FOOL ME ONCE, SHAME ON YOU; FOOL ME TWICE, SHAME ON ME: AN INVESTIGATION OF INDIVIDUAL DIFFERENCES, GOALS, AND ADAPTIVE PERFORMANCE IN A MULTIPLE CHANGE CONTEXT

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ABSTRACT

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The rapid rate of technological innovation taking place in an increasingly interconnected global business environment has created workplaces rife with change, both in terms of how work is performed inside organizations as well as in the environment within which the organization operates (Burke, Pierce, & Salas, 2006; Pulakos, Arad, Donovan, & Plamondon, 2000). As a result, the traditional means of defining and evaluating employee performance may no longer be valid because new behaviors (e.g. constant learning) and abilities (e.g. high-order thinking) are increasingly important (Cascio, 1995). This has led to the emergence of a new performance domain, adaptive performance, related to an individual's ability to effectively respond to changes in the workplace. Despite the importance of adaptive performance for modern organizations, relatively little is known about individual and contextual antecedents of adaptive performance. This study aims to begin addressing this deficiency by relying on control theory to further our knowledge of the relationships between initial and subsequent adaptive performance with historically important predictors of overall performance, including intelligence as well as performance relevant Big-5 personality traits. In addition, these relationships are evaluated in the presence of difficult, specific performance goals that are commonly employed by organizations. Novel software was developed to adapt the stock pricing exercise to the task change paradigm in order to test these hypotheses using a sample of 261 student participants.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The rapid rate of technological innovation taking place in an increasingly interconnected global business environment has created workplaces rife with change, both in terms of how work is performed inside organizations as well as in the environment within which the organization operates (Burke, Pierce, & Salas, 2006; Pulakos, Arad, Donovan, & Plamondon, 2000). New technologies and economic reforms have led to an increasingly interconnected business landscape characterized by frequent disruptions and increased competition from firms around the world that have contributed to dramatic shifts in how work is performed (Pearlman & Barney, 2000). Together, these changes have had profound effects not only on organizations, but also individual employees who have had to cope with an employment landscape laden with challenges, including the prospect of massive layoffs and constant change, for rank-and-file workers and managers alike (Cascio, 1995). As highlighted below, this shift is not only of interest to academics; practitioners have also noted the changes occurring.

For example, in the course of two decades, the number of U.S. companies dealing with international competition for their home markets increased by a factor of ten (Gwynne, 1992). The rate of change is immense: the transition to the modern economy occurred ten times faster than the last great paradigmatic shift from an agrarian to an industrial society (Maney, 1998). In fact, "as citizens of the 20th century, we have witnessed more change in our daily existence and in our environment than anyone else who has ever walked the planet", and the rate of change has only been increasing since (Cascio, 1995, p. 928). As a consequence of these changes, among other things, jobs are becoming more cognitively and perceptually demanding as employees are asked to deal with increasing amounts of knowledge as well as the quantity and sources of relevant information (Pearlman & Barney, 2000). Workplaces are increasingly novel, unstable, unpredictable and complex (Kozlowski, Gully, Nason, & Smith, 1999). In addition, the rate of change hinders the ability of organizations to rely solely on established procedures and employees are often asked to make effective decisions and judgments largely on their own (Pearlman & Barney, 2000).

It seems that, in modern organizations at least, Heraclitus was right when he observed over two millennia ago that "nothing endures but change" (as quoted in: Diogenes, c. 300/1925). In such a context, it is of paramount importance for industrial/organizational psychology to identify individual differences that lead to success in a variety of situations since change is what employees are likely to face in a modern workplace (Campbell, 1999). One such measure of success in dealing with change is adaptive performance (Pulakos et al., 2000), and the current study attempts to contribute to the identification of relevant individual differences by investigating antecedents of adaptive performance. This study also answers the more recent call of Lang and Bliese (2009) for researchers to build on existing work on general mental ability and identify incremental predictors of adaptive performance by examining personality and motivational variables.

The Importance of Adaptive Performance

In order to deal with the increasing amounts of change that they are subject to, organizations have had to make fundamental changes in the way that jobs are defined. No longer is it possible for organizations to buffer environmental uncertainty by relying on extensive standardization; instead organizations are increasingly focused on increasing flexibility and adaptability (Murphy & Jackson, 1999). As a result, work is increasingly defined in terms of roles and contexts instead of traditional, static task bundles (Morgeson & Dierdorff, 2011; Murphy & Jackson, 1999) with an increased emphasis on the constant change necessary to satisfy customer demands (Cascio, 1995). In order to effectively convey these new expectations to employees, changes in conceptualizations of performance have been made. As a result, the traditional means of defining and evaluating employee performance may no longer be valid because new behaviors (e.g. constant learning) and abilities (e.g. high-order thinking) are increasingly important (Cascio, 1995).

Researchers in the performance domain have long been working to address the criterion problem (Campbell, 1990) by adapting sufficiently comprehensive definitions of what exactly constitutes performance. Recently, these types of changes have led to an expansion of the performance domain beyond the existing distinctions of task and contextual performance. This new component of performance is referred to as adaptive performance, and while the specific definitions vary, adaptive performance is generally conceived of in terms of an individual's ability to effectively respond to changes in the nature of their work (e.g., Allworth & Hesketh, 1999; Cortina & Luchman, 2013; J. W. Johnson, 2001; Krischer & Witt, 2010; Pulakos et al., 2000).

While there has always been some degree of change in the workplace, explicit calls to include adaptive performance as a unique component of performance are relatively recent, having originated only in the past 15 years. This may be because the drivers discussed above have brought about an unprecedented rate of change, increasing the importance of capturing the adaptive performance portion of performance (Hesketh & Neal, 1999). Not only is adaptive performance important, but just as task and contextual performance tend to have different antecedents (Hoffman, Blair, Meriac, & Woehr, 2007), adaptive performance is likely to have unique antecedents as well (Schmitt, Cortina, Ingerick, & Wiechmann, 2003). In addition to having different antecedents, adaptive performance is conceptually unique from either task or contextual performance (Cortina & Luchman, 2013), and omitting the adaptive performance component of performance results in an incomplete conceptualization (Pearlman & Barney, 2000).

Aims and Structure of the Present Work

Despite the importance of adaptive performance for modern organizations, relatively little is known about individual and contextual antecedents of adaptive performance. This disconnect has the potential to diminish the efficacy of established organizational selection systems, resulting in a substantial loss of value for afflicted organizations (Pearlman & Barney, 2000). In light of these sorts of concerns, it is important to periodically review the validity of established selection programs, especially following institutional shifts that significantly redefine what constitutes performance (Morgeson, Reider, & Campion, 2005). This study aims to contribute to this process by further investigating the relationships between adaptive performance and historically important predictors of overall performance, including intelligence (Morgeson et al., 2007b) as well as performance relevant Big-5 personality traits (Barrick, Mount, & Judge, 2001). In addition, these relationships are evaluated in the presence of difficult, specific performance goals that are commonly employed by organizations (Locke & Latham, 2002), an important but understudied area for adaptive performance researchers (Dorsey, Cortina, & Luchman, 2010).

Some existing work has begun to address some of these questions, but the body of research is relatively sparse, driven in part by the relatively nascent state of the construct and associated literature, and unfortunately, the results compiled to date have been somewhat contradictory. Studies have found conscientiousness to be positively related to adaptation while openness was negatively related (e.g., Stewart & Nandkeolyar, 2006) while others have found a the inverse relationships – positive for openness and negative for conscientiousness (e.g., LePine, Colquitt, & Erez, 2000). Some of these differences may be attributable to differences in the level of conceptualization (e.g. trait vs. facet) for personality employed across studies, a decision that has seemingly been made relatively haphazardly in some instances. In addition, while the majority of existing work has found a positive relationship between intelligence and adaptive performance (e.g., Allworth & Hesketh, 1999; LePine et al., 2000; Pulakos et al., 2002), recent work by Lang and Bliese (2009) calls even this intuitively appealing and relatively (given the small body of existing work) established relationship into doubt.

Rather than simply dismissing this contradictory finding as some sort of sample or contextually driven anomaly, deeper consideration may be warranted. In analyzing their data, Lang and Bliese (2009) employ discontinuous random coefficient growth modeling, a robust method of analysis that has not been previously employed to investigate adaptive performance. Adaptive performance researchers have long recognized the importance of separating adaptive performance (performance after a change), from general task performance, or performance prior to the change (e.g., LePine et al., 2000); however, the methods employed previously have been only partially successful in maintaining this separation (Lang & Bliese, 2009). In particular, it is important to take into account the level of individual performance as well as the rate at which performance changes both before and after the change is introduced. Discontinuous growth modeling allows for this separation to be maintained fully while other methods employed previously do not (Lang & Bliese, 2009).

The present study attempts to contribute to building the limited and often contradictory information about potential antecedents of adaptive performance in several ways. First, a unifying and coherent theoretical framework is used to better understand potential avenues via which antecedents may influence adaptive performance. In contrast, many studies in the past have looked at a subset of antecedents known to affect overall performance, but lacked an overall conceptual framework to explain their choices. By applying control theory to guide hypothesis development, the current study has the potential to deepen our comprehension of why individual differences may lead to adaptive performance.

In addition to considering theoretically relevant individual differences, some of which are overdue for more consideration (e.g., neuroticism: Dorsey et al., 2010), the current study considers a potentially important contextual factor that has yet to be examined as well. Specifically, control theory highlights the potential importance of goals in predicting adaptive performance. While specific difficult goals are generally viewed as important to improving performance (Locke & Latham, 1990), there do seem to be important boundary conditions, including task complexity (Locke & Latham, 2002). Because the underlying changes that necessitate adaptation are likely to increase complexity (Dorsey et al., 2010), it is unclear how well goal setting theory can be applied in this context. Finally, the present study employs the well-established task-change paradigm (e.g., Lang & Bliese, 2009; LePine, 2003, 2005; LePine et al., 2000) coupled with random coefficient discontinuous growth modeling to robustly analyze both individual difference and contextual antecedents of adaptive performance.

LITERATURE REVIEW

This section attempts to lay the foundation for the present study by reviewing the relevant literature pertaining to adaptive performance. The first half of the section is primarily theoretical in nature, aimed at locating and defining adaptive performance. It begins with a brief history of how conceptualizations of performance have changed over the past forty years meant to place the recently proposed adaptive performance component in its historical context. Next, proposed conceptualizations of adaptive performance are discussed and a working definition adopted for purposes of this study is provided. Next, adaptive performance is differentiated from similar constructs including innovation and creativity.

The second half of the section is more empirically focused and reviews relevant empirical work pertaining to adaptive performance performed to date. The existent work is broken down into three categories for ease of presentation. The first group of studies presented focus primarily on measure development. The next group includes studies that focus primarily on identifying and investigating antecedents of adaptive performance. The last group of studies, albeit relatively sparse, focuses on outcomes of adaptive performance. Finally, while the present study is concerned with individual adaptive performance relevant studies for each of the three categories (measurement, antecedents, and outcomes) conducted at the team level are also discussed briefly in an effort to better illustrate the nature of adaptive performance research.

What Adaptive Performance Is

The 1970s were a tumultuous time for "human relations" researchers. The field was teetering on the verge of irrelevance after numerous reviews of 40 years' worth of empirical literature concluded that its central tenant, the positive relationship between job satisfaction and job performance, appeared nonexistent (Organ, 1977b). Against this specter, organizational researchers set about trying to reconcile the suppositions of established social exchange theory with these seemingly contradictory empirical results. In the years since, these efforts have proven fruitful, leading to a deeper, more nuanced understanding of the construct of performance. While our conceptualization of job performance has benefited greatly from this scholarly pursuit over the past thirty-five years, recent work indicates that our understanding may not yet be complete.

Twenty-five years after the initial journey began, the multifaceted and unprecedented changes confronting organizations (Pearlman & Barney, 2000; Pulakos et al., 2000) have again shed doubt on core aspects of organizational research. A fundamental building block, job analysis, has been so maligned that contemporary researchers have advocated a shift to the phrase "work analysis", not only to more accurately reflect the modified scope of their technique but also to avoid the outdated connotation of job analysis (Morgeson & Dierdorff, 2011; Murphy & Jackson, 1999). Given that job/work analysis has historically been the basis for defining performance (Borman, Bryant, & Dorio, 2010), it is not surprising that the "criterion problem" pertaining to contaminated and deficient conceptualizations of job performance (Campbell, 1990) first voiced nearly a quarter century ago remains a valid concern today (Borman et al., 2010; Wildman, Bedwell, Salas, & Smith-Jentsch, 2011). Recently, established conceptualizations of performance developed to address the existential concerns pertaining to the role of job satisfaction were decried for being incomplete because they do not include a component to capture the new, dynamic nature of work (Pearlman & Barney, 2000). Subsequently, expanded conceptualizations of performance building on past expansions have been put forth. In order to place the concept of adaptive performance in context, the evolution of our notions of job performance is briefly reviewed below.

Initially, job performance was defined solely in terms of core task performance. However, researchers soon discovered that this view was too narrow to adequately characterize the concept, resulting in an expansion of what job performance entails. For example, the changing and complex nature of work makes it difficult or impossible to accurately capture all necessary task elements in a formal job description (Ilgen & Hollenbeck, 1991). Others have gone further to argue that as work becomes more project focused, with employer expectations extending beyond a specified task list, the notion of a job itself has fundamentally changed (Howard, 1995) and may be little more than a "social artifact" (Bridges, 1994).

Performance dimensions such as organizational citizenship behaviors (Bateman & Organ, 1983; Organ, 1988) or the nearly synonymous (Organ, 1997) contextual performance (Borman & Motowidlo, 1993) have been proposed as unique components of job performance, reflecting the idea that it is generally desirable for employees to go above and beyond their listed responsibilities in order to support the organization. Conversely, the performance dimension of counterproductive work behaviors reflects the fact that employee discretionary behaviors can also be counterproductive to the organization's interests (Bennett & Robinson, 2000; Robinson & Bennett, 1995). As noted by Rotundo and Sackett (2002), modern conceptualizations of performance include both organizational citizenship behaviors (OCB) and counterproductive work behaviors (CWB) in addition to task performance, and all three dimensions uniquely contribute to employee job performance ratings. In addition, at an aggregate level, employee OCBs have been linked to organizational performance (N. P. Podsakoff, Whiting, Podsakoff, & Blume, 2009).

Because these performance dimensions are conceptually and empirically unique (Hoffman et al., 2007), in order to further our understanding of performance, researchers should investigate individual performance facets rather than just general performance measures (Campbell, Gasser, & Oswald, 1996). While work investigating dimensions such as OCB and

CWB has been instrumental in filling-in our understanding of job performance, recent theorizing indicates that this might not be adequate to fully characterize the performance domain. Specifically, both task and contextual performance requirements are likely to evolve over time (Schmitt et al., 2003) and this is likely to contribute to the systematic decrease in the validity between job performance and common behavioral and cognitive predictors as the time between the measurement of the two constructs increases (Henry & Hulin, 1987). Further, job performance conceptualizations that do not include an adaptive component are incomplete (Pearlman & Barney, 2000).

This realization has led researchers to propose an additional performance dimension to capture the importance of employees dealing successfully with changes in the workplace (Campbell, 1999; Hesketh & Neal, 1999). This dimension is generally referred to as adaptive performance, and it is proposed to be a unique dimension with different antecedents than task performance, OCB or CWB (Hesketh & Neal, 1999; Schmitt et al., 2003) . While this construct is relatively new, it reflects an increasingly important aspect of performance for modern organizations (Hollenbeck, LePine, & Ilgen, 1996; Ilgen & Pulakos, 1999). Driven by rapid technological change, frequent work restructuring, and increasing global competition "Workers need to be increasingly adaptable, versatile, and tolerant of uncertainty to operate effectively in these changing and varied environments – and this need will only increase as the pace of change continues to grow" (Pulakos, Dorsey, & White, 2006, p. 41).

While far-reaching changes in the way that organizations operate highlight the importance of adaptive performance, there are still some differences in how adaptive performance itself is defined. In the most comprehensive study of the nature of adaptive performance to date, Pulakos et al. (2000) began deductively, identifying six components of adaptive performance based on findings from diverse literatures including learning and culture. In addition, inductive methods were applied to a content analysis of critical incidents taken from 21 public and private sector jobs, resulting in confirmation of the a-priori components as well as identification of two additional components (handling work stress and emergency situations), leading to an eight-dimensional taxonomy of individual adaptive performance. Subsequent work led to the development of an analogous six-factor taxonomy that is hypothesized to be applicable in team contexts (Pulakos et al., 2006). The specific dimensions for each context and brief definitions are presented in Table 1. For a more complete discussion of the dimensions, interested readers are referred to the source work (Pulakos et al., 2000; Pulakos et al., 2006).

Given the nature of the sample and the methods employed, these taxonomies represent a very broad conceptualization of adaptive performance and as such were created in attempt to produce an exhaustive list of adaptive performance dimensions. For any specific job, the various dimensions are likely to be differentially important, and some dimensions may be only minimally important or even not applicable (Pulakos et al., 2000; Pulakos et al., 2002). In addition, due to the varied nature of the dimensions, it is likely that they will have different antecedents, which has important implications in a selection context, or any other focused on a subset of adaptive performance dimensions (Pulakos et al., 2006). For example, while not empirically validated, a survey of subject matter experts indicates that cognitive ability is more likely to be related to solving problems creatively than to handling work stress, something apt to be predicted by emotional stability (Pulakos et al., 2006). Thus, researchers should choose antecedent variables theoretically consistent with the subset of adaptive performance dimensions applicable to the chosen context, keeping in mind that the nature and magnitude of these relationships remains largely open to empirical investigation.

Table 1: Summary of Adaptive Performance Dimensions from Pulakos and colleagues

Dimension	Brief Definition	Individual Adaptability	Team Adaptability
Solving problems creatively	Solve complex, atypical problems [and share solutions]	X	 X
Handling unpredictable work situations	Act appropriately in response to unforeseen changes at work [update team roles and structure]	X	 X
Learning new tasks, technologies and procedures	Proactively acquire skills applicable to future work requirements [develop shared mental models of task environment]	X	 X
Handling work stress	Remain calm and unfrustrated at work [Resilient to setbacks]	X	 X
Handling emergency or crisis situations	Decisive and appropriate action taken during dangerous situations [member efforts seamlessly coordinated]	X	 X
Demonstrating interpersonal adaptability	Adjust interactional style as appropriate when dealing with new people	X	-
Demonstrating cultural adaptability	Effective performance in new cultures	X	-
Demonstrating physically oriented adaptability	Work effectively in adverse physical conditions (e.g. hot, cold, windy, etc.)	X	-
Handling interactions across team boundaries	[Learn about other groups and how to interact to maintain positive relationships]	-	X

Notes: Definitional text relevant to both the individual and team context appears first. Any additional team-specific material appears on a subsequent line and is enclosed in square brackets [ ].

Despite the work that went into creating this taxonomy and the current interest in adaptive performance, published research into the validity of this model is sparse. Empirical investigations are undoubtedly hampered by the fact that the Job Adaptability Inventory (JAI) scale items developed by Pulakos et al. (2000) to capture their eight facet taxonomy and subsequently employed to measure adaptive performance by Pulakos et al. (2002) is not commonly available for other researchers to employ (E. Pulakos, personal communication, November 9, 2012), limiting the ability to further investigate and extend the existing model. While the published research is extremely limited, the eight-factor structure has been demonstrated using confirmatory factor analysis on data obtained from a large sample of employees in a subsequent study (Pulakos et al., 2002).

