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ADAPTIVE PERFORMANCE, COGNITIVE ABILITY AND THE MODERATING EFFECT OF TASK CHARACTERISTICS

A DISSERTATION APPROVED FOR THE

DEPARTMENT OF PSYCHOLOGY

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Abstract

An adaptive individual can be characterized as an individual who displays a general propensity to perform well in complex environments that are often unpredictable and ambiguous (Schunn & Reder, 2001). Lang and Bliese (2009) propose a framework that allows the researcher to look at the unique effects of adaptive performance, relative to overall performance. The authors used a discontinuous growth model to partition performance in to four major performance components, namely basal task performance, skill acquisition, transition adaptation and reacquisition adaptation. This proposal focuses on basic cognitive processes and how they relate to each performance component. Simple reaction time and perceptual and processing speed predicted significant differences in basal task performance and skill acquisition. Faster reaction time and higher perceptual and processing speed led to higher scores for basal task performance and skill acquisition. Cognitive flexibility predicted significant differences in transition adaptation, whereby individuals higher in cognitive flexibility had more errors on the adaptive performance task after the task unexpectedly changed, relative to individuals low in cognitive flexibility. No significant predictors of reacquisition adaptation were found. It was also hypothesized that differences in task complexity would moderate the relationship between cognitive ability and performance. However, no significant moderating effect was found.

Adaptive Performance, Cognitive Ability and the Moderating Effect of Task Characteristics

One of the skills that companies desire is the ability to deal with complex and unpredictable work environments and the ability to quickly respond in unknown and ambiguous situations (e.g., Burke, Pierce & Salas, 2006). A great deal of research has focused on determining the types of individual differences that predict this ability. Such research has obvious and important implications for the development of selection and training procedures within the working environment. However, even more fundamental to such industrial applications is research that focuses on the basic or theoretical processes that underlie adaptive performance. This proposal focuses on basic cognitive processes and how they relate to adaptive performance.

An adaptive individual can be characterized as an individual who displays a general propensity to perform well in complex environments that are often unpredictable and ambiguous (Schunn & Reder, 2001). Research on adaptive individuals has typically taken two theoretical paths: one proposes that adaptivity is mostly innate and one proposes that adaptivity is learned. The first approach to adaptivity is founded in an individual difference perspective that assumes a certain subset of lower-order individual differences is at the root of the ability to adapt. *Adaptability*, then, is a set of inherent individual differences that enable a person to respond well in complex environments. The current study is concerned with these innate aspects of adaptivity rather than learned aspects.

Adaptive performance is broadly operationalized as performance after a change in the environment (Jundt, 2009) and has most frequently been examined in laboratories using the task-change paradigm. This paradigm involves an experimental design where participants are trained on a complex, novel task until they reach some level of mastery. After training, some aspect of the task will change, thereby requiring a change in behavior. As mentioned previously, adaptive performance is simply operationalized as performance after a change. Reder and Schunn's research (1999; Schunn & Reder, 2001) provides an example of how the task-change paradigm is used to evaluate adaptive performance. In their studies, participants were trained in an air traffic control simulation program. A number of rules were involved that needed to be followed to attain high performance. One of these rules was that large planes (i.e., 747s) could only land on long runways, while smaller planes (e.g., DC-10) could land at short or long runways. The main manipulation in this study was the proportion of 747s to smaller planes. The authors surmised that to be adaptive, a participant should "save" the long runways for 747s if (and only if) there is a large number of 747s on the screen. However, if there are few 747s on the screen, then one does not need to be as selective and can land smaller planes at either the short or long runway. Thus, adaptive performance is operationalized as performance after the change in proportion of planes. In a related study using the task-change paradigm and an air traffic control simulation program, adaptive performance was simply operationalized as performance after a substantially easier and less complex training session (Chen, Thomas & Wallace, 2005).

The majority of studies utilizing the task-change paradigm for the study of adaptive performance use similar measurements. That is, they operationalize adaptive performance as performance after a change in the environment. However, there may be better ways of measuring adaptive performance. In addition, task change in previous studies frequently involved an increase in complexity or level of workload. The task-change manipulation is also typically the same for all participants in a study making an analysis of the effects of various task characteristics on adaptive performance difficult (e.g., Kozlowski et al., 2001; Lepine, 2005; Lepine, Colquitt & Erez, 2000). Therefore, the addition of varying types of task changes may help to clarify the effects of task characteristics on adaptive performance.

While the traditional task-change paradigm has been partially successful in providing an experimental structure for research on adaptive performance, Lang and Bliese (2009) argue that a better experimental design and analytical approach is needed to better evaluate this construct. Recall that the task-change paradigm assumes some level of mastery is attained by all participants prior to the actual change. However, complete task mastery is extremely rare. There are also individual differences in the speed with which individuals reach mastery (or an acceptable level of) performance. Simply looking at performance after a change in the task environment does not allow one to account for these individual differences. A number of researchers (e.g., Chan, 2000; Jundt, 2009; Lang & Bliese, 2009) also argue that adaptive performance cannot be fully understood with a single measurement because it tends to change over time. Thus, adaptive performance should be measured at multiple time points to truly capture the process nature of the construct.

Lang and Bliese (2009) sought to create a framework that accounted for the process nature of adaptive performance. The authors propose that there are two important types of adaptive performance within the task-change paradigm. The first feature of adaptive performance is called *transition adaptation*. Transition adaptation captures the degree of knowledge and learned skills from the training period that are immediately transferred to the task after there is a change in the environment. Thus, transition adaptation is an immediate reaction to changes in the task. Following the initial decrease in overall performance due to the task- change, individuals presumably improve their performance as they continue to perform the changed task. *Reacquisition adaptation* refers to the time it takes an individual to regain normal performance levels after the task change.

Lang and Bliese (2009) surmise that one of the problems with current research on adaptive performance is that the measurement of the construct is often clouded by other aspects of performance, most notably basal task performance and skill acquisition. *Basal task performance* refers to mean differences in the overall level of performance prior to task change. *Skill acquisition* refers to the rate of changes in performance prior to task change. Thus, the authors sought to develop an analytical framework that would allow them to control for the effects of basal task performance and skill acquisition while looking at the unique effects of transition adaptation and reacquisition adaptation. Figure 1 displays the four performance components discussed in Lang and Bliese's study, namely basal task performance, skill acquisition, transition adaptation and reacquisition adaptation.

Two further issues that have plagued research on adaptive performance are task inconsistency and task complexity. Task inconsistency simply refers to a diverse number of tasks being used in different experiments on adaptive performance. Presumably, this is done to enhance the generalizability of adaptive performance research to different task environments. Task complexity describes the relationships between task inputs (behavioral acts and information cues) and outputs (effectiveness) (Jundt, 2009). In many situations, as the complexity of the task increases, so does the cognitive demand. Variations between experiments in the type of task used and the task's level of complexity may lead to differing results. In turn, this may lead to difficulties in the comparability of studies that seek to understand adaptive performance.

Jundt (2009) sought to illustrate how differences in task complexity can lead to differing levels of adaptive performance . More specifically, the author examined three different ways that a task can change and the processes that individuals use to adapt to those changes. The first type is *task difficulty*, which refers to the total number of behavioral acts that one has to engage in to complete the task as well as the overall amount of time needed to complete the task. Typically, task difficulty is increased in an experimental setting by increasing the number of stimuli. The second type of task complexity is referred to as *coordinative complexity*. This type of task characteristic deals with the relationships between aspects of the task and the timing or order in which they need to be performed. For example, some complex tasks may have a sequencing of behavior that needs to take place because of the higher importance or priority of some aspects of the task over others. (Wood, 1986). One way to manipulate coordinative complexity within an experimental setting is by increasing time pressure. The third important task change is *component complexity*. Tasks with a high level of component complexity have a large number of distinct acts that need to be performed and information cues that need to be processed. Increases or changes in component complexity require individuals to learn how to use new strategies, execute new behaviors and process new cues (Wood, 1986). Jundt (2009) hypothesized that varying processes would be important for individuals in adapting to these three types of changes. More specifically, it was hypothesized that: (1) Task effort would be a strong predictor of adaptive performance when adapting to task difficulty changes, (2) Correct sequencing and prioritization of behavioral acts would positively predict adaptive performance with coordinative task changes, and (3) Correct use of new information cues would positively predict adaptive performance in component task changes.

Jundt (2009) used a radar tracking simulation program called TANDEM as the experimental task. During the simulation, participants were asked to defend a geographic area and gather information about targets and use that information to decide whether or not to attack the targets. Participants were split into three groups that differed in the type of task complexity change they would see. Each participant completed six training trials and six adaptation trials. Jundt found only moderate support for the differing impact of task complexity types on adaptive performance. However, this study operationalized adaptive performance similarly to many previous studies in that performance was based on the scores from one scenario. More specifically, the performance score was simply a composite score taken from the last adaptation trial. These results make it difficult to determine how variations in task complexity might influence adaptive performance when it is operationalized as a fluid process as it is proposed in Lang and Bliese's (2009) study.

In the current study, task complexity type will be examined for its effect on transition adaptation and reacquisition adaptation. It is hypothesized that cognitive demand will play a role in an individual's ability to adapt to different types of task complexity. Concerning the three aforementioned types of task complexity, it is hypothesized that component complexity involves a higher degree of cognitive demand because of the need to formulate new strategies, execute new behaviors and process new cues. In contrast, task difficulty and coordinative complexity involve a lower degree of cognitive demand, because they entail a simple increase in workload.

Hypothesis One: Component complexity will have a different effect on transition and reacquisition adaptation, relative to task difficulty and coordinative complexity.

a) A simple increase in workload (i.e., task difficulty and coordinative complexity) are low in cognitive demand.

b) A fundamental change in the task that requires the learning of new information and a modification of behavior (i.e., component complexity) is high in cognitive demand.

As mentioned previously, a number of researchers believe that a subset of inherent, individual differences exist that facilitate adaptive performance. A wide variety of individual differences including cognitive constructs and personality traits, have been examined for their relationship to adaptive performance (see Wheeler, 2009, for review). Perhaps one of the most widely examined constructs is general mental ability (GMA), which refers to an individual's overall cognitive ability. GMA is meant to measure the *g* factor, which was first postulated by Charles Spearman in 1904. GMA is an overarching intelligence factor that encompasses a number of lower-order cognitive abilities. A meta-analysis on the relationship between cognitive abilities and job performance shows that GMA is most often measured by creating a composite score from computerized tests of mathematical, verbal and spatial abilities (Bertua, Anderson & Salgado, 2005). However, some researchers believe GMA is equally represented by other criteria, such as SAT scores (Jundt, 2009).

GMA has been shown to be a strong predictor of performance in many settings. A meta-analytic study shows that the relationship between GMA and performance is stronger for complex tasks (such as those used to study adaptive performance), relative to simple tasks (Hunter & Hunter, 1984). It is thought that high-GMA individuals perform better on tasks with high cognitive demands and information processing demands, because they have more cognitive resources available, relative to low-GMA individuals. However, the relationship between GMA and adaptive performance has proven to be more complex than the relationship between GMA and overall performance. Some studies have found positive relationships between adaptive performance and GMA (e.g., Jundt, 2009; Lepine, Colquitt & Erez, 2000), while others have found negative relationships (e.g., Lang & Bliese, 2009). It may be that part of this discrepancy lies in the operationalization and measurement of adaptive performance.

Lang and Bliese (2009) examined the relationship between GMA and adaptive performance using TankSoar. TankSoar is a tank battle scenario where participants control one tank and make decisions on whether or not to fight computer-controlled enemy tanks. The authors found a positive relationship between GMA and overall performance. More specifically, high-GMA individuals displayed higher performance at every time-related measurement (i.e., basal task performance, skill acquisition, transition adaptation and reacquisition adaptation) relative to low-GMA individuals. However, high-GMA individuals had a significantly larger decline in performance when the task unexpectedly changed (i.e., transition adaptation). Concerning reacquisition adaptation, there were no significant differences in how quickly high-GMA and low-GMA individuals recovered from their performance decrements due to the task change.

