to lead to somewhat more metacognitive behaviors (checking on strategy effectiveness), which lead to even better performance in the next trial. Individuals may also have not wanted to focus on their failures and instead were more motivated to look at feedback when their performance was higher. Finally, the positive relationship between metacognition and performance may have been due to the similar sawtooth pattern that developed for all of these variables. This suggests that even though the trajectories were in the opposite direction (with metacognition being slightly negative and performance being positive), accounting for the previous levels of these variables (i.e., the autoregressive component) allowed for the remaining variance to be distributed differently such that instead of an expected negative relationship, the result show a positive relationship due to the way in which they fluctuated and not their overall trajectories. This presents an interesting conclusion – trajectories and relationships tell different parts of the story when it comes to unpacking a dynamic process.

In the performance process, the three pathways discussed above were in the opposite direction as predicted. Similar to the above, the relationship between performance and evaluation being positive may have to do with a desire to continue to increase performance (and is likely driven by the coordinative complexity condition where performance did not stabilize in the performance environment). However, that positive relationship may be associated with the fatigue individuals faced as the experiment continued, resulting in evaluation behaviors being less frequent. Considering there was a strong relationship between performance and evaluation in the performance process, it makes sense that if more evaluation were conducted in the previous trial, this would lead to less subsequent metacognitive behavior. For instance, if more participants spent time evaluating performance in a routine environment, and receiving feedback that effective performance levels were achieved, it is less likely that more effort would need to be devoted to thinking about different strategies to enhance performance. However, it is still logical to assert that thinking about more effective strategies, even if the thinking is not entirely necessary, would lead to enhanced performance given that more efficient strategies to deal with the task may be discovered. This logic supports the positive relationship between metacognition and performance, although that relationship was not anticipated. It is likely that, with an extended investigation of the performance process, this may change when it is clear to the individual that the task is no longer changing and that spending time strategizing may not be beneficial. This positive relationship may have been enhanced given that individuals may not have recognized that the task ceased to change, particularly in the coordinative condition.

Motivational Cycle Observations. Of particular interest in the motivational sub-cycle was the consistently positive impact of motivation. As expected in the adaptation process, the relationship between performance and self-efficacy was high, even with the sawtooth pattern of performance, the relationship between self-efficacy and goals was strong, and the relationships between self-efficacy and effort, and goals and effort, were weak. This is understandable given that, even though one may feel more confident or set higher goals, effort may not follow that increase either because they are already performing at a maximal level, or because effort may not have been well-calibrated in an adaptive environment where the change is still not understood. It was, however, surprising that performance would have a strong positive impact on goals in the adaptation process, rather than the expected weak positive relationship, but this may have been an artifact of goals being measured on the same scale and very soon after performance feedback was available. This may have resulted in the two scores being more related than if these two factors were different. It appears that when performance was poor, individuals set a lower goal; however, when performance was high, they set a higher goal, despite their not fully understanding why. Also somewhat unexpected was the strong positive relationship between outcome effort and performance. The trajectories of the two conditions show that this relationship may have been primarily influenced by the component condition, as they maintained effort levels over time given that the nature of the adaptive change required a high level of effort behaviors.

The performance process also correctly anticipated that there would be strong positive relationships between performance, goals, outcome effort, and performance. However, it was unexpected that there would be a strong relationship between performance and self-efficacy. This may have been due to self-efficacy stabilizing at a level lower than expected, perhaps showing a need to extend the measurements of the performance environment to capture the process for longer period of time to see if self-efficacy would recover. There was also a strong relationship between self-efficacy and goals, even though only a weak one was anticipated. This may have been due to both variables being low in level, but still following a small sawtooth pattern, possibly resulting in even small changes in the variables but in the same direction, which is likely the contributing factor for the strong relationship. Most surprisingly, was the positive relationship between self-efficacy and outcome effort. The literature suggests that there would be a negative relationship, since overestimation of ability would lead to less effort being devoted to the task. The findings suggest that there may have been insufficient time to capture the performance process or it may have been an artifact of both variables having less variance over time. However, given the sawtooth trajectories, the small fluctuations in the same direction may have caused the resultant significant relationship.

Although much of the explication above has been focused on the interesting, unexpected elements of the results, the preponderance of the evidence suggests that the findings are consistent with many aspects of the theory. This is evident in that although several hypotheses were not supported, they were in a promising direction where the relationship was strong instead of weak (or vice versa, though that was much less common) or when the weak relationship (i.e., non-significant) was positive rather than negative. This is promising given that a null relationship was expected in any event, and also since this was the first attempt to specify the relationship changes between processes in as detailed a way as to present weak and strong relationships. The next section will take a more macro view of the findings to discuss the ramifications of the results.

Overall Observations of the Results

First, motivation was more important in the adaptation process than expected. This suggests that more motivated individuals, regardless of their overconfident state, were able to increase their performance in an adaptive environment. Thus, even in the face of a change, maintaining confidence in one's ability, pursuing high goals, and putting forth effort remained just as valuable in the adaptation process as it was in the performance process, despite participants' not fully understanding the impact of their behaviors, as they would in a more typical performance environment.

Second, cognition was more important in the performance process than expected. This suggests that maintaining a level of understanding of the impact of one's actions on performance outcomes was still beneficial in a performance environment. This may also indicate that there was insufficient time to capture the performance process, particularly since performance followed a sawtooth pattern. It is possible that this situation may have confused the participants, causing them to believe that they were not operating in a truly routine performance environment, but rather one that was more dynamic than it was before the change. Although this was not the case and the task scenarios fluctuated just as they had before the change, the additional complexity of the task, coupled with small task variations (e.g., positioning of the targets, changing the types of targets), may have given the impression that the task had not yet stabilized and changes were consistently being introduced.

Third, although the processes appear similar at first glance from the results presented here, it is likely that they are still distinct. The number of trials given in this experimental design were likely insufficient to capture the performance process, particularly given that performance in the coordinative complexity condition did not stabilize. This is a limitation of a laboratory design, as fatigue was already evident and extended time would likely not be possible. Therefore, a field setting would provide insight into what the processes may look like without the fatigue factor, which may have caused self-efficacy and goals to stabilize at such a low level during this study. Although these items would not be able to be measured in the same way, it is likely that variables, such as self-efficacy, would rebound slightly, or individuals would voluntarily (or involuntarily) leave the organization. Alternatively, the possibility that participants may have felt as if they were not in a routine performance environment (given the sawtooth trajectory of performance), as discussed earlier, could have resulted in the variables having more fluctuations in the performance process than expected, resulting in stronger (and possibly more positive) relationships in both processes. This may have contributed to the similarities evident in the results.

Finally, and most critically, the differences in the conclusions of the trajectory changes as compared to the relationship changes strongly indicate that it is necessary for research to be conducted not only beyond investigating performance trajectories but also expanded beyond exploring the trajectories of the self-regulatory variables to truly capture the dynamics of processes. This is probably the most essential contribution of this dissertation in that it empirically explicates that investigating trajectory changes is insufficient for examining a process. Without examining the relationships, it would have been assumed from the trajectories of the motivational variables, that there would be a negative relationship with performance in both of the processes. However, the cross-lag analysis shows that this was not the case, likely because this analysis examines the data in a very different way. First, it accounts for the variance due to the variable at the last time point tending to remain on the same path at the next point (the autoregressive component). Second, it allows the remaining variance to then be distributed among the variables that are predicting it. Therefore, even though goals were decreasing in the adaptation process while performance was increasing, there can still be a positive relationship with the remaining variance. This is directly interpreted as: controlling for the fact that previously low levels of goals tended to elicit similarly low goals in the subsequent trial, the changes in goal level were positively related to performance such that as performance increased between those two trials, and goals followed suit and deviated from the path that they would take otherwise. This research not only is among the first to provide specific dynamics in the theorizing of the adaptation process, but it is the first endeavor to utilize an analytical model to test whether the anticipated dynamics provided an accurate picture of the process.

Practical Implications

As it was mentioned briefly above, this research extends the adaptation literature by not only adding to the few efforts that have conceptualized adaptation as a process incorporating self-regulatory mechanisms, but it is the first to specifically theorize the trajectory and relationship dynamics involved. Furthermore, this study utilized analyses that appropriately examined a process framework. This will hopefully encourage and assist future researchers to make similarly specific dynamic hypotheses and test them appropriately. The utility in examining adaptation as a process does not merely lie in its novelty, but it is because processes are typically generalizable, at least to a certain extent, and processes can be influenced (e.g., through training), unlike an individual difference or a performance dimension. The similarity between the trajectories, and relationships between the two complexity conditions, lend further support to the robustness of the adaptation process in explaining behavior across different types of changes. Therefore, contributing to this perspective of adaptation has the potential to cause change in behavior, not just to understand behavior.

The findings not only have relevance to theory, but also to practice. As mentioned above, with a process perspective to adaptation there is opportunity for manipulations to be implemented to enhance the outcome of the process or possible speed with which it occurs. Previous research has demonstrated that training impacts adaptive performance (e.g., Baard, 2013; Bell & Kozlowski, 2008). Therefore, it may be that training can enhance the process itself as well. Cognitively focused training may assist individuals in where to look for information should an adaptive event occur, prepare them in how to test different strategies without wasting valuable time and resources, and help them recognize when to stop strategizing and gathering information and maximize on performance as over-strategizing can hurt adaptive performance. Motivationally focused training can help encourage employees to keep putting forth effort despite performance drops and push through fatigue or discouragement that may accompany change as maintaining high goals and effort was seen to be a critical component for effective performance during adaptation.

Limitations and Future Research

One of the primary limitations of this study was the number of adaption trials. Although this study goes beyond most of the literature in measuring 15 adaptation performance trials, and is the only study in the adaptation literature to examine self-regulatory processes for an extended period of time after a change, it appears that seven trials was not sufficient to capture the performance process. Given the lack of performance stabilization in the coordinative complexity condition, it appears that equilibrium in performance was not yet met, resulting in an incomplete picture of the performance process. Future researchers should extend their research design to incorporate more measurements after introducing the change.

In that same line of thinking, given the lack of consistency in performance during all of the adaptation trials, it would be beneficial to attempt to create a more stable task environment. The sawtooth pattern may have been a result of the scenarios being slightly altered in order to make the task more engaging for individuals so they did not cease to investigate information about the targets when they recognized the pattern. However, it is possible that individuals attempted to engage with the task as if it were a recurring pattern every trial, resulting in some key targets being misidentified every other trial.

Furthermore, the laboratory setting itself presents a limitation to the study of adaptation. One reason is that additional trials were not possible in a laboratory design given the fatigue individuals reported and splitting adaptive performance trials was not deemed feasible. In addition, a lab presents a very sterile environment for the participants and it may have been that the reward was not great enough to merit continued effort in the face of a difficult change. This may have contributed to why a sawtooth pattern of performance was seen. If individuals were not engaged or thought they were being tricked, as they often are in studies, they may not have tried to adjust their behaviors, but rather came to expect a pattern of performance. Therefore, it is recommended that future research attempt to attempt to make experimental platform as similar to what individuals would experience on a job as much as possible. For instance, measuring individuals over the course of a semester would allow for an expanded view of the adaptation and performance processes where the period of time would now extend to months rather than days. Furthermore, such a setting may have more relevant tasks (e.g., papers and projects) and rewards (e.g., grades) for individuals, presenting them with a stronger reason to effectively adapt.

Finally, additional research can be done on the utility of the partially crossed, partially time varying cross-lag panel regression model. Although DeShon (2012) posed the utility of dynamic analyses to investigate phenomena such as the complex relationship between self-efficacy and performance, it appears that research has not yet started applying these dynamic analyses in empirical works. The cross-lag analysis used in this research is one of the first to attempt to bring dynamic analyses to the organizational literature to investigate processes dynamically. However, there is still much to learn about the model, assumptions, limitations, and applications. The series of simulations conducted for this study in Appendix A presented a small set of parameters that can be investigated.

One key limitation of the cross lag panel model is that it is a pooled model of the individual dynamics, making an assumption that each individual has the same dynamic system. This assumption was retained in the current study, as the goal of this research was to capture the overall performance adaptation process. Although the cross lag model is very sophisticated and extremely informative about the overall dynamic system, it does not provide an easy way to understand the dynamics of the individuals. There are, however, two extensions of this analysis that provide avenues for future research. First, instead of averaging the paths across the trials in the adaptation process, it is possible to unconstrain the paths of the relationships to allow them to change over each time period. In other words, in model used in this research, two sets of relationships were obtained, representing the adaptation and performance processes in Trials 19-25 and Trials 26-33, respectively. However, future research could estimate different relationships between each trial, resulting in 15 sets of relationships, thereby providing a more fine-grained view of both the adaptation and performance processes.

Second, there is a need to explore the person in the process. That is, the current study did not capture either the individuals' phenomenological experiences when they were exposed to the change (e.g., How did they feel? Stressed? Confident?), nor did it focus on the individual trajectories, though there was evidence of differences among individuals in how they responded with regard to the self-regulatory variables under investigation. With regard to the first, when individuals are faced with a change, several responses can, theoretically, ensue. Individuals may feel intensely motivated to adapt and put extra effort toward pursuing a high goal to re-attain their pre-change performance. Others may feel defeated by a large drop in performance and either give up or settle for a very low performance level. Although these ideas cannot be answered with the data in this research, Figure 13 provides a brief overview of what the individuals' performance dynamics were in current study in the two adaptive conditions: component and coordinative complexity increases. The figure shows not only the mean trajectories, as presented earlier, but also the error bars display the differences in individual responses across the trials in the adaptation and performance environments. To make this even more explicit, the "spaghetti plots" below those graphs show the change in performance levels of 30 of the individuals in each condition. These plots show large variability in how individuals change in their performance levels over time, suggesting that individuals may follow different patterns in their processing of a change.

In addition to the differential effect on performance, individuals may also have different affective, cognitive or motivational reactions. As referenced to above, a high stress situation may elicit a fight reaction in some, where these individuals become excited and determined. However, others, having a flight reaction, may shut down and no longer care about the task. It may also be that these motivational or affective components have differing relationships with performance or with other self-regulatory variables in the face of a change. For instance, some individuals may consistently have large goal-performance discrepancies; others may have consistently small discrepancies; and still others may change in their responses over time where they start with large discrepancies and then calibrate their goals more effectively as the learn about the change. It would be interesting to examine whether these differences impact the relationships in the overall adaptation process. In order to demonstrate the differences the individual variability in the self-regulatory variables, Figure 14 adds error bars to the graphs of the trajectories of these variables in the adaptive trials. It is clear that individuals differ in their responses, but it is unclear why these differences appear. Were some individuals more engaged than others? Were some more stressed than others? Did the different types of changes trigger different responses among individuals, causing different patterns to emerge?

These questions, among others, would be fruitful avenues for additional research and it is strongly encouraged that future endeavors explore the differences among individuals' dynamics in the investigation of the process of adaptation. Specifically, it is recommended that future researchers investigate several questions with regard to individual variability. First, researchers must determine what types of patterns individuals may follow in response to a change (e.g., a failure to adapt, the decision to adopt a lower standard, or a desire to increase in performance and thrive in adaptation). Then efforts can be devoted to understanding whether individual differences impact or predict those patterns (e.g., individuals with higher learning goal orientations tend to follow the "desire to increase in performance and thrive in adaptation" pattern). Finally, researchers can examine whether these patterns are also seen in differences in the relationships between the self-regulatory variables involved in the adaptation process.