Even though limited in quantity, empirical and conceptual support for the model is not universal. For example, in the same study that replicated the eight-factor structure using employee surveys, corresponding supervisor data obtained to evaluate employee adaptive performance as a criterion measure supported only a single-dimensional adaptive performance conceptualization (Pulakos et al., 2002). The authors concede that this may be indicative of problems with the measure employed or reflective of an inability or disinterest on the part of supervisors in trying to differentiate between the sub-dimensions. As a result, additional study in differing contexts and further measure refinement are proposed as a fruitful avenue for future research (Pulakos et al., 2002).

Further, drawing on individual level research, J. W. Johnson (2001, p.985) defined adaptive performance as "the proficiency with which a person alters his or her behavior to meet the demands of the environment, an event, or a new situation." Based on this definition, he went on to argue that six of the eight dimensions proposed by Pulakos et al. (2000) are subsumed under existing task or contextual performance dimensions. For example, he proposed that physical adaptability is a necessary component of task performance because task performance necessarily takes place in a changing physical environment. Similarly, he proposed that social aspects such as cultural and interpersonal adaptability are related to getting along with others, a necessary part of individual focused organizational citizenship behaviors as laid out by L. J. Williams and Anderson (1991). In summary, J. W. Johnson (2001) proposed a two dimensional conceptualization composed of dealing with uncertainty and learning new tasks and technology. In a similar vein, subsequent research has further narrowed this focus, equating adaptive performance primarily with only the "dealing with uncertainty" component (Dorsey et al., 2010; Griffin, Neal, & Parker, 2007; J. W. Johnson, 2003).

Finally, organizational researchers studying other discretionary work behaviors have proposed models with fewer constructs, each with numerous potential behavioral manifestations (e.g., Hanisch, 1995; Hulin, 1991). Due to differences in job constraints across jobs and work contexts, the avenues available to employees for exhibiting these behaviors is likely to vary greatly. For example, while a disgruntled professional may take long lunches, sneak out early, or work slowly on assigned tasks, these avenues of withdrawal are not likely to be available to an hourly worker on a paced assembly line, especially if he/she must punch in and out on a time-clock. Instead, this person might express dissatisfaction with their job by taking unnecessary sick days or putting effort into trying to incite unrest amongst peers. Because of these varying situational constraints, researchers focusing on each possible manifestation individually risk missing out on understanding the shared, higher level phenomena (Schmitt et al., 2003). While these recommendations were not offered to adaptive performance researchers directly, the similarities concerning differing behavioral manifestations across different contexts seem apparent enough to warrant consideration.

More in line with this general conceptualization approach, in one of the earlier studies investigating individual adaptive performance, Allworth and Hesketh (1999, p.98) defined it as "behaviours [*sic*] demonstrating the ability to cope with change and to transfer learning from one task to another as job demands vary." Inherent in this definition are two sub-dimensions, a cognitive dimension related to learning and an emotional dimension related to coping (Allworth & Hesketh, 1999). Subsequent work has narrowed this definition, excluding the ability to adapt and only including manifested adaptive behavior necessitated by change (Griffin et al., 2007).

Drawing on role theory (Katz & Kahn, 1978), adaptive performance has been alternatively defined in terms of changing role expectations (Murphy & Jackson, 1999). In terms of dimensionality, Murphy and Jackson (1999) add a third component hinging around confidence in tackling new tasks, in addition to a cognitive and emotional sub-dimension mentioned above. Likewise, in a recent review of the personality-performance literature, Penney, David, and Witt (2011) rely on a three component definition of adaptive performance put forth by Krischer and Witt (2010) who proposed that adaptive performance is a behavioral construct with the components: recognition of the necessity or opportunity to change, competency enhancement to deal with the change, and effective application of new competencies in the workplace.

Other researchers have focused more intently on this application facet. For example, Chen, Thomas, and Wallace (2005, p. 828) focus exclusively on the application dimension in a training context, defining adaptive performance as "the extent to which trainees perform effectively in complex and novel situations following training." Similarly, Han and Williams (2008, p. 659) define adaptive performance as "the learning and application of new skills and knowledge to changing task requirements."

Even though team adaptive performance is different than individual adaptive performance (Burke, Stagl, Salas, Pierce, & Kendall, 2006; Chen et al., 2005; Han & Williams, 2008; Pulakos et al., 2006), it is interesting to note that definitions in this domain also include application of new knowledge (e.g., Cannon-Bowers, Tannenbaum, Salas, & Volpe, 1995;

Kozlowski et al., 2001). In addition, researchers in this domain note that the application of new knowledge at the team level often manifests as a reorganization of a team's structure or routines (e.g., Kozlowski et al., 1999; LePine, 2003). Burke, Stagl, et al. (2006, p. 1190) attempt to integrate these conceptions into a single definition of team adaptive performance noting that "team adaptation is manifested in the innovation of new or modification of existing structures, capacities, and/or behavioral or cognitive goal-directed actions." Consistent with earlier arguments based on the recommendations of Schmitt et al. (2003), when compared to individuals, team adaptation may be thought of in much the same way. However, teams are generally thought to exhibit an additional and unique manifestation of this adaptation; namely the modification of their team structure in response to environmental change (i.e. process adaptation: Baard, Rench, & Kozlowski, 2014).

Even though there are differences in the definitions of adaptive performance present in the literature, there are some similarities that bear keeping in mind as well. First, when reviewing the definitions above, it is evident that adaptive performance is generally conceived of as a behavioral construct. In addition to being included as a part or the whole of the definitions above, it has been named as a necessary aspect explicitly in the literature as well (e.g., Burke, Pierce, et al., 2006; Griffin et al., 2007; Pulakos et al., 2006). This focus on behavior is consistent with established conceptualizations of work performance that equate behavior with performance (e.g., Campbell, 1999; Campbell et al., 1996; Campbell, McCloy, Oppler, & Sager, 1993). Further, these models make a distinction between outcomes and performance since the former is likely to be contaminated by things outside of the employee's control.

In addition to the behavioral aspect of adaptive performance, it is also important to note that it is generally defined in terms of responding to changes in the workplace (Ployhart &

Bliese, 2006). While this seems to be the prevailing view, it is not universal, and some authors allow for the existence of a proactive aspect of adaptive performance (e.g., Krischer & Witt, 2010) as well. However, the inclusion of a proactive component risks confounding adaptive performance with generally recognized concepts of innovation (LePine, 2003). In addition, the motivation put forth in the literature for the importance of adaptive performance is predicated on a generally increasing need for employees to react to changing business conditions (e.g., Pulakos et al., 2006), inherently focusing on the reactive nature of the construct.

Further, in order to place some bounds on what constitutes adaptive performance, it is important to note that not all events or changes that occur in the workplace will necessitate an adaptive response. For example, while representing a change that an employee must confront, responses to the rescheduling of a standing meeting or the presentation of an additional unit of work that must be processed using established procedures do not constitute adaptive performance. The changes that necessitate adaptive performance involve changes (typically increases) in the complexity of the task environment (Dorsey et al., 2010; LePine, 2005). Wood (1986) proposed three aspects of complexity that should be considered when evaluating the nature of the change event: component, coordinative, and dynamic. *Component* complexity deals with the number of acts and information cues linking the input with the output while *coordinative* complexity is concerned with the nature of the linkages between the input and output. *Dynamic* complexity captures changes to the input-output causal linkages. While change events can impact all 3 components, by virtue of their occurrence dynamic complexity is inherently increased, hence the general supposition that adaptive performance is associated with an increase in complexity noted above.

Building on the definitions and themes previously discussed, I define adaptive performance as the proficiency with which individuals effectively modify behavior in response to changes in the component, coordinative or dynamic complexity of the task environment. In terms of this definition, adaptive performance is behavioral in nature and manifests in response to a subset of experienced changes. Because specific manifestations of change are likely to vary across jobs, to avoid limiting generalizability across varying workplace manifestations the definition focuses instead on the importance of changes in complexity. To do this, I rely on the complexity typology laid out by Wood (1986) and integrated into the conceptual architecture for adaptation developed by Baard et al. (2014). Finally, consistent with previous work and theorizing (e.g., Allworth & Hesketh, 1999; Baard et al., 2014; Lang & Bliese, 2009; LePine, 2003, 2005; LePine et al., 2000; Pulakos et al., 2000; Stewart & Nandkeolyar, 2006), adaptive performance is reflected in terms of successful task performance after the occurrence of a relevant change event.

It is also important to note that the definition above implies two components of adaptive performance. Consistent with other contemporary conceptualizations of adaptive performance (e.g., Dorsey et al., 2010; Krischer & Witt, 2010; Penney et al., 2011) individuals must first notice that something has changed and rapidly modify their behavior in response to it. In addition, adaptive performance considers the extent to which the modified behavior is effective in the post-change context. In addition, prevailing conceptualizations (e.g., Dorsey et al., 2010; Krischer & Witt, 2010; Penney et al., 2011) also include a secondary component related to the longer-term process of gauging the effectiveness of the modified behavior and making changes as necessary to improve performance. Successfully executing in the aftermath of a change by unlearning previously effective behaviors and relearning newly effective ones is an important component of adaptive performance (LePine et al., 2000).

However, it is noted that the process of performance monitoring and improvement is not novel or unique to adaptive performance in itself. In fact, this type of activity has long been conceptualized as an integral part of control theory driven descriptions of general goal striving activities (e.g., Carver & Scheier, 1981, 1998; Powers, 1973) and is discussed as such in the discussion of control theory below. Despite its applicability to adaptive performance when it occurs in a specific context, it is important to note that not all instances of this goal striving process are considered to comprise an aspect of adaptive performance. Over time, initial changes to this process brought on by the novelty of the change diminish, and after a prolonged period of practice and experimentation, a steady-state response pattern is likely to emerge (Ackerman, 1988; Anderson, 1982) that is no longer pertinent to conceptualizations of adaptive performance.

With this limitation in mind, the two components of adaptive performance identified here are also related to the two types of adaptation recognized by Lang and Bliese (2009). Specifically, they define transition adaptation in terms of the ability to minimize performance decrements immediately following an unexpected change while reacquisition adaptation is related to the ability to identify ways of attaining effective, sustained performance in the post-change setting. While Lang and Bliese (2009) discuss transition and reacquisition adaptation both in terms of individual abilities (e.g., p. 415) as well as actual aspects of adaptive performance (e.g., p. 414), consistent with the current discussion and prior theorizing in the area of adaptive performance (e.g., Dorsey et al., 2010; Krischer & Witt, 2010; Penney et al., 2011), they are conceptualized here as the latter.

Specifically, in order to respond to a change, the change must first be noticed. The aspect of adaptive performance focused primarily on timely recognition and rapid responsiveness is *transition adaption*. Conversely, *reacquisition adaptation* is more concerned with the long-term effectiveness of the behaviors enacted to maximize performance in the post-change work environment. In addition, because events driving a need to adapt are prevalent in modern organizations, and becoming more so (Burke, Pierce, et al., 2006; Cascio, 1995; Cortina & Luchman, 2013; Pulakos et al., 2000), these notions can be further refined by adding a temporal element to these aspects of adaptive performance.

The response of an individual may evolve when exposed to a previously novel stimulus multiple times (Ackerman, 1988; March & Simon, 1958). In other words, it would seem reasonable to expect people to respond differently the first time they are confronted with a change than after they experience a similar change multiple times. In order to investigate potential differences along these lines, transition and reacquisition adaptation can each be thought of as potentially varying temporally. To capture this idea, they are divided into *initial* and *subsequent* components. The initial elements are relevant when discussing adaptive performance in the wake of a novel change event. Alternatively, after experiencing multiple related change events, the patterns of adaptation may metamorphosis, and the subsequent elements become more meaningful concepts when considering adaptive performance in such a setting. Figure 1 provides a quick overview of the temporal distinctions between these aspects of adaptive performance, and potential differences in the drivers of these two temporal categories of transition and reacquisition performance are discussed in more depth below.

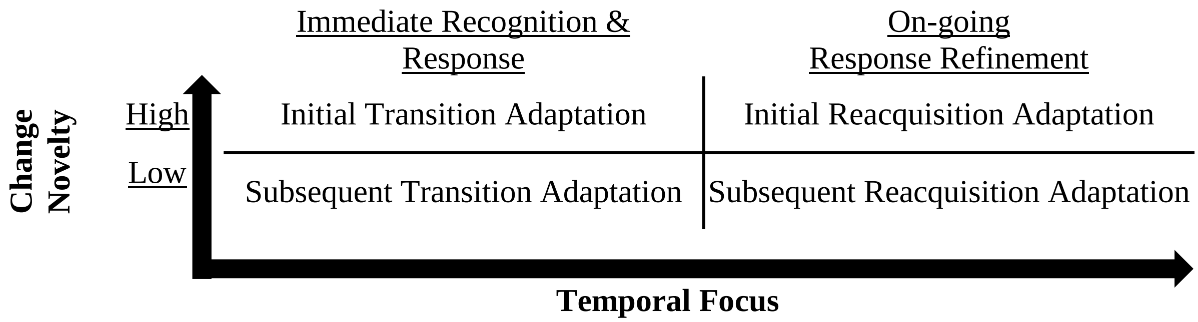

Figure 1: Temporal and Novelty Based Separation of Adaptive Performance

What Adaptive Performance is Not

Despite these similarities with the work of Ployhart and Bliese (2006), it is important to note that this conceptualization of adaptive performance differs from their recently introduced construct of individual adaptability that represents the focus of their work. Individual adaptability is conceptualized as an individual difference that may lead to effective performance, depending on the nature of the work and the context in which it is performed. However, Ployhart and Bliese (2006) likewise make it clear that it is distinct from adaptive performance, which is consistent with previous findings that abilities do not necessarily equate to performance, especially when motivation is low (Klehe & Anderson, 2007).

In order to more fully understand adaptive performance, it is important to explore its nomological network (Cronbach & Meehl, 1955) more in depth. While the differences between adaptive performance and other performance dimensions (i.e. task performance, OCB & CWB) have already been discussed, this section focuses on differentiating adaptive performance from other constructs that are not in themselves performance dimensions in order to further establish its uniqueness. A discussion of antecedents likely to be related to adaptive performance is reserved or the hypothesis development section.

One obviously related idea is innovation. As previously alluded to, the reactive nature of this conceptualization of adaptive performance differentiates it from innovation, which is generally proactively focused (LePine, 2003). Other scholars apply the term innovation to higher levels in the organization, including the adoption of a new strategy (including adoption of existing strategies that are new to the focal organization) or development of a new product (S. L. Brown & Eisenhardt, 1995). This conceptualization obviously contrasts with the individual level nature of adaptive performance. Even when conceptualized at the individual level, innovation takes on a large scale quality. Seen as a multi-stage process, innovation requires the individual to conceive of the innovation, build a base of support, and roll it out to others in the organization so that it can be employed widely for the organization's benefit (e.g., Kanter, 1988; Scott & Bruce, 1994), encompassing a wide variety of cognitive, behavioral, and outcome based components. Thusly defined, innovation is a much broader, large scale, more involved process than is individual adaptive performance. While individual adaptive behaviors may be copied and adopted by others in the organization, there is no requirement for promotion and their widespread adoption is not a necessary condition for adaptive performance.

Another construct closely related to innovation is creativity. While some have noted that these two constructs are largely interchangeable (e.g., West & Farr, 1990), others make a distinction. Namely, creativity is limited to novel idea generation (e.g., Mumford & Gustafson, 1988; Perry-Smith & Shalley, 2003). Thusly defined, creativity differs from adaptive performance in at least three important ways. First, creativity requires nothing more than an idea while adaptive performance requires action. Second, creativity is defined in terms of the novelty or newness of the idea generated. This is not a requisite of adaptive performance. Recycling and reapplying behaviors from other contexts qualifies just as much as adaptive performance as does the generation of novel, never-before seen actions. Finally, adaptive performance is limited to responses to change, while creativity is able to manifest either in response to change as well as a proactive means of circumventing an anticipated problem.

Another construct with similarity to adaptive performance is openness to organizational change. Openness to organizational change is a two dimensional construct with both attitudinal and affective components. Specifically, the components are a willingness to support the change and positive affect towards the change initiative (Miller, Johnson, & Grau, 1994; Wanberg & Banas, 2000). While conceptual and empirical work in this area is sparse (Devos, Buelens, & Bouckenooghe, 2007), even given the shared focus on change, adaptive performance and openness to organizational change are quite different conceptually. First, openness to organizational change is an attitudinal and affective construct while adaptive performance is behavioral. While some of the earlier definitions of adaptive performance also included affective components (e.g., Allworth & Hesketh, 1999), the focus has been largely behavioral (e.g., Griffin et al., 2007), as it is here. In addition, openness to organizational change is conceptualized in the context of planned organizational change efforts, being seen as a necessary condition for success (Miller et al., 1994), while adaptive performance may be desirable due to both planned and unplanned changes arising from both internal and external sources.

Finally, some researchers have equated adaptive performance with outcomes of training applied in novel situations, including learning (e.g., Han & Williams, 2008) and transfer (e.g., Chen et al., 2005). Regarding learning, it is generally defined in terms of changes in knowledge or skill (Weiss, 1990). Thusly defined, learning tends to be a cognitively focused construct. In addition, while new knowledge and skills may facilitate or result from adaptive performance, learning and adaptive performance are not synonymous. Learning does not necessarily have to result from a change in the task, social or environmental features of the workplace.

In contrast, training transfer is generally defined in terms of successfully applying what was learned in training to work (Baldwin & Ford, 1988; Baldwin, Ford, & Blume, 2009), which could conceivably have more of a behavioral component than the learning itself. However, training scholars routinely differentiate between transfer and performance (Kraiger, 2003). For example, the failure to conduct a needs assessment often encountered in organizations can reduce training effectiveness when the wrong content is presented to the wrong participants (K. G. Brown & Sitzmann, 2011). In such situations, even a high level of transfer (of the wrong knowledge) is unlikely to improve performance.

In addition, even to the extent that the training is effective in modifying employee behavior in a desired manner, training transfer is both too broad and too narrow to capture adaptive performance. First, to distinguish training from other means of learning, it is necessarily formal in nature and planned by the organization (K. G. Brown & Sitzmann, 2011). However, this is only one means of eliciting behavioral modification. Employees may exhibit adaptive performance without going through any sort of training as they encounter and respond to changes in their daily work life. In addition, the training itself may not be taken in response to any sort of task, social or environmental change. In this case, any resulting behavioral modification would not have any adaptive component to it. In light of these shortcomings, training transfer seems to be both contaminated and deficient, making it a poor proxy for adaptive performance.

Empirical Investigations of Adaptive Performance

Despite the importance of adaptive performance to contemporary models of job performance, because most drivers of this importance have accelerated dramatically during the past 30 years, interest and research in the phenomena of adaptive performance is correspondingly recent and as a result, relatively little work has been conducted to date (Ployhart & Bliese, 2006). Nonetheless, some work has been completed and has begun to inform theories of adaptive performance by identifying potential relations with several other constructs. The empirical studies that have been completed to date are reviewed in this section along with the theoretical work that has accompanied them to illustrate what has been investigated and what remains to be explored. This information is summarized in Table 2 as well. Finally, a few notes about the organization of this section are provided below.