Research on expert performance may help to understand the relationship between GMA and transition adaptation. By definition, an expert is an individual who devotes a great deal of time and practice to a given task until they reach mastery performance levels. Research shows that, after long periods of practice, experts' responses become automatic (Beilock & Carr, 2001) and require a reduced amount of effortful cognitive control. When experts are confronted with an unexpected change in their mastered task, they often display short-term performance decrements. Beilock and Carr (2001; 2004) propose that experts do not adapt well to change because they need to switch from an automatic, proceduralized form of task execution back to a step-by-step mode in order to deal with a change in the task environment. In contrast, trained novices tend to display higher performance after an unfamiliar change in the task environment relative to experts. It is thought that novices have yet to develop a proceduralized form of task execution because they have not built up the knowledge and skills necessary to do so. As long as an individual remains a novice on the task at hand they tend to use a step-by-step process to complete the task (e.g., Beilock & Carr, 2001; Beilock & Carr, 2004).

Recall that, in Lange and Bliese's (2009) study, high-GMA individuals had a significantly lower drop in performance after the task change (i.e., transition adaptation) relative to low-GMA individuals. The authors contend that high-GMA individuals may be performing similarly to experts. That is, high-GMA individuals may be executing the task in a more proceduralized, automatic fashion and thus had difficulties returning to a step-by-step strategy at the transition adaptation point. High-GMA individuals may also have learned more about the task during the practice period, or simply learned faster. If this were the case, a high-GMA individual would have more to lose in terms of performance scores at the transition adaptation point because of their greater knowledge.

Contrary to the negative relationship found between GMA and adaptive performance in the aforementioned study, Jundt (2009) hypothesized that there would be a positive relationship between these variables. More specifically, the author surmised that GMA would play an important role in predicting adaptive performance in response to changes in type of task complexity. This hypothesis was based on previous findings that show that high-GMA individuals do better on tasks with higher cognitive demands and information processing demands (e.g., Hunter & Hunter, 1984; Lepine, Colquitt & Erez, 2000). Task difficulty, component complexity and coordinative complexity were the three types of task complexity types used in Jundt's (2009) study that are thought to increase sequentially in cognitive demand (although this was not directly tested). The prediction was that, as cognitive demand in the task increases due to task complexity, the relationship between GMA and adaptive performance would also strengthen. This hypothesis was not supported. However, the author did find a significant positive main effect of GMA on adaptive performance. In other words, high-GMA individuals performed better overall, but the effect of task complexity was not significant.

In a related study, Lepine, Colquitt and Erez (2000) hypothesized that task context would moderate the relationship between GMA and adaptive performance. However, different types of task changes were not used. Instead, one type of task change (conceivably a coordinative change) occurred twice during the experiment. The research design was similar to Schunn and Reder's (2001) design in that participants were informed of all the rules and possible strategies for completing the task prior to the training session. However, when the task change occurred, the previously used strategy was no longer the best and most efficient strategy. Thus, to be adaptive, participants must select a different strategy that optimizes performance. Concerning GMA, Lepine, Colquitt and Erez (2000) hypothesized that the task change would moderate the relationship between GMA and adaptive performance, such that high-GMA would be more beneficial after the unforeseen change in the task environment, relative to before the change. The results of this study showed a complex relationship where GMA was a better predictor for post-task-change performance, but was also important for pre-task-change performance.

Jundt (2009) and Lepine, Colquitt and Erez (2000) both used experimental designs where it is difficult to determine whether or not any unique adaptive phenomena are being captured. That is, their measurement of adaptive performance may be confounded by other performance factors, such as basal task performance and skill acquisition. If this is true, then the positive relationship found between GMA and adaptive performance in these studies may better reflect the relationship between GMA and overall performance.

Mixed results in assessing the relationship between GMA and adaptive performance may also be a result of varying measurements of GMA. For example, Jundt (2009) used SAT/ACT scores as a measure of GMA. Lepine, Colquitt and Erez (2000) used the Wonderlic Personnel Test, which measures verbal, quantitative and spatial abilities. Lang and Bliese (2009) used a composite score from three tests of verbal, quantitative and spatial abilities. Most researchers recommend the use of more than one test to assess a specific cognitive construct in order to avoid potential contamination of that construct with test-specific variance (e.g., Ackerman, Beier & Boyle, 2005; Bertua, Anderson & Salgado, 2005; Lang & Bliese, 2009). It is my hope that a composite score for GMA and the use of a discontinuous growth model proposed by Lang and Bliese (2009) will help to clarify some of these complex relationships.

As mentioned previously, attempts were made to validate Lang and Bliese's (2009) experimental and analytical framework. In their study, participants completed twelve scenarios. The first six scenarios in the pre-task-change period are meant to measure basal task performance and skill acquisition, while the second six scenarios in the post-task-change period are meant to measure transition adaptation and reacquisition adaptation. In the current study, I am also interested in looking at different cognitive abilities that are related to these four different types of performance. Indeed, previous research does suggest that different subsets of cognitive abilities relate to pre-change performance and post-change performance in the task-change paradigm. For example, Lepine, Colquitt and Erez (2000) found that GMA was a better predictor of performance after a change in the task environment relative to performance before a change. Ackerman, Kanfer and Goff (1995) looked at the relationship between skill acquisition and cognitive abilities and found memory, perceptual encoding and learning to be better predictors of skill acquisition than tests measuring GMA. Voelkle, Wittman and Ackerman (2006) reanalyzed the above study with a growth model approach. In this second analysis, spatial and numerical abilities were a better predictor of basal task performance, while perceptual speed was a better predictor of skill acquisition. Wheeler (2009) also looked at the relationship between cognitive abilities and overall performance in a complex task environment. A variety of cognitive domains were assessed such as reasoning ability, perceptual speed, reaction time and working memory. Results showed a positive relationship between overall performance and cognitive ability. That is, high performers displayed faster reaction time on six out of six measures and higher percent correct on two of five measures (one of the tests, simple reaction time, did not provide a percent correct score).

In the current study, a battery of tests will be used to assess the relationship between cognitive ability and different aspects of performance (i.e., basal task performance, skill acquisition, transition adaptation, reacquisition adaptation and overall performance). A battery of tests will be used that measure lower-order and higher-order cognitive abilities. More specifically, tests will be used that measure simple reaction time, perceptual and processing speed, and GMA. Based on previous research, two hypotheses were made regarding these specific cognitive abilities.

Hypothesis Two: There will be a stronger relationship between GMA and adaptive performance, relative to pre-task-change performance (i.e., basal task performance and skill acquisition).

Hypothesis Three: Simple reaction time and perceptual and processing speed will be stronger predictors of pre-task-change performance (i.e., basal task performance and skill acquisition), relative to adaptive performance.

It is also believed that cognitive flexibility may play an important role in the ability to adapt to changes. Cognitive flexibility is an executive function that encompasses the ability to reorganize one's knowledge and skills in response to complex, changing situational demands (Spiro, Coulson, Feltovich & Anderson, 1988). It also involves the need to switch from an automatic processing mode of action to a more controlled processing mode of action. In the task-change paradigm, it is assumed that an individual needs to enter into a higher level of attentional control to detect a change in the task and to decide how to handle that change. As mentioned previously, some research suggests that experts are worse at adapting to changes, relative to novices. This occurs presumably because experts are not as quick to recognize a change in the task (a result of automaticity) and have to switch from a proceduralized form of action back to a step-by-step form of action (Beilock & Carr, 2001; 2004). Research also shows that experts score lower on measures of cognitive flexibility, relative to novices (Adelson, 1984; Frensch & Sternberg, 1989). Furthermore, when people view themselves as skillful at a task, they are less prone to switch their strategies after a change in the task environment and/or they are less able to notice changes in the first place (Canas, Quesada, Antoli & Fajardo, 2003; Edland, Svenson & Hollnagel, 2000).

Hypothesis Four: Cognitive flexibility will be positively related to adaptive performance. Individuals high in cognitive flexibility will display greater adaptive performance, relative to individuals low in cognitive flexibility.

With regard to previous hypotheses, predictions were made concerning the separate influences of task-change type and cognitive ability on adaptive performance. However, it seems feasible that these two variables may interact to influence performance. More specifically, because of differences in cognitive demand, task-change type may moderate the relationship between cognitive ability and adaptive performance.

Hypothesis Five: The type of task change (task difficulty, coordinative complexity or component complexity) will moderate the relationship between cognitive ability and adaptive performance such that:

a) GMA and adaptive performance will be positively related within the task difficulty and coordinative complexity conditions, because these changes do not inherently place a noticeable level of additional cognitive demand on the individual. In contrast, GMA and adaptive performance will be negatively related within the component complexity condition, because it is inherently more cognitively demanding.

b) The relationship between cognitive flexibility and adaptive performance will be smaller within the task difficulty and coordinative complexity conditions, because of less cognitive demand, relative to the component complexity condition.

In the current study, Lang and Bliese's (2009) framework for studying adaptive performance will be used. That is, a series of discontinuous growth models will be used to look at pre-task-change performance (basal task performance and skill acquisition) and post-task-change performance (transition adaptation and reacquisition adaptation). This framework is beneficial because it allows an analysis of the unique effects of adaptive performance while controlling for the effects of basal task performance and skill acquisition. Additionally, this framework allows an analysis of individual differences in growth over time and how the relationship between individual differences and performance varies depending upon the performance component discussed.

The cognitive ability domains tested in the current study include simple reaction time, perceptual and processing speed, GMA and cognitive flexibility. It was hypothesized that simple reaction time and perceptual and processing speed will have a stronger relationship to basal task performance and skill acquisition, while GMA and cognitive flexibility will have a stronger relationship to transition adaptation and reacquisition adaptation.

It was hypothesized that there will be differences in cognitive demand, but no noticeable differences in overall performance scores between the three types of task changes. More specifically, it was hypothesized that the component task change will involve higher cognitive demand, relative to the other two types of task changes. As a result of differences in cognitive demand, the relationship between cognitive ability and adaptive performance will be moderated by task-change type . Concerning GMA, it was hypothesized that there will be a positive relationship between GMA and adaptive performance within the task difficulty and coordinative complexity conditions, but a negative relationship within the component complexity condition. Concerning cognitive flexibility, it was hypothesized that the relationship between cognitive flexibility and adaptive performance will be smaller within the task difficulty and coordinative complexity conditions, relative to the component complexity condition.

Before testing the moderating effect of task-change type, an additional analysis will be conducted to ensure that task-change type does not produce noticeable differences in overall performance scores. If there are no significant differences in overall performance between task-change types, and a moderating effect of task change is still found, it can be assumed that the task-change types differ on another variable aside from simple overt task difficulty (i.e., cognitive demand).

Method

Participants

A total of 132 (76 female) students from the University of Oklahoma participated in this study. Students ranged in age from 17-30 years (M=19.5, SD=2.21) and were all enrolled in a psychology course. Participants were given research participation credits as partial fulfillment of their course requirements or extra credit. Participants were recruited online via the psychology department's subject pool website or from an advertisement shown during class offering extra credit for participation.

Task

The behavioral test used in this study was the Air Traffic Scenarios Test (ATST) (Broach & Brecht-Clark, 1993), which is an air traffic control simulation program developed by the Federal Aviation Association (FAA) for training air traffic controllers (ATC). Similar ATC simulation programs have been used in studies on adaptive performance and other studies of complex performance (e.g., Ackerman, Beier & Boyle, 2005; Schunn & Reder, 2001). The main goals for participants are to monitor air traffic safety between aircraft, land planes at appropriate airports and direct planes out of appropriate exit gates. Participants must also attend to rules regarding the appropriate speed and altitude level for aircraft. Two dependent variables were of interest in the current study. The first was *Percent Destination*, which refers to the percent of aircraft that an individual lands at the correct airport or sends out the correct exit gate. The second was *Errors*, which refers to the sum total of various errors that an individual can make including: allowing an aircraft to get too close to another aircraft or to a boundary, landing an aircraft at the wrong airport, sending an aircraft out of the wrong exit gate and landing or exiting a plane at the wrong speed or altitude level.