Figure 13

Individual Variability in Performance Trajectories

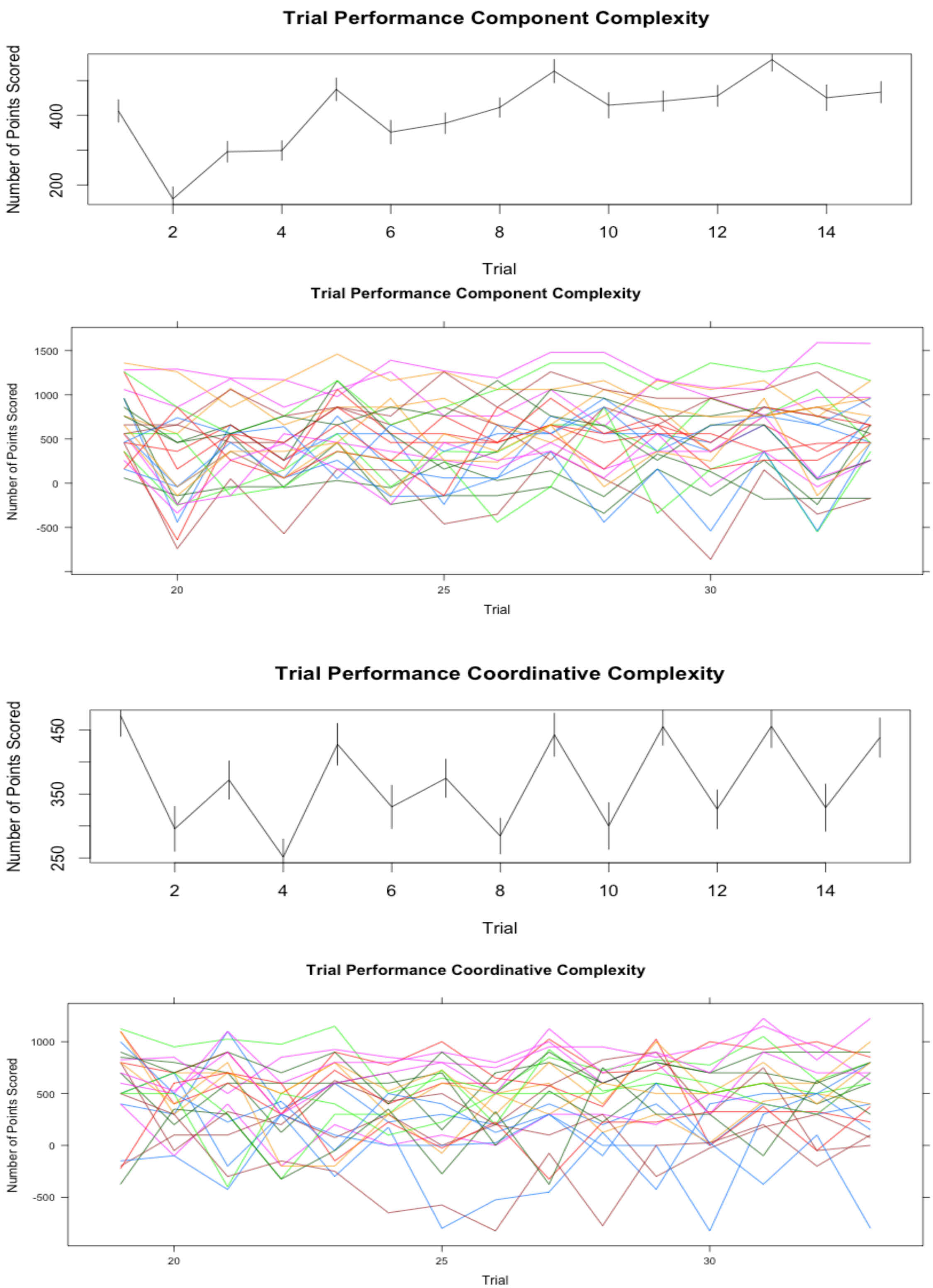
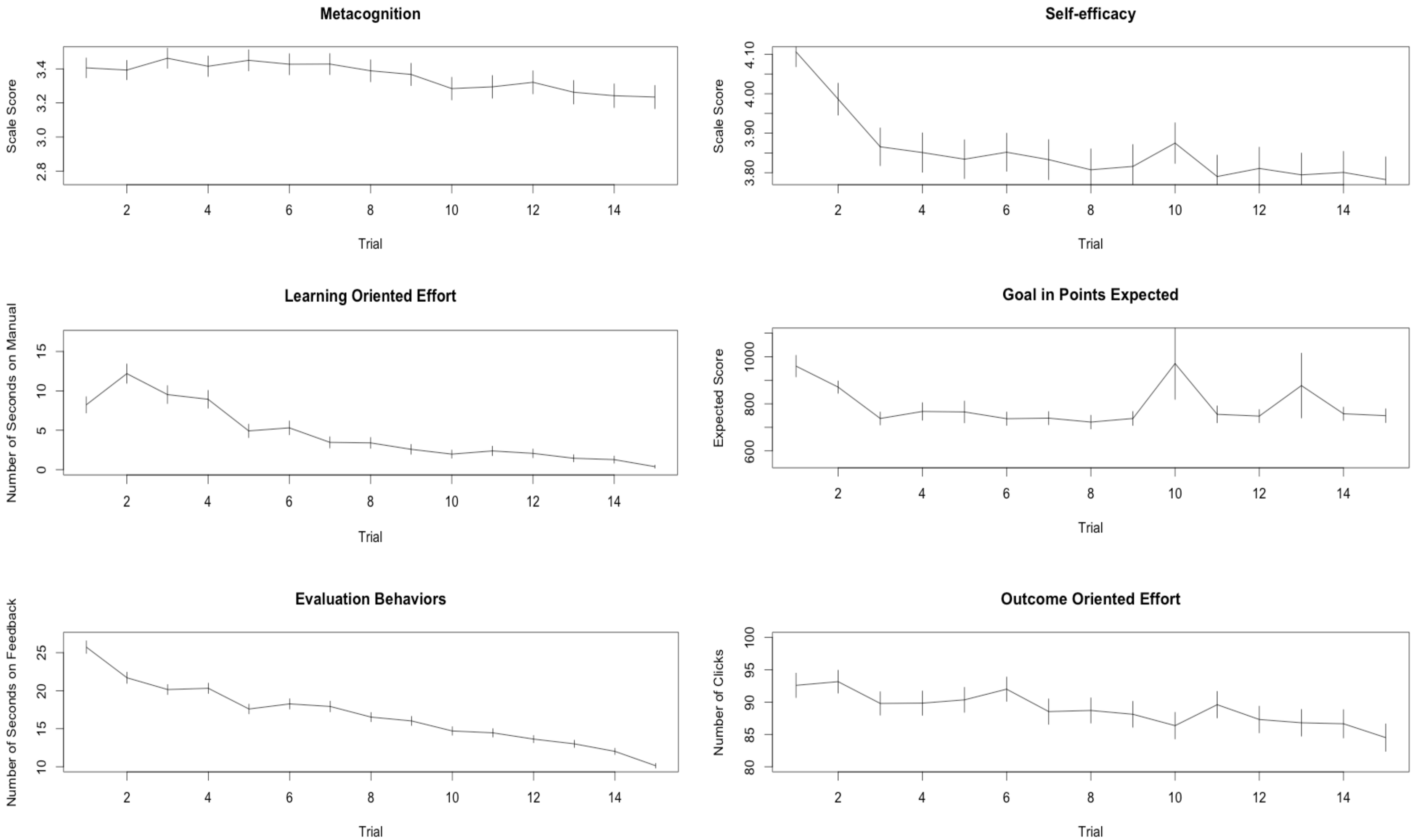


Figure 14

Individual Variability in Self-Regulatory Variables



Conclusion

The primary purpose of this research effort was to extend the theory on the process of adaptation to incorporate specific dynamics, and to test these dynamics with the most appropriate analyses available. The results show support for the majority of the hypotheses, suggesting that this theory provides a reasonable stepping-stone for additional work to be conducted on the adaptation process. Given the consistency of the trajectories and relationship changes in the component and complexity change conditions, the adaptation and post-change performance processes appear to be consistent across different types of change. This suggests that these processes are generalizable to multiple types of change, and that, if trainings or interventions are implemented, organizations could assist individuals in dealing with different types of adaptive situations. Furthermore, it is clear from the results that it is critical to push research beyond investigating trajectories (i.e., through growth curve analyses) and start pursuing more complex ways of representing dynamic data. The cross-lag analysis allowed for the investigation of all the variables in one model, resulting in the conclusion that relationship changes are not fully driven by trajectory changes, but incorporate autoregressive relationships and the other relationships accounting for variance in the model. This research provides a first step into what could be a very fruitful path investigating the dynamics of the adaptation process.

APPENDICES

APPENDIX A:
Longitudinal Cross-Lag Simulations

In order to examine the limitations of the longitudinal cross-lag simulation, I conducted a two-part simulation study where I examined the requirements of the model with respect to the number of time points (T), people (N), error variance, and effect sizes of the autoregressive and cross-lag estimations. In the first set of simulations with only two variables with time invariant relationships, I asked the question: are there differences in the effectiveness of this model in re-creating the data based on the T and the N, and is that dependent on the effect sizes of the relationships or the error in the data?

In the second set of simulations, I use my findings from the first set of simulations to test whether the model could handle seven variables and partially time-varying relationships (i.e., two sets of relationships – adaptation process and performance process). In these simulations I asked the question: given the expected effect sizes and the T I will have in my study, what is the impact of various effect sizes, the N, and *when* the shift between the processes occurs? This final part of the question is critical because it is likely that the individuals in the component complexity condition go through the adaptation process more rapidly and I wanted to ensure there is sufficient statistical power to detect the relationships in the adaptation process in only a few trials, even with small effect sizes and larger error rates.

The results of these simulations were used in the design of the experiment as well as in the indication of the needed number of participants in each condition, given the expected effect sizes, ease of complexity change, and duration of the experiment.

Simulation 1: Time Invariant Longitudinal Cross-Lag Panel Regression Models With Two

Variables

Method. In order to examine the impact of the number of time points (T), number of individuals (N), error variance, and effect sizes of the autoregressive and cross-lag parameters on the validity of the model estimates, Monte Carlo simulations were used. In this series of models, two variables with time invariant relationships were simulated with varying Ts, Ns, and parameter estimates. Variations of the below equations were used to estimate the parameters.

$$Y_{(t)} = ARy_{(t-1)} + CLx_{(t-1)} + e$$

$$X_{(t)} = ARx_{(t-1)} + CLy_{(t-1)} + e$$

Ten datasets were estimated for each of the 243 models investigated. The models were based on the manipulation of the above 5 parameters (note that the autoregressive and cross-lag parameters were estimated as the same in the simulated data for X and Y). The number of time points in the model was 5, 10 or 15; the number of people was 100, 150 or 200; and the effect sizes, autoregressive and cross-lag parameters were .1, .3, or .5. The values chosen for these final parameters were based on Cohen 1988 who provided a series of benchmarks from which to make comparisons. He presents certain thresholds that should be used when determining the effect sizes of correlations. In this paper he proposed that small effects are .1, medium are .3 and large are .5. Given that the basis of cross-lag regression is correlational, I used this framework to examine the impact of different relationship strengths on the model.

Monte Carlo Evidence. Table 13 shows the results of the simulations. The first set of columns show the parameters set in the data; the second set of columns show the values of Y that were estimated from the model; and the third set of columns show the same for X. When the estimate from the analysis was .01 (or greater) less than the initial parameters set in the simulated data, the value in Table 13 was bolded; when the estimate was .01 (or greater) more than the simulated data parameter, the value in Table 13 is bolded and italicized. This highlights instances of under- and overestimation.

Specifically examining situations where the estimates were beyond the accepted .01 absolute difference, the Monte Carlo simulations suggest that when there was a small T (5) and a small N (100) and the standard error was moderate (.3) or large (.5), there were multiple errors in the cross-lag and autoregression estimates. Furthermore, unlike the other models, where the parameters estimates were statistically significant, when the standard error was large and the autoregressive parameter was small (.1), the pvalue of the predicted autoregressive component was not always statistically significant. The simulations also revealed that when there was a small T (5) and a moderate N (150), when the standard error was moderate and the autoregressive parameter was large, the cross-lag estimate can be incorrect; when the standard error is large, both the autoregressive and the cross-lag estimates can be beyond the .01 threshold. Fewer errors were found when there was a moderate T (10) and a small N (100), although some inaccuracies were detected in the cross-lag and autoregressive estimates when the standard errors were moderate or large and the cross-lag or autoregressive parameters were set to be small. Also, very few errors in the cross-lag and autoregressive estimates were found when there was a large T (15) and a small N (100) if the standard error was high.

All other values were within the accepted range, suggesting that the following situations provide a level of confidence in the output of the models. When a small T (5) must be accepted, a large N (200) is needed. If a large N is not possible, a moderate N (150) is acceptable if the amount of error expected is low to moderate. A moderate or large T is preferred in these models as they are fairly robust to large error rates in the ability of the model to accurately estimate even small effect sizes, particularly with moderate to high Ns. If there were errors made in the estimation, they were typically overestimated by a small amount when there was a large T, regardless of the N. Finally, in general, the size of the cross-lags and autoregressive parameters did not have much impact on the estimates.

In conclusion, having five time points is risky, but if that is needed, a large N is required. Having 10 time points is preferred, but if there is a possibility of high amounts of error in the data, a large N or large expected effects sizes are necessary. Finally, having 15 time points is the best option as it allows for flexibility in expected error rates and effect sizes regardless of N.

Simulation 2: Partially Time Varying Longitudinal Cross-Lag Panel Regression Models With Seven Variables

Method. Based on the first set of simulations, I constrained the next set of simulations to have 15 total time points. I also limited the variance of the N to either moderate (150) or large (200). The amount of error was manipulated (.1, .3, or .5), as was the point at which the relationships were expected to change. This is based on the expectation that when individuals are exposed to a change, they engage in an adaptation process; however, once the source of the change is determined and a strategy is chosen, individuals will enter a performance process. As these two processes have different expected relationships, there are two sets of regression equations estimated (see the below equations). The autoregressive effects were constrained to be large (.5) as this is a typical finding in the literature, small hypothesized effects were set as .2 while large effects were simulated as .4, and these effect sizes were constrained to be consistent with the hypothesized relationships across all models. Most importantly, since it is unknown at which point individuals will switch from an adaptation to a performance process, this Monte Carlo simulation was conducted to investigate whether the point at which this transition will occur will influence the reliability of the model estimates.

$$\text{Performance}_{(t)} = AR\text{performance}_{(t-1)} + CL\text{metacognition}_{(t-1)} + CL\text{outcome-effort}_{(t-1)} + e$$

$$\text{Learning-effort}_{(t)} = AR\text{learning-effort}_{(t-1)} + CL\text{performance}_{(t-1)} + CL\text{evaluation}_{(t-1)} + e$$

$$\text{Metacognition}_{(t)} = AR\text{metacognition}_{(t-1)} + CL\text{learning-effort}_{(t-1)} + CL\text{evaluation}_{(t-1)} + e$$

$$\text{Evaluation}_{(t)} = AR\text{evaluation}_{(t-1)} + CL\text{performance}_{(t-1)} + e$$

$$\text{Goals}_{(t)} = AR\text{goals}_{(t-1)} + CL\text{performance}_{(t-1)} + CL\text{self-efficacy}_{(t-1)} + e$$

$$\text{Outcome-effort}_{(t)} = AR\text{outcome-effort}_{(t-1)} + CL\text{goals}_{(t-1)} + CL\text{self-efficacy}_{(t-1)} + e$$

$$\text{Self-efficacy}_{(t)} = AR\text{self-efficacy}_{(t-1)} + CL\text{performance}_{(t-1)} + e$$

Ten datasets were estimated for each of the 36 models investigated. The models were based on the manipulation of the duration of time individuals are engaging in an adaptation process (for 3, 4, 5, 6, 7, or 8 trials of the 15 total trials), the number of individuals in the dataset (150 or 200), and the error estimate (.1, .3, or .5).

Monte Carlo Evidence. Table 14 presents the results from the 36 models. Estimates were specified for both the adaptation and performance processes. The first column indicates which variable was being predicted. The column labeled trial change indicates which was the first performance process trial (e.g., if the trial change variable reads 7, then the first 6 trials where the adaptation process was occurring and Trials 7 through 15 were when the performance process was taking place). Since the autoregressive relationships were constrained to be the same across both the adaptation and performance process, there is only one estimate reported for this parameter. The following cross-lags (CL), standard error (Se), and pvalues (P) are separated by the process investigated and the relationship estimated. For instance, performance was predicted by the autoregressive effect of performance, the cross-lag effect of metacognition, and the cross-lag of outcome-oriented effort.

Similar to the previous set of simulations, instances of under- and overestimation were determined by the difference between the model estimate and the simulated data parameter exceeding .01. Underestimates were bolded and overestimates were bolded and highlighted in Table 14. The results of the simulation suggest that not only can the cross-lag model run with the number of parameters and individuals, but the estimates are within .01 of the specified simulated values. This indicates that the model will be able to analyze the hypothesized relationships with accuracy. When there is a discrepancy below .01 in the simulated and estimated values, it tends to be when there is a small adaptation process phase, resulting in fewer trials to estimate the process. However, this occurs rarely and does not seem to be dependent on the effect size of the variables but rather on the amount of error apparent in the data. Therefore, minimizing error would be beneficial to the model's accuracy, but this set of simulations clearly show that this analysis technique will be able to reliably test the hypotheses presented in this research endeavor.