As previously mentioned, individual level and team level adaptive performance are different constructs with different means of manifestation, and the focus on this manuscript is on individual level adaptive performance. However, given the overall paucity of research in this domain, relevant studies considering facets of team level adaptive performance that may inform future research at the individual level are presented as well, but because these are not synonymous constructs, the research is presented separately to highlight the fact that findings at one level do not necessarily apply at the other (K. J. Klein & Kozlowski, 2000). Additionally, an attempt was made to err on the side of inclusiveness rather than exclusion when reviewing the literature in this section in an effort to give the reader a more extensive understanding of the current status of the field. As such, some of the studies presented did not consider adaptive performance directly, but if these studies looked at closely related constructs, they were included to illustrate the potential for crossover to the adaptive performance domain.

Finally, in order to help highlight the areas in which work has been done, studies are grouped according to their focus. The first subgroup of studies focuses on the development of measures to capture adaptive performance. Out of necessity, some of the earliest work in the field falls into this category. The next set of studies focus on antecedents of adaptive performance. To date, this has been the most researched area in this domain. Finally, the last group of studies looks at potential consequences of adaptive performance, attempting to validate the assertion that adaptation is important in today's workplace. Of course, a single study may investigate multiple aspects of adaptive performance falling into more than one of these categories. In such cases, the study was assigned to the category that seemed to be the primary focus of the work.

Measure Development - Individual Adaptive Performance

One of the earliest efforts to measure adaptive performance was undertaken by Allworth and Hesketh (1999). The 16 item Graphic Distributional Performance Rating (GDPR) scale (Hesketh & Feiler, 1994) was completed by supervisors to assess employee job performance. Based on a job performance paradigm with 3 factors: task, contextual, and adaptive performance, the authors performed an experimental factor analysis with three factors specified a-priori. As a result of this analysis, they identified four of the 16 items that seemed to correspond to an adaptive factor, though no model fit statistics are provided. Subsequently, one of the items was dropped to improve the reliability of their adaptive performance scale, but the discarded item is not identified. As such, their measure of adaptive performance included supervisor ratings of 3 of the following: employee flexibility, task learning, confidence in learning, and administrative/clerical performance.

In turn, the authors used this adaptive performance measure as a criterion and investigated potential antecedents of supervisor rated adaptive performance. They found a small (Cohen, 1992) positive correlation with a biodata measure of experience dealing with change, but not experience dealing with people. In addition, they reported a moderate positive correlation with cognitive ability. Contrary to expectations, no significant relationships were found for any of the Big-5 personality factors and supervisor rated adaptive performance.

Shortly after this work, a much more comprehensive measure development effort was published by Pulakos et al. (2000). While this effort was grand in its own right, the authors focused solely on the development of the measure itself and did not attempt to locate the construct in its nomological network by investigating relationships with other constructs. The resulting Job Adaptability Inventory (JAI) measure consisted of 68 items spread across the eight facets discussed at length previously. The items were selected based on the results of an exploratory factor analysis (EFA) and subsequently validated by a confirmatory factor analysis (CFA) performed on a sample comprised primarily of non-managerial employees (e.g. secretarial, administration, transportation) from a single enterprise, along with some military personnel and a handful of scientists.

More recently, Ployhart and Bliese (2006) have published the I-ADAPT-M measure that is available in the public domain for research purposes. This measure includes 55 items and is intended to capture the same 8 factors previously identified by Pulakos et al. (2000). This measure was derived from subject matter expert (SME) input and subsequently revised and expanded based on empirical CFA results; however, more in-depth information pertaining to the development and validation of the scale is not provided by the scale authors (Ployhart & Bliese, 2006). A portion of this scale has subsequently been used to measure adaptability and as part of a larger measurement model, the items intended to measure the cultural, work stress, learning, interpersonal and uncertainty facets of adaptability seem to load on the appropriate factor (Wang, Zhan, McCune, & Truxillo, 2011). In addition, the reported results provide some indication that these five facets are unique from other dispositional constructs including proactive personality and openness to experience (Wang et al., 2011).

Measure Development - Team Adaptive Performance

Compared with the efforts put into developing individual measures of adaptive performance, the development of measures appropriate for use in teams is sparse. Perhaps this is not surprising since the majority of work on adaptive performance has been conducted at the individual level (LePine, 2005). As an illustration, no studies focused on developing (and publishing) a team-level adaptive performance measure could be located. Although, a 14-item scale has recently been published as part of a larger study (Han & Williams, 2008), accompanying information pertaining to the rigor of its development and validation is less than effusive. Instead, most studies in this domain utilize outcome based measures comprised of team performance in the face of changing conditions (as is discussed in the subsequent sections).

As previously mentioned, Pulakos et al. (2006) have laid the conceptual groundwork for a robust measure to be developed, proposing a six facet conceptualization that has significant overlap with its individual level analogue, but they do not provide a means to actually assess those dimensions. The authors do go on to note that more work is required to validate the comprehensiveness of the proposed structure and subsequently develop items to measure the proposed facets (Pulakos et al., 2006). More recently, M. A. Rosen et al. (2011) propose six guiding principles deemed relevant for the development of a team-based adaptive performance measure in the context of improving performance management systems. While both of these articles attempt to lay a conceptual foundation for future measure development, a problem still faces researchers in this area: a lack of validated scale measures. This sentiment is echoed by Burke, Stagl, et al. (2006, p. 1203) who note that developing and validating measures for team-level adaptive performance is "of primary importance to any future empirical investigations." Thus, there appears to be a limited amount of measurement development at this level that could be applied to enhancing measurement at the individual level.

Antecedents of Individual Adaptive Performance

Numerous studies investigating potential antecedents of adaptive performance have been published. Following up on the initial development of the JAI measure, Pulakos et al. (2002) investigated several different antecedents of a unidimensional measure of supervisor rated adaptive performance. They developed measures that captured individual experience and attitudes pertaining to adaptation, proposing that past experience with, interest in, and self-efficacy relating to adaptation would be predictive of increased adaptive performance, consistent with prevailing relationships between these dimensions and job performance (Pulakos et al., 2002). Despite several significant individual correlations between these dimensions and adaptive performance, only a subset of the experiential based measures provided incremental validity over more established measures, including personality dimensions and general mental ability (GMA). Specifically, emotional stability, achievement motivation and GMA were all positively related to adaptive performance while no significant relationship was found with openness to experience (Pulakos et al., 2002).

Other researchers have investigated adaptive performance using conceptualizations that differed from that put forth by (Pulakos et al., 2000). For example, Griffin et al. (2007) looked at antecedents of adaptation in response to changes in task requirements (i.e. individual adaptability), team processes (i.e. team member adaptability) and overall organizational changes (i.e. organization member adaptability). The authors propose that the strength of the relationship between some of the antecedents of adaptability may vary based on the underlying cause of the change that the employee is responding to. The importance of conceptually matching personality antecedents and outcomes has been demonstrated regarding the different components of OCB, namely those behaviors directed at the organizational and individual levels (Ilies, Fulmer, Spitzmuller, & Johnson, 2009), and this study takes an analogous look at different aspects of adaptation, categorized by the source of the disruption.

Similarly, the authors proposed that the links between antecedents and adaptation should be strongest when the level of the antecedent and the level of the adaptive behavior match. For example, individual adaptation was found to be negatively related to trait levels of negative affect, but adaptation in response to team or organization level changes was not significantly related to affect (Griffin et al., 2007). Similarly, there was some indication that perceptions of team support were more strongly related to team member adaptation than either of the two other adaptation components, and perceived organizational support seemed to be the most strongly related to organizational member adaptation (Griffin et al., 2007).

While they found some differences in antecedent effect sizes across the different components in their conceptualization of adaptation, (Griffin et al., 2007) also uncovered antecedents related to adaptation regardless of the source of the underlying environmental change. Specifically, role clarity, openness, and role breadth self-efficacy were all positively related to adaptation at the individual, team member, and organizational member levels. In addition, gender was positively related to each of the three dimensions such that women demonstrated higher levels of adaptation. Thus, there seem to be both universal as well as level specific antecedents of adaptive performance when it is defined in terms of the source of the variation.

In addition to direct, survey based measures, many studies in the adaptive performance domain employ a task change paradigm to evaluate performance. This is accomplished by subjecting participants to a sudden change in their environment, typically by changing the underlying nature of the task being performed. In many cases, participants are not told to expect a change nor are they told when a change has occurred, as recognizing the existence of a change is an important component of the adaptation process (Ployhart & Bliese, 2006). In these contexts, adaptive performance is inferred based on some conceptualization of the individual's performance on the focal task, subsequent to the change manifesting itself.

One of the earliest studies to utilize this paradigm compared performance on a structured laboratory task with an unstructured one. Performance across these domains was thought to be related to different configurations of personality facets (Mumford, Baughman, Threlfall, Uhlman, & Costanza, 1993). Based on a qualitative review of the literature, the authors identified 15 personality facets thought to promote adaptation (e.g. openness, self-esteem, achievement motivation) and 13 facets proposed to inhibit it (e.g. anxiety, depression, shame). Based on the data obtained, composite traits were created and the authors contend that creative achievement (incorporating the facets of openness, category flexibility, ego resiliency and achievement motivation) and self-discipline (incorporating the facets of delay of gratification, maturity and self-awareness, and ego control) seem to promote adaptability, defined as continued high performance when faced with ill-defined tasks, while defensive rigidity (comprised of defensiveness, naiveté, persistence, and anxiety) seems to inhibit it (Mumford et al., 1993).

While not employing the task-change paradigm per say, in one of the few field studies to evaluate adaptation, Stewart and Nandkeolyar (2006) looked at performance driven by naturally occurring variations in environmental resources. Specifically, the number of referrals sales people received varied on a weekly basis. This variation was in turn related to weekly performance, measured as individual sales. While it is unclear to what extent this variation captures the essence of adaptive performance since it did not require a behavioral change to successfully respond to the situation. Nor did it seem to convey the necessity for individuals to engage in either task revision (the establishment and pursuit of a new, unsanctioned task on their own volition) or task pursuit (switching to and pursing a new objective specified by the organization) that they characterized as the two relevant methods of adaptation. To the extent that they did capture adaptive performance, the results of the study indicate that conscientiousness is positively associated with adaptation, presumably because conscientiousness is associated with goal pursuit; conversely, openness to experience was found to be negatively related to adaptive performance presumably because it led employees to focus their efforts elsewhere (besides on the referrals).

LePine et al. (2000) evaluated adaptive performance by employing the task change paradigm to evaluate shifts in decision making accuracy after an unannounced change to the rules governing the task. Specifically, the authors looked at the role of GMA as well as two personality dimensions, openness to experience and conscientiousness, in predicting performance prior to and after these unannounced changes occurred. In order to evaluate antecedents of adaptive performance, the authors looked for indications of differential relationships before and after the change had occurred. The results of this study indicate that GMA, conscientiousness, and openness are all more strongly related to performance post-change than pre-change, providing some evidence that they are antecedents of adaptive performance. In addition, conscientiousness and openness demonstrated incremental validity over and above the role of GMA (LePine et al., 2000). Consistent with the study's predictions, GMA and openness were positively related to adaptive performance; however, contrary to expectations, conscientiousness was found to be negatively related to adaptive performance. Subsequent analysis revealed that this unexpected finding was driven exclusively by the dependability facets (i.e. order, dutifulness and deliberation) of conscientiousness, while the achievement facets (i.e. competence, achievement and self-discipline) were unrelated (LePine et al., 2000).

Building on this work, Lang and Bliese (2009) proposed a two dimensional conceptualization of adaptive performance comprised of "transition adaptation" and "reacquisition adaptation". As alluded to previously, they note that the former is related to diminished performance immediately following a change in the environment while the latter is related to the rate at which performance increases following the initial drop. These two dimensions are proposed to be conceptually distinct, and the authors investigate the relationship between GMA and each of these components of adaptive performance. Counter to the longstanding and commonly held notion that GMA is positively related to performance (e.g., Salgado, Anderson, Moscoso, Bertua, & De Fruyt, 2003; F. L. Schmidt & Hunter, 1998; F. L. Schmidt, Hunter, & Pearlman, 1981) and the specific finding of a positive relationship between adaptive performance and GMA of LePine et al. (2000), GMA was negatively related to transition adaptation and unrelated to reacquisition adaptation (Lang & Bliese, 2009). This implies that on average, those higher in GMA suffer larger decrements in performance when an underlying change in the environment occurs. In addition, GMA seems unrelated to the rate at which previously attained levels of performance are regained. Thus while the overall relationship between performance and GMA appears robust, the relationship between the adaptive facet of performance and GMA appears to be a bit more nuanced (Lang & Bliese, 2009).

Finally, in contrast the majority of work that investigated the impact of individual differences, Drach-Zahavy and Erez (2002) looked at the effects of contextual factors, namely manipulated stress perceptions and goal conditions. Employing a version of the stock-pricing task (described later) adapted to fit the task change paradigm (by adopting differing pricing algorithms unbeknownst to participants), they found that performance declined after a change occurred in situations perceived as being threatening while it increased when the situation was perceived as being challenging. The addition of a difficult goal further increased adaptive performance for those who were in the challenge stressor condition.

Antecedents of Team Adaptive Performance

As previously mentioned, the focus of the present discussion is on individual level adaptive performance. As such, the focus of this section (and the subsequent section on outcomes of team adaptive performance) is not to summarize the team level adaptive performance literature in general. Rather, it is focused on highlighting work relevant to the current discussion.

For example, the teams literature is rife with contingency theories that are predicated on the belief that no one type of team structure is optimal, focusing instead on specifying the conditions under which a particular structure is optimal (Hollenbeck, Ellis, Humphrey, Garza, & Ilgen, 2011). Against a backdrop of accelerating changes in the environments that teams operate in (Kozlowski, Watola, Jensen, Kim, & Botero, 2009), this contingent point of view has led to considerable interest in understanding how team structures change. Not surprisingly then, a key component of team adaptive performance is the ability to change the team's structure and processes (Kozlowski et al., 1999). In fact, a reconfigurable network of roles may be a key to successfully adapting to environmental change (Kozlowski & Bell, 2008). However, reconfiguring team roles is an aspect of team performance that is unique to the team-level without a direct, individual level analog (Pulakos et al., 2006).

Similarly, shared team mental models are proposed to be important to team adaptive performance (Burke, Stagl, et al., 2006). However, they too are unique to the team-level conceptualization of adaptive performance (Pulakos et al., 2006), and as such work investigating the role of shared mental models in team adaptive performance (e.g., Randall, Resick, & DeChurch, 2011) is not reviewed here. Thus, even though work on team adaptive performance is sparse when compared to other areas of team research (Kozlowski & Bell, 2008), the content of this section should not be taken as representative of the body of work that has been conducted; it is merely a specific subset, one that is believed to shed light on adaptive performance at the individual level.

For example, Waller (1999) studied the performance of flight crews in a flight simulator when faced with a mechanical failure that required them to diagnose the problem and subsequently divert to an airport other than the one that they planned on using at the beginning of the exercise. While the sample employed was quite modest (10 teams), in this context, she found some (weak) evidence that information collection was positively related to adaptive performance (although the statistic did not reach typical standards for statistical significance, which is not surprising given the exceedingly small sample), in this case measured in terms of error rate after the unexpected failure. In addition, the speed with which teams reprioritized (and redistributed) their many tasks after the change occurred was positively related to post-change performance while the overall amount of time spent on this activity was not associated with team adaptive performance (Waller, 1999). Thus, in this team context, regular information collection may lead to early recognition of the change, and when coupled with a timely response to the event, allow teams to reduce the number of errors committed, increasing their performance after the disruption (i.e. adaptive performance).

Following up on the individual-level study discussed previously (LePine et al., 2000), Jeffrey LePine has conducted studies relating to adaptive performance in team contexts that have implications for individual adaptive performance. LePine (2003) investigated the role of the same independent variables included in LePine et al. (2000), namely GMA, openness, and conscientious, in predicting team level adaptive performance. Like the individual level work, this study utilized the task change paradigm. In this instance, team members had to work together to identify simulated aircraft as either friend or foe, a task that became more complex following a partial failure of the intra-team communication system that was simulated part-way through the focal task (requiring team members to find an alternative path to communicate with one another). Team adaptive performance was operationalized as the accuracy of decision making after the change occurred. However, unlike the previous study, due to the nature of the study design and the research question being addressed, adaptation had to take place at the team level, requiring the combined efforts of multiple team-members.

In this context, team-level measures of GMA, openness, and conscientiousness were created by averaging the individual scores of team members. This corresponds to an additive model of aggregation (Chan, 1998) and is appropriate when team members can compensate for each other (LePine, 2003). The results of this study generally mirror the previous individual level study. GMA and openness were both found to be positively related to team adaptive performance while the dependability facets of conscientiousness were negatively related (LePine, 2003); however, in this context, the achievement facets of conscientiousness were found to be positively related to adaptive performance. In addition, as suggested by theory on team adaptive performance and the initial work of Waller (1999), role reconfiguration seemed to play an important role in the ability of the team to perform well after the change had occurred (LePine, 2003).

In a follow-up study also utilizing a task-change paradigm, the speed of role reconfiguration, measured as the number of elapsed decision iterations since the environmental change occurred, was used as the focal measure of team level adaptive performance (LePine, 2005). In this context, individual GMA and goal orientation measures were averaged at the team level and used to predict the probability of adaptation having taken place by a particular iteration. While a positive relationship between cognitive ability and adaptive performance was found, no relationship was found for either trait performance or learning goal orientation (LePine, 2005).

To investigate the role of contextual factors, teams were also assigned to one of two goal conditions which corresponded to either an easy or difficult goal level. While no interactive effect was found for goal level and cognitive ability, goal difficulty did moderate the relationship between team adaptive performance and goal orientation such that teams with low learning orientation or high performance orientation adapted quicker when assigned an easy goal than did teams assigned a difficult goal (LePine, 2005). It is interesting to note that in this study, assignment of a difficult goal was not universally advantageous in terms of the team's ability to adapt quickly, a finding contrary to the established paradigm that assignment of difficult goals generally improves performance (e.g., Locke & Latham, 1990).

Work investigating potential cross-level moderators has also been conducted. Han and Williams (2008) conceptualized team adaptive performance using the additive model (Chan, 1998) of aggregation from the individual level based on the norms and procedures in place in the organization in which their study took place. In addition, they collected managerial ratings of overall team adaptive performance using a novel 14 item survey measure administered to high-level managers. This manager supplied assessment was found to be positively related to the mean level of individual level adaptive performance obtained by generating novel items to measure four of the dimensions of the JAI thought to be most relevant to the focal jobs. These values were reported by the team leader responsible for directly supervising a particular employee.

In addition, Han and Williams (2008) presented some evidence that individual adaptive performance is positively related to both individual continuous learning activities (e.g. attending work-sponsored training courses, cross-training activities) as well as the group level construct of team learning climate (e.g. tolerance of mistakes, openness to new ideas). Thus, while there is evidence of a cross-level moderation effect, individual level adaptive performance in a team based workplace seems to be related to training and experiences. This may be because these developmental activities expand the repertoire of potential solutions that employees can apply to dealing with an unforeseen problem (Han & Williams, 2008).