Task Manipulations. Three types of task change were used that differ in the level of cognitive demand. The first type of task change was task difficulty. To increase task difficulty in ATST, one must increase the number of behavioral acts needed to complete the task. This was done by simply increasing the number of aircraft by 50% (from 12 to 18 aircraft).

The second type of task change was a coordinative task change, which involves changing the timing or order of behaviors. In this study, a coordinative task change involved an acceleration of the speed of the aircraft. In all other scenarios, the refresh rate was set at six seconds. In other words, aircraft move positions on the screen every six seconds. With a coordinative task change, the refresh rate will be reduced to three seconds. Thus, participants will have to make decisions much more rapidly and prioritize their responses depending upon the urgency of each aircraft's situation. Each coordinative task change scenario started with 12 aircraft.

The third type of task change was a component task change, which required individuals to learn how to use new strategies, execute new behaviors and process new cues. In the current study, the specific component task change entailed a new rule that the participants had to learn. During the training scenarios, participants learned to land aircraft at two airports where the cardinal direction of landing did not change. However, during component task change scenarios, the cardinal direction of landing for the two airports changed every thirty seconds and the participants had no prior knowledge that this feature would change. Each component task change scenario started with 12 aircraft.

Measures

Cognitive Ability. The Automated Neuropsychological Assessment Metric (ANAM4™)[1] was used to measure cognitive ability. This test is a computerized test battery that assesses neuropsychological or neurocognitive functioning. There is support for ANAM4™'s clinical utility as well as its utility as a laboratory tool for the

[1] ANAM4 is the most recently released version of ANAM™.

assessment of fundamental cognitive abilities (Reeves, Winter, Bleiberg & Kane, 2007). Areas that ANAM4™ has been utilized for cognitive assessment include traumatic brain injuries (e.g., Gil, Yael, Zilmerman, Koren & Klein, 2005) Parkinson's disease (e.g., Kane, Roebuck-Spencer, Short, Kabat & Wilken, 2007), Alzheimer's disease (e.g., Levinson, Reeves, Watson & Harrison, 2005) and sports medicine (e.g., Collie, Darby & Maruff, 2006), among others. The full test library includes approximately twenty tests that provide precise measurement of neurocognitive performance and processing efficiency.

Instead of using the full test library, a battery (or subset) of ANAM4™ tests were used that were most appropriate in addressing the research questions. The cognitive domains assessed include 1) simple reaction time, 2) perceptual and processing speed, and 3) general mental ability. These domains will be assessed using ANAM4™ test 1) Simple Reaction Time, 2) Matching to Sample and Code Substitution (Learning and Delayed), and 3) Mathematical Processing, Logical Relations and the Tower Puzzle. Reaction time and percent correct were collected as dependent variables for each test. Before each of the tests, the participant performed a series of brief training trials to familiarize themselves with the rules and constraints of each test.

Simple Reaction Time

This test measures simple reaction time by requesting the participant to respond as quickly as possible to a series of "*" symbols on the display.

Matching to Sample

For this test, the participant first saw the sample, which was a shaded block pattern in a 4x4 grid, followed by a blank screen. Two comparison patterns were then displayed side by side. One grid was identical to the sample grid and the other grid was different. The participant chooses the comparison pattern that matches the sample.

Code Substitution

Two versions of this test were administered. In the Code Substitution Learning test, digit-symbol pairs were displayed on the screen and the participant was asked to compare this to an answer key of digit-symbol pairs. The participant was also asked to remember the correct pairings shown in the key. In the Code Substitution Delayed test, the digit-symbol pairs were displayed without the answer key and the participant must recall, from memory, whether the pair was correct or not. Code Substitution Delayed was presented after a few intervening tests to provide a period of alternate activity.

Mathematical Processing

This test measures the ability to solve simple, single-digit math equations requiring addition and subtraction. The participant indicated whether the solution was greater or less than five.

Logical Relations

This test requires participants to evaluate the truth of a statement (e.g., "& comes after #") followed by these symbols displayed on the screen in a specific order (e.g.,"& #").

Tower Puzzle

The Tower Puzzle is similar to the Tower of Hanoi or Tower of London, which are well known in the cognitive literature. Three spindles and five disks of different sizes were displayed on the screen. The participant arranges all the disks on the center spindle with the largest disk on the bottom and the smallest on the top. Only one disk can be moved at a time, and larger disks can never be placed on top of smaller disks.

Composite Scores. Most researchers recommend the use of more than one test to assess a specific cognitive construct in order to avoid potential contamination of that construct with test-specific variance (e.g., Ackerman, Beier & Boyle, 2005; Lang & Bliese, 2009). As mentioned previously, GMA is often measured by creating composite scores from computerized tests of mathematical, verbal and spatial abilities to avoid the problem of test-specific variance (Bertua, Anderson & Salgado, 2005). In the current study, three tests were used that are similar to other composite measures of GMA, namely Mathematical Processing, Logical Relations and the Tower Puzzle. In addition, Matching-to-Sample, Code Substitution and Code Substitution Delayed measure perceptual and processing speed. In order to determine whether or not the first three measures are valid indicators of GMA, and the second three are valid measures of perceptual and processing speed, a confirmatory factor analysis was conducted. Recommendations for values that serve as an indicator of adequate fit were taken from Hu and Bentler (1998; 1999). The model provided an adequate fit to the data. The χ^2 (6, N=132) = 9.836 was not significant (p=.1317) indicating that there was not a significant deviation between the expected and observed covariance matrices. Bentler's

Comparative Fit Indices (CFI) was equal to .97, which meets the standard of values above .95 displaying good fit. Finally, the root mean square residual (.0699), NFI (.9564), NNI (.9564), and RMSEA (.0699) all meet the criteria of adequate model fit.

The next step in verifying the two factors of interest was to look at the factor loadings. All factors loadings were of adequate size for both the Perceptual and Processing Speed factor (values ranged from 8.83 to 19.02) and the GMA factor (values ranged from 5.99 to 12.68).

Given the results of the confirmatory factor analysis, a composite score was created for Perceptual and Processing Speed that was created by combining the values of equally weighted z-scores of Code Substitution, Code Substitution Delayed, and Matching-to-Sample. A composite score was also created for GMA that included equally weighted z-scores of Mathematical Processing, Logical Relations and the Tower Puzzle.

Cognitive Flexibility. The Wisconsin Card Sorting Task (Grant & Berg, 1948) was used to measure cognitive flexibility. The Wisconsin Card Sorting Task is one of the most widely used tests for the measurement of this construct (Crone, Ridderinkhof, Worm, Somsen & van der Molen, 2004).

<u>Wisconsin Card Sorting</u>

This test requires the participant to sort cards according to colors, shapes and numbers. Participants are asked to match items depicted on a test card to items on one of four comparison cards. The participant must infer the categorization rules from the positive or negative feedback that is presented after each trial. When the rule has been deduced and positive feedback has been given for a certain amount of trials, the comparison rule changes without warning. Thus, the participant must display a readiness to detect change as well as the ability to find new solutions to obtain high scores on this task.

Subjective Cognitive Demand. The NASA-TLX is a questionnaire developed by NASA that assesses perceived workload on six different subscales that include: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration (Hart & Staveland, 1988). Scores on all six subscales were used to compare subjective levels of workload on the three task-change types.

Person Variables. Age and gender were collected because they may have an effect on ANAM4™ and ATST performance. The ANAM4™ and ATST measures are computerized tasks that entail game-like qualities and one's past experience with similar activities could affect the results of the study. For that reason, two simple questions regarding one's computer and computer-based game use were also collected. One question assessed how often an individual participated in these activities and a second question assessed self-reported expertise level.

Design and Procedures. Participants were assigned to one of six groups. These groups differed in the type of task change (task difficulty, coordinative change or component change) and the order of tests (ANAM/Wisconsin Card Sorting Task and ATST). First, they were given an informed consent, a general description of the study, and a demographic questionnaire. The order that participants completed ATST and the cognitive ability tests was counterbalanced. Participants completed all ATST scenarios or all cognitive ability tests before switching to the second set of tests.

During the ATST phase of the study, participants completed a total of twelve scenarios. All scenarios were three minutes in duration. The first six scenarios were equivalent for all participants and served as training/skill acquisition scenarios. All training/skill acquisition scenarios had twelve aircraft. The last six scenarios were the adaptive performance scenarios and differed depending upon the assignment of task-change type. The coordinative change scenarios and component change scenarios each had a total of twelve aircraft, while differing in other characteristics (see page 17). The characteristic that changed in the task difficulty scenario was the number of aircraft. When the task change occurred, each task difficulty scenario had a total of eighteen aircraft. Participants rated the workload level of each scenario after completion of each scenario via the NASA-TLX.

The cognitive ability tests were presented in the same order for all participants. All six ANAM tests were followed by the Wisconsin Card Sorting Test. Lastly, a debriefing form was given to participants explaining the general purpose and major hypotheses of the study.

Statistical Analyses. The first analysis conducted was a one-way ANOVA to determine whether or not the three types of task changes were equivalent in terms of overt task difficulty. Overt task difficulty was measured via the two dependent variables, namely Percent Destination and Errors. No differences between-groups in terms of overt task difficulty is an important pre-condition for later analyses testing the moderating effect of task-change type on the relationship between cognitive ability and adaptive performance. If there are no differences between groups in terms of overt task difficulty, and a moderating effect of task-change type is still found, it can be assumed that the task-change types differ in another variable aside from overt task-difficulty (i.e., cognitive demand).

Subjective assessments of overt task difficulty (i.e., NASA-TLX ratings) were also examined to determine differences in cognitive demand between the three types of task change. If a component task change is more cognitively demanding, participants should rate them higher on mental demand, relative to the other two types of changes. A one-way ANOVA was conducted to make this comparison.

The primary analytical tool used in the current study was growth curve modeling. A growth model can be thought of as a combination between two sets of regression analyses. The first set involves the estimation of fixed effects and is similar to a traditional regression model that ignores the fact that observations are nested within individuals. The second set involves the estimation of random effects and is similar to a series of regression models that estimate a model for each individual (Bliese & Ployhart, 2002). Traditional regression analyses also treat person-specific deviations from the mean as error variance. However, when using growth curve modeling, the person-specific deviations from the mean growth trajectory are considered to be systematic individual differences in growth. In other words, growth modeling allows you to examine fixed effects similar to a standard regression model and random effects that involve individual difference deviations (Singer & Willett, 2002).

Another advantage of growth modeling techniques is that they can handle non-independence. Ignoring non-independence can lead to standard errors that are too large, thereby decreasing the likelihood of detecting significant results that actually exist (Bliese & Ployhart, 2002). In the current study, individual scenarios over time were nested within individuals. One of the reasons growth modeling was used in the current study was to account for the nested nature of the data.

A series of discontinuous growth models was conducted in the current study. All models were two-level hierarchical models that look at individual change in performance scores over time and individual differences that predict changes in performance. The first level was used to describe the growth form (e.g., linear, quadratic). In other words, the first level captures the effect of time (*within-factor*). The second level captures individual differences in patterns of growth (*between-factor*). Thus, performance scores at level-one were nested within individuals at level-two.

Three important sets of analyses were conducted based upon the recommendations from other studies (Bliese & Ployhart, 2002; Lang & Bliese, 2009; Pinheiro & Bates, 2000). First, level-one change was examined by calculating a sequence of models with Level-1 TIME predictors only, which include basal task performance, skill acquisition, transition adaptation and reacquisition adaptation. The two dependent variables of interest for the current study were Percent Destination and Errors. A separate score for Percent Destination and Errors was collected for all twelve air traffic control scenarios. All four TIME variables were used to predict the growth of Percent Destination and Errors over time. A series of analyses were conducted to determine the model that most accurately explains performance growth.