Table 13
Fully Crossed Time Invariant Longitudinal Cross-Lag Simulation With Two Variables

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
5	100	0.1	0.1	0.1	0.097	0.105	0.010	0.009	0.000	0.000	0.097	0.106	0.009	0.010	0.000	0.000
5	100	0.1	0.1	0.3	0.099	0.297	0.010	0.009	0.000	0.000	0.102	0.298	0.008	0.009	0.000	0.000
5	100	0.1	0.1	0.5	0.098	0.500	0.009	0.008	0.000	0.000	0.103	0.497	0.008	0.009	0.000	0.000
5	100	0.1	0.3	0.1	0.300	0.098	0.010	0.008	0.000	0.000	0.298	0.101	0.009	0.010	0.000	0.000
5	100	0.1	0.3	0.3	0.301	0.296	0.009	0.008	0.000	0.000	0.300	0.302	0.008	0.009	0.000	0.000
5	100	0.1	0.3	0.5	0.297	0.502	0.008	0.008	0.000	0.000	0.303	0.500	0.008	0.008	0.000	0.000
5	100	0.1	0.5	0.1	0.495	0.101	0.009	0.008	0.000	0.000	0.498	0.096	0.008	0.009	0.000	0.000
5	100	0.1	0.5	0.3	0.499	0.302	0.008	0.008	0.000	0.000	0.499	0.305	0.007	0.008	0.000	0.000
5	100	0.1	0.5	0.5	0.496	0.500	0.008	0.007	0.000	0.000	0.502	0.495	0.007	0.008	0.000	0.000
5	100	0.3	0.1	0.1	0.093	**0.117**	0.027	0.024	0.010	0.001	0.092	**0.114**	0.024	0.026	0.002	0.008
5	100	0.3	0.1	0.3	0.096	0.293	0.027	0.024	0.032	0.000	0.105	0.291	0.023	0.025	0.001	0.000
5	100	0.3	0.1	0.5	0.097	0.497	0.024	0.022	0.028	0.000	0.108	0.492	0.022	0.023	0.000	0.000
5	100	0.3	0.3	0.1	0.301	0.098	0.026	0.023	0.000	0.001	0.297	0.099	0.024	0.027	0.000	0.007
5	100	0.3	0.3	0.3	0.299	**0.290**	0.025	0.022	0.000	0.000	0.301	0.306	0.023	0.025	0.000	0.000
5	100	0.3	0.3	0.5	0.291	0.508	0.022	0.021	0.000	0.000	0.304	0.503	0.021	0.022	0.000	0.000
5	100	0.3	0.5	0.1	**0.483**	0.101	0.024	0.022	0.000	0.000	0.494	0.092	0.022	0.024	0.000	0.005
5	100	0.3	0.5	0.3	0.492	***0.311***	0.023	0.021	0.000	0.000	0.498	0.310	0.021	0.023	0.000	0.000
5	100	0.3	0.5	0.5	**0.489**	0.502	0.021	0.020	0.000	0.000	0.504	**0.489**	0.020	0.021	0.000	0.000
5	100	0.5	0.1	0.1	0.093	**0.128**	0.038	0.036	0.072	0.018	0.090	**0.117**	0.034	0.037	0.048	0.070
5	100	0.5	0.1	0.3	0.095	0.290	0.037	0.035	0.086	0.000	0.106	**0.284**	0.033	0.036	0.031	0.000
5	100	0.5	0.1	0.5	0.098	0.492	0.034	0.032	0.125	0.000	**0.110**	**0.488**	0.032	0.034	0.007	0.000
5	100	0.5	0.3	0.1	0.301	0.100	0.037	0.034	0.000	0.025	0.300	0.096	0.034	0.037	0.000	0.087
5	100	0.5	0.3	0.3	0.295	**0.287**	0.035	0.033	0.000	0.000	0.302	0.310	0.033	0.036	0.000	0.000
5	100	0.5	0.3	0.5	**0.286**	***0.511***	0.032	0.031	0.000	0.000	0.302	0.509	0.031	0.032	0.000	0.000
5	100	0.5	0.5	0.1	**0.475**	0.100	0.035	0.032	0.000	0.012	0.490	0.090	0.032	0.035	0.000	0.061
5	100	0.5	0.5	0.3	**0.485**	**0.320**	0.033	0.031	0.000	0.000	0.498	0.309	0.030	0.033	0.000	0.000
5	100	0.5	0.5	0.5	**0.484**	0.502	0.031	0.030	0.000	0.000	0.503	**0.488**	0.029	0.030	0.000	0.000
5	150	0.1	0.1	0.1	0.101	0.097	0.008	0.008	0.000	0.000	0.100	0.101	0.008	0.008	0.000	0.000
5	150	0.1	0.1	0.3	0.102	0.299	0.008	0.007	0.000	0.000	0.099	0.305	0.007	0.008	0.000	0.000
5	150	0.1	0.1	0.5	0.101	0.501	0.007	0.007	0.000	0.000	0.094	0.501	0.007	0.007	0.000	0.000
5	150	0.1	0.3	0.1	0.304	0.101	0.008	0.007	0.000	0.000	0.303	0.094	0.008	0.008	0.000	0.000
5	150	0.1	0.3	0.3	0.299	0.297	0.008	0.007	0.000	0.000	0.302	0.300	0.007	0.007	0.000	0.000
5	150	0.1	0.3	0.5	0.298	0.500	0.007	0.007	0.000	0.000	0.301	0.497	0.007	0.007	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
5	150	0.1	0.5	0.1	0.500	0.096	0.007	0.007	0.000	0.000	0.502	0.101	0.007	0.007	0.000	0.000
5	150	0.1	0.5	0.3	0.499	0.304	0.007	0.007	0.000	0.000	0.499	0.301	0.007	0.007	0.000	0.000
5	150	0.1	0.5	0.5	0.499	0.501	0.006	0.006	0.000	0.000	0.501	0.501	0.006	0.006	0.000	0.000
5	150	0.3	0.1	0.1	0.102	0.091	0.022	0.021	0.000	0.001	0.097	0.103	0.021	0.022	0.000	0.000
5	150	0.3	0.1	0.3	0.107	0.298	0.021	0.020	0.002	0.000	0.096	*0.312*	0.020	0.021	0.000	0.000
5	150	0.3	0.1	0.5	0.104	0.500	0.019	0.019	0.000	0.000	**0.084**	0.502	0.019	0.019	0.000	0.000
5	150	0.3	0.3	0.1	0.310	0.100	0.021	0.020	0.000	0.000	0.309	**0.088**	0.020	0.021	0.000	0.003
5	150	0.3	0.3	0.3	0.295	0.291	0.021	0.020	0.000	0.000	0.302	0.302	0.019	0.020	0.000	0.000
5	150	0.3	0.3	0.5	0.297	0.501	0.019	0.018	0.000	0.000	0.302	0.495	0.018	0.019	0.000	0.000
5	150	0.3	0.5	0.1	0.501	**0.090**	0.019	0.018	0.000	0.000	0.502	0.101	0.019	0.020	0.000	0.000
5	150	0.3	0.5	0.3	0.497	*0.310*	0.019	0.018	0.000	0.000	0.496	0.301	0.018	0.019	0.000	0.000
5	150	0.3	0.5	0.5	0.502	0.501	0.018	0.017	0.000	0.000	0.498	0.508	0.017	0.017	0.000	0.000
5	150	0.5	0.1	0.1	0.103	**0.088**	0.031	0.030	0.010	0.032	0.092	0.104	0.030	0.031	0.027	0.017
5	150	0.5	0.1	0.3	**0.113**	0.299	0.030	0.029	0.009	0.000	0.093	*0.315*	0.029	0.029	0.024	0.000
5	150	0.5	0.1	0.5	0.107	0.499	0.027	0.027	0.002	0.000	**0.081**	0.501	0.027	0.028	0.013	0.000
5	150	0.5	0.3	0.1	*0.314*	0.099	0.030	0.029	0.000	0.014	*0.313*	**0.087**	0.029	0.030	0.000	0.044
5	150	0.5	0.3	0.3	0.291	**0.287**	0.029	0.029	0.000	0.000	0.300	0.305	0.028	0.028	0.000	0.000
5	150	0.5	0.3	0.5	0.298	0.502	0.027	0.026	0.000	0.000	0.302	0.496	0.026	0.027	0.000	0.000
5	150	0.5	0.5	0.1	0.504	**0.087**	0.027	0.026	0.000	0.011	0.499	0.099	0.027	0.028	0.000	0.002
5	150	0.5	0.5	0.3	0.497	*0.314*	0.027	0.026	0.000	0.000	0.494	0.301	0.026	0.027	0.000	0.000
5	150	0.5	0.5	0.5	0.506	0.500	0.025	0.025	0.000	0.000	0.495	*0.516*	0.025	0.025	0.000	0.000
5	200	0.1	0.1	0.1	0.100	0.102	0.007	0.008	0.000	0.000	0.100	0.098	0.008	0.007	0.000	0.000
5	200	0.1	0.1	0.3	0.099	0.303	0.007	0.007	0.000	0.000	0.101	0.297	0.007	0.006	0.000	0.000
5	200	0.1	0.1	0.5	0.101	0.504	0.006	0.006	0.000	0.000	0.102	0.496	0.006	0.006	0.000	0.000
5	200	0.1	0.3	0.1	0.296	0.101	0.006	0.007	0.000	0.000	0.299	0.096	0.007	0.007	0.000	0.000
5	200	0.1	0.3	0.3	0.300	0.299	0.006	0.007	0.000	0.000	0.301	0.296	0.007	0.006	0.000	0.000
5	200	0.1	0.3	0.5	0.304	0.499	0.006	0.006	0.000	0.000	0.299	0.501	0.006	0.006	0.000	0.000
5	200	0.1	0.5	0.1	0.499	0.103	0.006	0.007	0.000	0.000	0.502	0.102	0.007	0.006	0.000	0.000
5	200	0.1	0.5	0.3	0.502	0.301	0.006	0.006	0.000	0.000	0.499	0.301	0.006	0.006	0.000	0.000
5	200	0.1	0.5	0.5	0.499	0.501	0.006	0.006	0.000	0.000	0.499	0.500	0.006	0.006	0.000	0.000
5	200	0.3	0.1	0.1	0.101	0.105	0.018	0.020	0.000	0.000	0.098	0.097	0.020	0.018	0.000	0.000
5	200	0.3	0.1	0.3	0.095	0.307	0.018	0.020	0.000	0.000	0.103	0.297	0.019	0.018	0.000	0.000
5	200	0.3	0.1	0.5	0.102	0.510	0.016	0.018	0.000	0.000	0.105	0.490	0.017	0.016	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
5	200	0.3	0.3	0.1	0.291	0.101	0.018	0.019	0.000	0.000	0.296	**0.089**	0.020	0.018	0.000	0.000
5	200	0.3	0.3	0.3	0.299	0.296	0.017	0.019	0.000	0.000	0.305	**0.288**	0.018	0.017	0.000	0.000
5	200	0.3	0.3	0.5	0.309	0.499	0.016	0.017	0.000	0.000	0.298	0.501	0.017	0.016	0.000	0.000
5	200	0.3	0.5	0.1	0.495	0.108	0.016	0.018	0.000	0.000	0.502	0.105	0.018	0.016	0.000	0.000
5	200	0.3	0.5	0.3	0.504	0.305	0.016	0.017	0.000	0.000	0.500	0.301	0.017	0.015	0.000	0.000
5	200	0.3	0.5	0.5	0.496	0.503	0.015	0.016	0.000	0.000	0.497	0.501	0.016	0.015	0.000	0.000
5	200	0.5	0.1	0.1	0.103	0.107	0.026	0.028	0.005	0.004	0.095	0.097	0.028	0.026	0.040	0.007
5	200	0.5	0.1	0.3	0.092	0.308	0.026	0.027	0.008	0.000	0.104	0.301	0.027	0.025	0.002	0.000
5	200	0.5	0.1	0.5	0.103	***0.511***	0.023	0.025	0.003	0.000	0.106	**0.488**	0.025	0.023	0.000	0.000
5	200	0.5	0.3	0.1	**0.288**	0.100	0.025	0.027	0.000	0.012	0.295	**0.086**	0.027	0.025	0.000	0.036
5	200	0.5	0.3	0.3	0.297	0.293	0.025	0.026	0.000	0.000	0.308	**0.281**	0.026	0.024	0.000	0.000
5	200	0.5	0.3	0.5	***0.310***	0.500	0.023	0.024	0.000	0.000	0.299	0.500	0.024	0.023	0.000	0.000
5	200	0.5	0.5	0.1	0.491	***0.110***	0.023	0.025	0.000	0.000	0.500	0.107	0.025	0.023	0.000	0.000
5	200	0.5	0.5	0.3	0.504	0.308	0.023	0.024	0.000	0.000	0.501	0.301	0.024	0.022	0.000	0.000
5	200	0.5	0.5	0.5	0.494	0.505	0.022	0.022	0.000	0.000	0.495	0.502	0.023	0.022	0.000	0.000
10	100	0.1	0.1	0.1	0.095	0.101	0.010	0.009	0.000	0.000	0.099	0.103	0.009	0.010	0.000	0.000
10	100	0.1	0.1	0.3	0.095	0.293	0.009	0.008	0.000	0.000	0.100	0.296	0.009	0.010	0.000	0.000
10	100	0.1	0.1	0.5	0.097	0.497	0.008	0.008	0.000	0.000	0.098	0.502	0.008	0.008	0.000	0.000
10	100	0.1	0.3	0.1	0.299	0.102	0.009	0.008	0.000	0.000	0.300	0.097	0.008	0.009	0.000	0.000
10	100	0.1	0.3	0.3	0.302	0.303	0.009	0.008	0.000	0.000	0.295	0.300	0.008	0.009	0.000	0.000
10	100	0.1	0.3	0.5	0.300	0.500	0.008	0.007	0.000	0.000	0.300	0.498	0.007	0.008	0.000	0.000
10	100	0.1	0.5	0.1	0.499	0.105	0.009	0.008	0.000	0.000	0.501	0.105	0.008	0.009	0.000	0.000
10	100	0.1	0.5	0.3	0.504	0.298	0.008	0.007	0.000	0.000	0.498	0.299	0.007	0.008	0.000	0.000
10	100	0.1	0.5	0.5	0.501	0.498	0.007	0.007	0.000	0.000	0.502	0.496	0.007	0.007	0.000	0.000
10	100	0.3	0.1	0.1	0.095	0.103	0.024	0.022	0.012	0.001	0.096	0.102	0.021	0.023	0.001	0.006
10	100	0.3	0.1	0.3	0.097	**0.285**	0.022	0.020	0.001	0.000	0.104	0.290	0.021	0.023	0.000	0.000
10	100	0.3	0.1	0.5	**0.089**	0.493	0.020	0.019	0.000	0.000	0.092	0.506	0.019	0.020	0.001	0.000
10	100	0.3	0.3	0.1	0.295	0.108	0.022	0.021	0.000	0.000	0.297	0.093	0.020	0.022	0.000	0.001
10	100	0.3	0.3	0.3	0.305	0.307	0.020	0.019	0.000	0.000	**0.288**	0.300	0.019	0.021	0.000	0.000
10	100	0.3	0.3	0.5	0.302	0.499	0.019	0.018	0.000	0.000	0.301	0.493	0.018	0.019	0.000	0.000
10	100	0.3	0.5	0.1	0.496	**0.114**	0.021	0.019	0.000	0.000	0.506	0.108	0.019	0.020	0.000	0.000
10	100	0.3	0.5	0.3	0.510	0.294	0.019	0.018	0.000	0.000	0.498	0.298	0.018	0.019	0.000	0.000
10	100	0.3	0.5	0.5	0.503	0.493	0.017	0.017	0.000	0.000	0.501	0.493	0.017	0.017	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
10	100	0.5	0.1	0.1	0.098	0.104	0.029	0.028	0.019	0.012	0.094	0.100	0.027	0.028	0.023	0.031
10	100	0.5	0.1	0.3	0.102	**0.283**	0.028	0.027	0.006	0.000	0.107	**0.288**	0.027	0.028	0.001	0.000
10	100	0.5	0.1	0.5	**0.085**	0.492	0.025	0.024	0.013	0.000	**0.088**	0.508	0.024	0.025	0.019	0.000
10	100	0.5	0.3	0.1	0.293	***0.112***	0.028	0.027	0.000	0.000	0.295	0.092	0.026	0.028	0.000	0.008
10	100	0.5	0.3	0.3	0.305	0.308	0.026	0.025	0.000	0.000	**0.286**	0.301	0.025	0.026	0.000	0.000
10	100	0.5	0.3	0.5	0.305	0.497	0.024	0.023	0.000	0.000	0.302	0.491	0.023	0.024	0.000	0.000
10	100	0.5	0.5	0.1	0.494	***0.118***	0.026	0.024	0.000	0.000	0.510	0.107	0.024	0.025	0.000	0.005
10	100	0.5	0.5	0.3	***0.512***	0.292	0.024	0.023	0.000	0.000	0.500	0.298	0.023	0.024	0.000	0.000
10	100	0.5	0.5	0.5	0.505	0.491	0.022	0.022	0.000	0.000	0.499	0.493	0.022	0.022	0.000	0.000
10	150	0.1	0.1	0.1	0.101	0.098	0.008	0.007	0.000	0.000	0.102	0.103	0.007	0.008	0.000	0.000
10	150	0.1	0.1	0.3	0.100	0.301	0.008	0.007	0.000	0.000	0.099	0.296	0.007	0.008	0.000	0.000
10	150	0.1	0.1	0.5	0.101	0.500	0.007	0.007	0.000	0.000	0.102	0.499	0.007	0.007	0.000	0.000
10	150	0.1	0.3	0.1	0.301	0.101	0.007	0.007	0.000	0.000	0.304	0.100	0.007	0.007	0.000	0.000
10	150	0.1	0.3	0.3	0.301	0.300	0.007	0.007	0.000	0.000	0.304	0.294	0.007	0.007	0.000	0.000
10	150	0.1	0.3	0.5	0.298	0.499	0.006	0.006	0.000	0.000	0.301	0.500	0.006	0.006	0.000	0.000