Individual Outcomes of Adaptive Performance

Despite the aforementioned theoretical importance of adaptive performance in modern organizations, empirical investigations of the link between adaptive performance and other desirable outcomes is sparse. This may be due in part to the pervasiveness of lab-based investigations of adaptive performance due to the difficulties generally associated with implementing a task-change paradigm in field settings (LePine, 2003). Given this limitation and the lack of readily available, validated measures suitable for survey-based data collection, researchers wishing to look at the outcomes of adaptive performance in the field face a formidable challenge. As a result of the above mentioned challenges, investigation of the outcomes associated with adaptive performance represents a relatively underdeveloped area of the adaptive performance literature (Cortina & Luchman, 2013).

One recent study looked at the relationship between a subset of adaptive performance dimensions and supervisor rated overall performance directly. The authors found a positive zero-order relationship between supervisor rated work performance and each of five adaptive performance dimensions, namely: cultural, interpersonal, learning, uncertainty, and work stress adaptability (Wang et al., 2011). However, when testing a structural model including several fit measures as potential mediators, only learning adaptability was directly related to supervisor rated job performance; although, the stress dimension was related through an increased level of perceived demand-ability fit. In this model, interpersonal, cultural and uncertainty adaptability were not related to overall performance ratings (Wang et al., 2011). While this study is informative, direct investigations of adaptive performance outcomes are limited, but there are a few avenues through which some initial insights into this domain may be gleaned.

At the individual level, Arthur, Day, McNelly, and Edens (2003) conducted a meta-analysis of the validity of six assessment center dimensions (consideration/awareness of others, communication, drive, influencing others, organizing & planning, and problem solving) with job performance. While adaptation was not considered itself, of the dimensions considered, problem solving seems to incorporate one aspect of adaptability, solving atypical problems (Pulakos et al., 2000), and included sub-dimensions including originality, problem detection and innovative thinking. This dimension was not only found to be positively related to job performance, there was also some indication that it had the highest validity of the dimensions considered; although, a rigorous analysis of relative effect sizes was not conducted (Arthur, Day, et al., 2003). In addition, there was a seventh dimension, tolerance for stress/uncertainty, considered that included items that seem to capture a portion of the adaptive performance construct as defined by Pulakos et al. (2000), including handling stress and unpredictable situations. However, a lack of primary studies coupled with a lack of conceptual equivalence across them prevented analysis of the relationship between this dimension and job performance (Arthur, Day, et al., 2003).

As previously discussed, transfer of training is distinct from adaptive performance, however, training can impact components of adaptive performance including the ability to successfully cope with stressful situations (Driskell, Johnston, & Salas, 2001) and has been linked to increased innovation (Barber, 2004). In turn, training has been meta-analytically linked to both objective (e.g. productivity) and subjective (e.g. supervisor ratings) measures of employee as well as organizational level performance (Arthur, Bennett, Edens, & Bell, 2003). However, some important caveats are worth noting. First, ties between training and organizational performance seem to be much more robust for subjective compared to objective measures (Tharenou, Saks, & Moore, 2007). In addition, the reported ability of training to effect change in the participants seems to be dependent on the rating source, with peer and subordinate sources indicating smaller effect sizes than self and supervisor reports (Taylor, Taylor, & Russ-Eft, 2009). While differences in perceptions of adaptability have not likewise been explored, it bears keeping in mind for future investigations. Finally, some types of training (i.e. error management training) may be more adept at encouraging subsequent adaptation than more traditional training methods (Keith & Frese, 2008). Thus, as discussed previously, while there would seem to be some overlap between training transfer and adaptive performance, it is far from a direct correspondence, and as such, determining whether the relationships discussed in this section also hold for adaptive performance remains an open question, and due to the dearth of information pertaining to the relative importance of adaptive performance currently available, it is an important question for adaptive performance researchers to tackle (Cortina & Luchman, 2013).

Outcomes of Team Adaptive Performance

Much like at the individual level, team level adaptive performance is generally assumed to be beneficial and direct tests of this presumption in the literature are even more sparse. While, recent theorizing on team adaptive performance by M. A. Rosen et al. (2011) includes several emergent states (e.g. shared mental models, psychological safety) and behavioral (e.g. backing-up behavior, coordination) indicators of adaptive performance that have been previously linked to performance, the theory stops short of including outcomes beyond team adaptation itself. In addition, the indicators included in the model lend little support to outcomes at the individual level because, as the examples above indicate, they are largely team-specific constructs without individual-level counterparts. In sum, the ability of the literature on team adaptive performance to inform the present work on individual adaptive performance is hampered not only by the dearth of studies investigating team level outcomes but also the general lack of individual level analogs for many of the constructs thought to operate at the team level, and in keeping with the current focus on individual level adaptive performance this section is correspondingly brief.

Table 2: Summary of Selected Empirical Research on Adaptive Performance

Study	N	Measure	Antecedents	Outcomes
~ Individual Level Studies ~				
Mumford, et al., 1993	250	Task-change paradigm (performance on structured and unstructured tasks)	(+) Creative Achievement (+) Self-Discipline (-) Defensive Rigidity	N/A
Allworth & Hesketh, 1999	169-216	GDPR subset – Supervisor Rated	(+) Change Experience (ns) People Experience (ns) Big 5 – trait level (all) (+) GMA	N/A
LePine, Colquitt & Erez, 2000	73	Task-change paradigm (decision making accuracy pre vs. post change)	(+) GMA (+) Openness (-) Conscientiousness (-) -Dependability facets (ns) -Achievement facets	N/A
Pulakos, et al., 2000	1311-1715	Job Adaptability Inventory (JAI)	N/A	N/A
Pulakos, et al., 2002	327-331	Job Adaptability Inventory (JAI)	(+) Emotional Stability (+) Achievement Motivation (+) GMA (AFQT) (ns) Openness (+) Change Experience* (+) Change Interest* (+) Change Self-efficacy*	N/A
Drach-Zahavy & Erez, 2002	155	Task-change paradigm	(+) Challenge Stressor (-) Threat Stressor	N/A
Stewart & Nandkeolyar, 2006	167	Weekly sales ($)	(+) Conscientiousness (-) Openness	N/A

Table 2 (cont'd)

Study	N	Measure	Antecedents	Outcomes
Griffin, Neal & Parker, 2007	927-1228	3-level adaptability measure including individual, team member and organizational member adaptation	(+) Role clarity (+) Openness (+) Role Breadth Self-efficacy (+) Gender – female (-) Negative Affect** (+) Team Support** (+) Org. Commitment**	N/A
Lang & Blise, 2009	184	Task-change paradigm (transition & reacquisition adaptation)	(-) GMA	N/A
Wang, et al., 2011	671	I-ADAPT-M (short-form) Cultural, Interpersonal, Learning, Stress and Uncertainty dimensions only	N/A	(+) Job performance (Supervisor Rated)
		~ Team Level Studies ~		
Waller 1999	10	Task-change paradigm (rate of error commission post-change)	(ns) Information Collection Task Reprioritization: (+) -Timing (ns) - Frequency Task Redistribution: (+) - Timing (ns) - Frequency	N/A
LePine 2003	73	Task-change paradigm (decision making accuracy pre vs. post change)	(+) GMA (+) Openness Conscientiousness (-) -Dependability facets (+) -Achievement facets	N/A

Table 2 (cont'd)

Study	N	Measure	Antecedents	Outcomes
LePine 2005	64	Task-change paradigm (speed of team role reconfiguration)	(+) GMA (ns) Learning GO (ns) Performance GO (+) Goal Diff X Learning GO (-) Goal Diff X Perf. GO	N/A
Han & Williams 2008	37-39	Job Adaptability Inventory (JAI) – 4 factor subset	(+) CLA (+) TLC	N/A

Notes: N/A indicates that the study did not include data on this aspect of adaptive performance. Non-significant findings are indicated by (ns). N indicates the number of data points used in the analyses. For individual level studies it represents participants; for team level studies it indicates the number of teams included. CLA = continuous learning activities. GMA = general mental ability. GO = Goal Orientation. TLC = team learning climate. * Some facets were positively related to adaptive performance; others were unrelated. ** Most strongly related to adaptive performance aimed at overcoming changes introduced at a commensurate level.

THEORETICAL DEVELOPMENT

Despite its widespread application in understanding organizationally relevant phenomena (Vancouver, 2005) and its apparent relevance to several aspects of adaptive performance, the literatures on control theory and adaptive performance have not yet been integrated. This section attempts to begin that integration process by employing control theory as an overarching theoretical framework to motivate theory driven hypotheses aimed at better understanding how and why individual and contextual differences may impact adaptive performance. The section begins with a general, but abbreviated introduction to self-regulation and an overview of control theory intended to acquaint the reader with its core tenants (those seeking a more in-depth discussion of control theory itself are referred to: Carver & Scheier, 1981, 1998; Powers, 1973). Subsequently, control theory is used to identify relevant individual and contextual differences likely to be antecedents of adaptive performance and specific hypotheses relating them to adaptive performance are developed and presented.

Since its introduction 40 years ago, control theory (Carver & Scheier, 1981, 1998; Powers, 1973) has become an established theory in organizational research, having received support in a wide variety of contexts (Katzell, 1994; Vancouver, 2005). While not without its critics (e.g. A. Bandura & Locke, 2003), control theory has been successfully employed to investigate a wide variety of relevant outcomes. For example, in terms of affective outcomes, a lack of progress (K. J. Williams & Alliger, 1994) or even an insufficient rate of progress (Chang, Johnson, & Lord, 2010) in goal attainment has been found to be associated with negative affective outcomes. Behavioral outcomes including voluntary turnover (Hollenbeck, 1989) and the job search behaviors of unemployed workers (Wanberg, Zhu, & Van Hooft, 2010) have been considered in a control theory framework as performance on an assigned task (e.g., Vancouver, Thompson, Tischner, & Putka, 2002; Vancouver, Thompson, & Williams, 2001). Attitudes including job satisfaction and organizational commitment (Hollenbeck, 1989) have been examined, and control theory has also been proposed as an appropriate theory to understand diverse processes including stress and coping (Edwards, 1992) and emotional labor (Diefendorff & Gosserand, 2003). Before discussing how control theory can be applied to help understand antecedents of adaptive performance, a general discussion of control theory and self-regulation is presented.

Self-Regulation

Self-regulation describes the ubiquitous process of setting goals and striving to achieve them (Carver & Scheier, 1998; R. E. Johnson, Chang, & Lord, 2006; H. J. Klein, 1989). Self-regulation is a widely studied phenomenon for organizational researchers because it is critical to understanding and predicting a wide range of individual behaviors and outcomes (Lord, Diefendorff, Schmidt, & Hall, 2010). It is particularly adept at explaining dynamic behavior. Drawing on the work of Kopp (1982), Kuhl (1992, p. 104) notes, "The ability to deal with unexpected situational changes in a creative and flexible way seems to be a major characteristic of self-regulatory behaviour." A central aspect of the self-regulation process is the existence of goals, defined as mental representations of desired states (Austin & Vancouver, 1996). When discrepancies exist between one's current state and a more desirable state, represented by a goal, attention, effort, and action in pursuit of that goal are elicited. As a result, behavioral or cognitive changes aimed at attaining the desired state manifest.

As alluded to previously, the motivational processes encompassed by self-regulation are driven by two primary sub-processes: goal setting and goal striving, and these two processes work to in tandem to promote goal-relevant behaviors (Carver & Scheier, 1998; Kanfer, 1991; Lord et al., 2010). Goal setting refers to the processes relating to the establishment of goals. In particular, it encompasses processes leading to the creation of specific mental goal representations taken from the many potential goal candidates available. For example, in modern organizations, employees are increasingly required to pursue multiple goals, and because the goals often conflict, it is often not possible to attain all of them (O'Leary, Mortensen, & Woolley, 2011; A. M. Schmidt & Dolis, 2009).

Environmental change can impact the goals being pursued by an employee in the workplace, and Stewart and Nandkeolyar (2006) expressly differentiate between two facets of adaptive performance depending on the source of the revised goal being pursued. In their conceptualization, the *task revision* component of adaptive performance occurs when the goal being pursued is internally generated and counter to existing expectations and directives of the organization. This is presented in contrast to the *task pursuit* component of adaptive performance that is comprised of the pursuit of new goals expressly conveyed and endorsed by the organization (Stewart & Nandkeolyar, 2006). Thus, the goal setting aspect of self-regulation seems relevant for understanding both of these components of adaptive performance.

Research conducted across a wide range of domains has consistently shown that the establishment of difficult, specific goals and subsequent commitment to attain them leads to increased performance. Researchers have identified several mechanisms that mediate the relationship between goals and performance, including increased effort, persistence, and attention (Locke & Latham, 2002). These mechanisms are the purview of the second sub-process, goal striving, which is focused on the pursuit of the goals established during the goal setting process. However, goal striving is not limited to these mechanisms, but rather encompasses all processes that direct individual behavior toward goal attainment (Austin & Vancouver, 1996).

Goal striving processes are broadly related to adaptive performance. For example, both task revision and task pursuit incorporate behaviors intended to realize revised goals, even if the source of the revised goal varies (Stewart & Nandkeolyar, 2006). The facets of adaptive performance put forth by Pulakos et al. (2000) are similarly pursuit oriented, including a facet related to creatively solving problems that have the potential to inhibit goal attainment and acting appropriately in response to unexpected changes (see Table 1 for a brief description of all eight facets). The reacquisition adaptation facet of adaptive performance put forth by Lang and Bliese (2009) is likewise focused on how well individuals are able to change their pursuit tactics in response to a disruptive environmental change. Thus, adaptive performance conceptualizations also implicitly include goal striving as well as goal setting.

Control Theory

Because goal setting and goal striving work in concert to explain behavior in organizations it is important for theories of self-regulation to address both of these components in order to be complete (R. E. Johnson, Howe, & Chang, 2013). This section introduces control theory and discusses how control theory incorporates both of these sub-processes in a unified framework. As alluded to earlier, this discussion is intended to familiarize (or refamiliarize) the reader with central aspects of control theory, but it is beyond the scope of the present document to exhaustively cover the topic. Such efforts have previously been undertaken and the interested reader is directed to these more focused and expansive works (e.g., Carver & Scheier, 1981, 1998; Powers, 1973).

A central tenant of control theory is that individuals have numerous goals and more specifically, that these goals are arranged in goal hierarchies (Powers, 1973). This structure inherently influences goal setting processes because higher level goals constrain the lower level goal choices made. Higher level goals act as the standards against which performance at lower levels is judged (Lord & Levy, 1994). In other words, goals cannot be chosen in isolation because the accomplishment of lower level goals is intended to bolster pursuit of goals higher in the hierarchy, and revising a lower level goal downward tends to bolster discrepancies at higher levels in the hierarchy, which is generally undesirable (Lord & Levy, 1994).

Lord and Levy (1994) built on the work of Powers (1973) and Newell (1990) to propose four broad goal categories that operate over increasingly long time frames as one moves up the hierarchy from the biological, to the cognitive, rational and social levels. Differences in the nature of goals at varying levels in the hierarchy were further explored by subsequent work. Carver and Scheier (1998) noted that goals at the lowest levels in the hierarchy pertain to successful execution of discrete, basic tasks and activities. Successful accomplishment of these goals allows for the successful execution of programs or routines that are the focus of middle-level "do" goals. In turn, these mid-level goals support accomplishment of broad and self-relevant goals at the highest levels of the hierarchy, labeled “be” goals. Thus, as one moves up the goal hierarchy, goals move away from concrete tasks and simple relationships, becoming increasingly focused on more abstract concepts and complex relationships.

While goals at each of the various levels may be active at different points in time, due to their slow changing and abstract nature, active regulation guided by high-level "be" goals is relatively rare, and in terms of guiding activities, mid-level, program based, "do" goals are pervasive, making them particularly important to understanding self-regulation (Carver & Scheier, 1981, 1982). In fact, in their subsequent work, Carver and Scheier (1998, p. 95) note that people spend the preponderance of their time regulating at the program level. Further, regulation at these more concrete levels may be particularly beneficial (and thus invoked more frequently) in novel situations because it may be unusually difficult to construct the accurate causal links necessary to translate abstract high level goals to actionable programs in such settings (Watkins, 2008). Nonetheless, high level goals still exert influence in such settings, even when the links become misspecified (Carver & Scheier, 1981).

This type of hierarchical goal functioning implies a top-down structure where the output of a control loop at a given level serves as the goal for control loops at the next lower level (Lord & Levy, 1994). However, more recent theorizing notes that the interaction across levels must be more bidirectional in order to maintain an effective goal hierarchy. Specifically, progress made accomplishing goals at a given level is likely to provide feedback that is used to evaluate goal accomplishment at the next level up in the hierarchy (R. E. Johnson et al., 2006). This bidirectional flow across the hierarchy is necessary if feedback pertaining to low-level goal accomplishment (or lack thereof) is to move up the hierarchy, allowing low-level goal attainment to affect the evaluation of their higher level counterparts.

Whatever the level, once a goal is established, it exerts a biasing effect on attentional and information processing systems such that information relevant for its completion is more likely to be attended to (Lord & Levy, 1994). In addition, the goal also serves as a performance standard, influencing goal striving behavior via a series of negative feedback loops (which are discussed more in depth below). To foreshadow, if the current state falls below the desired goal state, there exists a negative discrepancy. The existence of a negative discrepancy is undesirable, and it acts as an attentional mechanism, focusing attention on a particular goal, as well as a motivating factor for action aimed at reducing and eventually eliminating the negative discrepancy (Carver & Scheier, 1998). As previously discussed, control theory is quite broadly applicable and this feedback based control mechanism can be used to understand a wide variety of phenomena. In addition to regulating physical actions, it is important to keep in mind that control theory is applicable for understanding the deployment of cognitive resources and associated mental activities as well (Watkins, 2008).

In control theory and other theories of self-regulation (e.g. goal theory; Locke & Latham, 1990, 2002), the presence of feedback is necessary for successful self-regulation. As discussed above, in control theory the negative discrepancy between a current state and a goal state is a fundamental determinant of behavior. In the absence of feedback about the current situation, it is impossible to compare the current state to the desired goal state. Without a comparison, it is likewise impossible for a negative discrepancy to exist, and because negative discrepancies form the basis for behavior in control theory, feedback is necessary for the goal striving aspect of self-regulation to function (Erez, 1977; Neubert, 1998). Specifically, this feedback serves as the main input to the aforementioned negative feedback loops. An example of a negative feedback loop is presented in Figure 2.

As shown in Figure 2, feedback originates in the environment. It can arise from the task itself or come from some other source (e.g. co-worker). This feedback is interpreted by the individual and this interpreted signal serves as one input for a comparator mechanism. The other input to the comparator is typically referred to as the referent signal. It is derived from the desired goal level (established during the goal setting process). The comparator mechanism compares the input signal to the referent signal and determines whether a negative discrepancy exists, based on the relative magnitude of these two signals. Control theory predicts that the presence of a negative discrepancy (i.e. input signal is below referent signal) elicits an effort to eliminate the detected difference. This effort can take the form of a behavioral or a cognitive change, and regardless of the nature of the change, it is aimed at reducing and eliminating the discrepancy between these two signals.