After the best level-one model was found, the second important set of analyses included adding cognitive ability, person variables and task-change type (i.e., task-difficulty, coordinative complexity and component complexity) at level-two to explain individual differences in level-one performance growth. All four TIME variables (i.e., basal task performance, skill acquisition, transition adaptation and reacquisition adaptation) at level-one become dependent variables at level-two.

Third, task-change type was analyzed for its moderating effect on the relationship between cognitive abilities and the level-one predictors. Interactions in growth models were tested similarly to interactions in regression analyses. Step one involved identifying cognitive ability factors and task-change types that account for a significant amount of variance in level-one performance variability. Step two includes creating interaction terms between the two variables to test the moderating effect.

Discontinuous growth curves were used to run the aforementioned analyses, which are a special class of growth curve modeling. Traditional growth curve models allow an individual to model the starting point (i.e., intercept) and the growth (i.e., slope) of a given variable over time. Two-piece growth models are also common, which allow an individual to model the intercept and two slopes (e.g., pre treatment and post treatment, or pre task change and post task change). However, neither of these models is capable of modeling all of the TIME variables of interest. If a two-piece growth model was used, transition adaptation would be left out of the model, which happens to be one of the most important variables in the current study. In addition, a two-piece growth model simply models the two slopes separately. Thus, the effects of basal task performance and skill acquisition could not be controlled for. In contrast, the use of a discontinuous growth model allows an individual to model the intercept (i.e., basal task performance), two slopes (i.e., one for skill acquisition and one for reacquisition adaptation) and a discontinuity that reflects performance immediately after the change in the task (i.e., transition adaptation). The adaptive performance variables are also specifically coded to control for the effects of basal task performance and skill acquisition.

The exact coding scheme for the TIME variables can be found in Table 1, which was adopted from Lang and Bliese (2009). The coding schemes for all three linear variables (i.e., skill acquisition, transition adaptation and reacquisition adaptation) interact to give estimates of the TIME variables of interest. Skill acquisition (SA) simply reflects the passage of time over all twelve scenarios. If this variable was entered into the growth model by itself, a traditional growth model where the intercept and one slope for all scenarios would be estimated. The addition of the transition adaptation (TA) term to the model in addition to SA provides a model similar to a two-piece growth model. In other words, this model provides estimates for the intercept and two slopes, where the second slope begins after the task change. Entering reacquisition adaptation (RA) into the model accomplishes two things. Notice in Table 1, that the coding scheme for measurement occasion one through six for SA is the same as the coding scheme for measurement occasion seven through eleven for RA. This coding scheme allows an estimation of the additional effects, or unique effects of RA. In other words, the estimate of RA is what is left after partialing out the effects of SA in the first six scenarios. The inclusion of RA also changes the interpretation of TA to reflect the instantaneous change in performance after the task change.

In sum, a discontinuous growth model was used to examine the growth of performance over twelve air traffic control scenarios. Percent Destination and Errors were used as measures of performance. Two different sets of analyses were conducted to model the growth of Percent Destination and Errors separately. At level-one, four TIME variables were used to predict performance, including basal task performance (i.e., intercept), SA, TA and RA. All four time variables were modeled at level-one and were nested within persons at level-two. A total of ten level-two variables were used to predict between-person differences in level-one growth. These variables include four cognitive ability variables (i.e., Simple Reaction Time, Perceptual and Processing Speed, GMA and Cognitive Flexibility), four person variables (i.e., Age, Sex, Video Game Use and Video Game Expertise) and task-change type (i.e., Task Difficulty, Coordinative Complexity and Component Complexity).

Results

Comparability of Task-Change Types

Objective Evaluations. Objective performance scores were compared between the three task-change types by assessing group differences on the two dependent variables. Percent Destination scores and Error scores were divided in to pre-task-change scenarios (one through six) and post-task-change scenarios (seven through eleven). A one-way analysis of variance was conducted to compare groups and Tukey's post-hoc test was used to determine significant differences between groups. The task difficulty manipulation involved an increase in number of planes on the screen (Count), coordinative complexity required participants to prioritize and speed up their actions (Speed), and component complexity required participants to learn a new rule (New Rule). For all further discussion, the task-change types will be referred to as the manipulations used in the current study, namely Count, Speed and New Rule.

During the pre-task-change period, there were no significant differences between groups on the Percent Destination variable. During the post-task-change period, there was a significant main effect of Percent Destination, $F\ (2, 129) = 70.499$, $p<.001$, whereby the Speed group ($M=298$, $SD=102.05$) correctly landed and exited more planes than did the New Rule group (M=143.76, SD=44.98) and the Count group (M=145.91, SD=47.26). There were no significant differences between the New Rule group and Count group. Importantly, the Count group did not land significantly more aircraft than the other two groups simply because they had more aircraft on their screen (18 aircraft versus 12 aircraft). There were no significant differences in Errors between groups for the pre-task-change period or the post-task-change period.

The results for Percent Destination suggest that the New Rule and Count manipulations were comparable in terms of overt task difficulty. However, the Speed group landed and exited more planes, meaning this manipulation may have been easier than the other two manipulations. Thus, in further analyses regarding Percent Destination, the comparison between the New Rule and Count manipulations may be more pertinent in testing the hypotheses regarding the moderating effect of task-change type. The results for Errors suggest that all three groups were comparable in terms of overt task difficulty.

Subjective Evaluations. To compare subjective task difficulty levels between task-change types, scores on the NASA-TLX were evaluated. This questionnaire asked individuals to rate each scenario on six factors: Mental Workload, Physical Workload, Temporal Workload, Effort, Frustration and Subjective Performance. A one-way analysis of variance was conducted with Tukey's post-hoc test to determine significant differences between groups. During the pre-task- change period, there were no significant differences found between groups on any of the six factors. Scores on Mental Workload for the post-task-change period were the most pertinent to testing the hypotheses regarding the moderating effect of task-change type. There was a significant main effect for Mental Workload, $F(2,123) = 3.427$, $p < .05$. Individuals in the Speed group ($M=80.45$, $SD=25.81$) believed that the air traffic control scenarios had significantly less Mental Workload after the task change, relative to the Count Group ($M=95.58$, $SD=17.89$). There were no significant differences between the Count Group and the New Rule group.

These results, coupled with the results of the objective performance scores, suggest that the Speed manipulation was easier and less cognitively demanding. Thus, in further analyses, the comparison between the New Rule and Count manipulations may be more pertinent in testing the hypotheses regarding the moderating effect of task-change type. However, the Speed manipulation was still included in further analyses to examine the effects of an easier, less cognitively demanding manipulation.

Descriptive Data and Intercorrelations

Table 2 presents the means, standard deviations and intercorrelations between the study variables. A partial correlation was conducted to partial out the effects of task-change type on the correlations. An important precondition for using a growth model to test the hypotheses is that a relationship between cognitive ability and performance actually exists. Table 2 illustrates that Errors, Simple Reaction Time, Perceptual and Processing Speed, GMA, Cognitive Flexibility, Age, Video Game Use and Video Game Expertise were all significantly correlated with Percent Destination. Table 2 also shows that Percent Destination, Perceptual and Processing Speed, GMA, Sex, Video Game Use and Video Game Expertise were all significantly correlated with Errors.

Discontinuous Growth Models

Two sets of growth modeling analyses were conducted. First, Percent Destination scores were modeled over time and steps were taken to identify the best-fitting model for the data. Second, Percent Destination scores were replaced by Error scores as the dependent variable.

Level-One Analyses for Percent Destination

Unconditional Means Model. The first step in the analyses was an unconditional means model that modeled the dependent variable with no predictors. The results of this analysis can be found in Table 3. The fixed effect for this model was significant (29.46, $p<.001$) meaning the coefficient was significantly different than zero. The random effect was also significant, meaning there was significant variability in Percent Destination scores. The main purpose of the unconditional means model is to calculate the Intraclass Correlation Coefficient (ICC), which gives an estimate of the amount of variability in level-one scores due to level-two units. More specifically, the ICC refers to the degree of variability due to between-person differences. The ICC can be calculated by $\pi^{00}/ \pi^{00} + \sigma^2$ where π^{00} = between-person variance and σ^2 = within-person variance (Singer & Willett, 2002). This analysis revealed that the ICC= .39 meaning between-person variance accounts for 39% of the variance of performance over time. This suggests that individual differences in Percent Destination scores exist and a growth model may be beneficial in explaining some of these differences. Figure 2 displays Percent Destination scores across all twelve scenarios for three randomly sampled participants within each task-change type. Similar to the ICC, this figure is important because it displays a great deal of between-person variability in Percent Destination scores.

Linear Change Model. The second level-one model conducted was the linear change model. To account for linear change, the time variables SA, TA, and RA were added to level-one. Centering variables has important implications for the interpretation of coefficients. However, Singer and Willett (2002) suggest using uncentered variables if "0" is a meaningful value within the level-one units. In the current study, all level-one time variables are coded with "0" as the beginning of the ATST scenarios and thus are entered as uncentered variables. The exact model tested for level-one was:

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}RA_{ti} + e_{ti}$$

where
Y equals performance for person i at time t
π_{0i} equals the intercept for person i
$\pi_{1i}SA_{ti}$ equals the slope of SA for person i
$\pi_{2i}TA_{ti}$ equals the discontinuity of TA for person i
$\pi_{3i}RA_{ti}$ equals the slope of RA for person i
e_{ti} equals the residual

At level-two, the level-one variables become the dependent variables and between-person variables are entered as predictors of each level-one variable. However, a level-one model that most accurately fits the Percent Destination data must be identified first. Thus, the error at level-two is allowed to vary at random. The level-two model tested was:

$$\pi_{0i} = \beta_{00} + r_0$$

$$\pi_{1i} = \beta_{10} + r_1$$

$$\pi_{2i} = \beta_{20} + r_2$$

$$\pi_{3i} = \beta_{30} + r_3$$

where
π_{0i} (intercept) is a function of the population intercept + person i's deviation from the population intercept
π_{1i} (SA) is a function of the population slope for SA + person i's deviation from the population slope for SA
π_{2i} (TA) is a function of the population slope for TA + person i's deviation from the population slope for TA

π_{3i} (RA) is a function of the population slope for RA + person i's deviation from the population slope for RA

Results from the linear change analysis can be found in Table 4. Analyses revealed that three of the four fixed effects were significant. The intercept coefficient, 20.47 ($p<.001$) reflects mean performance at the start of the task. The SA slope revealed that, on average, Percent Destination increased over the skill acquisition period by 2.1 ($p<.001$) per unit of time (scenarios 2-6). At the TA point, on average, Percent Destination decreased by -6.48 (scenario 7). The RA slope was not significant (scenarios 8-12). However, as displayed in Figure 2, there may be a curvilinear relationship of performance over time. This can be tested by adding quadratic terms for SA and RA.

Before moving on to the quadratic model, homogeneity of level-one variances was tested. Hierarchical linear models assume that the errors at level-one are normally distributed with expected mean zero and equal variance (Raudenbush & Bryk, 2002). A test of homogeneity revealed significant results ($\chi^2=187.83$ (129), $p=.001$), indicating that the null hypothesis of homogeneity of level-one variance is rejected. In other words, significant variability was found among the level-two units in terms of the level-one variance. However, given that a task-change manipulation was used, it is not unexpected that level-one variance is not homogeneous across scenarios. Figure 3 is a line graph displaying the differences in Percent Destination produced by task-change type. Heterogeneous variances at level-one can be modeled as a function of another measured variable (Singer & Willett, 2002). Thus, the next analysis conducted was to determine whether a model allowing heterogeneous errors at level-one as a function of task-change type fits the data better than a model that assumes homogenous errors at level-one.