10	150	0.1	0.5	0.1	0.501	0.096	0.007	0.007	0.000	0.000	0.504	0.100	0.007	0.007	0.000	0.000
10	150	0.1	0.5	0.3	0.499	0.304	0.007	0.006	0.000	0.000	0.503	0.299	0.006	0.006	0.000	0.000
10	150	0.1	0.5	0.5	0.501	0.499	0.006	0.006	0.000	0.000	0.498	0.502	0.006	0.006	0.000	0.000
10	150	0.3	0.1	0.1	0.105	0.095	0.019	0.018	0.000	0.000	0.099	0.106	0.018	0.019	0.000	0.000
10	150	0.3	0.1	0.3	0.102	0.301	0.018	0.017	0.000	0.000	0.101	0.296	0.017	0.018	0.000	0.000
10	150	0.3	0.1	0.5	0.103	0.498	0.016	0.016	0.000	0.000	0.103	0.498	0.016	0.016	0.000	0.000
10	150	0.3	0.3	0.1	0.304	0.103	0.018	0.017	0.000	0.000	0.309	0.103	0.017	0.018	0.000	0.000
10	150	0.3	0.3	0.3	0.301	0.298	0.017	0.017	0.000	0.000	0.307	**0.287**	0.017	0.017	0.000	0.000
10	150	0.3	0.3	0.5	0.298	0.499	0.015	0.015	0.000	0.000	0.302	0.502	0.015	0.015	0.000	0.000
10	150	0.3	0.5	0.1	0.504	0.095	0.016	0.016	0.000	0.000	0.508	0.101	0.016	0.016	0.000	0.000
10	150	0.3	0.5	0.3	0.498	0.308	0.016	0.015	0.000	0.000	0.507	0.298	0.015	0.015	0.000	0.000
10	150	0.3	0.5	0.5	0.504	0.496	0.014	0.014	0.000	0.000	0.495	0.504	0.014	0.014	0.000	0.000
10	150	0.5	0.1	0.1	0.108	0.094	0.023	0.023	0.001	0.005	0.096	0.106	0.023	0.023	0.004	0.001
10	150	0.5	0.1	0.3	0.102	0.299	0.022	0.022	0.004	0.000	0.103	0.298	0.022	0.023	0.000	0.000
10	150	0.5	0.1	0.5	0.105	0.497	0.021	0.020	0.000	0.000	0.102	0.497	0.020	0.021	0.000	0.000
10	150	0.5	0.3	0.1	0.307	0.103	0.022	0.022	0.000	0.000	0.310	0.106	0.022	0.022	0.000	0.000
10	150	0.5	0.3	0.3	0.300	0.296	0.022	0.021	0.000	0.000	0.306	**0.287**	0.021	0.021	0.000	0.000
10	150	0.5	0.3	0.5	0.300	0.499	0.020	0.019	0.000	0.000	0.302	0.502	0.019	0.020	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
10	150	0.5	0.5	0.1	0.505	0.097	0.021	0.020	0.000	0.000	0.508	0.102	0.020	0.021	0.000	0.001
10	150	0.5	0.5	0.3	0.497	0.308	0.020	0.020	0.000	0.000	0.508	0.299	0.019	0.019	0.000	0.000
10	150	0.5	0.5	0.5	0.504	0.494	0.018	0.018	0.000	0.000	0.492	0.504	0.018	0.018	0.000	0.000
10	200	0.1	0.1	0.1	0.098	0.104	0.007	0.007	0.000	0.000	0.101	0.102	0.007	0.007	0.000	0.000
10	200	0.1	0.1	0.3	0.100	0.300	0.007	0.007	0.000	0.000	0.098	0.298	0.007	0.006	0.000	0.000
10	200	0.1	0.1	0.5	0.100	0.502	0.006	0.006	0.000	0.000	0.100	0.502	0.006	0.006	0.000	0.000
10	200	0.1	0.3	0.1	0.303	0.101	0.006	0.007	0.000	0.000	0.298	0.101	0.007	0.006	0.000	0.000
10	200	0.1	0.3	0.3	0.295	0.301	0.006	0.007	0.000	0.000	0.300	0.300	0.007	0.006	0.000	0.000
10	200	0.1	0.3	0.5	0.299	0.502	0.006	0.006	0.000	0.000	0.301	0.502	0.006	0.006	0.000	0.000
10	200	0.1	0.5	0.1	0.503	0.099	0.006	0.006	0.000	0.000	0.500	0.098	0.006	0.006	0.000	0.000
10	200	0.1	0.5	0.3	0.499	0.305	0.006	0.006	0.000	0.000	0.503	0.300	0.006	0.006	0.000	0.000
10	200	0.1	0.5	0.5	0.500	0.500	0.005	0.005	0.000	0.000	0.499	0.501	0.005	0.005	0.000	0.000
10	200	0.3	0.1	0.1	0.093	0.108	0.016	0.017	0.000	0.000	0.102	0.105	0.017	0.016	0.000	0.000
10	200	0.3	0.1	0.3	0.099	0.297	0.015	0.016	0.000	0.000	0.095	0.292	0.016	0.015	0.000	0.000
10	200	0.3	0.1	0.5	0.099	0.502	0.014	0.015	0.000	0.000	0.100	0.505	0.015	0.014	0.000	0.000
10	200	0.3	0.3	0.1	0.305	0.103	0.015	0.016	0.000	0.000	0.296	0.104	0.016	0.015	0.000	0.000
10	200	0.3	0.3	0.3	0.291	0.306	0.015	0.016	0.000	0.000	0.298	0.299	0.016	0.015	0.000	0.000
10	200	0.3	0.3	0.5	0.299	0.505	0.013	0.014	0.000	0.000	0.304	0.506	0.014	0.013	0.000	0.000
10	200	0.3	0.5	0.1	0.504	0.100	0.014	0.015	0.000	0.000	0.498	0.095	0.015	0.014	0.000	0.000
10	200	0.3	0.5	0.3	**0.497**	***0.311***	0.013	0.014	0.000	0.000	0.505	0.298	0.014	0.014	0.000	0.000
10	200	0.3	0.5	0.5	0.501	0.500	0.012	0.013	0.000	0.000	0.496	0.503	0.012	0.012	0.000	0.000
10	200	0.5	0.1	0.1	0.090	0.110	0.020	0.021	0.011	0.000	0.102	0.107	0.021	0.020	0.000	0.000
10	200	0.5	0.1	0.3	0.098	0.293	0.019	0.020	0.000	0.000	0.094	**0.289**	0.020	0.019	0.000	0.000
10	200	0.5	0.1	0.5	0.098	0.502	0.018	0.018	0.000	0.000	0.099	0.504	0.018	0.018	0.000	0.000
10	200	0.5	0.3	0.1	0.305	0.105	0.019	0.020	0.000	0.000	0.296	0.105	0.020	0.019	0.000	0.000
10	200	0.5	0.3	0.3	0.292	0.308	0.019	0.019	0.000	0.000	0.297	0.299	0.019	0.019	0.000	0.000
10	200	0.5	0.3	0.5	0.300	0.505	0.017	0.017	0.000	0.000	0.306	0.509	0.017	0.017	0.000	0.000
10	200	0.5	0.5	0.1	0.503	0.101	0.017	0.018	0.000	0.000	0.496	0.094	0.018	0.018	0.000	0.000
10	200	0.5	0.5	0.3	**0.496**	***0.313***	0.017	0.017	0.000	0.000	0.505	0.296	0.018	0.017	0.000	0.000
10	200	0.5	0.5	0.5	0.501	0.500	0.016	0.016	0.000	0.000	0.493	0.504	0.016	0.016	0.000	0.000
15	100	0.1	0.1	0.1	0.098	0.100	0.010	0.009	0.000	0.000	0.103	0.097	0.008	0.009	0.000	0.000
15	100	0.1	0.1	0.3	0.103	0.298	0.009	0.008	0.000	0.000	0.101	0.308	0.008	0.009	0.000	0.000
15	100	0.1	0.1	0.5	0.097	0.499	0.008	0.008	0.000	0.000	0.101	0.503	0.008	0.008	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
15	100	0.1	0.3	0.1	0.302	0.098	0.009	0.008	0.000	0.000	0.304	0.093	0.008	0.009	0.000	0.000
15	100	0.1	0.3	0.3	0.297	0.302	0.009	0.008	0.000	0.000	0.302	0.296	0.008	0.009	0.000	0.000
15	100	0.1	0.3	0.5	0.305	0.496	0.008	0.007	0.000	0.000	0.298	0.496	0.007	0.008	0.000	0.000
15	100	0.1	0.5	0.1	0.502	0.102	0.008	0.007	0.000	0.000	0.502	0.106	0.007	0.008	0.000	0.000
15	100	0.1	0.5	0.3	0.504	0.299	0.008	0.007	0.000	0.000	0.501	0.303	0.007	0.008	0.000	0.000
15	100	0.1	0.5	0.5	0.499	0.502	0.007	0.007	0.000	0.000	0.500	0.501	0.007	0.007	0.000	0.000
15	100	0.3	0.1	0.1	0.100	0.101	0.020	0.019	0.001	0.000	0.106	0.091	0.019	0.020	0.000	0.001
15	100	0.3	0.1	0.3	0.102	0.297	0.019	0.018	0.000	0.000	0.100	***0.314***	0.018	0.020	0.000	0.000
15	100	0.3	0.1	0.5	0.094	0.502	0.018	0.017	0.000	0.000	0.100	0.505	0.017	0.018	0.000	0.000
15	100	0.3	0.3	0.1	0.308	0.098	0.020	0.018	0.000	0.000	0.309	**0.089**	0.019	0.020	0.000	0.001
15	100	0.3	0.3	0.3	0.297	0.307	0.019	0.018	0.000	0.000	0.305	0.294	0.018	0.019	0.000	0.000
15	100	0.3	0.3	0.5	***0.311***	**0.489**	0.017	0.016	0.000	0.000	0.298	0.494	0.016	0.017	0.000	0.000
15	100	0.3	0.5	0.1	***0.510***	0.102	0.018	0.017	0.000	0.000	0.503	***0.112***	0.016	0.018	0.000	0.000
15	100	0.3	0.5	0.3	0.507	0.299	0.017	0.016	0.000	0.000	0.502	0.304	0.016	0.016	0.000	0.000
15	100	0.3	0.5	0.5	0.499	0.501	0.015	0.015	0.000	0.000	0.500	0.503	0.015	0.015	0.000	0.000
15	100	0.5	0.1	0.1	0.103	0.102	0.024	0.024	0.003	0.000	0.105	**0.089**	0.023	0.024	0.000	0.009
15	100	0.5	0.1	0.3	0.099	0.297	0.023	0.022	0.001	0.000	0.099	***0.314***	0.022	0.023	0.000	0.000
15	100	0.5	0.1	0.5	0.093	0.505	0.021	0.021	0.000	0.000	0.098	0.505	0.020	0.021	0.000	0.000
15	100	0.5	0.3	0.1	0.310	0.101	0.023	0.022	0.000	0.000	***0.311***	0.091	0.022	0.023	0.000	0.003
15	100	0.5	0.3	0.3	0.299	0.310	0.022	0.021	0.000	0.000	0.306	0.294	0.022	0.022	0.000	0.000
15	100	0.5	0.3	0.5	***0.313***	**0.487**	0.020	0.020	0.000	0.000	0.299	0.494	0.020	0.020	0.000	0.000
15	100	0.5	0.5	0.1	***0.514***	0.101	0.021	0.020	0.000	0.000	0.503	***0.112***	0.020	0.021	0.000	0.000
15	100	0.5	0.5	0.3	0.507	0.300	0.020	0.020	0.000	0.000	0.502	0.303	0.019	0.020	0.000	0.000
15	100	0.5	0.5	0.5	0.500	0.500	0.018	0.018	0.000	0.000	0.499	0.504	0.018	0.018	0.000	0.000
15	150	0.1	0.1	0.1	0.102	0.098	0.008	0.007	0.000	0.000	0.099	0.104	0.007	0.008	0.000	0.000
15	150	0.1	0.1	0.3	0.103	0.300	0.008	0.007	0.000	0.000	0.101	0.300	0.007	0.008	0.000	0.000
15	150	0.1	0.1	0.5	0.101	0.502	0.007	0.007	0.000	0.000	0.101	0.499	0.006	0.007	0.000	0.000
15	150	0.1	0.3	0.1	0.299	0.100	0.007	0.007	0.000	0.000	0.300	0.101	0.007	0.007	0.000	0.000
15	150	0.1	0.3	0.3	0.300	0.304	0.007	0.007	0.000	0.000	0.303	0.296	0.007	0.007	0.000	0.000
15	150	0.1	0.3	0.5	0.303	0.497	0.006	0.006	0.000	0.000	0.302	0.499	0.006	0.006	0.000	0.000
15	150	0.1	0.5	0.1	0.502	0.096	0.007	0.006	0.000	0.000	0.501	0.099	0.006	0.007	0.000	0.000
15	150	0.1	0.5	0.3	0.502	0.297	0.006	0.006	0.000	0.000	0.504	0.296	0.006	0.006	0.000	0.000
15	150	0.1	0.5	0.5	0.500	0.499	0.006	0.006	0.000	0.000	0.499	0.501	0.006	0.006	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
15	150	0.3	0.1	0.1	0.110	0.097	0.016	0.016	0.000	0.000	0.098	0.105	0.016	0.016	0.000	0.000
15	150	0.3	0.1	0.3	0.106	0.297	0.016	0.016	0.000	0.000	0.098	0.303	0.016	0.016	0.000	0.000
15	150	0.3	0.1	0.5	0.104	0.502	0.015	0.014	0.000	0.000	0.100	0.499	0.014	0.014	0.000	0.000
15	150	0.3	0.3	0.1	0.302	0.100	0.016	0.015	0.000	0.000	0.297	0.104	0.016	0.016	0.000	0.000
15	150	0.3	0.3	0.3	0.301	0.306	0.015	0.015	0.000	0.000	0.309	0.295	0.015	0.015	0.000	0.000
15	150	0.3	0.3	0.5	0.305	0.494	0.014	0.014	0.000	0.000	0.304	0.497	0.013	0.014	0.000	0.000
15	150	0.3	0.5	0.1	0.505	0.092	0.015	0.014	0.000	0.000	0.504	0.097	0.014	0.014	0.000	0.000
15	150	0.3	0.5	0.3	0.502	0.292	0.014	0.013	0.000	0.000	0.509	0.291	0.013	0.014	0.000	0.000
15	150	0.3	0.5	0.5	0.502	0.498	0.012	0.012	0.000	0.000	0.496	0.504	0.012	0.012	0.000	0.000
15	150	0.5	0.1	0.1	*0.114*	0.096	0.020	0.019	0.000	0.000	0.098	0.104	0.019	0.019	0.000	0.000
15	150	0.5	0.1	0.3	0.106	0.295	0.019	0.019	0.000	0.000	0.096	0.305	0.019	0.019	0.000	0.000
15	150	0.5	0.1	0.5	0.106	0.502	0.017	0.017	0.000	0.000	0.099	0.500	0.017	0.017	0.000	0.000
15	150	0.5	0.3	0.1	0.304	0.101	0.019	0.018	0.000	0.000	0.294	0.105	0.019	0.019	0.000	0.000
15	150	0.5	0.3	0.3	0.301	0.305	0.018	0.018	0.000	0.000	*0.310*	0.297	0.018	0.018	0.000	0.000
15	150	0.5	0.3	0.5	0.304	0.493	0.016	0.016	0.000	0.000	0.304	0.497	0.016	0.016	0.000	0.000
15	150	0.5	0.5	0.1	0.505	0.092	0.017	0.017	0.000	0.000	0.505	0.096	0.017	0.017	0.000	0.000
15	150	0.5	0.5	0.3	0.502	0.291	0.016	0.016	0.000	0.000	0.510	0.290	0.016	0.016	0.000	0.000
15	150	0.5	0.5	0.5	0.504	0.497	0.015	0.015	0.000	0.000	0.494	0.506	0.015	0.015	0.000	0.000
15	200	0.1	0.1	0.1	0.099	0.103	0.006	0.007	0.000	0.000	0.098	0.100	0.007	0.006	0.000	0.000
15	200	0.1	0.1	0.3	0.102	0.306	0.006	0.007	0.000	0.000	0.101	0.299	0.007	0.006	0.000	0.000
15	200	0.1	0.1	0.5	0.098	0.502	0.006	0.006	0.000	0.000	0.099	0.498	0.006	0.006	0.000	0.000
15	200	0.1	0.3	0.1	0.300	0.102	0.006	0.007	0.000	0.000	0.297	0.104	0.007	0.006	0.000	0.000
15	200	0.1	0.3	0.3	0.302	0.300	0.006	0.007	0.000	0.000	0.297	0.299	0.007	0.006	0.000	0.000
15	200	0.1	0.3	0.5	0.301	0.503	0.005	0.006	0.000	0.000	0.300	0.501	0.006	0.005	0.000	0.000
15	200	0.1	0.5	0.1	0.501	0.099	0.006	0.006	0.000	0.000	0.502	0.099	0.006	0.006	0.000	0.000
15	200	0.1	0.5	0.3	0.499	0.303	0.005	0.006	0.000	0.000	0.501	0.298	0.006	0.005	0.000	0.000
15	200	0.1	0.5	0.5	0.502	0.500	0.005	0.005	0.000	0.000	0.500	0.502	0.005	0.005	0.000	0.000
15	200	0.3	0.1	0.1	0.097	0.102	0.014	0.015	0.000	0.000	0.094	0.099	0.015	0.014	0.000	0.000
15	200	0.3	0.1	0.3	0.100	*0.310*	0.013	0.014	0.000	0.000	0.102	0.297	0.014	0.013	0.000	0.000
15	200	0.3	0.1	0.5	0.096	0.505	0.012	0.013	0.000	0.000	0.097	0.495	0.013	0.012	0.000	0.000
15	200	0.3	0.3	0.1	0.303	0.106	0.014	0.014	0.000	0.000	0.298	**0.113**	0.014	0.013	0.000	0.000
15	200	0.3	0.3	0.3	0.303	0.300	0.013	0.014	0.000	0.000	0.296	0.295	0.014	0.013	0.000	0.000
15	200	0.3	0.3	0.5	0.301	0.505	0.012	0.012	0.000	0.000	0.300	0.502	0.012	0.012	0.000	0.000