If a negative discrepancy is detected by the comparator, a signal is sent to the decision mechanism indicating the need for action. In turn, the decision mechanism indicates that a decision must be made regarding which route to follow when attempting to address the detected shortcoming. As depicted in Figure 2, there are two general avenues available to alleviate the discrepancy, and a decision must be made whether to follow the behavioral route or the cognitive one. If the behavioral route is chosen, the exhibited behavior is changed in an attempt to reduce the discrepancy between the two signals by raising the input signal. This behavioral change can manifest in increased effort (working harder), the adoption of a new approach aimed at increasing efficiency (working smarter), or some combination of both (R. E. Johnson et al., 2013; Wood & Locke, 1990). Consequently, the effectiveness of the behavioral change in reducing the detected discrepancy is evaluated by interpreting the updated feedback signal provided by the environment as the process repeats itself.

In addition to the behavioral changes discussed above, it is possible to reduce detected discrepancies by cognitive means as well. Rather than attempting to modify the input signal by adopting a behavioral change, it is possible to modify the referent signal by enacting a cognitive change instead. By adopting a lower goal level that is more closely aligned with one’s current state, the referent signal is affected and as a result, the negative discrepancy is reduced. While modifying either the input signal (via a behavioral change) or the referent signal (via a cognitive change) can reduce a detected discrepancy, the two approaches are generally enacted in different situations. Specifically, the primary response to a noticed discrepancy is generally behavioral while stable discrepancies that endure over time are more likely to elicit cognitive changes

(Campion & Lord, 1982; Donovan & Williams, 2003). While the cognitive route would seem to be easier, goals cannot generally be revised downward arbitrarily. Reducing a lower level goal (e.g. weekly sales goal) is likely to adversely influence higher level goals within an individual's goal hierarchy (e.g. satisfactory annual performance review), limiting the overall desirability of this approach (Carver & Scheier, 1998; Powers, 1973).

Regardless of the route employed, when the comparator subsequently re-evaluates the difference between the referent and input signals, information about the success of the chosen course of action is garnered. While the behavioral and cognitive routes focus on modifying a different signal supplied to the comparator both approaches attempt to reduce discrepancies by bringing the two signals closer to one another. The reduction or elimination of the discrepancy indicates that the chosen course of action is working and no additional changes are likely to occur; conversely, stable discrepancies, indicating no or minimal effects from the selected approach, may signal the need for further attention and action (Carver & Scheier, 1998).

Before closing this section, it is also important to note existence of a disturbance factor in Figure 2. So far the discussion has focused internally on how an individual can affect the magnitude of the discrepancy between the input and referent signals; however, this discrepancy is not entirely under the control of an individual. Disturbances, or environmental factors, can also influence the magnitude of the discrepancy. For example, the unexpected loss of a major account can immediately increase the discrepancy between the goal state (e.g. monthly sales volume) and the current state (e.g. current sales) for a sales professional, resulting in the need to adopt a behavioral (e.g. identify and deliver new sales opportunities) or cognitively (e.g. adopt a lower monthly sales goal) focused strategy to address this shortcoming. While relatively innocuous disturbances can also draw attention to a particular situation (Weiss & Cropanzano, 1996), environmental or task changes inherent in the definition of adaptive performance put forth above necessarily act as disturbances because they impact the effectiveness of output on accomplishing the focal task or action.

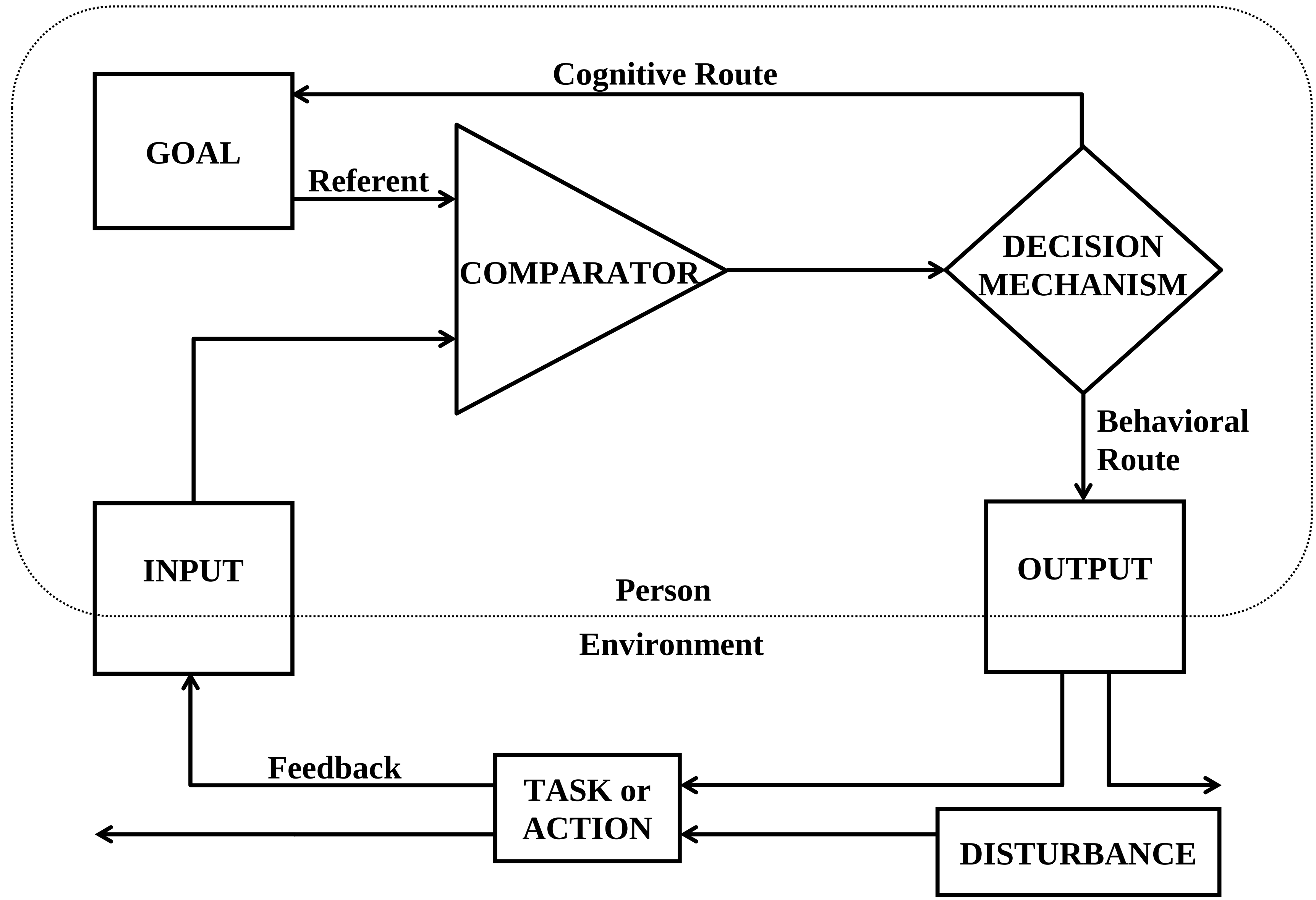

Figure 2: Example Negative Feedback Loop

The Nature of Feedback

It has long been known that in order for goals to be motivating, people must have access to feedback about their current level of performance (Erez, 1977; Neubert, 1998). Locke and Latham (2002, p.708) note the importance of feedback thusly: “For goals to be effective, people need summary feedback that reveals progress in relation to their goals. If they do not know how they are doing, it is difficult or impossible for them to adjust the level or direction of their effort or to adjust their performance strategies to match what the goal requires.” Not surprisingly, feedback is also a critical component of control theory (Carver & Scheier, 1998). Feedback forms the basis for the input signal, which serves as one of the two inputs to the comparator. Without the information about the current level of performance conveyed by feedback, it becomes impossible to compare the current state to the goal state. In turn, if no comparison can be made, no discrepancy is perceived to exist and the lack of a discrepancy precludes any systematic behavioral or cognitive changes implemented to reduce the magnitude of the discrepancy.

Feedback can be defined as the communication of goal relevant information from a sender (in the environment) to a recipient, who in turn perceives and interprets the information (Ilgen, Fisher, & Taylor, 1979). Feedback can come from a variety of sources, encompassing many different forms. For example, sometimes the task provides feedback directly (e.g. a sales-professional tasked with providing a sales forecast for each product line in the company portfolio can keep track of how many products have been finished and how many are left to complete). Often the availability of the feedback is delayed (e.g. the accuracy of each estimate is unavailable until the end of the year when the actual sales numbers are compiled and compared to the estimates). In other instances, feedback is provided directly by other individuals (e.g. subjective supervisor evaluation of estimates).

Regardless of the source (e.g. task, co-workers, supervisor) or communication mechanism employed (e.g. verbal, written, physical), feedback varies in its degree of consistency and clarity across these combinations and over time (Ilgen et al., 1979). In fact, feedback provided by these different mechanisms may be contradictory. For example, consider the task of rendering an accurate appraisal of employee performance in the context of multiple and often conflicting organizational goals, a situation which occurs commonly in modern organizations (A. M. Schmidt & DeShon, 2007). In such an environment, something as innocuous as the mood of the rater can influence how the feedback about a given individual's performance is incorporated. Specifically, raters in a positive mood tend to rate the performance of others higher than those who were in a neutral or negative mood, even though negative affect was associated with more accurate perceptions of job performance (Sinclair, 1988).

Similarly, the process of obtaining 360-degree performance feedback requires an individual to incorporate information provided by various sources of feedback. This approach intentionally takes advantage of different perspectives on an individual's performance provided by different people who interact with an individual in a variety of work roles. As a result, in order for an individual to effectively evaluate of the results of this exercise, complex and often contradictory feedback regarding job performance must be evaluated. The resulting synthesis is apt to be idiosyncratic since the perceived accuracy of a particular performance rating source may be influenced by the interaction of recipient affect and the feedback valence (Hammer & Stone-Romero, 1996).

Finally, in addition to the complexity resulting from different rating sources and conveyance mechanisms, interpretation of feedback is further complicated because feedback can also vary in the extent to which it emphasizes different temporal characteristics of performance discrepancies (Carver & Scheier, 1998; Chang et al., 2010). The examples discussed thus far were related to discrepancy feedback, or the magnitude of the gap between the current state and the desired, goal state. However, this is not the only type of feedback that exists. Feedback can also focus on the speed with which the gap between the current state and the goal state is changing (velocity feedback), and acceleration feedback focuses on changes in the rate of gap closure. These types of feedback are not only distinct and independent, but they serve unique functions in the realm of self-regulation as well (For a more in-depth discussion of the different types of feedback, see: Carver & Scheier, 1990, 1998; R. E. Johnson et al., 2006; R. E. Johnson et al., 2013).

In summary, to drive action, feedback must be both noticed and interpreted, and an error in either process can impair the ability to take prudent action aimed at maintaining the desired state after a change has occurred (Carver & Scheier, 1998; Kiesler & Sproull, 1982). Errors of this sort are particularly apt to occur when the feedback is inconsistent with other salient information, a situation likely to occur frequently in organizations, particularly after a change has occurred (Kiesler & Sproull, 1982). In addition to inconsistencies in the valence of the feedback signal, the quantity and ambiguity of feedback available can hinder control loop responsiveness; a problem discussed in more detail below.

Boundedly Rational Control

Taken together, the pervasiveness and multidimensionality of feedback can make it difficult for individuals to process it all effectively (Carver & Scheier, 1981, 1998; Kiesler &

Sproull, 1982; Lovett & Schuun, 1999; Sheridan, 2004). Because people are boundedly rational, they are often not able to adequately incorporate all of the information available to them (March & Simon, 1958). In the case of feedback, more is not necessarily better, and when presented with an overabundance of feedback, it can become difficult for boundedly rational individuals to regulate effectively, resulting in suboptimal performance (DeShon, Kozlowski, Schmidt, Milner, & Wiechmann, 2004). In order to regulate effectively while coping with these cognitive shortcomings, people employ control-driven regulatory strategies that allow them to attend to feedback from the environment to varying degrees (Sheridan, 2004).

This is consistent with the initial discussion of bounded rationality put forth by March and Simon (1958, p. 190), who noted that due to cognitive limitations when facing a demanding problem, people adopt "simplified models that capture the main features of a problem without capturing all its complexities." In other words, by ignoring some of the intricacies of the situation, people are able to construct a tractable problem that they can process given limited cognitive resources. As organizations increasingly confront technological, demographic, and competitive landscape changes, employees must cope with increasing amounts of information and interdependence as well as additional sources of information and stress, leading to increased cognitive, social, perceptual, and emotional demands (Pearlman & Barney, 2000). In such a setting, the necessity of adopting simplifying programs is apt to increase, given the inherent complexity and associated demands that accompany this sort of work environment (March & Simon, 1958).

In the context of problem solving, March and Simon (1958) refer to these simplifications as predefined "programs" of action that are initiated in response to a particular stimuli. These programs typically result from having adequately (not generally optimally) solved situations in the past that the problem solver deems similar to the current situation, and while the number of inputs specified for a particular program can be relatively large, it is a finite input list (determined by information deemed useful in past experience) and other information is neglected as it plays no role in the execution of the program (March & Simon, 1958).

Reducing the processing demands of a situation by adopting a model of the situation is also thought to occur in an analogous way within control theory, Specifically, due to the inability to gather and process all of the available feedback in a timely and accurate manner, people also incorporate information taken from internal models of the situation when self-regulating (Carver & Scheier, 1982; Sheridan, 2004). Not only is this approach less resource intensive, but it is also generally effective. Mathematical modeling has demonstrated that in situations where it is impossible to accurately obtain all of the necessary environmental information in a timely basis, control system performance is maximized via the use of a periodically updated model (Sheridan, 2004). Thus, in complex, resource intensive environments that typically characterize modern organizations (Pearlman & Barney, 2000), individuals are apt to create situational models that incorporate a pattern of assumed relationships along with some subset of available feedback to gauge current performance relative to the desired level of performance or goal state (Carver & Scheier, 1982; Sheridan, 2004).

These models or task representations are the "set of stimulus features an individual uses to encode the task environment" (Lovett & Schuun, 1999, p. 108). These models can reduce cognitive requirements enough to make problem solutions tractable, but they are not without drawbacks. By definition, feedback that is not included as part of these simplified programs is not considered relevant for outcome determination, and therefore does not indicate a performance discrepancy nor drive corrective action (Carver & Scheier, 1998; Lovett & Schuun, 1999). When this assumption is false and the neglected feedback is actually pertinent for the focal outcome, poor performance can result (Lovett & Schuun, 1999). Further, the selected subset of feedback may not just be suboptimal. It may be so misspecified and incomplete that it is essentially ineffective at providing any meaningful information about the actual current level of performance; even so, fluctuations in this feedback signal are wrongly interpreted as conveying such information, often to the detriment of the individual (Carver & Scheier, 1998).

The balance struck between relying on existing internal models versus incorporating environmentally driven feedback to update and improve the current model is analogous to the well-established explore-exploit conundrum (Levinthal & March, 1993) facing organizations. Just as organizations must try and effectively balance these competing demands (Gibson & Birkinshaw, 2004; Levinthal & March, 1993; Raisch & Birkinshaw, 2008), at the individual level, relying on one approach hinders the short term ability to successfully perform the other (Carver & Scheier, 1998; March & Simon, 1958). An individual may choose to focus on *exploring* the situation by attending to and incorporating novel feedback to validate and improve the accuracy of the current regulatory program (Carver & Scheier, 1981, 1982; Sheridan, 2004). Environmental monitoring and novel feedback incorporation are cognitive resource intensive endeavors (Braver, Gray, & Burgess, 2007) that rely to some extent on random processes and trial-and-error experimentation (March & Simon, 1958; Weick, 1979), even though programs aimed at developing effective exploration approaches can be created over time, preventing such search processes from being totally blind (March & Simon, 1958). Despite the accompanying reductions in efficiency due to increased resource demands, exploration is an important and necessary component for the maintenance of effective control, particularly in dynamic situations (Sheridan, 2004).

Alternatively, an individual can focus on *exploiting* past experience (incorporated into models of the situation) to conserve cognitive resources and to focus attention only on those portions of feedback deemed relevant for gauging progress relative to a particular goal. Not only is this routinized approach to discrepancy reduction generally cognitively efficient, it is also prevalent in organizations. March and Simon (1958, p. 163) note that, "most behavior, and particularly most behavior in organizations, is governed by performance programs." Weiss and Ilgen (1985, p. 57) echo this sentiment observing, "it is also apparent that much of the time people are not actively engaged in monitoring their environments, searching for information, making judgments and decisions, etc. Often behaviors in organizations are habitual responses to familiar situations." These "programs" or "habitual responses" can affect the input signal by biasing the feedback information that individuals attend to, causing them to focus on feedback relevant to the active model and discount or ignore information not incorporated in the programmed response (Carver & Scheier, 1981, 1982, 1998) which may impair the ability to effectively improve exploitation programs over time by incorporating newly relevant sources of feedback (Carver & Scheier, 1998; Lovett & Schuun, 1999).

The effect that the presence of these preconceived models has on the input signal can be further understood as a specific case of the more general phenomenon of confirmation bias (Evans, 1989). This is not surprising since confirmation bias is an omnipresent and weighty problem that plagues human reasoning in a variety of domains (Nickerson, 1998). Confirmation bias has long been known to psychologists (e.g., Thurstone, 1924) and used to help understand a variety of occurrences including primacy effects (e.g., Jones, Rock, Shaver, Goethals, & Ward, 1968), hypochondria (e.g., Pennebaker & Skelton, 1978) and perceptions of fairness (e.g., Hastorf & Cantril, 1954).

Specifically, confirmation bias is a general term for an "unwitting selectivity in the acquisition and use of evidence" (Nickerson, 1998, p. 175). Nickerson (1998) notes that it is important to note that the definition of confirmation bias identifies two mechanisms by which information (in general or feedback in this case) can be differentially attended to. First, information consistent with a previously held notion or model of relationships is more likely to be noticed. Second, when weighing different pieces of information (feedback), consistent information is apt to be more heavily weighted than disconfirming information. In addition, rationalization and distortion mechanisms may be applied to nominally conflicting information, resulting in a belief that the information actually supports a currently held belief.

Several explanatory mechanisms have been proposed to understand the existence of confirmation bias. For example, confirmation bias may be evolutionary beneficial because it allows for continued focus and limits overreactions to every incidence of information contradictory to currently held beliefs, minimizing switching costs (Nickerson, 1998). In addition, confirmation bias may help overcome cognitive limitations. For example, it may be related to the preferential activation of related memories from all possible memories (Evans, 1989). Alternatively, by effectively excluding some information, confirmation bias reduces the cognitive load imposed by a situation (Nisbett & Ross, 1980). Finally, people may be motivated to support a particular position (Matlin & Stang, 1978); for example, research has revealed a general tendency to overestimate self-reported performance levels (Nickerson, 1998)

Each of these potential mechanisms is consistent with the present discussion pertaining to control theory. For example, the selective exclusion or minimization of particular feedback serves to reduce cognitive demands. In addition, the stabilizing function of confirmation bias is consistent with enabling the general stability of high-level goals, which generally have cycle-times measured in months (Lord & Levy, 1994). Further, this goal stability coupled with a general desire to reduce discrepancies between current and desired performance (Carver & Scheier, 1998; Powers, 1973) may also lead to motivated processing of available feedback information. Thus, as it pertains to control theory, the phenomenon of confirmation bias predicts that the input signal will be biased towards feedback that is consistent with the currently active model. Also consistent with the current discussion, this may arise in part due to selectively attending to the available feedback.