The homogenous and heterogeneous models were compared using the deviance test, which is a measure of how much the model deviates from the actual data. The deviance test subtracts the smaller deviance from the larger deviance. The difference in these deviance scores is a chi square test with degrees of freedom equal to the number of parameters in the two models (Singer & Willett, 2002). Comparison of the fits of the two models suggest that the model with heterogeneous level-one variances fits the data better (χ^2=36.74(2), $p<.001$). Thus, for all further analyses, level-one variances will be modeled as heterogeneous as a function of task-change type. Results from this analysis can be found in Table 5.

Quadratic Change Model. To test the quadratic change of the SA and RA slopes, two new time variables were created (See Table 1 for the specific coding of these variables). RA^2 was calculated simply by squaring each value in the TIME coding scheme for RA. However, the calculation of SA^2 was not as straightforward. First, a new skill acquisition time variable was created that changed only during the skill acquisition period (measurement occasions 0-5). A constant value was given to scenarios after the task change (measurement occasions 7-11). Lang and Bliese (2009) used a constant value of 25 rather than zero to help provide an unconfounded estimate of TA. Specifically, this coding allows one to center both skill acquisition variables (i.e., SA and SA^2) at the origin of time and determine TA relative to skill acquisition at the origin of time. Lang and Bliese's (2009) design was adopted in the current study.

When testing for quadratic change, the linear change variables must also be included to control for linear effects (Singer & Willett, 2002). The quadratic terms SA^2

and RA_2 were added to the level-one model. Thus, the specific quadratic model tested was:

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}RA_{ti} + \pi_{4i}SA^2_{ti} + \pi_{5i}RA^2_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_0$$

$$\pi_{1i} = \beta_{10} + r_1$$

$$\pi_{2i} = \beta_{20} + r_2$$

$$\pi_{3i} = \beta_{30} + r_3$$

$$\pi_{4i} = \beta_{40} + r_4$$

$$\pi_{5i} = \beta_{50} + r_5$$

Results show that five of the six fixed effects were significant. The intercept coefficient, 18.75 ($p<.001$) reflects mean performance at the start of the task. The SA slope shows that, on average, Percent Destination increased about 5.03 ($p<.001$) per unit of time. However the SA^2 slope, (-.61, $p<.001$) shows that the SA slope flattened over time. These findings are similar to much of the research on skill acquisition and performance, whereby an individual's learning curve grows quickly at first as they are learning the task. However, once they have learned the basics of the task, performance flattens out. Recall that the adaptive performance scores control for the intercept and SA. The RA slope was not significant (.31, $p=.82$) meaning it was not significantly different than the SA slope. However, the RA^2 slope was significant (-.48, $p<.05$). The significant, negative coefficient for RA^2 may be interpreted similarly to SA^2 in that Percent Destination scores in the post-task-change period also flattened out over time as people re-learned the task.

The linear and quadratic change models revealed no significant fixed or random effects for the linear RA slope term. However, to continue to test the RA^2 term, the linear term must be left in the model. Thus, the RA slope error variance will be constrained meaning the random effect for RA will not be estimated nor will any level-two predictors be added to explain variance in this piece of the model. Constraining the RA slope error term creates a more parsimonious model, because it is one less term that needs to be estimated (Singer & Willett, 2002). Results in Table 6 reflect the results of the quadratic change model with a fixed error term for the RA slope.

Deviance testing to compare model fit showed that the quadratic change model fit the data significantly better than the linear change model. Thus, this was the level-one model used in further analyses. However, before entering level-two predictors to explain variance in Percent Destination, the reliability estimates for the level-one terms must be examined. The reliability estimates represent the proportion of variance in level-one estimates that is due to parameter variance. A separate reliability estimate is given for each level-one term and is calculated by estimated parameter variance / estimated total variance. If most of the variability is due to error, finding systematic relationships between level-one estimates and level-two predictors may be difficult. In other words, large error variance and poor reliability affect the power to detect significant differences (Bryk & Raudenbush, 1987).

In the current study, one of the six reliability estimates was of adequate size. The estimate for each level-one term was: Intercept=.481, SA=.071, TA=.154, RA=.102, SA^2=.015 and RA^2=.063. The intercept was the only term with an acceptable reliability estimate. The other five terms had low reliability estimates meaning there was very little variation in the growth parameters. Thus, it may be difficult to find systematic relationships between level-two predictor variables and all of the level-one terms except for the intercept.

Level-Two Analyses for Percent Destination

The next step in the analyses was to enter individual differences into the model at level-two to explain variance in Percent Destination over time. Four cognitive ability scores were used that include Simple Reaction Time, Perceptual and Processing speed, GMA and Cognitive Flexibility. Four person predictors were also used including Age, Sex, Video Game Use, and Video Game Expertise.

Task-change type was also used to predict differences in post-task-change performance, namely TA and RA^2. The three types of task change include New Rule, Count and Speed. To make comparisons between task-change types, two dummy coded variables were created. The first dummy code was labeled *Speed*, where group membership in Speed=1, Count=0, and New Rule=0. The second dummy code was labeled *Count*, where group membership in Count=1, Speed=0, and New Rule=0. The reference group for these dummy variables was the New Rule group. Thus, the comparison made with *Speed* was between New Rule and Speed, whereas the comparison made with *Count* was between New Rule and Count. When the dummy variables are present in the model, the coefficient for the intercept reflects the New Rule group.

A backwards stepwise process was used where all eight cognitive ability and person variables were first entered into the equation to explain variance at the intercept. Variables were removed one at a time, starting with the smallest t-ratio. This process ended when all variables were statistically significant. After identifying significant predictors of the intercept, all eight predictors were added to SA, TA, SA^2 and RA^2 in succession. In addition to the eight cognitive ability and person variables, task-change type was added to explain variability in TA and RA^2.

Three of the eight predictor variables explained a significant amount of variance at the intercept. The coefficient for Age was -.91 ($p<.001$), meaning younger individuals had a significantly higher intercept value than did older individuals. The coefficient for Video Game Use was 2.66 ($p<.001$), meaning the more an individual plays video games, the higher their intercept value. Finally, individuals who had higher Perceptual and Processing Speed had significantly higher intercept values (1.02, $p<.001$). The results for this model can be found in Table 7. Although it was not kept in the model, it should be noted that the effects of GMA were marginally significant (.93, $p=.062$). Individuals with higher scores on GMA tests tended to have higher intercept values. All eight predictors were then added to the model to explain variability in SA, followed by TA. Cognitive ability and person predictors did not explain a significant amount of variability for these time points.

At the transition adaptation point, task-change type did have a significant effect. The New Rule manipulation caused a significant drop in performance (-21.74, $p<.001$), and the Count manipulation caused a significant but smaller drop in performance (7.36, $p<.001$), relative to New Rule. In contrast, the Speed manipulation caused a significant increase in performance (27.60, $p<.001$). The moderating effect of task-change type on the relationship between cognitive ability and transition adaptation could not be analyzed because there were no significant cognitive ability predictors for this time point.

Simple Reaction Time was the only predictor that explained a significant amount of variance in SA^2 (.01, p=.054). Recall that the slope for skill acquisition was curvilinear. More specifically, it was found that Errors decreased over the skill acquisition period, but decreased less dramatically at the end of the skill acquisition period (i.e., flattened out). The results indicate that, at the end of the skill acquisition period, Percent Destination scores did not flatten out as quickly for individuals who have slow reaction time. This may be because it takes individuals with slower reaction time longer to learn the task. This finding supports Ackerman, Kanfer and Goff's (1995) study showing a significant relationship between reaction time and complex skill acquisition.

With regard to the RA^2 slope, cognitive ability and person predictors did not explain a significant amount of variability. However, individuals differed in RA^2 depending upon task-change type. The New Rule manipulation did not cause an increase or decrease in performance that was significantly different than zero. However, the RA^2 slope for the Speed and Count manipulations were significantly different than New Rule. Controlling for the intercept and skill acquisition, the Count manipulation caused the largest decrease in RA^2 (-.78, $p<.001$) followed by a smaller decrease by the Speed manipulation (-.37, $p<.001$) relative to New Rule. In other words, the beginning of the post-task-change slope (RA) was not significantly different from the pre-task-change slope (SA). However, over time, the Count and Speed manipulations caused Percent Destination scores to flatten out significantly more than the New Rule manipulation. As was the case with transition adaptation, the moderating effect of task-change type on the relationship between cognitive ability and reacquisition adaptation could not be analyzed because there were no significant cognitive ability predictors for this time point.

The final model for Percent Destination scores was:

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}RA_{ti} + \pi_{4i}SA^2_{ti} + \pi_{5i}RA^2_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}\,(AGE) + \beta_{02}(GAMEUSE) +$$

$$\beta_{03}(PERCEPTUAL) + r_0$$

$$\pi_{1i} = \beta_{10} + r_1$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(SPEED) + \beta_{22}(COUNT) + r_2$$

$$\pi_{3i} = \beta_{30} + r_3$$

$$\pi_{4i} = \beta_{40} + \beta_{41}(SIMPLE\ RT) + r_4$$

$$\pi_{5i} = \beta_{50} + \beta_{50} + \beta_{51}\,(SPEED) + \beta_{52}(COUNT) + r_5$$

More detailed information about this model can be found in Table 7.

Best Fitting Model. The last step in the analyses was to determine the best fitting model for the Percent Destination data. There are a number of goodness-of-fit statistics that can be used such as deviance statistics, the AIC and the BIC. To compare models for the current study, a series of deviance tests were conducted. One of the requirements for the use of deviance tests in model comparisons is that the reduced model must be nested within the full model. In other words, every parameter of the smaller model must also be present in the larger model (Bryk & Raudenbush, 1987). Five models were conducted in the current study and each lower-order model was nested within the higher-order model. Full maximum likelihood (FML) was also used instead of the default restricted maximum likelihood (RML) as the method of estimation. Under FML, one maximizes the likelihood of the sample data, whereas under RML one maximizes the likelihood of sample residuals. In other words, FML describes the fit of the entire model and RML only fits the stochastic part of the data (Bryk & Raudenbush, 1987). Given that hypotheses were made regarding the fixed and random effects of the model rather than simply the variance components, FML was used as the method of estimation.

Results on the comparison of models are provided in Table 8. A deviance score was calculated for each model and the deviance test describes the difference between these two scores. The difference is evaluated via a chi square test with degrees of freedom equal to the difference in the number of parameters between the two models (Singer & Willett, 2002). A significant chi square test means that the larger model explains a significant amount of additional variance over the smaller model. For all comparisons, the larger model explained a significant amount of additional variance. In other words, the linear change model fit the data better than the unconditional means model (χ^2 = 472.21(12), p<.001), the quadratic model fit the data better than the linear change model (χ^2 = 36.15 (9), p<.001), and the model that added level-two predictors to the model fit the data significantly better than the quadratic model (χ^2 =247.59 (8), p<.001). It should also be noted that a significant amount of random variability was still present in the last model for the intercept. Thus, there undoubtedly are other interesting between-person differences that explain variability in the intercept that were not included in the current study.

Level-One Analyses for Errors

After identifying the best fitting model for Percent Destination scores, Errors were used as the dependent variable. A series of growth models were run that were similar to those conducted with Percent Destination as the dependent variable. The first model conducted was the unconditional means model. This analysis revealed an ICC=.23, meaning between-person variance accounted for 23% of the variance of Errors over time.

This suggested that individual differences in performance across time exist and the utilization of growth modeling was appropriate.

The next step in the analyses was to identify the best fitting level-one model. A linear change model was conducted and it was found that the intercept and TA terms were significant, while the SA and RA terms were not significant. As with Percent Destination, this may be the result of a curvilinear relationship of performance over time. To test whether or not Error scores were curvilinear over time, a quadratic change model was conducted. This model showed that SA was curvilinear while RA was not. Given that RA and RA^2 were not significant, a third level-one model was conducted where RA and RA^2 were removed from the model. Deviance testing showed that this model fit the data significantly better than the quadratic model. Thus, the final level one model was:

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}SA^2_{ti} + e_{ti}$$

The coefficient for the intercept for this model was significant. On average, the mean score was 4.69 ($p<.001$), which was significantly different than zero. Over the SA slope, on average, Errors decreased by -.20 ($p<.05$) per unit of time. However, towards the end of the skill acquisition period, Errors decreased less dramatically (i.e., flattened out) as evidenced by a significant SA^2 term (.05, $p<.05$). At the TA point, on average, Errors significantly increased (1.29, $p<.001$). The results for the final level-one model can be found in Table 9.