Table 13 (cont'd)

Data Simulation Parameters					Model Parameter Estimates (Y)						Model Parameter Estimates (X)					
T	N	Std error	Auto reg	Cross -Lag	AR (Y)	CL (x->y)	Se (AR Y)	Se (CL x->y)	P (AR Y)	P (CL x->y)	AR (X)	CL (y->x)	Se (AR X)	Se (CL y->x)	P (AR X)	P (CL y->x)
15	200	0.3	0.5	0.1	0.503	0.100	0.012	0.013	0.000	0.000	0.502	0.099	0.013	0.012	0.000	0.000
15	200	0.3	0.5	0.3	0.499	0.303	0.012	0.012	0.000	0.000	0.499	0.299	0.012	0.012	0.000	0.000
15	200	0.3	0.5	0.5	0.504	0.499	0.011	0.011	0.000	0.000	0.501	0.503	0.011	0.011	0.000	0.000
15	200	0.5	0.1	0.1	0.096	0.099	0.017	0.017	0.000	0.000	0.093	0.098	0.017	0.017	0.000	0.000
15	200	0.5	0.1	0.3	0.097	0.309	0.016	0.017	0.000	0.000	0.102	0.296	0.017	0.016	0.000	0.000
15	200	0.5	0.1	0.5	0.096	0.505	0.015	0.015	0.000	0.000	0.097	0.494	0.015	0.015	0.000	0.000
15	200	0.5	0.3	0.1	0.305	0.107	0.016	0.017	0.000	0.000	0.300	**0.116**	0.017	0.016	0.000	0.000
15	200	0.5	0.3	0.3	0.302	0.300	0.016	0.016	0.000	0.000	0.297	0.293	0.016	0.016	0.000	0.000
15	200	0.5	0.3	0.5	0.300	0.506	0.014	0.014	0.000	0.000	0.299	0.503	0.014	0.014	0.000	0.000
15	200	0.5	0.5	0.1	0.504	0.101	0.015	0.015	0.000	0.000	0.500	0.100	0.015	0.015	0.000	0.000
15	200	0.5	0.5	0.3	0.499	0.301	0.014	0.014	0.000	0.000	0.498	0.300	0.014	0.014	0.000	0.000
15	200	0.5	0.5	0.5	0.506	0.499	0.013	0.013	0.000	0.000	0.502	0.502	0.013	0.013	0.000	0.000

Table 14
Partially Cross Partially Time Varying Longitudinal Cross-Lag Simulation With Seven Variables

					Both Processes			Adaptation Process						Performance Process					
Y	Model	Trial Δ	N	Error	AR perf	Se	p	CL meta	Se	P	CL outef	Se	P	CL meta	Se	P	CL outef	Se	P
Perf	1	4	150	0.1	0.498	0.01	0.00	0.399	0.01	0.00	0.199	0.01	0.00	-0.196	0.01	0.00	0.405	0.01	0.00
Perf	2	4	150	0.3	0.495	0.01	0.00	0.398	0.02	0.00	0.197	0.02	0.00	-0.195	0.01	0.00	***0.411***	***0.01***	0.00
Perf	3	4	150	0.5	0.495	0.01	0.00	0.398	0.03	0.00	0.197	0.03	0.00	-0.196	0.02	0.00	***0.413***	***0.02***	0.00
Perf	4	4	200	0.1	0.500	0.00	0.00	0.402	0.01	0.00	0.196	0.01	0.00	-0.199	0.01	0.00	0.401	0.01	0.00
Perf	5	4	200	0.3	0.500	0.01	0.00	0.406	0.02	0.00	0.190	0.02	0.00	-0.200	0.01	0.00	0.400	0.01	0.00
Perf	6	4	200	0.5	0.501	0.01	0.00	0.410	0.03	0.00	**0.187**	0.03	0.00	-0.201	0.01	0.00	0.400	0.01	0.00
Perf	7	5	150	0.1	0.498	0.01	0.00	0.401	0.01	0.00	0.199	0.01	0.00	-0.196	0.01	0.00	0.405	0.01	0.00
Perf	8	5	150	0.3	0.495	0.01	0.00	0.403	0.02	0.00	0.198	0.02	0.00	-0.195	0.01	0.00	***0.411***	***0.02***	0.00
Perf	9	5	150	0.5	0.495	0.01	0.00	0.405	0.03	0.00	0.198	0.03	0.00	-0.196	0.02	0.00	***0.412***	***0.02***	0.00
Perf	10	5	200	0.1	0.499	0.00	0.00	0.403	0.01	0.00	0.197	0.01	0.00	-0.201	0.01	0.00	0.401	0.01	0.00
Perf	11	5	200	0.3	0.500	0.01	0.00	0.407	0.01	0.00	0.191	0.02	0.00	-0.203	0.01	0.00	0.401	0.01	0.00
Perf	12	5	200	0.5	0.501	0.01	0.00	0.409	0.02	0.00	**0.188**	0.02	0.00	-0.204	0.01	0.00	0.400	0.01	0.00
Perf	13	6	150	0.1	0.499	0.01	0.00	0.401	0.01	0.00	0.199	0.01	0.00	-0.194	0.01	0.00	0.404	0.01	0.00
Perf	14	6	150	0.3	0.497	0.01	0.00	0.404	0.02	0.00	0.199	0.02	0.00	-0.195	0.02	0.00	0.409	0.02	0.00
Perf	15	6	150	0.5	0.497	0.01	0.00	0.407	0.02	0.00	0.200	0.02	0.00	-0.196	0.02	0.00	***0.411***	***0.02***	0.00
Perf	16	6	200	0.1	0.499	0.00	0.00	0.402	0.00	0.00	0.197	0.01	0.00	-0.203	0.01	0.00	0.400	0.01	0.00
Perf	17	6	200	0.3	0.499	0.01	0.00	0.406	0.01	0.00	0.193	0.02	0.00	-0.206	0.01	0.00	0.400	0.01	0.00
Perf	18	6	200	0.5	0.500	0.01	0.00	0.407	0.02	0.00	0.192	0.02	0.00	-0.206	0.01	0.00	0.400	0.01	0.00
Perf	19	7	150	0.1	0.499	0.01	0.00	0.402	0.01	0.00	0.199	0.01	0.00	-0.195	0.01	0.00	0.404	0.01	0.00
Perf	20	7	150	0.3	0.499	0.01	0.00	0.405	0.01	0.00	0.200	0.02	0.00	-0.197	0.02	0.00	0.407	0.02	0.00
Perf	21	7	150	0.5	0.499	0.01	0.00	0.408	0.02	0.00	0.203	0.02	0.00	-0.198	0.02	0.00	0.408	0.02	0.00
Perf	22	7	200	0.1	0.500	0.00	0.00	0.402	0.00	0.00	0.198	0.01	0.00	-0.204	0.01	0.00	0.400	0.01	0.00
Perf	23	7	200	0.3	0.500	0.01	0.00	0.404	0.01	0.00	0.195	0.01	0.00	-0.206	0.01	0.00	0.399	0.01	0.00
Perf	24	7	200	0.5	0.501	0.01	0.00	0.405	0.02	0.00	0.194	0.02	0.00	-0.206	0.02	0.00	0.398	0.02	0.00
Perf	25	8	150	0.1	0.499	0.01	0.00	0.402	0.01	0.00	0.199	0.01	0.00	-0.198	0.02	0.00	0.401	0.01	0.00
Perf	26	8	150	0.3	0.499	0.01	0.00	0.407	0.01	0.00	0.201	0.01	0.00	-0.200	0.02	0.00	0.406	0.02	0.00
Perf	27	8	150	0.5	0.499	0.01	0.00	***0.410***	0.02	0.00	0.205	0.02	0.00	-0.202	0.02	0.00	0.408	0.02	0.00
Perf	28	8	200	0.1	0.499	0.00	0.00	0.402	0.00	0.00	0.197	0.01	0.00	-0.202	0.01	0.00	0.404	0.01	0.00
Perf	29	8	200	0.3	0.499	0.01	0.00	0.403	0.01	0.00	0.193	0.01	0.00	-0.204	0.02	0.00	0.403	0.02	0.00
Perf	30	8	200	0.5	0.499	0.01	0.00	0.402	0.02	0.00	0.192	0.02	0.00	-0.203	0.02	0.00	0.402	0.02	0.00
Perf	31	9	150	0.1	0.499	0.01	0.00	0.403	0.01	0.00	0.199	0.01	0.00	-0.198	0.02	0.00	0.403	0.01	0.00
Perf	32	9	150	0.3	0.498	0.01	0.00	0.408	0.01	0.00	0.200	0.01	0.00	-0.202	0.02	0.00	***0.411***	***0.02***	0.00
Perf	33	9	150	0.5	0.498	0.01	0.00	***0.411***	0.02	0.00	0.202	0.02	0.00	-0.204	0.02	0.00	***0.413***	***0.02***	0.00
Perf	34	9	200	0.1	0.499	0.00	0.00	0.402	0.00	0.00	0.197	0.01	0.00	-0.206	0.02	0.00	0.403	0.01	0.00
Perf	35	9	200	0.3	0.498	0.01	0.00	0.404	0.01	0.00	0.193	0.01	0.00	-0.206	0.02	0.00	0.404	0.02	0.00
Perf	36	9	200	0.5	0.497	0.01	0.00	0.403	0.01	0.00	0.191	0.02	0.00	-0.206	0.02	0.00	0.404	0.02	0.00

Table 14 (cont'd)

					Both Processes			Adaptation Process						Performance Process					
Y	Model	Trial Δ	N	Error	AR lrnef	Se	p	CL perf	Se	P	CL eval	Se	P	CL perf	Se	P	CL eval	Se	P
Lrnef	1	4	150	0.1	0.501	0.01	0.00	-0.199	0.01	0.00	0.396	0.01	0.00	-0.399	0.01	0.00	0.197	0.01	0.00
Lrnef	2	4	150	0.3	0.500	0.01	0.00	-0.196	0.02	0.00	0.392	0.02	0.00	-0.402	0.01	0.00	0.198	0.02	0.00
Lrnef	3	4	150	0.5	0.499	0.01	0.00	-0.194	0.03	0.00	0.390	0.04	0.00	-0.404	0.02	0.00	0.199	0.02	0.00
Lrnef	4	4	200	0.1	0.499	0.01	0.00	-0.201	0.01	0.00	0.400	0.01	0.00	-0.403	0.01	0.00	0.195	0.01	0.00
Lrnef	5	4	200	0.3	0.496	0.01	0.00	-0.204	0.02	0.00	0.399	0.02	0.00	-0.405	0.01	0.00	0.193	0.02	0.00
Lrnef	6	4	200	0.5	0.494	0.01	0.00	-0.207	0.03	0.00	0.398	0.03	0.00	-0.406	0.01	0.00	0.194	0.02	0.00
Lrnef	7	5	150	0.1	0.501	0.01	0.00	-0.199	0.01	0.00	0.396	0.01	0.00	-0.398	0.01	0.00	0.201	0.01	0.00
Lrnef	8	5	150	0.3	0.501	0.01	0.00	-0.199	0.02	0.00	0.390	0.02	0.00	-0.400	0.02	0.00	0.201	0.02	0.00
Lrnef	9	5	150	0.5	0.500	0.01	0.00	-0.200	0.03	0.00	**0.387**	**0.03**	0.00	-0.401	0.02	0.00	0.201	0.02	0.00
Lrnef	10	5	200	0.1	0.499	0.01	0.00	-0.202	0.01	0.00	0.399	0.01	0.00	-0.402	0.01	0.00	0.197	0.01	0.00
Lrnef	11	5	200	0.3	0.496	0.01	0.00	-0.207	0.01	0.00	0.397	0.02	0.00	-0.404	0.01	0.00	0.196	0.02	0.00
Lrnef	12	5	200	0.5	0.494	0.01	0.00	***-0.211***	***0.02***	0.00	0.394	0.02	0.00	-0.405	0.01	0.00	0.196	0.02	0.00
Lrnef	13	6	150	0.1	0.501	0.01	0.00	-0.199	0.01	0.00	0.396	0.01	0.00	-0.400	0.01	0.00	0.201	0.02	0.00
Lrnef	14	6	150	0.3	0.501	0.01	0.00	-0.199	0.02	0.00	**0.390**	**0.02**	0.00	-0.401	0.02	0.00	0.202	0.02	0.00
Lrnef	15	6	150	0.5	0.500	0.01	0.00	-0.200	0.02	0.00	**0.386**	**0.03**	0.00	-0.402	0.02	0.00	0.202	0.02	0.00
Lrnef	16	6	200	0.1	0.499	0.01	0.00	-0.202	0.00	0.00	0.399	0.01	0.00	-0.403	0.01	0.00	0.197	0.01	0.00
Lrnef	17	6	200	0.3	0.496	0.01	0.00	-0.207	0.01	0.00	0.396	0.02	0.00	-0.404	0.01	0.00	0.197	0.02	0.00
Lrnef	18	6	200	0.5	0.494	0.01	0.00	***-0.212***	***0.02***	0.00	0.392	0.02	0.00	-0.405	0.01	0.00	0.197	0.02	0.00
Lrnef	19	7	150	0.1	0.501	0.01	0.00	-0.200	0.01	0.00	0.396	0.01	0.00	-0.401	0.01	0.00	0.201	0.02	0.00
Lrnef	20	7	150	0.3	0.501	0.01	0.00	-0.200	0.02	0.00	0.390	0.02	0.00	-0.402	0.02	0.00	0.202	0.02	0.00
Lrnef	21	7	150	0.5	0.500	0.01	0.00	-0.202	0.02	0.00	**0.388**	**0.03**	0.00	-0.402	0.02	0.00	0.202	0.02	0.00
Lrnef	22	7	200	0.1	0.499	0.01	0.00	-0.202	0.00	0.00	0.399	0.01	0.00	-0.404	0.01	0.00	0.195	0.01	0.00
Lrnef	23	7	200	0.3	0.496	0.01	0.00	-0.208	0.01	0.00	0.396	0.02	0.00	-0.405	0.01	0.00	0.197	0.02	0.00
Lrnef	24	7	200	0.5	0.494	0.01	0.00	***-0.213***	***0.02***	0.00	0.392	0.02	0.00	-0.405	0.02	0.00	0.197	0.02	0.00
Lrnef	25	8	150	0.1	0.501	0.01	0.00	-0.200	0.01	0.00	0.396	0.01	0.00	-0.401	0.01	0.00	0.200	0.02	0.00
Lrnef	26	8	150	0.3	0.500	0.01	0.00	-0.202	0.01	0.00	0.392	0.02	0.00	-0.402	0.02	0.00	0.199	0.02	0.00
Lrnef	27	8	150	0.5	0.499	0.01	0.00	-0.203	0.02	0.00	0.391	0.02	0.00	-0.403	0.02	0.00	0.199	0.02	0.00
Lrnef	28	8	200	0.1	0.499	0.01	0.00	-0.202	0.00	0.00	0.399	0.01	0.00	-0.400	0.01	0.00	0.202	0.02	0.00
Lrnef	29	8	200	0.3	0.496	0.01	0.00	-0.208	0.01	0.00	0.394	0.01	0.00	-0.401	0.02	0.00	0.201	0.02	0.00
Lrnef	30	8	200	0.5	0.494	0.01	0.00	***-0.212***	***0.02***	0.00	0.390	0.02	0.00	-0.401	0.02	0.00	0.201	0.02	0.00
Lrnef	31	9	150	0.1	0.501	0.01	0.00	-0.200	0.01	0.00	0.396	0.01	0.00	-0.405	0.02	0.00	0.195	0.02	0.00
Lrnef	32	9	150	0.3	0.500	0.01	0.00	-0.202	0.01	0.00	0.392	0.02	0.00	-0.404	0.02	0.00	0.197	0.02	0.00
Lrnef	33	9	150	0.5	0.499	0.01	0.00	-0.203	0.02	0.00	0.391	0.02	0.00	-0.404	0.02	0.00	0.198	0.02	0.00
Lrnef	34	9	200	0.1	0.499	0.00	0.00	-0.202	0.00	0.00	0.399	0.01	0.00	-0.399	0.01	0.00	0.205	0.02	0.00
Lrnef	35	9	200	0.3	0.496	0.01	0.00	-0.207	0.01	0.00	0.393	0.01	0.00	-0.401	0.02	0.00	0.204	0.02	0.00
Lrnef	36	9	200	0.5	0.494	0.01	0.00	***-0.210***	***0.02***	0.00	**0.389**	**0.02**	0.00	-0.401	0.02	0.00	0.204	0.02	0.00