Before concluding this discussion on the potential effects of bounded rationality on control theory, it is important to highlight the difference between perceived and actual goal progress. Specifically, control theory posits that when faced with a goal that seems unattainable based on a lack of progress, individuals may withdraw from the goal and accordingly cease goal striving activities (Carver & Scheier, 1981, 1982, 1998). However, it is important to note that the activation of misspecified models combined with the selective attention to feedback in support of those models (as discussed thus far) can cause a divergence between actual and perceived goal attainability (Carver & Scheier, 1981, 1982, 1998).

Specifically Carver & Scheier (1981, 1982, 1998) point out that, if the presumed relations across goal levels are misspecified, inappropriate lower level goals can be set, creating the possibility that achieving a lower level goal can actually be detrimental to the high level goal, even though the individual perceives progress toward the high level goal. Conversely, behavior may actually result in progress toward the high level goal, even though this is likely not to be perceived unless progress on the lower level goal occurs simultaneously, something that may not occur when the relationship among goals is misspecified (Carver & Scheier, 1981, 1982, 1998). In instances such as these, individuals may continue to persist with goal striving activities due to perceived goal progress when in actuality none is being made. Updating the active model of inter-goal relationships via the incorporation of additional feedback (i.e. exploration) presents an avenue for escape from this potentially damaging control cycle characterized by either ineffective goal striving or unrecognized goal progress.

In addition to presenting a general overview of control theory, this section highlights the presence of some additional nuance imposed by boundedly rational actors. Specifically, individuals are likely to incorporate internal models along with a guided subset of available feedback when synthesizing the input signal that is critical to the functioning of the control loop (see Figure 2). Various combinations of selective environmental scanning and internally derived situational models can be seen as analogous to favoring exploration or exploitation. Depending on the orientation selected, the selection and interpretation of available feedback is apt to vary significantly. Consistent with I-ADAPT theory (Ployhart & Bliese, 2006) and the preceding discussion, it would seem that high levels of adaptive performance are facilitated by the adoption of self-regulation processes that effectively balance sufficient situation simplification with a continued ability to recognize and incorporate feedback signaling a need for change along with an ability to modify this balance as appropriate over time. The balance of this section discusses individual differences that are likely to play a significant role in determining the activation of these two competing orientations (i.e. explore and exploit) in the presence (and absence) of an externally imposed, difficult, specific goal.

The Role of Intelligence in Adaptive Performance

The Case for a General Conceptualization of Intelligence

Defining intelligence is a challenge that has confronted researchers for the better part of a century (e.g., "Intelligence and its measurement: A symposium," 1921) and work in this field continues today (e.g., Hampshire, Highfield, Parkin, & Owen, 2012). During that time, numerous conceptualizations of intelligence have been put forth. While some conceptualizations favor a single factor model of intelligence (e.g., Brand, 1996; Jensen, 1998), most contemporary models of intelligence include a hierarchical structure with a single higher order general intelligence factor and multiple lower order constructs relating to intelligence in more specific domains (Sternberg, 2003). Traditional multi-level conceptualizations include Cattell's (1971) crystalized and fluid intelligence factors. More contemporary research in this domain has proposed additional sub-facets of intelligence including emotional intelligence (Salovey & Mayer, 1990), cultural intelligence (Ang, Van Dyne, & Koh, 2006), and successful intelligence (Sternberg, 2003). Many of these dimensions are in turn thought to be comprised of multiple sub-dimensions (e.g. the meta-cognitive, cognitive, motivational & behavioral factors of cultural intelligence, Ang et al., 2006).

While the various theories of intelligence vary in their degree of granularity, at their foundation is a common theme, namely that intelligence is related to the ability to successfully interact with the environment, via some combination of adaptation, shaping, and selection (Sternberg, 2003). Also supporting the applicability of a general conceptualization of intelligence, a recent analysis of 13 existing meta-analyses spanning 25 years found that the median corrected correlation between general intelligence (or general mental ability, GMA) and performance across a wide variety of blue and white collar occupations ranging from clerical to managerial, firefighters to computer programmers was 0.40 (Morgeson et al., 2007b). In addition, even though Hampshire et al. (2012) use recent neural imaging data indicating that different portions of the brain may be associated with different sub-facets of intelligence to argue for separation, they concede that many tasks require activation of more than one of these cognitive systems, supporting a coarser conceptualization.

Consistent with previous work investigating adaptive performance (e.g., Lang & Bliese, 2009; LePine et al., 2000; Pulakos et al., 2002) and the discussion above highlighting ongoing disagreement about the various sub-facet structures of intelligence as well as evidence supporting the utility of GMA, for the balance of this manuscript, intelligence is conceptualized in terms of GMA. This decision allows for this work to build directly on the previous examples cited above and is consistent with the broad conceptualization of adaptive performance put forth earlier. It is not meant to imply that more granular facets of intelligence might not be beneficial for future inquiry. For example, a prima facie analysis would seem to imply that cultural intelligence would be particularly relevant to the cultural adaptability facet put forth by Pulakos et al. (2000), and future work can begin to flesh out these relationships, though they are beyond the scope of the present investigation. Finally, in order to help guide the reader through the remainder of this section, Table 3 summarizes the hypotheses that will be developed going forward.

Table 3: Summary of Hypothesized Relationships

Antecedent	Initial TA	Initial RA	Subsequent TA	Subsequent RA
GMA	H1: – H16a: (↑)	N/A N/A	H2: + H16b: (↑)	H3: + H16c: (↑)
Conscientiousness				
Industriousness	H4a: – H17a: (↓)	H5a: + H17c: (↓)	H4b: – H17b: (↓)	H5b: + H17d: (↓)
Orderliness	H6a: – H18a: (↓)	H7a: – H18c: (↓)	H6b: – H18b: (↓)	H7b: – H18d: (↓)
Openness				
Intellect	H8a: + H19a: (↓)	H9a: + H19c: (↓)	H8b: + H19b: (↓)	H9b: – H19d: (↓)
Openness	N/A	N/A	N/A	N/A
Neuroticism				
Volatility	H12a: + H20a: (↑)	H10a: – H20c: (↑)	H12b: + H20b: (↑)	H10b: – H20d: (↑)
Withdrawal	H13a: + H21a: (↑)	H11a: – H21c: (↑)	H13b: – H21b: (↑)	H11b: – H21d: (↑)
Performance Goal	H14a: –	H15a: –	H14b: –	H15b: +

Notes: TA is transition adaptation. RA is reacquisition adaptation. N/A indicates that a relationship was not hypothesized for this cell. Performance Goal indicates the presence of a specific, difficult performance goal in comparison to a "do your best" goal. The numbers and letters following a "H" refer to the hypothesis number where the nature of the relationship is specified. A "+" indicates that a positive relationship is hypothesized. A "–" indicates that a negative relationship is hypothesized. Symbols in parenthesis refer to the direction of the hypothesized interaction with goal condition. (↑) indicates that the hypothesized relationship is stronger in the presence of a performance goal while (↓) indicates that the relationship is hypothesized to be weaker in that goal condition.

Proposed Effect of Intelligence on Initial Transition Adaptation

Since the work of Schmidt, Hunter and colleagues in the early 80's (e.g., Hunter & Hunter, 1984; Pearlman, Schmidt, & Hunter, 1980; F. L. Schmidt et al., 1981), a moderate

(Cohen, 1988), positive relationship between intelligence and job performance has generally and consistently been found (Morgeson et al., 2007b). With evidence of this magnitude, one may be tempted to consider the relationship between intelligence and adaptive performance likewise settled. However, there is also evidence indicating that such a conclusion might be premature. First, as previously discussed, the work environment has changed considerably in the 30 plus years since the preponderance of this data was collected (Burke, Pierce, et al., 2006; Cascio, 1995; Pearlman & Barney, 2000; Pulakos et al., 2000). In addition, work from domains other than work performance has often revealed mixed effects for intelligence. Relevant work from those areas is discussed below, indicating that the relationship between intelligence and adaptive performance might be actually be more complex than it may seem at first glance.

As discussed previously, cognitive limitations inherent in human processing limit the ability to process all available feedback (March & Simon, 1958; Sheridan, 2004). Further, this limited processing is apt to result in an input signal that is inaccurate and biased towards supporting the current program (Evans, 1989). This program-specific focus allows for the application of a larger proportion of available resources towards accomplishing the desired goal. In terms of control theory, this can be characterized as the "working harder" aspect of the behavioral approach to discrepancy reduction laid out by R. E. Johnson et al. (2013); Winters and Latham (1996).

However, as mentioned previously, it is possible for perceived goal progress and actual goal progress to diverge when the program being executed (and the feedback attended to as a result) do not accurately depict the reality of the situation (Carver & Scheier, 1981, 1998). When this happens, the inaccuracy of the input signal may inhibit the comparator from detecting a discrepancy between the current state and desired state. Without a detected discrepancy, there is not an impetus for action (Carver & Scheier, 1998; Powers, 1973) even though the objective situation may warrant the taking of corrective action. Because cognitive limitations form the basis for this explanatory chain of failed discrepancy recognition and subsequent call to action, it might be natural to assume that low intelligence would increase susceptibility to experiencing these effects. However, that may not be the case, and in actuality, while higher intelligence may enable people to work harder by better focusing available cognitive resources (Braver et al., 2007; Kane & Engle, 2002), this process may also lead to greater novel feedback inattention.

Before delving into specific hypothesis development, it should be noted that much of the research that will be drawn upon has looked at attentional differences associated with variations in working memory capacity (WMC). WMC has traditionally been conceptualized as being functionally synonymous with GMA (Jensen, 1998). As a result of recent work, this view has been expanded somewhat. Now, WMC is viewed as being at least a key sub-facet of GMA (Ackerman, Beier, & Boyle, 2005) and may be an explanatory driver of individual differences in GMA (Kane, Hambrick, & Conway, 2005; Oberauer, Schulze, Wilhelm, & Süß, 2005). While the exact nature of the relationship between GMA and WMC remains subject to debate, the two constructs are generally recognized as being substantially related (Ackerman et al., 2005; Kane et al., 2005; Oberauer et al., 2005), and as such research findings from the WMC literature should be relevant to the current discussion of the relationship between GMA and adaptive performance (Lang & Bliese, 2009).

Specifically, WMC researchers have proposed that the ability to maintain increased focus on feedback relevant to the presently activated program, thereby minimizing the impact of other information (inherently deemed to be irrelevant), is one mechanism by which intelligence may lead to increased performance (Braver et al., 2007; Hutchinson, 2011; Kane & Engle, 2003).

This effect has been demonstrated primarily using a Stroop task (Stroop, 1935) in which participants are asked to indicate the color of the displayed text and ignore the content of the text itself. The text forms a word that describes a color and it can be either congruent with (i.e. match) the font color or it can be incongruent (i.e. mismatch) the displayed color. For example, in a congruent case, "red" would be displayed in a red font while in the incongruent case, "red" might be displayed in green (or orange or any other color besides red) font.

Kane and Engle (2003) found that compared to high WMC, low WMC was associated with increased error rates when participants were exposed to mainly congruent lists of words. They attributed this finding to an inability for low WMC individual to maintain focus on the goal of responding to the color of the text rather than falling back into the habit of reading the word itself when there was infrequent external reinforcement to do so. In other words, because the low effort strategy of reading the word itself yielded the correct response in most cases for the largely congruent trials, individuals were tempted to incorporate the text-driven information when making their response. However, this effect was found to be related to WMC such that high WMC was associated with making fewer errors, presumably because those high in WMC were able to successfully execute the program of relying the on the font color while excluding information obtained from the word formed by the text itself (Hutchinson, 2011; Kane & Engle, 2003).

Additionally, low WMC was associated with longer response times for a Stroop task characterized by mostly incongruent trials , and these effects even spilled over to hinder response times on the block of trials following the incongruent block (Hutchinson, 2011; Kane & Engle, 2003). It would appear that even when the textual information is only minimally relevant to the task at hand, low WMC impedes an individual's ability to suppress the irrelevant information, and as such they must evaluate both sources of color information and subsequently chose the correct response. Again, these results support the contention that high WMC is associated with increased focus on program relevant information at the expense of information that is not required for program execution.

Braver et al. (2007) incorporate information pertaining to brain structure and function in order to integrate these sorts of findings into dual methods of control (DMC) theory. This theory proposes that working memory can be controlled either proactively or reactively and that the method of control employed varies both between and within individuals. Proactive and reactive refer to whether the program is activated prior to or after exposure to a stimulus. Specifically, when proactive control is engaged, a program thought to be relevant for the situation at hand is engaged prior to stimulus exposure, and as a result, attention is dramatically biased toward information required to execute the selected program. This can make it more difficult to notice and react to a change. Conversely, DMC predicts that reactive control relies on the stimulus itself to activate a particular program, and as such, this method of control results in much more egalitarian attention allocation when exposed to the stimulus. Because proactive control requires continual activation of the pre-frontal cortex to differentially focus attention, it is more cognitively resource intensive, and "it is likely that individuals possessing greater cognitive resources will be those most willing and able to adopt a proactive mode" (Braver et al., 2007, p. 88).

The results discussed previously are consistent with this view. Those high on WMC were able to engage in proactive control and effectively exclude the irrelevant textual information, resulting in faster response times and fewer errors. Conversely, low WMC individuals had to rely primarily on reactive control, requiring them to evaluate multiple streams of information from the on-screen stimulus before selecting the appropriate program to execute. This additional post-stimulus processing is likely to increase response times and the possibility of selecting inappropriate programs, increasing error rates.

However, while proactive control may be beneficial for Stroop task performance, it is not without its drawbacks. Because proactive control relies more heavily on preconceived models of the situation, information signaling an underlying environmental change is more easily discarded than when reactive control is employed (Braver et al., 2007). This propensity to discard feedback is further exacerbated by the cognitive resource requirements required to engage in proactive control. When proactive control is active, environmental monitoring is greatly diminished, further reducing the ability to capitalize on feedback signaling the need for a change.

Consistent with DMC theory and the empirical evidence considered, GMA would seem to be related to how feedback information is attended to and incorporated into an input signal necessary for effective operation of a negative control loop. Specifically, higher levels of GMA tend to increase focus on information relevant to the program being executed. This differential focus can increase performance in static settings where the activated program is more likely to correspond to the objective reality (Braver et al., 2007) because the control loop focuses effort on successful execution of the program and as such, successful accomplishment of the intended goal. Conversely, this program oriented focus is apt to limit receptiveness feedback indicating that the underlying program may no longer be adequately accurate. As a result, recognition of the need for change may be delayed, resulting in diminished performance after a change has occurred, which is aligned with the negative relationship between GMA and adaptive performance reported by Lang and Bliese (2009).

Hypothesis 1: GMA will be negatively associated with initial transition adaptation.

Proposed Effect of Intelligence on Initial Reacquisition Adaptation

As previously discussed, increased focus on program relevant feedback and the subsequent consolidation and application of available resources to resolve detected discrepancies can be thought of as one means of exercising the behavioral route to goal striving by "working harder". In addition, the cited research indicates that high GMA is associated with an increased ability to execute this approach, potentially leading to the increased performance generally attributed to higher levels of GMA. However, high GMA may also enable individuals to also "work smarter" when striving to reduce detected discrepancies between current and desired states as well.

Specifically, higher levels of GMA are thought to lead to increased performance via selection and execution of more complex, cognitively demanding goal striving programs (Beilock & Carr, 2005; Beilock & DeCaro, 2007). This ability does not seem to be totally context independent, and research has identified situations under which these high performance programs enabled by high GMA must be abandoned due to increased cognitive demands from other sources. In addition, when these generally "superior" programs are applied in inappropriate situations, performance may actually suffer. The implications of these findings for understanding how individuals may perform after a change has been recognized are discussed below.

Beilock and colleagues (Beilock & Carr, 2005; Beilock & DeCaro, 2007) have consistently shown that one thing that seems to disrupt the ability of high GMA individuals to employ more effective programs is the presence of anxiety. They have primarily investigated this effect while trying to understand the phenomenon of choking, "performing more poorly than expected given one's skill" (Beilock & Carr, 2005, p. 101). Specifically, they have found that in low pressure conditions, WMC is positively associated with performance on cognitively demanding tasks (e.g. complex math problems) due to the application of more complex problem solving programs (Beilock & DeCaro, 2007). However, when there is elevated pressure to perform, those with high WMC tend to "choke" and their performance becomes indistinguishable from those with low WMC (Beilock & Carr, 2005; Beilock & DeCaro, 2007).

This effect seems to be due primarily to the additional cognitive demands induced by the additional pressure (Beilock, Kulp, Holt, & Carr, 2004). Specifically, performance anxiety can induce worrisome thoughts that occupy some cognitive resources that were previously applied to executing the problem solving program (Ashcraft & Kirk, 2001; M. W. Eysenck, Derakshan, Santos, & Calvo, 2007). In addition, performance anxiety can induce a negative emotional response (Gray, 2001), which in turn consumes additional resources (Beal, Weiss, Barros, & MacDermid, 2005).

Thus, performance anxiety can negate the advantage associated with high GMA on both of the potential behavioral paths available for goal striving. First, individuals can become distracted by the source of the anxiety (Beilock et al., 2004), limiting their ability to focus all available resources on completing the task at hand (i.e. working harder). In addition, this distraction combined with worrisome thoughts and negative affective responses that further consume resources that tend to prevent high GMA individuals from utilizing the complex programs (i.e. working smarter) that enable them to excel in low pressure situations (Beilock & DeCaro, 2007). While adaptive performance doesn't necessarily entail additional external pressure, individuals are apt to feel self-imposed pressure to perform after a change-induced performance decrement has occurred (Lang & Bliese, 2009). Further, this is consistent with control theory models that propose that an internally perceived lack of goal progress (i.e. feedback indicating insufficient or negative velocity) is likely to induce a negative emotional response (Carver & Scheier, 1990; R. E. Johnson et al., 2013; Lawrence, Carver, & Scheier, 2002).

Even without inducing performance anxiety, additional work regarding WMC and dual-task performance may be relevant to adaptive performance. The dual-task literature has consistently demonstrated a link between WMC and decrements in complex task performance when a secondary, simultaneously performed task is added (Kane & Engle, 2002; Kane & Engle, 2000; V. M. Rosen & Engle, 1997). Specifically, as expected, these researchers have found that WMC is positively related to performance when participants worked on a single, complex task, presumably for the reasons discussed thus far. However, when an additional task is processed in parallel, the relationship between performance on the primary task and WMC disappears. Further, it is the high WMC individuals who experience the largest decrement, becoming indistinguishable from those with low WMC (Kane & Engle, 2002; Kane & Engle, 2000; V. M. Rosen & Engle, 1997). These authors contend that this is because the secondary tasks requires high WMC individuals to abandon the more complex programs that they normally adopt and instead execute simpler programs, mimicking those typically employed by low WMC individuals.