A test of homogeneity of level-one variance revealed significant results (χ^2=347.39 (130), $p<.001$) indicating that the null hypothesis of homogeneity was rejected. As with Percent Destination scores, this was not unexpected given the manipulation of task-change type. Figure 4 displays the differences in Errors produced by task-change type. Thus, the homogenous model was compared to a heterogeneous model where variance at level-one was modeled as a function of task-change type. Comparison of the fits of the two models suggests that the model with heterogeneous level-one variances fits the data better (χ^2=26.36 (2), p<.001). Thus, for all further analyses, variance at level-one was modeled as a function of task-change type. Results on the comparison between models can be found in Table 10. The reliability estimates for the level-one model were: Intercept=.54, SA=.154, TA=.165 and SA^2=.037. Similar to the analyses using Percent Destination as the dependent variable, the reliability estimate for the intercept term was the only estimate of adequate size. The reliability estimates for SA, TA and SA^2 are small, which may lead to difficulties finding systematic relationships between level-two predictor variables and level-one terms.

Level-Two Analyses for Errors

The next step in the analyses was to enter individual differences into the model at level-two to explain variance in Errors over time. A backwards stepwise process was used where all eight cognitive ability and person variables were first entered into the equation to explain variance at the intercept. Variables were removed one at a time, starting with the smallest t-ratio. This process ended when all variables were statistically significant. After identifying significant predictors of the intercept, all eight predictors were added to SA, TA and SA^2 in succession. Task-change type was also added to the model to explain variance in TA, which was the only remaining post-task-change time variable.

Four of the eight predictor variables explained a significant amount of variance at the intercept. Higher Video Game Use scores led to less Errors at the beginning of the air traffic control task (-.39, $p<.01$). Less Errors were also made when individual's had higher GMA scores (-.22, $p<.05$) , higher Cognitive Flexibility scores (-.34, $p<.05$) and higher Perceptual and Processing Speed scores (-.37, $p<.001$). All eight predictors were then added to the SA term, but no predictors explained a significant amount of variability.

Between-person predictors were then added to the TA term and Cognitive Flexibility was the only predictor that explained a significant amount of variance (.77, $p<.001$). This result indicates that individuals with higher Cognitive Flexibility had a more pronounced increase in Errors after a change in the task. This finding is similar to Lang and Bliese's (2009) study showing that higher GMA individuals had a more pronounced decline in performance after a change in the task, relative to individuals lower in GMA. The authors surmised that this relationship was due to high GMA individuals learning the task more quickly and entering a stage of automaticity. In the current study, it seems Cognitive Flexibility may have a similar effect on Errors.

Task-change type was then added to the model at the transition adaptation point. The New Rule manipulation caused a non-significant decrease in Errors (-.45, $p >.05$). In contrast, the Count manipulation caused the largest increase in Errors (3.99, $p<.001$) followed by a smaller increase in Errors caused by the Speed manipulation (1.93, $p<.001$), relative to New Rule. The moderating effect of task-change type on the relationship between Cognitive Flexibility and Errors was then tested. To test this effect, interactions terms were created by multiplying both dummy coded task-change variables by Cognitive Flexibility. However, no significant moderating relationships were found.

Lastly, between-person predictors were added to the model to explain variability in SA^2. Recall that the slope for skill acquisition was curvilinear. More specifically, it was found that Errors decreased over the skill acquisition period, but decreased less dramatically at the end of the skill acquisition period (i.e., flattened out). Reaction time on Perceptual and Processing Speed predicted significant differences in SA^2 (.01, $p<.05$). This result indicates that Errors decrease (or flatten out) more quickly at the end of the skill acquisition period for individuals higher in Perceptual and Processing Speed, relative to individuals lower in Perceptual and Processing Speed. This suggests that individuals lower in Perceptual and Processing Speed take longer to learn the task. This finding supports Ackerman, Kanfer and Goff's (1995) study showing a significant relationship between perceptual speed and complex skill acquisition.

The final model for Error scores was:

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}SA^2_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}\text{(GAMEUSE)} + \beta_{02}\text{(PERCEPTUAL)} + \beta_{03}\text{(GMA)}$$

$$+ \beta_{04}\text{(COGFLEX)} + r_0$$

$$\pi_{1i} = \beta_{10} + r_1$$

$$\pi_{2i} = \beta_{20} + \beta_{21}\text{(COGFLEX)} + \beta_{22}\text{(SPEED)} + \beta_{23}\text{(COUNT)} + r_2$$

$$\pi_{3i} = \beta_{30} + \beta_{31}\text{(PERCEPTUAL)} + r_3$$

More detailed information about this model can be found in Table 11.

Lastly, deviance testing was used to compare all growth models using Errors as the dependent variable. These results can be found in Table 12. The best fitting model was the last model where cognitive ability, person variables and task-change type was used to predict individual differences in level-one growth.

Discussion

With the multitude of technological advances in the modern era, increased experimental attention has been paid to determining the types of individual differences that aid individuals in adapting to complex environments. The task-change paradigm is the most commonly used experimental paradigm in testing this phenomenon. Adaptive performance is often operationalized simply as performance after a change. Such a simplistic operationalization ignores intercorrelations between different types of performance (e.g., pre-task-change performance and post-task-change performance) and the possibility that individual differences differentially impact different types of performance. In the current study, a discontinuous growth model was used in an effort to control for the effects of basal task performance and skill acquisition when evaluating adaptive performance. In addition, a discontinuous growth model was used to look at the possibility that cognitive ability has a differential relationship to pre-task-change performance and post-task-change performance. The analytical framework used in the current study was proposed by Lang and Bliese (2009). Thus, a third goal was to test the utility of this framework with regards to research on adaptive performance.

Based upon Lang and Bliese's design, four time variables were used including basal task performance, skill acquisition, transition adaptation and reacquisition adaptation. With regard to the task-change paradigm, the first two components comprise the pre-task-change period and the last two comprise the post-task-change period. Percent Destination and Error scores were the dependent variables that were modeled separately in two sets of growth analyses. The first step was to confirm a level-one model for the first dependent variable, namely Percent Destination. Results show that the data was curvilinear and thus a quadratic change model fit the data significantly better than a linear change model. The results of the quadratic model show that performance increased over the skill acquisition period but flattened out at the end of the skill acquisition period. These findings are similar to much of the research on skill acquisition and performance, whereby an individual's learning curve grows quickly at first as they learn the task. However, once they have learned the basics of the task, performance scores flatten out. At the transition adaptation point (i.e., when the task changed), performance dropped significantly. After the task changed, performance increased again over the reacquisition adaptation period and flattened out at the end of this period. However, the slope of reacquisition adaptation was not significantly different from the slope of skill acquisition until the slopes began to flatten out. At this point, the reacquisition adaptation slope was significantly flatter (or lower) than the skill acquisition slope. The results from the level-one model were similar to Lang and Bliese's (2009) level-one results.

The second step in the analyses was to add level-two factors to explain individual differences in Percent Destination over time. At the beginning of the task, it was found that younger individuals, individuals who spend more time playing video games and individuals higher in perceptual and processing speed score significantly higher. There was also a marginally significant relationship between higher scores on GMA tests and higher scores on the first scenario. For skill acquisition, Percent Destination scores did not flatten out as quickly for individuals with slow reaction time. This finding supports Ackerman, Kanfer and Goff's (1995) study showing a significant relationship between reaction time and complex skill acquisition.

For transition and reacquisition adaptation, task change was the only variable that explained a significant amount of variance. Results show that the New Rule manipulation caused performance to drop significantly at the transition adaptation point. The Count manipulation caused a significant, but smaller drop in performance relative to New Rule. In contrast, the Speed manipulation caused a significant increase in performance, relative to New Rule. For reacquisition adaptation, on average, performance flattened out, or decreased over time. The Count and Speed manipulations caused a larger decrease in performance at this point, relative to the New Rule manipulation. Given that there were no significant cognitive ability predictors for Percent Destination scores, the moderating effect of task-change type on the relationship between the two variables could not be analyzed in the current study sample.

After identifying the best fitting model for Percent Destination, the growth modeling process was repeated using Errors as the dependent variable. The best level-one model included SA, TA and SA^2. Results from this model demonstrated that Errors decreased over the skill acquisition slope but flattened out at the end of this period. At the transition adaptation point, on average, Errors tended to increase. These findings are in line with the Percent Destination results. However, unlike the analyses for Percent Destination and Lang and Bliese's (2009) study, there was no significant random variability in the reacquisition slope. In other words, the slope after the task change was not significantly different from the slope prior to the task change.

Level-two analyses began by adding all eight between-person predictor variables to the model to explain variability at the intercept. Four of the eight predictor variables explained a significant amount of variance. Video Game Use, GMA, Cognitive

Flexibility and Perceptual and Processing Speed were all negatively related to Errors at the beginning of the air traffic control task.

After identifying significant predictors of basal task performance, between-person predictors were added to the model to explain variability in SA, TA and SA^2. Results for SA and SA^2 revealed that there were no significant predictors of Errors at the beginning of the skill acquisition period. However, toward the end of the skill acquisition period, Errors decrease (or flatten out) for individuals higher in Perceptual and Processing Speed, relative to individuals lower in Perceptual and Processing Speed. This suggests that individuals lower in Perceptual and Processing Speed take longer to learn the task. This finding supports Ackerman, Kanfer and Goff's (1995) study showing a significant relationship between perceptual speed and complex skill acquisition.

For TA, there was a significant positive relationship between Cognitive Flexibility and Errors such that individual's with higher Cognitive Flexibility had more pronounced increases in Errors after the change in the task. The moderating effect of task-change type on the relationship between Cognitive Flexibility and Errors was tested, but no significant relationship was found.

There were five hypotheses in the current study. Hypothesis One predicted that component complexity (i.e., New Rule) would have a differential effect on adaptive performance relative to task difficulty and coordinative complexity (i.e., Count and Speed). Analyses revealed a complex relationship between task-change type and performance. At the transition adaptation point, Percent Destination increased in the Speed condition but decreased in the New Rule and Count conditions. Also at the transition adaptation point, Errors was non-significant for the New Rule manipulation (decreasing trend) but increased in the Count and Speed groups. With regard to reacquisition adaptation, task-change type created small differences in Percent Destination scores, but not in Error scores. Although the current study was a step in the right direction, further research is needed to describe the effects that task difficulty, coordinative complexity and component complexity have on adaptive performance. In addition, the differing results with Percent Destination and Errors as dependent variables suggest that task-change types have varying effects on different aspects of performance outputs, which may be a fruitful area for future research.

Hypotheses Two predicted that GMA would have a stronger relationship with adaptive performance, relative to pre-task-change performance. This hypothesis was not supported because no relationship was found between GMA and adaptive performance using the current study sample. It is believed that these results may be due to the method for assessing cognition in the current study rather than a true null relationship given that a number of previous studies have found a relationship between these variables (e.g., Jundt, 2009; Lang & Bliese, 2009; Lepine, Colquitt & Erez, 2000). All of the cognitive ability factors were measured via ANAM4™ except for Cognitive Flexibility. These tests are strongly influenced by reaction time and occasionally ceiling effects become an issue. One or both of these factors may have influenced the measurement of cognitive ability. In future studies, it may be beneficial to include a more typical measure of GMA.

Hypothesis Three predicted that Simple Reaction Time and Perceptual and Processing Speed would be a better predictor of basal task performance and skill acquisition, relative to adaptive performance. This hypothesis was supported and corroborates Ackerman, Kanfer and Goff's (1995) study showing a significant relationship between perceptual speed, simple reaction time and complex skill acquisition.