Table 14 (cont'd)

					Both Processes			Adaptation Process						Performance Process					
Y	Model	Trial Δ	N	Error	AR meta	Se	p	CL lrnef	Se	P	CL eval	Se	P	CL lrnef	Se	P	CL eval	Se	P
Meta	1	4	150	0.1	0.500	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	0.197	0.01	0.00	0.205	0.02	0.00
Meta	2	4	150	0.3	0.497	0.01	0.00	0.399	0.02	0.00	0.402	0.02	0.00	0.197	0.02	0.00	0.208	0.02	0.00
Meta	3	4	150	0.5	0.496	0.02	0.00	0.397	0.03	0.00	0.404	0.04	0.00	0.198	0.02	0.00	0.210	0.02	0.00
Meta	4	4	200	0.1	0.500	0.01	0.00	0.398	0.01	0.00	0.397	0.01	0.00	0.203	0.01	0.00	0.194	0.01	0.00
Meta	5	4	200	0.3	0.498	0.01	0.00	0.396	0.02	0.00	0.391	0.02	0.00	0.203	0.01	0.00	0.192	0.02	0.00
Meta	6	4	200	0.5	0.497	0.01	0.00	0.394	0.03	0.00	**0.387**	0.03	0.00	0.203	0.01	0.00	0.192	0.02	0.00
Meta	7	5	150	0.1	0.500	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	0.195	0.01	0.00	0.207	0.02	0.00
Meta	8	5	150	0.3	0.498	0.01	0.00	0.400	0.02	0.00	0.401	0.02	0.00	0.196	0.02	0.00	0.209	0.02	0.00
Meta	9	5	150	0.5	0.497	0.01	0.00	0.399	0.03	0.00	0.402	0.03	0.00	0.197	0.02	0.00	***0.210***	0.02	0.00
Meta	10	5	200	0.1	0.500	0.00	0.00	0.399	0.01	0.00	0.398	0.01	0.00	0.205	0.01	0.00	0.191	0.01	0.00
Meta	11	5	200	0.3	0.499	0.01	0.00	0.398	0.02	0.00	0.394	0.02	0.00	0.204	0.01	0.00	**0.189**	0.02	0.00
Meta	12	5	200	0.5	0.497	0.01	0.00	0.397	0.03	0.00	0.393	0.03	0.00	0.204	0.01	0.00	**0.189**	0.02	0.00
Meta	13	6	150	0.1	0.500	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	0.193	0.01	0.00	0.208	0.02	0.00
Meta	14	6	150	0.3	0.498	0.01	0.00	0.401	0.02	0.00	0.402	0.02	0.00	0.195	0.02	0.00	0.209	0.02	0.00
Meta	15	6	150	0.5	0.497	0.01	0.00	0.400	0.02	0.00	0.404	0.03	0.00	0.196	0.02	0.00	0.210	0.02	0.00
Meta	16	6	200	0.1	0.500	0.00	0.00	0.399	0.01	0.00	0.397	0.01	0.00	0.204	0.01	0.00	0.192	0.02	0.00
Meta	17	6	200	0.3	0.499	0.01	0.00	0.398	0.02	0.00	0.393	0.02	0.00	0.204	0.01	0.00	0.191	0.02	0.00
Meta	18	6	200	0.5	0.497	0.01	0.00	0.397	0.02	0.00	0.391	0.02	0.00	0.204	0.02	0.00	0.191	0.02	0.00
Meta	19	7	150	0.1	0.499	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	0.193	0.02	0.00	0.207	0.02	0.00
Meta	20	7	150	0.3	0.498	0.01	0.00	0.400	0.02	0.00	0.402	0.02	0.00	0.195	0.02	0.00	0.208	0.02	0.00
Meta	21	7	150	0.5	0.497	0.01	0.00	0.400	0.02	0.00	0.404	0.03	0.00	0.197	0.02	0.00	0.209	0.02	0.00
Meta	22	7	200	0.1	0.500	0.00	0.00	0.399	0.01	0.00	0.397	0.01	0.00	0.203	0.01	0.00	0.195	0.02	0.00
Meta	23	7	200	0.3	0.499	0.01	0.00	0.398	0.02	0.00	0.391	0.02	0.00	0.203	0.02	0.00	0.194	0.02	0.00
Meta	24	7	200	0.5	0.497	0.01	0.00	0.399	0.02	0.00	**0.387**	0.02	0.00	0.203	0.02	0.00	0.194	0.02	0.00
Meta	25	8	150	0.1	0.499	0.01	0.00	0.400	0.01	0.00	0.401	0.01	0.00	0.195	0.02	0.00	0.206	0.02	0.00
Meta	26	8	150	0.3	0.498	0.01	0.00	0.399	0.02	0.00	0.403	0.02	0.00	0.198	0.02	0.00	0.209	0.02	0.00
Meta	27	8	150	0.5	0.498	0.01	0.00	0.398	0.02	0.00	0.404	0.02	0.00	0.199	0.02	0.00	0.210	0.02	0.00
Meta	28	8	200	0.1	0.500	0.00	0.00	0.399	0.01	0.00	0.397	0.01	0.00	0.203	0.01	0.00	0.196	0.02	0.00
Meta	29	8	200	0.3	0.499	0.01	0.00	0.399	0.01	0.00	0.392	0.02	0.00	0.203	0.02	0.00	0.194	0.02	0.00
Meta	30	8	200	0.5	0.497	0.01	0.00	0.399	0.02	0.00	**0.388**	0.02	0.00	0.204	0.02	0.00	0.194	0.02	0.00
Meta	31	9	150	0.1	0.499	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	0.194	0.02	0.00	***0.211***	0.02	0.00
Meta	32	9	150	0.3	0.499	0.01	0.00	0.399	0.02	0.00	0.399	0.02	0.00	0.199	0.02	0.00	***0.214***	0.02	0.00
Meta	33	9	150	0.5	0.499	0.01	0.00	0.397	0.02	0.00	0.399	0.02	0.00	0.200	0.02	0.00	***0.215***	0.02	0.00
Meta	34	9	200	0.1	0.500	0.00	0.00	0.399	0.01	0.00	0.397	0.01	0.00	0.206	0.02	0.00	0.193	0.02	0.00
Meta	35	9	200	0.3	0.498	0.01	0.00	0.398	0.01	0.00	0.393	0.01	0.00	0.208	0.02	0.00	0.192	0.02	0.00
Meta	36	9	200	0.5	0.497	0.01	0.00	0.397	0.02	0.00	0.391	0.02	0.00	0.209	0.02	0.00	0.192	0.02	0.00

Table 14 (cont'd)

Y	Model	Trial Δ	N	Error	Both Processes AR eval	Se	p	Adaptation Process CL perf	Se	P	Performance Process CL perf	Se	P
Eval	1	4	150	0.1	0.500	0.01	0.00	-0.199	0.01	0.00	-0.399	0.01	0.00
Eval	2	4	150	0.3	0.499	0.01	0.00	-0.194	0.02	0.00	-0.402	0.01	0.00
Eval	3	4	150	0.5	0.499	0.02	0.00	***-0.188***	0.03	0.00	-0.404	0.01	0.00
Eval	4	4	200	0.1	0.500	0.01	0.00	-0.198	0.01	0.00	-0.403	0.01	0.00
Eval	5	4	200	0.3	0.498	0.01	0.00	-0.195	0.02	0.00	-0.406	0.01	0.00
Eval	6	4	200	0.5	0.496	0.01	0.00	-0.193	0.03	0.00	-0.406	0.01	0.00
Eval	7	5	150	0.1	0.500	0.01	0.00	-0.198	0.01	0.00	-0.400	0.01	0.00
Eval	8	5	150	0.3	0.500	0.01	0.00	-0.194	0.02	0.00	-0.404	0.01	0.00
Eval	9	5	150	0.5	0.500	0.02	0.00	***-0.189***	0.03	0.00	-0.405	0.02	0.00
Eval	10	5	200	0.1	0.500	0.01	0.00	-0.199	0.01	0.00	-0.403	0.01	0.00
Eval	11	5	200	0.3	0.498	0.01	0.00	-0.197	0.02	0.00	-0.406	0.01	0.00
Eval	12	5	200	0.5	0.496	0.01	0.00	-0.195	0.02	0.00	-0.407	0.01	0.00
Eval	13	6	150	0.1	0.500	0.01	0.00	-0.197	0.01	0.00	-0.404	0.01	0.00
Eval	14	6	150	0.3	0.500	0.01	0.00	-0.191	0.02	0.00	-0.408	0.01	0.00
Eval	15	6	150	0.5	0.500	0.02	0.00	***-0.186***	0.02	0.00	-0.410	0.02	0.00
Eval	16	6	200	0.1	0.501	0.01	0.00	-0.200	0.00	0.00	-0.402	0.01	0.00
Eval	17	6	200	0.3	0.498	0.01	0.00	-0.199	0.01	0.00	-0.406	0.01	0.00
Eval	18	6	200	0.5	0.496	0.01	0.00	-0.197	0.02	0.00	-0.406	0.01	0.00
Eval	19	7	150	0.1	0.500	0.01	0.00	-0.198	0.01	0.00	-0.404	0.01	0.00
Eval	20	7	150	0.3	0.500	0.01	0.00	-0.194	0.02	0.00	-0.409	0.02	0.00
Eval	21	7	150	0.5	0.500	0.02	0.00	-0.191	0.02	0.00	***-0.410***	0.02	0.00
Eval	22	7	200	0.1	0.500	0.01	0.00	-0.200	0.00	0.00	-0.403	0.01	0.00
Eval	23	7	200	0.3	0.498	0.01	0.00	-0.198	0.01	0.00	-0.406	0.01	0.00
Eval	24	7	200	0.5	0.497	0.01	0.00	-0.196	0.02	0.00	-0.406	0.01	0.00
Eval	25	8	150	0.1	0.500	0.01	0.00	-0.198	0.01	0.00	-0.405	0.01	0.00
Eval	26	8	150	0.3	0.500	0.01	0.00	-0.196	0.01	0.00	-0.408	0.02	0.00
Eval	27	8	150	0.5	0.500	0.02	0.00	-0.194	0.02	0.00	-0.408	0.02	0.00
Eval	28	8	200	0.1	0.501	0.01	0.00	-0.200	0.00	0.00	-0.403	0.01	0.00
Eval	29	8	200	0.3	0.499	0.01	0.00	-0.200	0.01	0.00	-0.405	0.01	0.00
Eval	30	8	200	0.5	0.497	0.01	0.00	-0.200	0.02	0.00	-0.404	0.01	0.00
Eval	31	9	150	0.1	0.501	0.01	0.00	-0.199	0.01	0.00	-0.403	0.01	0.00
Eval	32	9	150	0.3	0.501	0.01	0.00	-0.197	0.01	0.00	-0.405	0.02	0.00
Eval	33	9	150	0.5	0.500	0.02	0.00	-0.195	0.02	0.00	-0.405	0.02	0.00
Eval	34	9	200	0.1	0.501	0.01	0.00	-0.200	0.00	0.00	-0.403	0.01	0.00
Eval	35	9	200	0.3	0.499	0.01	0.00	-0.201	0.01	0.00	-0.404	0.01	0.00
Eval	36	9	200	0.5	0.497	0.01	0.00	-0.200	0.02	0.00	-0.405	0.02	0.00

Table 14 (cont'd)