In the context of adaptive performance, recognition that a change has occurred can introduce the equivalent of a secondary task as people work to understand what has changed and how to respond, all while continuing to execute their job duties (Lang & Bliese, 2009). Control theorists have noted that the realization that a program was inaccurate may trigger the activation of a higher level goal aimed at program refinement (Carver & Scheier, 1981, 1982). The activation of this additional goal may temporarily shift focus to feedback previously marginalized, diverting attentional resources away from the accomplishment of the initial task.

This is likely to reduce or eliminate the attentional benefits of high GMA that allow them to effectively work harder on the focal task. Further, updating and improving the program to incorporate relevant additional information tends to preclude optimal execution of the program itself (March & Simon, 1958). As a result, the temporary unavailability of the more complex program limits the viability other behavioral avenue generally available to reduce performance discrepancies. Specifically, the ability of high GMA individuals to work smarter by deploying superior problem solving approaches is likely to be temporarily curtailed.

Finally, it should be noted that the more complex programs generally preferred by high GMA individuals (Beilock & Carr, 2005; Beilock & DeCaro, 2007) are not universally advantageous. For example, WMC has been shown to be negatively related to remote associates task (Mednick, 1962) performance (Ricks, Turley-Ames, & Wiley, 2007). In this creative problem solving task, participants must select a single word that completes three phrases. However, when the phrases were selected such that only the first two phrases of each triplet could be successfully completed by selecting a word related to a particular domain (i.e. baseball), the performance advantage afforded by high WMC was negated for those with an extensive knowledge of that particular domain (Ricks et al., 2007). The authors propose that this effect was due to overreliance on presumed domain relevancy when focusing attention on a subset of potential words for retrieval. In other words, those high on WMC seemed to develop a more complex program of problem solution. They presumably built a more complex program that incorporated not only the information stated in the problem, but also assumed that a particular domain could be used to limit potential word choices. Further, the domain chosen for this filter was something they were familiar with, consistent with the differential attentional effects predicted by confirmation bias (Evans, 1989).

A similar relationship between WMC and program complexity was reported by Beilock and DeCaro (2007). Specifically, they found that when solving math problems, those high on WMC consistently adopted more complex problem solving programs and maintained them over time, even though simpler methods of solution were equally accurate and faster and therefore preferable in terms of efficiency. Because problems early in the exercise had to be solved with the more complex program, continued solution of the math problems at rates consistent with earlier trials, did not signal a discrepancy indicating the need to update the program. As a result, high WMC individuals did not initiate search activities that might have uncovered a quicker solution algorithm by incorporating previously ignored feedback. This failure to switch over to an optimal solution approach when the current approach is adequate is consistent with satisficing (March & Simon, 1958) arguments of program selection. On the other hand, those lower on WMC presumably had trouble executing the complex program and when they had difficulty achieving the goal of problem solution, adopted the simpler approach as their default method of problem solution.

Collectively, this research illustrates that while the more complex programs typically utilized by those high on GMA (Beilock & Carr, 2005; Beilock & DeCaro, 2007) are generally advantageous, the effects are not universal. The presence of additional demands likely to occur in situations requiring adaptation can cause these resource intensive programs to be abandoned. In addition, if the programs are misspecified, they can result in suboptimal performance even when executed. In light of these arguments and consistent with the work of Lang and Bliese (2009) in the domain of adaptive performance, no relationship between GMA and initial reacquisition adaption is hypothesized.

Proposed Effect of Intelligence on Subsequent Adaptation

Conceptual work extoling the importance of adaptive performance describes an increasingly dynamic organizational landscape (e.g., Burke, Pierce, et al., 2006; Pulakos et al., 2000). In such a dynamic environment, employees are confronted with unprecedented rates of change (Cascio, 1995). The rate of change limits the ability of organizations to develop processes in real time, and employees often must decide how to respond on their own (Pearlman & Barney, 2000). If this is the type of environment in which adaptive performance regularly occurs, it seems important to consider how people might respond to repeated change episodes. Since both goal striving and search programs can be developed and refined over time, the response of an individual to subsequent change events may be markedly different from their response to the initial change (March & Simon, 1958). Again, control theory is a useful vehicle for understanding specifically how these changes may occur and what their effects on subsequent adaptive performance might be.

As a result of the increased program-relevant focus typically exhibited by high GMA individuals (Braver et al., 2007; Hutchinson, 2011; Kane & Engle, 2003), feedback indicating a change has occurred may tend to be ignored. In such a situation, control theory predicts that the discrepancy between perceptions of the current state and the goal state necessary for signaling the need for corrective action will not be registered. As a result, when a change occurs, high GMA individuals may be caught particularly unaware. However, control theory also predicts that realizing that a change has occurred and that a program is no longer adequate will serve as a discrepancy relative to a higher level goal, and efforts to update the program will be undertaken as a result (Carver & Scheier, 1981, 1982), and a program can be developed to incorporate previously novel feedback (March & Simon, 1958).

This control theory derived explanation of hierarchical goal driven program revision is also consistent with neurobiological aspects of DMC theory. Specifically, DMC predicts that one portion of the brain, the midbrain dopamine system, is responsible for updating the information used by a second system, the medial prefrontal cortex, to keep attention focused on information deemed to be task relevant (Braver et al., 2007). While the midbrain dopamine system is slower to change than the medial prefrontal cortex, it is capable of learning over time, and as a result can influence the information that the prefrontal cortex is biased towards processing when striving toward achieving a particular goal (Braver et al., 2007). This is consistent with the control theory prediction that a slower cycling, higher level control loop that incorporates performance information over time can influence the content of a mid-level, program focused loop (R. E. Johnson et al., 2006; Lord & Levy, 1994).

To the extent that this effort is successful, feedback indicating the presence of a change that was previously ignored will be integrated into the updated operating program. Further, the process of searching for and identifying relevant feedback can itself be programmed (March & Simon, 1958), and just as high GMA allows individuals to adopt more complex (and generally more effective) goal striving programs at lower levels (Beilock & Carr, 2005; Beilock & DeCaro, 2007), they are also likely to employ more complex, effective search programs relative to goal striving at higher levels as well. This is consistent with established theories that positively link GMA to learning, especially for complex tasks (Ackerman, 1987). In addition, cognitive ability has been meta-analytically found to be positively related to learning in the context of organizational training (Colquitt, LePine, & Noe, 2000). Thus, GMA should be related to an individual's ability to learn from the initial change and effectively incorporate additional feedback relevant for detecting and dealing with similar changes in the future into lower level goal striving programs.

Hypothesis 2: GMA will be positively related to subsequent transition adaptation episodes.

There is also reason to believe that GMA may be related to subsequent reacquisition adaptation as well. While anxiety has been generally found to disproportionally reduce performance for those high on WMC (Beilock & Carr, 2005; Beilock & DeCaro, 2007), there is also evidence that these effects may diminish over time. For example, practicing math problems ahead of time can reduce the magnitude of subsequent decrements when they are performed in high pressure (vs. low pressure) situations (Beilock et al., 2004). In addition, performing a task in a high pressure situation can make one less susceptible to subsequent pressure induced performance decrements, even when the source of the pressure varies from the previous condition (Beilock & Carr, 2001). Thus, after repeated changes, high GMA individuals may not be particularly susceptible to anxiety induced performance decrements.

In addition, drawing on theories of WMC and learning, it was previously argued that high GMA individuals should be better able to update their goal striving programs to incorporate previous change-related information. This is consistent with a general preference for and ability to execute more complex and generally more effective programs (Beilock & Carr, 2005; Beilock & DeCaro, 2007) throughout their goal hierarchies. If this is the case, these programs are apt to be more effective than the programs enacted by those lower on GMA (consistent with the generally observed positive relationship between performance and GMA). In addition, the secondary task processing requirements that tend to disproportionally affect high GMA individuals (Kane & Engle, 2002; Kane & Engle, 2000; V. M. Rosen & Engle, 1997) are apt to be reduced.

The more effective the modified programs are performing, the less likely a search-inducing discrepancy between desired and actual states will be signaled, reducing the probability that a second task will be introduced for those high on GMA. Beyond the predictions of control theory, this is consistent with notions of satisficing (March & Simon, 1958) and previous work demonstrating that high WMC individuals are disinclined to search for more effective programs if the current program demonstrates consistent performance over time (Beilock & DeCaro, 2007). Finally, with opportunities to learn from previous change events, it becomes less likely that the programs employed by high GMA individuals will be incorrect.

In summary, many of the factors of post-change performance thought to disproportionally affect high GMA individuals and limit their ability to perform in the initial reacquisition performance episode are no longer likely to be as problematic. As a result, these hindrances should be less likely to counter the generally observed positive relationship between performance and GMA (Morgeson et al., 2007b). In other words, there should be few impediments to focusing on an appropriate subset of the available feedback with task relevancy (including change relevancy) and cognitively intensive programs that are generally superior at realizing goal attainment.

Hypothesis 3: GMA will be positively related to subsequent reacquisition adaptation episodes.

The Role of Personality in Adaptive Performance

Lang and Bliese (2009) note that while GMA seems to play an important role in adaptive performance, it does not appear to be the only relevant predictor, and they advocate future investigations focused on exploring the potential role of personality. The relationship between personality and performance has been a topic of interest for the better part of a century (Barrick et al., 2001). Despite numerous efforts to demonstrate a consistent and practically relevant relationship between personality and performance, reviews covering the work conducted during the first half of this extended period of inquiry concluded that evidence supporting such a relationship did not exist (e.g., Guion & Gottier, 1965; Locke & Hulin, 1962). The ability to demonstrate such a relationship was undoubtedly hindered by the numerous conceptualizations and operationalizations of personality that characterized this early work (Barrick et al., 2001). While numerous conceptualizations of personality still exist today (DeYoung, Quilty, & Peterson, 2007), the proposal that personality can be categorized by five general personality traits (e.g., W. T. Norman, 1963; Tupes & Christal, 1961) has resulted in some support for the existence of the long-sought relationship between personality and performance.

The components of this five factor model (FFM), or the big-five are generally known as Conscientiousness, Agreeableness, Neuroticism (or its polar opposite Emotional Stability), Openness, and Extraversion (Barrick et al., 2001; DeYoung et al., 2007; W. T. Norman, 1963; Tupes & Christal, 1961). Barrick and Mount (1991) used this taxonomy in their seminal meta-analysis to demonstrate meaningful relationships between several of the traits and performance. Since this work, several other meta-analyses have been conducted (e.g., Hough, 1992; Salgado, 1998; Tett, Jackson, & Rothstein, 1991) and while there is some variation, they generally support the presence of a significant relationship between some aspects of the FFM of personality and job performance. Based on the results of a second-order meta-analysis conducted on 15 primary meta-analyses Barrick et al. (2001) conclude that Conscientiousness and to a lesser extent Emotional Stability were positively and generally related to job performance while

Agreeableness, Extraversion, and Openness are positively related to some facets of performance (e.g. teamwork) across occupations and to overall performance in certain types occupations (e.g. professionals).

Despite the substantial evidence linking personality to performance, belief in the usefulness of personality for predicting performance is not universal. Some have expressed concerns about the practical usefulness of personality given the comparatively modest effect sizes when compared to GMA (Morgeson et al., 2007a, 2007b). However, others have pointed out that there are other considerations beyond absolute effect size. For example, personality has incremental validity above GMA when predicting performance (Ones, Dilchert, Viswesvaran, & Judge, 2007). Hough (2001) has called the recognition of the importance of personality in predicting job performance a major advance for I/O psychology. In addition, because personality is generally independent of intelligence (McCrae & Costa, 1987) personality can allow for the maintenance of adequate predictive validity while still mitigating the adverse impact concerns that prevent many U.S. based firms from over-reliance on GMA heavy selection procedures (Outtz, 2011). As a result, research on the relationship between personality and performance is experiencing a "renaissance", remaining an area of interest for researchers and practitioners alike (Barrick et al., 2001, p. 10).

In addition to general concerns about the utility of personality, support for the "big-five" structure of personality itself is not universal, and this conceptualization has been criticized on numerous fronts (e.g., Ashton et al., 2004; Block, 1995; H. J. Eysenck, 1992; Hough & Dilchert, 2010). However, data supporting the appropriateness of the FFM exists beyond the factor analyses that initially gave rise to it. For example, research on heritability has demonstrated similar genetic effect sizes for factors in the FFM (Bouchard, 1997). In addition, the FFM has demonstrated stability over numerous theoretical frameworks, data collection methods, cultures, and languages (e.g., Digman & Shemelyov, 1996). Longitudinal data collected over the course of several years also indicates that the FFM is stable within individuals over time (Costa & McCrae, 1988).

As a result, since the 1990's most personality research has been conducted using the FFM taxonomy (Barrick et al., 2001) and the FFM remains the most widely used personality taxonomy today (Hough & Dilchert, 2010). Barrick et al. (2001, p. 11) characterize the current situation by noting "While there is not universal agreement on the Big Five model, it is a useful taxonomy and currently the one considered most useful in personality research" Thus, consistent with this sentiment and the prevailing direction of the field, a FFM conceptualization of personality is adopted here. In addition, the development of theoretical predictions relating personality to adaptive performance answers the call of Thoresen, Bradley, Bliese, and Thoresen (2004) to investigate personality, and in particular more granular conceptualizations of personality in the context of dynamic performance, rather than the unrealistic static performance conceptualizations that characterize much of the existing body of personality-performance research.

The Case for a Facet Conceptualization of Personality

Even though much work on the relationship between personality and performance in general has been conducted, research in this area is hindered by a criterion problem, like most research on performance (Barrick et al., 2001). Specifically, most research on personality and performance included generally static conceptualizations of performance including granular aspects such as objective performance, supervisor ratings, and teamwork, (Barrick et al., 2001). This problem has previously been recognized and Barrick et al. (2001) called for future researchers to utilize more nuanced conceptualizations of performance. However, even the taxonomy of performance that they recommend employing (Viswesvaran, 1993) does not contain an adaptive component. As a result, much less is known about the relationship between personality and adaptive performance than about relationships between the Big-5 traits and more established components of performance that have been repeatedly meta-analyzed.

Even though the body of work done in the area of personality and adaptive performance is relatively small, some initial themes have emerged. For example, in contrast to the broad conceptualization of intelligence discussed previously, there are conceptual and empirical reasons to consider personality traits at a more granular level in this domain, and failure to do so may help explain why prior research in this area has reported conflicting relationships between some of the big-five personality traits and adaptive performance.

Specifically, across different studies, Conscientiousness and Openness have each been found to be both positively and negatively related to adaptation (e.g., LePine et al., 2000; Stewart & Nandkeolyar, 2006). A more fine-grained analysis of Conscientiousness revealed that the reported negative relationship was driven primarily by the Dependability facets while the Achievement facets were unrelated (LePine et al., 2000). Further, in a team context, the dependability aspect was still negatively related while the achievement aspect actually demonstrated a positive relationship with adaptation (LePine, 2003). This sort of counter-balancing relationship may help explain other work that found a null relationship between Conscientiousness and adaptive performance (e.g., Allworth & Hesketh, 1999).

The decision of whether to focus on the more granular traits of the big-five or the more narrow facets that are proposed to comprise each trait is one that personality researchers in a broad range of domains are faced with (Hough & Dilchert, 2010). More generally, it is a question of balance between bandwidth and fidelity; a question that has been faced by psychology researchers for more than 50 years (e.g., Cronbach, 1960). Due to increased bandwidth, the broader, more encompassing traits of the FFM are more likely to be relevant across a wide range of settings; for example, for general conceptualizations of performance (e.g. overall performance) or performance measured across a variety of job contexts, including team and individual based work environments (Mount & Barrick, 1995; Ones & Viswesvaran, 1996).

In contrast, the individual facets are less likely to be universally applicable, but their narrower focus may result in stronger relationships with similarly specific aspects of performance (Mount & Barrick, 1995; Stewart, 1999), especially when there are a-priori, theoretical reasons to link a specific aspect of performance with a particular facet of personality (Ashton, Jackson, Paunonen, Helmes, & Rothstein, 1995). In a related vein, the finer grained personality facets also have the advantage of being theoretically clearer and more focused than the broader, more nebulous higher level trait conceptualizations of personality (Block, 1995; Hough, 1992; Hough, Eaton, Dunnette, Kamp, & McCloy, 1990). This makes them particularly important for advancing theory relative to understanding the underlying mechanism by which personality influences performance (Dudley, Orvis, Lebiecki, & Cortina, 2006). As a result, researchers have been encouraged to go beyond the general traits of the FFM and investigate relationships at more granular levels (Barrick et al., 2001; Dudley et al., 2006; Hough & Dilchert, 2010).

One issue that has hindered researchers' ability to implement this recommendation is disagreement over the number and content of the facets that comprise each trait of the FFM of personality (Barrick et al., 2001). The Revised NEO Personality Inventory (NEO-PI-R; Costa & McCrae, 1992), which is the most commonly employed factorization (Saucier & Ostendorf, 1999), incorporates 30 facets, 6 for each of the big-five traits. However, this is far from the only employed conceptualization. Other established scales include 12 (PCI; Mount, Barrick, Laffitte, & Callans, 1999), 18 (Saucier & Ostendorf, 1999), 32 (GPI; Schmit, Kihm, & Robie, 2000), 44 (HPI; R. T. Hogan & Hogan, 1992) and 45 (A5BC; Hofstee, de Rand, & Goldberg, 1992) facets distributed across the big-five traits in various manners.

More recently, researchers have identified meso-level personality "aspects" that reside in the important middle-ground between the high level traits of the FFM and the low level facets underlying each trait (DeYoung et al., 2007). Jang, Livesley, Angleitner, Reimann, and Vernon (2002) analyzed the 30 facets of the NEO-PI-R using twin data and identified two biologically based, genetic factors that seem to underlie the shared variance across facets. While Jang et al. (2002) may have identified a potential biological basis for the existence of two aspects per trait for all of the big-five, they are by no means alone in proposing this sort of structure. Nearly 20 years ago, J. A. Johnson (1994) proposed separating the trait of Openness into Ideas and Aesthetics, focusing on an interest in truth and beauty respectively. Shortly thereafter, Depue and Collins (1999) proposed a neurobiological model supporting decomposing the core trait of Extraversion into Agency and Sociability components. Similarly, Anxiety and Irritability components have been proposed for Neuroticism (Saucier & Goldberg, 2001). More recently, Ashton et al. (2004) identified two aspects of Agreeableness, and Roberts, Chernyshenko, Stark, and Goldberg (2005) proposed Industriousness and Order components for Conscientiousness.

When one considers the nature of adaptive performance, these meso-level attributes would seem to be suitable for investigating the role of personality because adaptive performance likewise seems to reside at a mid-level within conceptualizations of performance. Adaptive performance is viewed as a specific component of performance, along with other aspects including OCB, CWB, and task performance (Hesketh & Neal, 1999; Schmitt et al., 2003). While this degree of specificity within the overall performance hierarchy might suggest considering specific personality facets instead of macro traits, it is also important to consider how adaptive performance can manifest itself.

Many conceptualizations of adaptive performance propose a multi-dimensional construct with 6-8 facets (Ployhart & Bliese, 2006; Pulakos et al., 2000; Pulakos et al., 2006). Due to their narrow scope, each of these facets of adaptive performance would seem to be more suitable for prediction at the individual facet level of personality. In the present paper, transition and reacquisition adaptation represent a meso, two aspect conceptualization of adaptive performance. This conceptualization is analogous to the two aspect conceptualization of each personality trait previously discussed. Further, the use of meso-level personality aspects is consistent with previous work in this domain. For example, Conscientiousness has previously been examined in terms of its Achievement and Dependability aspects (LePine, 2003; LePine et al., 2000; Pulakos et al., 2002). Thus, the aspect level of personality seems to be conceptually relevant for examining adaptive performance as defined in the present discussion, and this level of specificity will be employed going forward.