Hypothesis Four predicted that Cognitive Flexibility would have a stronger, positive relationship to adaptive performance, relative to pre-task-change performance. This hypothesis was partially supported in that Cognitive Flexibility was related to adaptive performance. However, a negative relationship was found, while a positive relationship was hypothesized. This finding is similar to Lang and Bliese's (2009) study showing high GMA individuals had more pronounced declines in performance after a change in the task, relative to individuals low in GMA. The authors surmised that this relationship was due to high GMA individuals learning the task more quickly and entering a stage of automaticity. As a result, they form more automatic and proceduralized strategies. However, when the task changes, they have difficulty returning to a step-by-step strategy of task execution. In contrast, low GMA individuals always use a step-by-step strategy and thus do not incur large performance decrements, relative to high GMA individuals. It may be the case that a similar relationship exists between Cognitive Flexibility and adaptive performance.

Hypotheses Five addressed the moderating effect of task-change type on the relationship between cognitive ability (GMA and Cognitive Flexibility specifically) and adaptive performance. A pre-condition for testing this hypothesis is that cognitive ability and task-change type both have a significant effect on performance. For Percent Destination, no relationship was found between cognitive ability and performance. Thus, no interaction terms could be created between the two variables to test the moderating effect of task-change type. For Errors, the moderating effect of task-change type on the relationship between Cognitive Flexibility and TA was tested. However, no significant relationship was found.

Lack of variability in the data may have contributed to difficulties in finding systematic relationships between individual differences and performance. The lack of variation led to low reliability estimates and low statistical power. Hertzog, Lindenberger, Ghisletta and Oertzen (2006) evaluated the statistical power of growth models as a function of sample size, number of level-one measurement occasions and reliability. The authors found a positive relationship between larger sample size, more measurement occasions and increased power, which was anticipated. However, they did not expect the degree to which reliability influenced power. The study showed that even with large samples (n=500) and several measurement occasions (4 to 5) the statistical power to detect significant differences was low unless the reliability estimate at the onset of the study was above .90. The reliability estimate from the unconditional model for Percent Destination as the dependent variable was .88, while the reliability estimate for Errors as the dependent variable was .78. Although these estimates are close, they do not meet the threshold suggested by Hertzog, Lindenberger, Ghisletta and Oertzen (2006). Also recall that the reliability estimates from the final level-one models (one for Percent Destination and one for Errors) were all low except for the reliability for the intercept. This suggests that, aside from the intercept, there was not enough variance in the level-one terms, which decreased the power to detect significant differences. Thus, it cannot be concluded that the individual difference variables used in the current study were unrelated to performance scores. Rather, there may not have been enough statistical power to detect significant differences.

The lack of random variability in the data could also be due to characteristics of the individuals within the sample. In a previous study conducted by the author (Wheeler & Faneros, unpublished) the same air traffic control measure was used as well as the NASA-TLX. However, instead of having twelve three-minute long scenarios the previous study had one twenty-minute long scenario. These two studies were compared on subjective levels of performance, effort and frustration as well as Percent Destination. The participants in the previous study reported higher levels of performance (M=12.73), higher levels of effort (M=14.33) and higher levels of frustration (M=11.39) than did participants in the current study, i.e., performance (M=11.39), effort (M=13.29) and frustration (M=10.05). Given that the two experiments used scenarios of varying length, Percent Destination per minute was compared. On average, participants in the previous study landed 2.46 percent of planes, while individuals in the current study landed 2.01 percent of planes per minute. Although these are not large differences, it seems plausible that participants did not put forth as much effort in the current study, which may have influenced the results.

Lack of random variability may also be due to characteristics of the task itself. For example, the task could have been too easy. If this were true, variability between subjects would be minimized. Initial pilot testing of the air traffic control scenarios was favorable given that there was a great deal of variability between subjects in performance scores and participants did not rate any of the scenarios as too easy on the NASA-TLX. Nonetheless, variability decreased as the study progressed. Modest to low correlations between cognitive ability and performance was also indicative of the task being too simple to produce differences in cognitive ability or possibly a lack of systematic variability in cognitive ability scores. With regard to ANAM4^{TM}, the strong influence of reaction time and ceiling effects may have contributed to low correlations.

In future research, it may be beneficial to make the task more difficult or more challenging in an attempt to maintain or elevate participant's motivation. This could help increase variability, which in turn would increase reliability and power. It may also be beneficial to include a more typical measure of GMA. Lastly, further research is needed to describe the effects that task difficulty, coordinative complexity and component complexity (and other types of task characteristics) have on adaptive performance. Two promising areas of research include: 1) More direct testing of the relationship between cognitive demand and task complexity and how these variables interact to influence adaptive performance, and 2) The varying effects that task-change types have on different aspects of performance outputs, such as production (e.g., percent destination) versus error rates.

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Table 1

Coding of Time Variables

	Measurement Occasion											
Variables	1	2	3	4	5	6	7	8	9	10	11	12
Linear Change Terms												
Skill acquisition (SA)	0	1	2	3	4	5	6	7	8	9	10	11
Transition adaptation (TA)	0	0	0	0	0	0	1	1	1	1	1	1
Reacquisition adaptation (RA)	0	0	0	0	0	0	0	1	2	3	4	5
Quadratic Change Terms												
Skill acquisition (SA^2)	0	1	4	9	16	25	25	25	25	25	25	25
Reacquisition adaptation (RA^2)	0	0	0	0	0	0	0	1	4	9	16	25

* Coding obtained from Lang and Bliese (2009)

Table 2

Means, Standard Deviations and Intercorrelations of Study Variables

(Intercorrelations controlling for task-change type)

Variable	M	SD	1	2	3	4	5	6	7	8	9	10
1. Percent Destination	166.8	72.33	1	-.48*	-.22*	.38**	.23*	-.22**	-.18*	-0.15	.23*	.21*
2. Errors	27.55	12.24	-.48**	1	0.07	-.36**	.36**	0.11	0.01	.29**	-.30**	-.35**
3. Simple Reaction Time	247.7	25.23	-.22*	0.07	1	-.30**	-.26*	0.08	-0.01	.25*	-.21*	-0.12
4. Perceptual Speed	0	2.48	.38**	-.36**	-.30**	1	.28**	-.20*	-0.15	-.26*	.23*	.30**
5. General Mental Ability	0	1.49	.23*	.36**	-.26*	.28**	1	-0.1	-0.02	-0.1	-0.01	0.08
6. Cognitive Flexibility	36.55	6.05	-.22**	0.11	0.08	-.20*	-0.1	1	0.07	.20*	-0.01	-0.02
7. Age	19.46	2.21	-.18*	0.01	-0.01	-0.15	-0.02	0.07	1	-.21*	0.15	.24*
8. Sex	1.58	0.5	-0.15	.29**	.25*	-.26*	-0.1	.20*	-.21*	1	-.52**	-.51**
9. Video Game Use	1.77	1.05	.23*	-.30**	-.21*	.23*	-0.01	-0.01	0.15	-.52**	1	.68**
10. Video Game Expertise	1.94	1	.21*	-.35**	-0.12	.30**	0.08	-0.02	.24*	-.51**	.68**	1

Table 3

Unconditional Means Model (Percent Destination as dependent variable)

Fixed Effect		Standard Error	t-ratio	Approx. df	p-value
Intercept	29.46	1.01	29.12	131	<.001
Reliability Estimate: .88					
Intraclass Correlation Coefficient: .39					
Deviance: 12728.36 Number of Estimated Parameters: 3					

Table 4

Linear Change Model (Percent Destination as dependent variable)

Fixed Effect	Coefficient	Standard Error	t-ratio	Approx. df	p-value
Intercept	20.47	1	21	131	<.001
SA	2.1	0.22	9.62	131	<.001
TA	-6.48	1.25	-5.19	131	<.001
RA	0.13	0.33	0.39	131	>.05
Deviance: 12256.14					
Number of Estimated Parameters: 15					

Table 5

Comparison of Models with Homogeneous and Heterogeneous Variance at Level-One

(Percent Destination as dependent variable)

Model	Number of Parameters	Deviance	
1. Homogeneous σ2	19	12078.35	
2. Heterogeneous σ2	21	12041.61	
Model Comparison	χ2	df	p-value
Model 1 versus Model Two	36.74	2	p<.001

Table 6

Quadratic Change Model (Percent Destination as dependent variable)

Fixed Effect	Coefficient	Standard Error	t-ratio	Approx. df	p-value
Intercept	18.75	1.06	17.7	131	<.001
SA	5.03	0.69	7.25	131	<.001
TA	-11.53	1.85	-6.22	131	<.001
RA	0.31	1.38	-0.23	883	>.05
SA^2	-0.61	0.14	-4.35	131	<.001
RA^2	-0.48	0.2	-2.43	131	<.05
Deviance: 12219.99					
Number of Estimated Parameters: 24					

Table 7

Adding Level-Two Predictors (Percent Destination as dependent variable)

Fixed Effect		Coefficient	Standard Error	t-ratio	Approx. df	p-value
Intercept		19.09	1.01	18.94	128	< .001
	(Age)	-0.91	0.23	-3.96	128	< .001
	(GameUse)	2.66	0.67	3.98	128	< .001
	(Perceptual)	1.02	0.32	-3.16	128	< .01
SA		4.83	0.70	6.95	131	< .001
TA		-21.74	1.55	-14.00	129	< .001
	(Speed)	26.60	1.69	15.72	129	< .001
	(Count)	7.36	1.33	5.53	129	< .001
RA		0.78	1.35	0.58	883	> .05
SA^2		-0.60	0.14	-4.25	130	< .001
	(Simple RT)	0.01	0.01	-1.94	130	p =.054
RA^2		-0.18	0.21	-0.87	129	> .05
	(Speed)	-0.37	0.09	-4.29	129	< .001
	(Count)	-0.78	0.09	-9.12	129	< .001

Random Effect	Standard Deviation	Variance Component	df	$\chi 2$	p-value
Intercept	7.99	63.88	126	236.33	< .001
SA	0.66	0.43	129	109.64	> .5
TA	2.73	7.44	127	107.64	> .5
RA	0.32	0.10	128	113.22	> .5
SA^2	0.32	0.10	128	113.22	> .5
RA_2	0.10	0.01	127	108.96	>.5

Deviance: 11972.40

Number of Estimated Parameters: 32

Table 8

Comparison of Models (Percent Destination as dependent variable)

		Original Model		Comparison Statistics	
Model		Deviance	Estimated Parameters	$\chi 2$ (df)	p-value
A	Unconditional Model	1278.36	3	--	--
B	Linear Change Model	12256.14	15	A:472.21(12)	<.001
C	Quadratic Change Model	12219.99	24	B:36.15 (9)	<.001
D	Adding Level-Two Predictors	11972.40	32	C: 247.59(8)	<.001

Table 9

Final Level-One Model (Errors as dependent variable)

Fixed Effect	Coefficient	Standard Error	t-ratio	Approx. df	p-value
Intercept	4.69	0.25	18.73	131	<.001
SA	-0.20	0.08	-2.33	131	<.05
TA	1.29	0.37	3.51	131	<.001
SA^2	0.05	0.02	2.44	131	<.05

Deviance: 8308.27
Number of Estimated Parameters: 17

Table 10

Comparison of Models with Homogeneous and Heterogeneous Variance at Level-One

(Errors as dependent variable)

Model	Number of Parameters	Deviance	
1. Homogeneous σ2	15	8334.63	
2. Heterogeneous σ2	17	8308.27	
Model Comparison	χ2	df	p-value
Model 1 versus Model Two	26.36	2	p<.001

Table 11

Adding Level-Two Predictors (Errors as dependent variable)