					Both Processes			Adaptation Process						Performance Process					
Y	Model	Trial Δ	N	Error	AR goals	Se	p	CL perf	Se	P	CL se	Se	P	CL perf	Se	P	CL se	Se	P
Goals	1	4	150	0.1	0.498	0.01	0.00	0.201	0.01	0.00	0.402	0.01	0.00	0.401	0.01	0.00	-0.197	0.01	0.00
Goals	2	4	150	0.3	0.495	0.01	0.00	0.201	0.02	0.00	0.405	0.02	0.00	0.402	0.01	0.00	-0.192	0.02	0.00
Goals	3	4	150	0.5	0.495	0.01	0.00	0.200	0.03	0.00	0.409	0.03	0.00	0.402	0.02	0.00	-0.191	0.02	0.00
Goals	4	4	200	0.1	0.503	0.00	0.00	0.200	0.01	0.00	0.400	0.01	0.00	0.399	0.01	0.00	-0.202	0.01	0.00
Goals	5	4	200	0.3	0.506	0.01	0.00	0.200	0.02	0.00	0.402	0.02	0.00	0.398	0.01	0.00	-0.203	0.02	0.00
Goals	6	4	200	0.5	0.505	0.01	0.00	0.199	0.03	0.00	0.406	0.03	0.00	0.399	0.01	0.00	-0.203	0.02	0.00
Goals	7	5	150	0.1	0.498	0.01	0.00	0.201	0.01	0.00	0.401	0.01	0.00	0.400	0.01	0.00	-0.195	0.01	0.00
Goals	8	5	150	0.3	0.496	0.01	0.00	0.202	0.02	0.00	0.405	0.02	0.00	0.401	0.01	0.00	-0.191	0.02	0.00
Goals	9	5	150	0.5	0.495	0.01	0.00	0.201	0.03	0.00	0.409	0.03	0.00	0.401	0.02	0.00	-0.191	0.02	0.00
Goals	10	5	200	0.1	0.503	0.00	0.00	0.200	0.01	0.00	0.400	0.01	0.00	0.400	0.01	0.00	-0.203	0.01	0.00
Goals	11	5	200	0.3	0.506	0.01	0.00	0.200	0.02	0.00	0.401	0.02	0.00	0.399	0.01	0.00	-0.203	0.02	0.00
Goals	12	5	200	0.5	0.506	0.01	0.00	0.199	0.02	0.00	0.402	0.02	0.00	0.400	0.01	0.00	-0.202	0.02	0.00
Goals	13	6	150	0.1	0.499	0.01	0.00	0.201	0.01	0.00	0.401	0.01	0.00	0.396	0.01	0.00	-0.190	0.02	0.00
Goals	14	6	150	0.3	0.498	0.01	0.00	0.203	0.02	0.00	0.404	0.02	0.00	0.397	0.02	0.00	**-0.189**	0.02	0.00
Goals	15	6	150	0.5	0.498	0.01	0.00	0.202	0.02	0.00	0.408	0.02	0.00	0.397	0.02	0.00	**-0.189**	0.02	0.00
Goals	16	6	200	0.1	0.503	0.00	0.00	0.200	0.01	0.00	0.400	0.01	0.00	0.402	0.01	0.00	-0.204	0.01	0.00
Goals	17	6	200	0.3	0.505	0.01	0.00	0.197	0.01	0.00	0.400	0.02	0.00	0.402	0.01	0.00	-0.202	0.02	0.00
Goals	18	6	200	0.5	0.505	0.01	0.00	0.195	0.02	0.00	0.401	0.02	0.00	0.403	0.01	0.00	-0.201	0.02	0.00
Goals	19	7	150	0.1	0.499	0.01	0.00	0.200	0.01	0.00	0.401	0.01	0.00	0.399	0.01	0.00	-0.191	0.02	0.00
Goals	20	7	150	0.3	0.498	0.01	0.00	0.200	0.02	0.00	0.406	0.02	0.00	0.400	0.02	0.00	-0.191	0.02	0.00
Goals	21	7	150	0.5	0.497	0.01	0.00	0.198	0.02	0.00	***0.410***	0.02	0.00	0.400	0.02	0.00	-0.191	0.02	0.00
Goals	22	7	200	0.1	0.503	0.00	0.00	0.200	0.00	0.00	0.399	0.01	0.00	0.400	0.01	0.00	-0.198	0.01	0.00
Goals	23	7	200	0.3	0.506	0.01	0.00	0.199	0.01	0.00	0.397	0.01	0.00	0.401	0.01	0.00	-0.198	0.02	0.00
Goals	24	7	200	0.5	0.507	0.01	0.00	0.197	0.02	0.00	0.396	0.02	0.00	0.402	0.01	0.00	-0.198	0.02	0.00
Goals	25	8	150	0.1	0.500	0.01	0.00	0.200	0.01	0.00	0.401	0.01	0.00	0.396	0.01	0.00	-0.190	0.02	0.00
Goals	26	8	150	0.3	0.498	0.01	0.00	0.202	0.01	0.00	0.406	0.02	0.00	0.397	0.02	0.00	-0.192	0.02	0.00
Goals	27	8	150	0.5	0.497	0.01	0.00	0.202	0.02	0.00	***0.411***	0.02	0.00	0.397	0.02	0.00	-0.193	0.02	0.00
Goals	28	8	200	0.1	0.503	0.00	0.00	0.200	0.00	0.00	0.399	0.01	0.00	0.403	0.01	0.00	-0.202	0.02	0.00
Goals	29	8	200	0.3	0.506	0.01	0.00	0.200	0.01	0.00	0.398	0.01	0.00	0.404	0.01	0.00	-0.199	0.02	0.00
Goals	30	8	200	0.5	0.506	0.01	0.00	0.199	0.02	0.00	0.397	0.02	0.00	0.404	0.02	0.00	-0.199	0.02	0.00
Goals	31	9	150	0.1	0.500	0.01	0.00	0.200	0.01	0.00	0.402	0.01	0.00	0.398	0.01	0.00	-0.194	0.02	0.00
Goals	32	9	150	0.3	0.498	0.01	0.00	0.198	0.01	0.00	0.407	0.02	0.00	0.398	0.02	0.00	-0.193	0.02	0.00
Goals	33	9	150	0.5	0.496	0.01	0.00	0.196	0.02	0.00	***0.410***	0.02	0.00	0.398	0.02	0.00	-0.193	0.02	0.00
Goals	34	9	200	0.1	0.503	0.00	0.00	0.200	0.00	0.00	0.399	0.01	0.00	0.400	0.01	0.00	-0.196	0.02	0.00
Goals	35	9	200	0.3	0.507	0.01	0.00	0.200	0.01	0.00	0.396	0.01	0.00	0.402	0.02	0.00	-0.195	0.02	0.00
Goals	36	9	200	0.5	0.508	0.01	0.00	0.199	0.02	0.00	0.395	0.02	0.00	0.402	0.02	0.00	-0.195	0.02	0.00

Table 14 (cont'd)

Y	Model	Trial Δ	N	Error	Both Processes AR outef	Se	p	Adaptation Process CL goals	Se	P	CL se	Se	P	Performance Process CL goals	Se	P	CL se	Se	P
Outef	1	4	150	0.1	0.499	0.01	0.00	0.199	0.01	0.00	0.200	0.01	0.00	0.406	0.01	0.00	0.196	0.01	0.00
Outef	2	4	150	0.3	0.499	0.01	0.00	0.196	0.02	0.00	0.200	0.02	0.00	0.407	0.02	0.00	0.196	0.02	0.00
Outef	3	4	150	0.5	0.499	0.01	0.00	0.196	0.03	0.00	0.199	0.03	0.00	0.407	0.02	0.00	0.196	0.02	0.00
Outef	4	4	200	0.1	0.502	0.01	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.398	0.01	0.00	0.203	0.01	0.00
Outef	5	4	200	0.3	0.504	0.01	0.00	0.198	0.02	0.00	0.201	0.02	0.00	0.397	0.01	0.00	0.203	0.02	0.00
Outef	6	4	200	0.5	0.504	0.01	0.00	0.194	0.03	0.00	0.204	0.03	0.00	0.397	0.01	0.00	0.202	0.02	0.00
Outef	7	5	150	0.1	0.499	0.01	0.00	0.199	0.01	0.00	0.201	0.01	0.00	0.407	0.01	0.00	0.193	0.02	0.00
Outef	8	5	150	0.3	0.499	0.01	0.00	0.201	0.02	0.00	0.199	0.02	0.00	0.405	0.02	0.00	0.195	0.02	0.00
Outef	9	5	150	0.5	0.499	0.01	0.00	0.206	0.03	0.00	0.196	0.03	0.00	0.404	0.02	0.00	0.195	0.02	0.00
Outef	10	5	200	0.1	0.502	0.00	0.00	0.200	0.01	0.00	0.201	0.01	0.00	0.400	0.01	0.00	0.201	0.01	0.00
Outef	11	5	200	0.3	0.504	0.01	0.00	0.198	0.02	0.00	0.202	0.02	0.00	0.398	0.01	0.00	0.202	0.02	0.00
Outef	12	5	200	0.5	0.504	0.01	0.00	0.196	0.02	0.00	0.204	0.02	0.00	0.397	0.01	0.00	0.202	0.02	0.00
Outef	13	6	150	0.1	0.499	0.01	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.405	0.01	0.00	0.195	0.02	0.00
Outef	14	6	150	0.3	0.499	0.01	0.00	0.202	0.02	0.00	0.197	0.02	0.00	0.404	0.02	0.00	0.196	0.02	0.00
Outef	15	6	150	0.5	0.500	0.01	0.00	0.205	0.02	0.00	0.193	0.03	0.00	0.403	0.02	0.00	0.196	0.02	0.00
Outef	16	6	200	0.1	0.501	0.00	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.399	0.01	0.00	0.205	0.01	0.00
Outef	17	6	200	0.3	0.503	0.01	0.00	0.198	0.01	0.00	0.202	0.02	0.00	0.398	0.01	0.00	0.204	0.02	0.00
Outef	18	6	200	0.5	0.504	0.01	0.00	0.195	0.02	0.00	0.204	0.02	0.00	0.398	0.02	0.00	0.203	0.02	0.00
Outef	19	7	150	0.1	0.499	0.01	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.404	0.01	0.00	0.198	0.02	0.00
Outef	20	7	150	0.3	0.499	0.01	0.00	0.201	0.02	0.00	0.196	0.02	0.00	0.405	0.02	0.00	0.198	0.02	0.00
Outef	21	7	150	0.5	0.499	0.01	0.00	0.203	0.02	0.00	0.192	0.02	0.00	0.405	0.02	0.00	0.197	0.02	0.00
Outef	22	7	200	0.1	0.502	0.00	0.00	0.200	0.00	0.00	0.201	0.01	0.00	0.400	0.01	0.00	0.201	0.01	0.00
Outef	23	7	200	0.3	0.505	0.01	0.00	0.197	0.01	0.00	0.206	0.01	0.00	0.399	0.02	0.00	0.199	0.02	0.00
Outef	24	7	200	0.5	0.505	0.01	0.00	0.193	0.02	0.00	*0.211*	0.02	0.00	0.398	0.02	0.00	0.198	0.02	0.00
Outef	25	8	150	0.1	0.499	0.01	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.405	0.02	0.00	0.192	0.02	0.00
Outef	26	8	150	0.3	0.499	0.01	0.00	0.203	0.02	0.00	0.197	0.02	0.00	0.404	0.02	0.00	0.192	0.02	0.00
Outef	27	8	150	0.5	0.500	0.01	0.00	0.206	0.02	0.00	0.194	0.02	0.00	0.403	0.02	0.00	0.193	0.02	0.00
Outef	28	8	200	0.1	0.501	0.00	0.00	0.200	0.00	0.00	0.201	0.01	0.00	0.402	0.01	0.00	0.200	0.02	0.00
Outef	29	8	200	0.3	0.503	0.01	0.00	0.197	0.01	0.00	0.204	0.01	0.00	0.401	0.02	0.00	0.200	0.02	0.00
Outef	30	8	200	0.5	0.504	0.01	0.00	0.194	0.02	0.00	0.207	0.02	0.00	0.400	0.02	0.00	0.199	0.02	0.00
Outef	31	9	150	0.1	0.499	0.01	0.00	0.200	0.01	0.00	0.200	0.01	0.00	0.403	0.02	0.00	0.194	0.02	0.00
Outef	32	9	150	0.3	0.500	0.01	0.00	0.203	0.01	0.00	0.196	0.02	0.00	0.402	0.02	0.00	0.194	0.02	0.00
Outef	33	9	150	0.5	0.500	0.01	0.00	0.207	0.02	0.00	0.193	0.02	0.00	0.402	0.02	0.00	0.194	0.02	0.00
Outef	34	9	200	0.1	0.501	0.00	0.00	0.200	0.00	0.00	0.201	0.01	0.00	0.400	0.01	0.00	0.201	0.02	0.00
Outef	35	9	200	0.3	0.503	0.01	0.00	0.198	0.01	0.00	0.203	0.01	0.00	0.401	0.02	0.00	0.202	0.02	0.00
Outef	36	9	200	0.5	0.503	0.01	0.00	0.195	0.02	0.00	0.205	0.02	0.00	0.401	0.02	0.00	0.202	0.02	0.00

Table 14 (cont'd)

					Both Processes			Adaptation Process			Performance Process		
Y	Model	Trial Δ	N	Error	AR se	Se	p	CL perf	Se	P	CL perf	Se	P
Se	1	4	150	0.1	0.498	0.01	0.00	0.401	0.01	0.00	0.199	0.01	0.00
Se	2	4	150	0.3	0.496	0.01	0.00	0.402	0.02	0.00	0.200	0.01	0.00
Se	3	4	150	0.5	0.495	0.02	0.00	0.403	0.03	0.00	0.201	0.01	0.00
Se	4	4	200	0.1	0.501	0.01	0.00	0.398	0.01	0.00	0.198	0.01	0.00
Se	5	4	200	0.3	0.504	0.01	0.00	0.395	0.02	0.00	0.198	0.01	0.00
Se	6	4	200	0.5	0.505	0.01	0.00	0.393	0.03	0.00	0.198	0.01	0.00
Se	7	5	150	0.1	0.499	0.01	0.00	0.401	0.01	0.00	0.199	0.01	0.00
Se	8	5	150	0.3	0.496	0.01	0.00	0.404	0.02	0.00	0.200	0.01	0.00
Se	9	5	150	0.5	0.495	0.02	0.00	0.404	0.03	0.00	0.200	0.01	0.00
Se	10	5	200	0.1	0.501	0.01	0.00	0.398	0.01	0.00	0.199	0.01	0.00
Se	11	5	200	0.3	0.504	0.01	0.00	0.395	0.02	0.00	0.198	0.01	0.00
Se	12	5	200	0.5	0.505	0.01	0.00	0.392	0.02	0.00	0.199	0.01	0.00
Se	13	6	150	0.1	0.498	0.01	0.00	0.400	0.01	0.00	0.202	0.01	0.00
Se	14	6	150	0.3	0.496	0.01	0.00	0.398	0.02	0.00	0.203	0.01	0.00
Se	15	6	150	0.5	0.496	0.02	0.00	0.395	0.02	0.00	0.202	0.01	0.00
Se	16	6	200	0.1	0.501	0.01	0.00	0.398	0.01	0.00	0.199	0.01	0.00
Se	17	6	200	0.3	0.504	0.01	0.00	0.394	0.01	0.00	0.199	0.01	0.00
Se	18	6	200	0.5	0.505	0.01	0.00	0.392	0.02	0.00	0.199	0.01	0.00
Se	19	7	150	0.1	0.498	0.01	0.00	0.401	0.01	0.00	0.202	0.01	0.00
Se	20	7	150	0.3	0.497	0.01	0.00	0.402	0.02	0.00	0.201	0.01	0.00
Se	21	7	150	0.5	0.496	0.02	0.00	0.402	0.02	0.00	0.200	0.02	0.00
Se	22	7	200	0.1	0.501	0.00	0.00	0.398	0.00	0.00	0.200	0.01	0.00
Se	23	7	200	0.3	0.504	0.01	0.00	0.395	0.01	0.00	0.199	0.01	0.00
Se	24	7	200	0.5	0.505	0.01	0.00	0.394	0.02	0.00	0.198	0.01	0.00
Se	25	8	150	0.1	0.499	0.01	0.00	0.401	0.01	0.00	0.202	0.01	0.00
Se	26	8	150	0.3	0.497	0.01	0.00	0.401	0.01	0.00	0.201	0.02	0.00
Se	27	8	150	0.5	0.496	0.02	0.00	0.400	0.02	0.00	0.200	0.02	0.00
Se	28	8	200	0.1	0.501	0.00	0.00	0.398	0.00	0.00	0.202	0.01	0.00
Se	29	8	200	0.3	0.504	0.01	0.00	0.395	0.01	0.00	0.201	0.01	0.00
Se	30	8	200	0.5	0.505	0.01	0.00	0.394	0.02	0.00	0.200	0.01	0.00
Se	31	9	150	0.1	0.498	0.01	0.00	0.401	0.01	0.00	0.202	0.01	0.00
Se	32	9	150	0.3	0.496	0.01	0.00	0.402	0.01	0.00	0.199	0.02	0.00
Se	33	9	150	0.5	0.496	0.02	0.00	0.400	0.02	0.00	0.197	0.02	0.00
Se	34	9	200	0.1	0.501	0.00	0.00	0.398	0.00	0.00	0.202	0.01	0.00
Se	35	9	200	0.3	0.503	0.01	0.00	0.397	0.01	0.00	0.199	0.01	0.00
Se	36	9	200	0.5	0.504	0.01	0.00	0.397	0.02	0.00	0.198	0.02	0.00

APPENDIX B: Overall Flow of the Two-Day Experiment

Table 15
Day 1: Training

Time	Minutes	Description	Action
0:10	0:10	Familiarization	Consent, Demographics and Trait Goal Orientation
0:15	0:05	Familiarization	TANDEM Demo by Experimenter
0:17	0:02	Familiarization	Manual Familiarization
0:18	0:01	Familiarization	Familiarization Trial
0:19	0:01	Familiarization	Feedback Familiarization
0:23	0:04	Training - Block 1	**Instructions – Block 1**
0:25	0:02	Training - Block 1	Manual
0:29	0:04	Training - Block 1	Training Scenario 1
0:30	0:01	Training - Block 1	Feedback
0:32	0:02	Training - Block 1	Manual
0:36	0:04	Training - Block 1	Training Scenario 2
0:37	0:01	Training - Block 1	Feedback
0:39	0:02	Training - Block 1	Manual
0:43	0:04	Training - Block 1	Training Scenario 3
0:44	0:01	Training - Block 1	Feedback
0:48	0:04	Training - Block 2	**Instructions – Block 2**
0:50	0:02	Training - Block 2	Manual
0:54	0:04	Training - Block 2	Training Scenario 4
0:55	0:01	Training - Block 2	Feedback
0:57	0:02	Training - Block 2	Manual
1:01	0:04	Training - Block 2	Training Scenario 5
1:02	0:01	Training - Block 2	Feedback
1:04	0:02	Training - Block 2	Manual
1:08	0:04	Training - Block 2	Training Scenario 6
1:09	0:01	Training - Block 2	Feedback
1:13	0:04	Training - Block 3	**Instructions – Block 3**
1:15	0:02	Training - Block 3	Manual
1:19	0:04	Training - Block 3	Training Scenario 7
1:20	0:01	Training - Block 3	Feedback
1:22	0:02	Training - Block 3	Manual
1:26	0:04	Training - Block 3	Training Scenario 8
1:27	0:01	Training - Block 3	Feedback
1:29	0:02	Training - Block 3	Manual
1:33	0:04	Training - Block 3	Training Scenario 9
1:34	0:01	Training - Block 3	Feedback
1:49	0:15	Measures	TANDEM Knowledge Test, State Goal Orientation

Day 1 TOTAL TIME = 2:00 = 4 credits

Table 16
Day 2: Performance

Time	Minutes	Description	Action
0:08	0:08	Re-training	Re-Read Training Topics
0:10	0:02	Re-training	Manual familiarization
0:14	0:04	Re-training	Training Scenario
0:15	0:01	Re-training	Feedback
0:25	0:10	Measures	TANDEM Knowledge Test, State Goal Orientation
0:27	0:02	Routine	Instructions
0:28	0:01	Routine	SR Measures
0:29	0:01	Routine	Manual
0:33	0:04	Routine	Scenario 1 (Routine Performance Trial)
0:34	0:01	Routine	Feedback
0:41	0:07	Routine	SR Measures, Manual, Scenario 2, Feedback
0:48	0:07	Routine	SR Measures, Manual, Scenario 3, Feedback
0:55	0:07	Routine	SR Measures, Manual, Scenario 4, Feedback
1:02	0:07	Routine	SR Measures, Manual, Scenario 5, Feedback
1:05	0:03	Adaptive	Instructions (and Reminder of Reward)
1:06	0:01	Adaptive	SR Measures
1:07	0:01	Adaptive	Manual
1:11	0:04	Adaptive	Scenario 6 (Adaptive Performance Trial)
1:12	0:01	Adaptive	Feedback
1:19	0:07	Adaptive	SR Measures, Manual, Scenario 7, Feedback
1:26	0:07	Adaptive	SR Measures, Manual, Scenario 8, Feedback
1:33	0:07	Adaptive	SR Measures, Manual, Scenario 9, Feedback
1:40	0:07	Adaptive	SR Measures, Manual, Scenario10, Feedback
1:47	0:07	Adaptive	SR Measures, Manual, Scenario11, Feedback
1:54	0:07	Adaptive	SR Measures, Manual, Scenario12, Feedback
2:01	0:07	Adaptive	SR Measures, Manual, Scenario13, Feedback
2:08	0:07	Adaptive	SR Measures, Manual, Scenario14, Feedback
2:15	0:07	Adaptive	SR Measures, Manual, Scenario15, Feedback
2:22	0:07	Adaptive	SR Measures, Manual, Scenario16, Feedback
2:29	0:07	Adaptive	SR Measures, Manual, Scenario17, Feedback
2:36	0:07	Adaptive	SR Measures, Manual, Scenario18, Feedback
2:43	0:07	Adaptive	SR Measures, Manual, Scenario19, Feedback
2:50	0:07	Adaptive	SR Measures, Manual, Scenario20, Feedback
2:51	0:01	Adaptive	SR Measures
2:52	0:01	Adaptive	Debrief

Day 2   TOTAL TIME = 4:00 = 6 credits

APPENDIX C:

Training Materials

Practice Topics

<u>Training Topics for Training Block 1</u>
In this first block of three 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.

<u>Training Topics for Training Block 2</u>
In this second block of three 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.

<u>Training Topics for Training Block 3</u>
In this last block of three 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.

Possible Errors

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.

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.

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.

<u>Contact type</u>

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

<u>Contact class</u>

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

<u>Contact intent</u>

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

<u>Final engagement decision</u>

CLEAR	If INTENT = Peaceful
SHOOT	If INTENT = Hostile

APPENDIX D:

Measures

Metacognition
For each of the items below, rate the extent to which you were thinking about these issues during THE LAST TRIAL. Please use the scale shown below to make your ratings.

1	2	3	4	5
Never	Rarely	Sometimes	Frequently	Constantly

1) During the trial, I monitored how well I was learning its requirements.
2) When my methods were not successful, I experimented with different procedures for performing the task.
3) I thought about new strategies for improving my performance.
4) I monitored closely the areas where I needed the most study and practice.

Self-efficacy
This set of questions asks you to describe how you feel about your capabilities for performing ON THE NEXT TRIAL of this simulation using the following scale.

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.

1) How many points do you plan to score during the next trial? ________
2) How many targets do you plan to prosecute correctly? ______
3) Please indicate which goal is more important to you for THE NEXT TRIAL using the following scale.

Figure out as much as I can — Do as much as I can

|_________|_________|_________|_________|_________|_________|_________|_________|
1 2 3 4 5 6 7 8 9

Evaluation

(Behavioral) Total amount of time spent reviewing performance feedback information.

Learning-oriented Effort

(Behavioral) Amount of information sought (number of pages viewed) from the manual
(Behavioral) Amount of time spent investigating information from the manual

1) Please use the following scale to indicate the extent to which you focused on understanding what changed in the task IN THE LAST TRIAL.

1	2	3	4	5
Not at All	A very small extent	A small extent	A moderate extent	A great extent

Outcome-oriented Effort

(Behavioral) Total amount of behaviors (total number of clicks)

Performance

(Behavioral) Total score = (Correct execution of targets - penalties for incorrect decisions - penalties for inner perimeter crosses - penalties for outer perimeter crosses)

Additional Measures

1) When you think you've figured out what changed in the task, answer this question: What changed in the task? ____
2) Please use the scale below to indicate the focus of your attention and action IN THE LAST TRIAL.

Executing as many targets as I could ... Figuring out what changed

|_______|_______|_______|_______|_______|_______|_______|_______|
1 2 3 4 5 6 7 8 9

3) Choose the option below that best represents the level of the goal you are making:

1	2	3	4	5
Very low	Low	Medium	High	Very High

TANDEM Knowledge Test

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. Your 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

Individual Differences and Demographic Measures Explained

Cognitive ability was gathered through asking individuals for their ACT, SAT and GPA scores. Participants were ensured that their scores will remain confidential and only be used for research purposes. Previous research suggested that these are acceptable measurements of cognitive ability (e.g., Phillips & Gully, 1997) and are known to be highly reliable (e.g., KR-20 = .96 for the ACT composite score; American College Testing Program, 1989). Self-reported cognitive ability scores have also 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).

Individual adaptability, a trait-level, was creased by Ployhart and Bliese (2006) as a 55-item measure (i.e., the I-ADAPT) that captures individual variability in adaptation, based on the eight dimensions of adaptive performance developed by Pulakos and colleagues (2000) This measure uses a five-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5) and was given to individuals as soon as they enter the lab on Day 1. Cronbach's alpha shows that this scale was reliable (α = .827).

Trait goal orientation was measured using a modified version of the 13-item measure developed by VandeWalle (1997). The measure had a six-point Likert-type rating scale with the range of "strongly disagree" (1) to "strongly agree" (6) and has three subscales with the following reliabilities: mastery orientation, performance-prove, and performance-avoid (VandeWalle, 1997). Cronbach's alpha suggests that the overall measure was reliable (α = .751).

State goal orientation measured learning and performance orientations with regard to the specific task both at the end of day 1 and beginning of day 2. The measure was used by Bell and Kozlowski (2008) in the same task environment, adapted the version published by Horvath, Scheu, and DeShon (2001), consisted of 15 items, and had three subscales (learning, performance prove and performance avoidance) using a five-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5). Cronbach's alpha suggests that both times this scale was administered, it was reliable (α = .811, day 1 and .835, day 2).

Demographics Questionnaire and Cognitive Ability

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.

State Goal Orientation

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 Not 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.

I-ADAPT

Please use the scale below to answer this survey that will ask you a number of questions about your preferences, styles, and habits at work. Read each statement carefully. There are no right or wrong answers.

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

1. I am able to maintain focus during emergencies
2. I enjoy learning about cultures other than my own
3. I usually over-react to stressful news
4. I believe it is important to be flexible in dealing with others
5. I take responsibility for acquiring new skills
6. I work well with diverse others
7. I tend to be able to read others and understand how they are feeling at any particular moment
8. I am adept at using my body to complete relevant tasks
9. In an emergency situation, I can put aside emotional feelings to handle important tasks
10. I see connections between seemingly unrelated information
11. I enjoy learning new approaches for conducting work
12. I think clearly in times of urgency
13. I utilize my muscular strength well
14. It is important to me that I respect others' culture
15. I feel unequipped to deal with too much stress
16. I am good at developing unique analyses for complex problems
17. I am able to be objective during emergencies
18. My insight helps me to work effectively with others
19. I enjoy the variety and learning experiences that come from working with people of different backgrounds
20. I can only work in an orderly environment
21. I am easily rattled when my schedule is too full
22. I usually set up and take action during a crisis
23. I need for things to be 'black and white'

24. I am an innovative person
25. I feel comfortable interacting with others who have different values and customs
26. If my environment is not comfortable (e.g., cleanliness) I cannot perform well
27. I make excellent decisions in times of crisis
28. I become frustrated when things are unpredictable
29. I am able to make effective decisions without all relevant information
30. I am an open-minded person in dealing with others
31. I take action to improve work performance deficiencies
32. I usually am stressed when I have a large workload
33. I am perceptive of others and use that knowledge in interactions
34. I often learn new information and skills to stay at the forefront of my profession
35. I often cry or get angry when I am under a great deal of stress
36. When resources are insufficient, I thrive on developing innovative solutions
37. I am able to look at problems from a multitude of angles
38. I quickly learn new methods to solve problems
39. I ten to perform best in stable situations and environments
40. When something unexpected happens, I readily change hears in response
41. I would quit my job if it required me to be physically stronger
42. I try to be flexible when dealing with others
43. I can adapt to changing situations
44. I train to keep my work skills and knowledge current
45. I physically push myself to complete important tasks
46. I am continually learning new skills for my job
47. I perform well in uncertain situations
48. I can work effectively even when I am tired
49. I take responsibility for staying current in my profession
50. I adapt my behavior to get along with others
51. I cannot work well if it is too hot or too cold
52. I easily respond to changing conditions
53. I try to learn new skills for my job before they are needed
54. I can adjust my plans to changing conditions
55. I keep working even when I am physically exhausted

APPENDIX E:

IRB Documentation

Figure 15
IRB Informed Consent and Approval Documents

Project Title: Radar Control Simulation

Investigators:
Samantha Baard and Dr. Steve Kozlowski

General Description and Explanation of Procedure:
This study is designed to explore how individuals solve problems. If you agree to participate, you will participate in a two-day study in which you will perform a series of scenarios in a computer based simulation.

On the first day (today) you will be trained on how to operate the task and you will be asked to respond to short surveys before and after the task that ask about your motivations, knowledge, and personal characteristics. You will receive 4 credits for the 2 hours you will be engaged in the study on this day.

The second day should be completed as soon as possible after day 1. On this day you will preform the task with intermittent measures of your motivation and cognitions for 3 hours and will receive 6 credits for your participation as well as an opportunity to earn a cash award of up to $50 for performing highly in the task on the second day

Estimated time required:
Five hours [10 credits] – Two hours on day 1; three hours on day 2.

Compensation:
45 individuals with the highest performance on day 2 will receive a cash reward.
The top 10 individuals will receive $50.
The next 15 individuals will receive $20.
The following 20 individuals will receive $10.

Risks and discomforts:
There are no expected risks of participating in this study. All of the survey measures and task data will not be associated with your name. While it is possible that performing this task over three hours may be frustrating or boring at times, previous research using similar tasks has been without incident.

Benefits:
You will learn about conducting psychological research, and will gain experience completing standard psychological measures. You will have increased exposure to computer based scenarios. You will also have the opportunity to earn $20 based on your performance in the task.

Agreement to Participate:
Participation in this study is completely voluntary. By consenting, you also give permission to the experimenters to access or verify your ACT/SAT score from the University Registrar. Your refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You are free to withdraw this consent and discontinue participation in this project at any

This consent form was approved by a Michigan State University Institutional Review Board. Approved 09/15/14 – valid through 08/14/15. This version supersedes all previous versions. IRB # 14-838.

Figure 15 (cont'd)

time without penalty. If you choose to withdraw from the study prior to its completion, you will receive credit for the time you have spent in the study (1 credit per 30 minutes). If wish to obtain credit but do not desire to participate, please contact Samantha Baard at baardsam@msu.edu to make arrangements to meet for several hours to discuss research, methods, and other related topics for an equivalent amount of time.

If you have any concerns or questions about this study, such as scientific issues, how to do any part of it, or to report an injury (i.e., physical, psychological, social, financial, or otherwise), please contact the study coordinator (Samantha Baard, Department of Psychology, Michigan State University, East Lansing, MI 48824;baardsam@msu.edu; 517-353-9166) or the principal investigator (Dr. Steve Kozlowski, Department of Psychology, Michigan State University, East Lansing, MI 48824; stevekoz@msu.edu, 517-353-8924).

If you have any questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or email irb@msu.edu or regular mail at 207 Olds Hall, MSU, East Lansing, MI 48824.

All data will be stored for at least three years after the project closes at the researcher's address (above). Only authorized research team members and the Human Research Protection Program will have access to the data collected in this study, identifiers will be discarded once data are matched (de-identified), and all data reported for scientific purposes will be in aggregate form and therefore unidentifiable. The institutional review board will also have access to study data and results if requested in the case of an audit. Your confidentiality will be protected to the maximum extent allowable by law.

If you agree to participate and allow the researchers to access your SAT/ACT score from the University Registrar, please indicate your consent by typing your name below.

Name: ____

This consent form was approved by a Michigan State University Institutional Review Board. Approved 09/15/14 – valid through 08/14/15. This version supersedes all previous versions. IRB # 14-838.

Figure 15 (cont'd)

MICHIGAN STATE
UNIVERSITY

Revision Application Approval

September 18, 2014

To: Steve W. Kozlowski
309 Psychology Building

Re: **IRB# 14-838** Category: EXPEDITED 2-7
Revision Approval Date: September 15, 2014
Project Expiration Date: August 14, 2015

Title: Radar Control Simulation

The Institutional Review Board has completed their review of your project. I am pleased to advise you that **the revision has been approved.**

This revision includes changes to the title "Radar Control Simulation", recruitment materials, consent form, and changes to the subject incentive.

The review by the committee has found that your revision is consistent with the continued protection of the rights and welfare of human subjects, and meets the requirements of MSU's Federal Wide Assurance and the Federal Guidelines (45 CFR 46 and 21 CFR Part 50). The protection of human subjects in research is a partnership between the IRB and the investigators. We look forward to working with you as we both fulfill our responsibilities.

Renewals: IRB approval is valid until the expiration date listed above. If you are continuing your project, you must submit an ***Application for Renewal*** application at least one month before expiration. If the project is completed, please submit an ***Application for Permanent Closure***.

Revisions: The IRB must review any changes in the project, prior to initiation of the change. Please submit an ***Application for Revision*** to have your changes reviewed. If changes are made at the time of renewal, please include an ***Application for Revision*** with the renewal application.

Problems: If issues should arise during the conduct of the research, such as unanticipated problems, adverse events, or any problem that may increase the risk to the human subjects, notify the IRB office promptly. Forms are available to report these issues.

Please use the IRB number listed above on any forms submitted which relate to this project, or on any correspondence with the IRB office.

Good luck in your research. If we can be of further assistance, please contact us at 517-355-2180 or via email at IRB@msu.edu. Thank you for your cooperation.

Sincerely,

H. McGee

Harry McGee, MPH
SIRB Chair

c: Samantha Baard

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