Fixed Effect	Coefficient	Standard Error	t-ratio	Approx. df	p-value
Intercept	4.67	0.22	21.3	127	<.001
(GameUse)	-0.39	0.14	-2.86	127	<.01
(Perceptual)	-0.37	0.07	5.55	127	<.001
(GMA)	-0.22	0.1	-2.13	127	<.05
(CogFlex)	-0.34	0.14	-2.39	127	<.05
SA	-0.21	0.08	-2.54	131	<.05
TA	-0.45	0.37	-1.19	128	>.05
(CogFlex)	0.64	0.15	4.16	128	<.001
(Speed)	1.93	0.37	5.27	128	<.001
(Count)	3.99	0.53	7.47	128	<.001
SA^2	0.05	0.02	2.49	130	<.05
(Perceptual)	0.01	0.003	-2.1	130	<.05

Random Effect	Standard Deviation	Variance Component	df	$\chi2$	p-value
Intercept	1.58	2.48	126	218.96	<.001
SA	0.23	0.05	130	140.86	>.05
TA	1.4	1.96	127	136.61	>.05
SA^2	0.03	0.001	129	129.67	>.05

Deviance: 8193.70

Number of Estimated Parameters: 25

Table 12

Comparison of Models (Errors as dependent variable)

		Original Model		Comparison Statistics	
Model		Deviance	Estimated Parameters	$\chi 2$ (df)	p-value
A	Unconditional Model	8465.48	3	--	--
B	Linear Change Model	8337.70	15	A: 127.79 (12)	<.001
C	Quadratic Change Model	8287.49	28	B:50.21 (13)	<.001
D	No RA and RA^2	8308.27	17	C: 20.79 (11)	<.05
E	Adding Level-Two Predictors	8193.70	25	D: 114.57 (8)	<.001

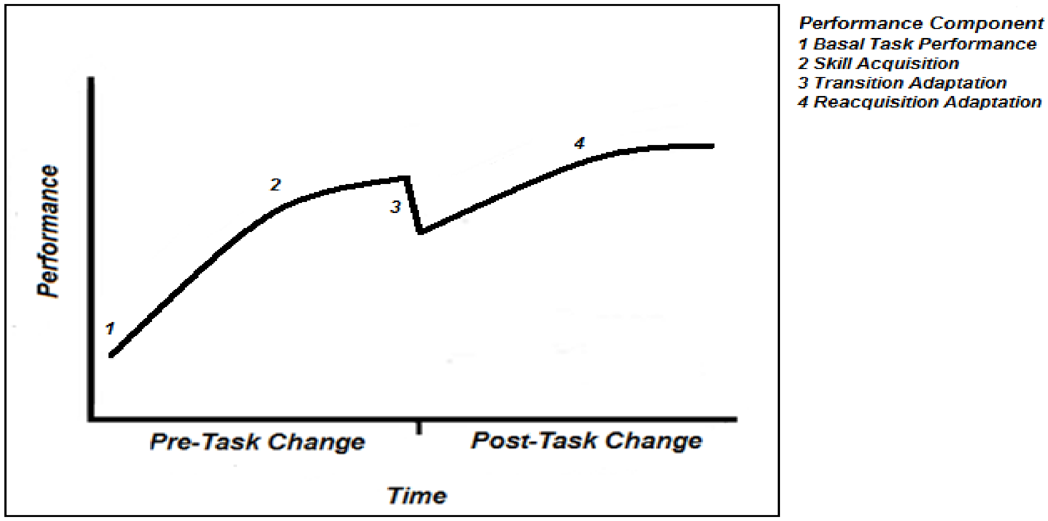

Figure 1. Lang and Bliese's (2009) Four Performance Components

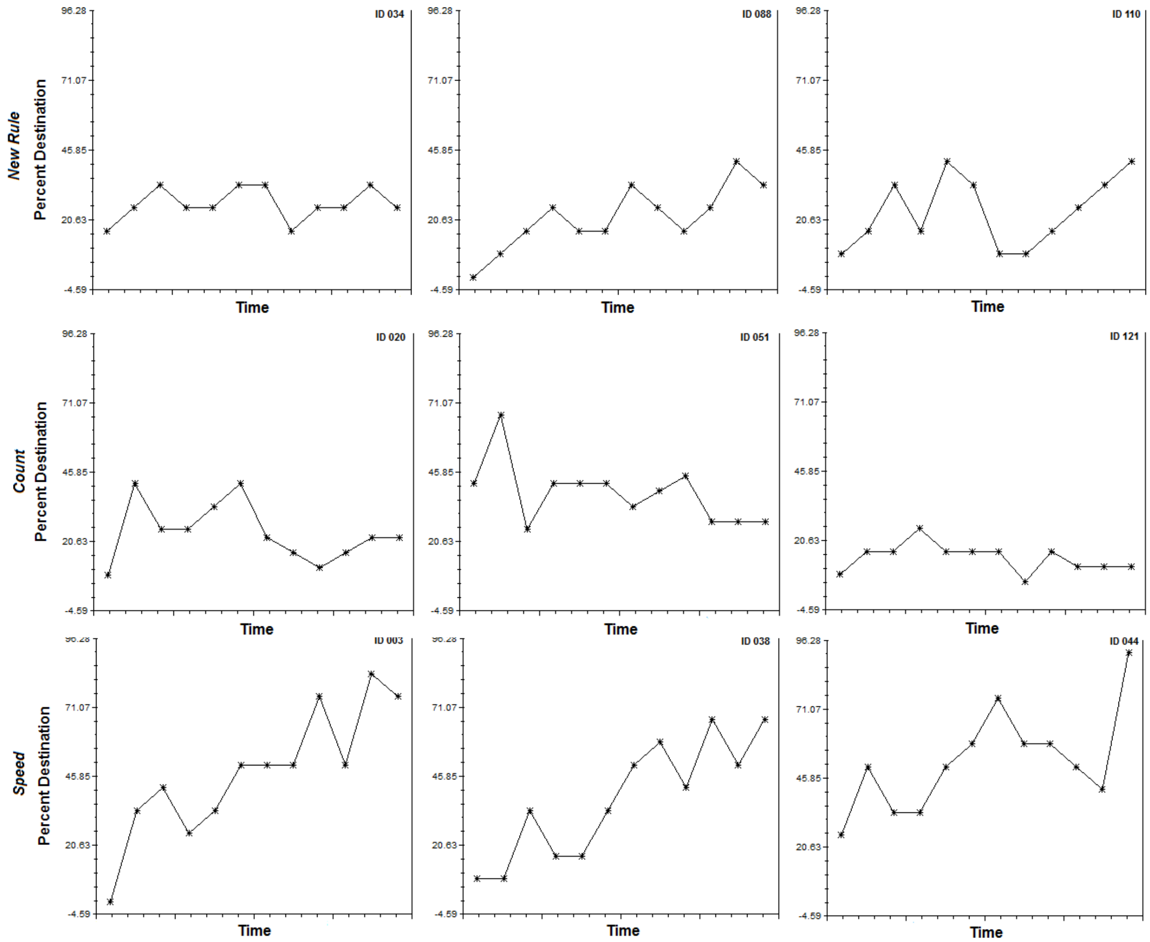

Figure 2. Growth Curves of Nine Randomly Sampled Participants (Grouped by task-change type)

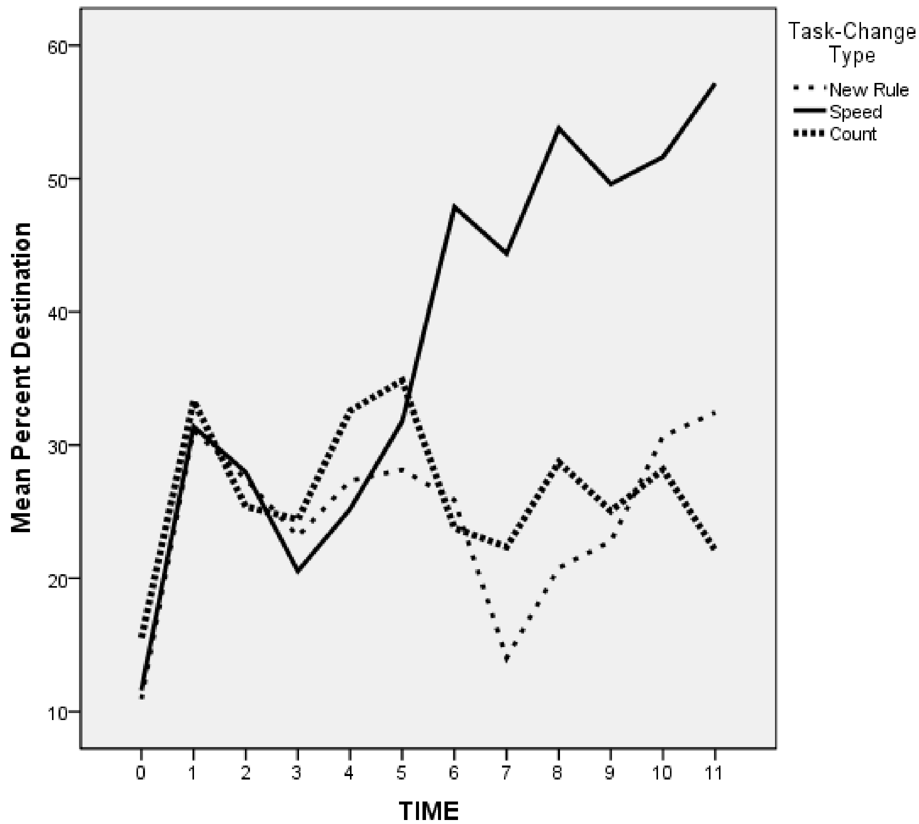

Figure 3. Performance Differences by Task-Change Type (Percent Destination as dependent variable)

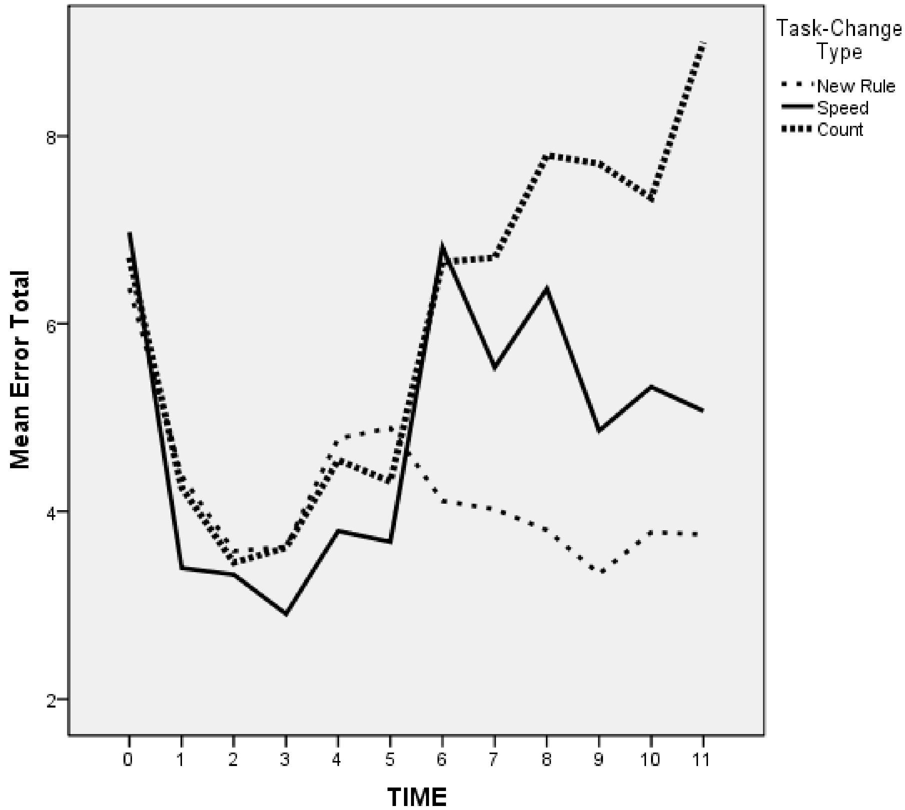

Figure 4. *Performance Differences by Task-Change Type (Errors as dependent variable)*