The work on personality aspects discussed above has recently been extended by DeYoung et al. (2007), who replicated this two aspect structure using not only the NEO-PI-R but also the more inclusive AB5C personality inventory and its associated 45 facets. Their results mirrored those of (Jang et al., 2002), resulting in 10 aspects, distributed evenly across the five traits of the FFM (such that each trait is composed of two aspects). In addition, their results were in-line with the previous personality factorizations discussed above. They also formalize their conceptualization by developing and testing a measure for their aspects comprised of items from the commonly available pool of items available as part of the International Personality Item Pool (IPIP) project (Goldberg, 2001).

In summary, the aspect conceptualization of personality (and associated measures) put forth by DeYoung et al. (2007) seems to be conceptually relevant for the study of adaptive performance, and it is the conceptualzation adopted here. Figure 3 shows this relationship graphically in the context of previous work aimed at elucidating the hierarchical nature of personality by identifying meta-traits (DeYoung, 2006; DeYoung, Peterson, & Higgins, 2002; Digman, 1997) along with a similar structure for performance. More specific descriptions of the investigated traits and aspects are provided in subsequent sections. In addition, more detailed information can be found in DeYoung et al. (2007).

Overall, theory pertaining to the mechanisms by which personality impacts performance is lacking and more work to elucidate these processes is needed (Barrick et al., 2001). An effort is made to attempt to begin answering this call below. Hypothesized relationships between relevant aspects of personality and adaptive performance are postulated by examining how these individual differences might impact the functioning of the negative feedback loops fundamental to control theory. By conceptualizing personality at a level congruent with the level of the aspect of performance being investigated and utilizing an established model of self-regulation to explore potential influence mechanisms it is hoped that progress toward understanding these mechanisms will result.

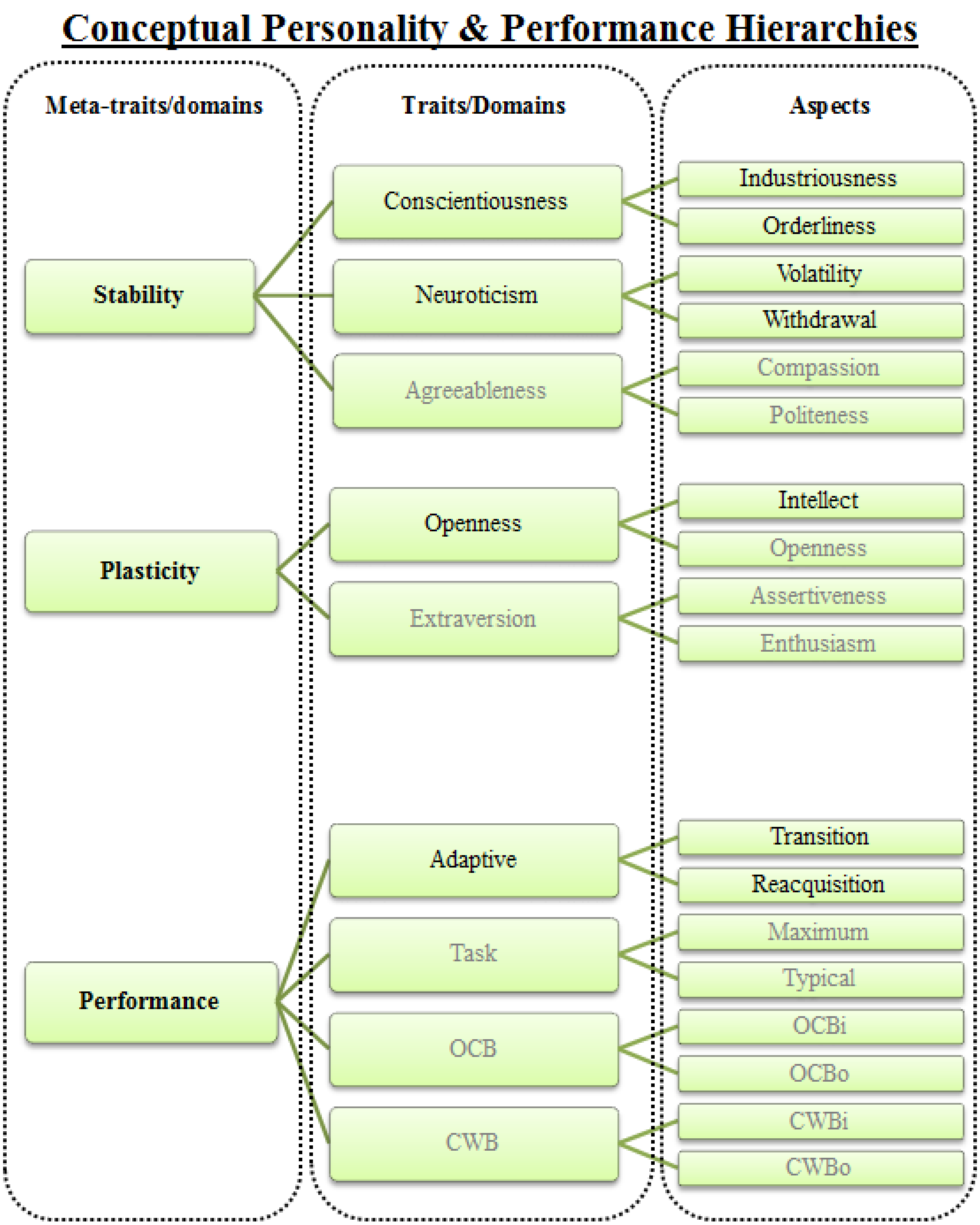

Figure 3: Conceptual Model of Associated Levels of Personality and Performance

Specifically, the discussion focuses on the aspects of Conscientiousness, Openness and Neuroticism. Both Conscientiousness and Openness have previously been included in previous work on adaptive performance. By and large, this is not surprising given the relative ease with which conceptual linkages between adaptive performance and these traits can be established. As such, we heed the call of Lang and Bliese (2009) and investigate these relationships using a more sophisticated and appropriate analytical framework than was available previously. In addition, these traits tend to be of a more cognitively focused nature and the conceptual linkages made during the previous discussion of GMA can be drawn upon to inform this discussion and facilitate their integration into the overarching control theory framework being applied to better understand the functioning of these antecedents.

Of the Big-5 personality traits, Neuroticism is the most valid and generalizable predictor of job performance, aside from Conscientiousness (Barrick et al., 2001). Even though it has not been extensively investigated in relation to adaptive performance, its importance for predicting performance in general would seem to suggest it as an important candidate for further investigation. Further, theoretical hypotheses linking this trait with adaptive performance can be generated by continuing to apply the focal control-theory frame guiding this investigation of adaptive performance. Specifically, negative affect, a central component of Neuroticism (DeYoung et al., 2007), has been found to impact both individual attention and information processing. As previously discussed in the context of GMA, these are both important processes for understanding adaptive performance; as such, inclusion of Neuroticism seems theoretically warranted. Finally, in the interest of completeness, this section concludes with a brief discussion of Extraversion and Agreeableness with a focus on the reasons for their exclusion from this investigation (as alluded to by their being greyed out in Figure 3).

Proposed Effect of Conscientiousness on Adaptive Performance

Conscientiousness has been called the most important trait of the big five for predicting performance (Cortina, Goldstein, Payne, Davison, & Gilliland, 2000; Dudley et al., 2006). Even though Conscientiousness has generally been found to be significantly and positively related to overall performance (Barrick et al., 2001), the relationship in the context of adaptive performance has been found to be more nuanced (e.g., LePine, 2003; LePine et al., 2000). This section attempts to build on earlier findings and discuss specific ways in which the aspects of Conscientiousness may influence program content, execution, and feedback inclusion. The impact that the other dimensions of personality may have on these processes are discussed in subsequent sections.

Conscientiousness has long been thought of as incorporating two aspects, dependability and achievement (e.g., Barrick & Mount, 1991; Digman, 1990; Smith, 1967). Consistent with more recent work by Roberts et al. (2005), in the present taxonomy of DeYoung et al. (2007), these two aspects are referred to as *Orderliness* and *Industriousness* respectively. Orderliness includes notions of organization, thoroughness, and routine while Industriousness incorporates concepts of efficiency, perseverance, and self-discipline (Barrick & Mount, 1991; DeYoung et al., 2007; Roberts et al., 2005). Consistent with previous work demonstrating differential relationships between these facets and work outcomes (e.g., Dudley et al., 2006; Hough, 1992; Roberts et al., 2005; Stewart, 1999), there is reason to believe that these two aspects may be differentially related to adaptive performance.

The volitional, or Industriousness, aspect of Conscientiousness has been found to be more strongly related to job performance in more routine, stable environments, presumably because employees exhibiting this trait were better able to maintain goal focus and a desire to excel (Stewart, 1999). In the context of control theory, this aspect is likely to impact both goal setting and goal striving processes. Specifically, the desire to achieve is associated with the establishment of difficult goals and persistent, dedicated efforts to attain them (Barrick, Mount,

& Strauss, 1993; Hollenbeck & Klein, 1987). Motivation to perform is an important determinant of performance in settings characterized by high levels of routine (Kanfer & Ackerman, 1989). In such settings, industrious individuals are continually motivated to perform since the existence of difficult goals creates a discrepancy between their current state and desired (goal) state (Carver & Scheier, 1998).

However, in more dynamic settings these goal striving activities may inhibit the ability to incorporate environmental information. For example, consistent with the efficiency component of this aspect (DeYoung et al., 2007; Roberts et al., 2005), Industriousness is likely to lead to the adoption of more efficient programs of action as part of the effort to obtain higher levels of performance. Because efficiency is a measure of the ratio of outputs to inputs the efficiency of a program can be increased if individuals are able to devote a smaller portion of their limited cognitive resources to goal striving activities while still accomplishing the desired outcome. One way that this can be accomplished is by refining programs so that incorporate only the subset of the available information deemed to be goal relevant (March & Simon, 1958). However, as previously discussed, this biased information processing strategy can make it more difficult to realize that a change has occurred since the information signaling that possibility is apt to be largely ignored (i.e. confirmation bias). Further, the general desire to increase efficiency is likely to result in the exclusion of program-irrelevant information pertaining to future change episodes as well.

Hypothesis 4: Industriousness will be negatively related to (a) initial and (b) subsequent transition adaptation episodes.

In contrast, over time the lack of performance (i.e. low velocity) caused by the failure to include pertinent information is apt to activate higher level goals within an individual's goal hierarchy (R. E. Johnson et al., 2006) associated with maintaining the high levels of performance that industrious individuals desire (DeYoung et al., 2007; Roberts et al., 2005). In turn, the discrepancy created by the activation of higher level goals is likely to result in changes being made at the lower levels (Carver & Scheier, 1998; Lord & Levy, 1994; Powers, 1973). In this case, that is tantamount to program reevaluation and modification so that desired levels of performance can again be attained via execution of an improved program.

Because Industriousness is characterized by general desire to achieve (DeYoung et al., 2007; Roberts et al., 2005), it is generally associated with the adoption of difficult to attain performance goals (Barrick et al., 1993; Hollenbeck & Klein, 1987). As discussed above, control theory predicts that the presence of a higher level performance goal that is not being met will be a key driver for initiating action directed at program modification. This impetus for action should lead to search activities (March & Simon, 1958) aimed at generating an effective and efficient program that again enables performance to rise to the desired level.

Thus, while Industriousness may be a liability when it comes to the implementation of specialized programs that hinder the ability to recognize that a change has occurred initially, it may also influence goal states at higher levels within an individual's hierarchy and lead to a more timely and directed search aimed at program improvement. In addition, by serving as inputs for lower level, program-centric control loops (Carver & Scheier, 1998; Lord & Levy, 1994; Powers, 1973), the higher aspirations that tend to be associated with Industriousness will foster the development of more effective programs that can deliver the desired (elevated) level of performance in the new situation.

Hypothesis 5: Industriousness will be positively related to (a) initial and (b) subsequent reacquisition adaptation episodes.

In contrast to Industriousness, Orderliness has previously been shown to be important for job performance in novel work settings (Stewart, 1999). Individuals high on this dimension like to order and structure their life (Costa & McCrae, 1992), resulting in a preference for routine (DeYoung et al., 2007; Roberts et al., 2005). This preference can enable individuals to impose structure on nebulous situations, increasing their ability to apply previously learned information to their present situation (Stewart, 1999). In addition, Orderliness is associated with obedience pertaining to rules and procedures (Hough, 1992). In the context of learning a new job, this can be beneficial because it allows for employees to learn how to perform work activities in the expected manner by internalizing existing organizational procedures and guidelines (Stewart, 1999).

It is easy to classify the situation after a change has occurred as a novel situation and extend the previously identified positive relationship to the domain of adaptive performance. However, dealing with environmental change can differ in subtle ways from joining an established organization. Indeed, a more careful examination of the underlying mechanisms via which Orderliness operates in such a context may shed doubt on the robustness of such an extension.

While the desire to adhere to rules and procedures that characterizes Orderliness (Hough, 1992) can be helpful for learning to perform like other members of the organization (Stewart, 1999), if the previous way of doing things is no longer valid due to a change in the environment, continuing to adhere to the same rules can inhibit the ability to respond to poor performance in a timely manner. In a more general manner, the fastidiousness associated with Orderliness can reduce the ability to make a decision to deviate from the current program in a timely manner

(Costa & McCrae, 1992). This tendency can be explored in a control theory context by thinking about the underlying preference to maintain stability and routine whenever possible that is associated with Orderliness (DeYoung et al., 2007; Roberts et al., 2005) in terms of a salient higher level goal within an individual's goal hierarchy.

This higher level stability goal may reduce the sensitivity of the comparator mechanism when it comes to signaling the need for corrective action. All control systems incorporate some degree of "deadband" (Carver & Scheier, 1998), such that input signals that fall within this specified range (i.e. band) of the desired state do not elicit a system response (i.e. the system acts dead). The width of this deadband affects the sensitivity of the control system, and is important to the overall functioning of the system (Sheridan, 2004). More specifically, if the deadband is overly narrow, the system will have poor steady-state performance because any noise in the system will be mistaken for a meaningful deviation and the system will "hunt" or oscillate back and forth attempting to address these minor deviations; this often leads to overshooting of the desired state and an immediate attempt to reverse course (Sheridan, 2004). The undesirability of this rapid shifting forms the basis for the proposed evolutionary explanation for the pervasiveness of confirmation bias: namely damping out rapid changes in direction (Nickerson, 1998). Conversely, if the deadband is too wide, transient response capabilities will suffer because the system will not react to significant deviations from the desired signal; a call for action is made only when the difference between the perceived actual state and the desired state exceeds the deadband (Sheridan, 2004).

The desire to maintain stability would seem to indicate that Orderliness might be associated with a larger performance deadband and the associated transient response problems discussed above. That is, initial indications that the current program is not functioning as intended may not elicit any corrective activity due to the relative insensitivity of the comparator. The high level goal of maintaining stability leads individuals high on Orderliness to err on the side of caution, allowing small or temporary performance deviations to go unaddressed. This approach allows them to avoid having to make unnecessary program changes. However, it also makes those who are high in Orderliness "less likely to abandon old habits after an unexpected change and therefore more likely to 'go down with the sinking ship'" (LePine, 2003, p. 31).

Hypothesis 6: Orderliness will be negatively related to (a) initial and (b) subsequent transition adaptation episodes.

In addition to slowing recognition of potential problems, a high level stability goal may also influence the ability to regain previous levels of performance in the post-change period. For example, the process of searching for and selecting new programs can itself become routinized (March & Simon, 1958). In the case where stability is a prime concern, search programs are likely to focus on minimizing the magnitude of changes implemented relative to the initial program, and they may stipulate long "trial periods" to evaluate their effectiveness, facilitated by large comparator deadbands, before another change attempt is made. However, when the underlying environment has shifted significantly, this slow rate of change may be inefficient, resulting in many failed attempts to adjust program parameters incrementally.

In addition to being potentially slow to identify a suitable program, a desire for stability may influence the quality of the final program selected. In this instance, the presence of ambiguity represents a disturbance from the desired state of routinization, individuals will strive to correct this deviation (Carver & Scheier, 1998). The continued presence of this deviation as a slow and methodical search program unfolds may result in a long-standing problem that is more likely to be addressed via the cognitive path of discrepancy reduction (Campion & Lord, 1982;

Donovan & Williams, 2003). In this case, this route would correspond to reduced performance goals, potentially resulting in the adoption of a suboptimal program for the sake of expediency. While all people are prone to make such satisficing decisions when potential outcomes aren't known (March & Simon, 1958), the inherent desire to maintain stability and order characterized by Orderliness (DeYoung et al., 2007; Roberts et al., 2005) may exacerbate this tendency resulting in suboptimal performance.

Hypothesis 7: Orderliness will be negatively related to (a) initial and (b) subsequent reacquisition adaptation episodes.

Proposed Effect of Openness on Adaptive Performance

Another personality trait that has been investigated in the context of adaptive performance is Openness, although the results to date have been ambiguous. Some research has identified a positive relationship between Openness and adaptive performance (e.g., Griffin et al., 2007; LePine et al., 2000), other research has failed to find a hypothesized relationship (e.g., Allworth & Hesketh, 1999; Pulakos et al., 2002), and at least one study has reported a negative relationship (e.g., Stewart & Nandkeolyar, 2006). In light of these conflicting findings and previous work and theory indicating that some facets of Openness might be more relevant for adaptive performance than others (LePine et al., 2000), it would seem prudent to consider aspect level relationships in an attempt to further clarify this relationship.

Historically, Openness has been the most difficult of the big-five traits to identify, with several proposed components including curiousness, imaginative, broad-minded, cultured, and artistically sensitive (Barrick & Mount, 1991). This has resulted in some spirited debates over its character (DeYoung et al., 2007) over the years. However, some theorists have argued that these apparent differences may reflect different levels of emphasis on particular areas of the domain rather than incompatibilities (DeYoung, Peterson, & Higgins, 2005; J. A. Johnson, 1994). In fact, conceptually and empirically, Openness is quite well represented by two aspects, *Intellect* and *Openness*, that encompass these diverse facets (DeYoung et al., 2007). Intellect encompasses facets like quickness, ingenuity, and ideas while Openness includes aesthetics, imagination, and fantasy (DeYoung et al., 2007). This distinction has been described succinctly as an interest in truth and beauty respectively (J. A. Johnson, 1994).

It is relatively easy to see how Intellect and the associated interest in understanding situations and enjoyment of solving problems (DeYoung et al., 2007) would be relevant for influencing adaptive performance. In contrast, the aspect of Openness and an associated interest in arts (e.g. poetry, music), beauty (e.g. nature, paintings), and imaginative thought (DeYoung et al., 2007) would seem to be less relevant. This is consistent with LePine et al. (2000) who did not generally find a relationship between adaptive performance and NEO-PI-R Openness facets like fantasy, aesthetics and values (i.e. liberalism). Due to a lack of an apparent conceptual connection between the Openness aspect of this trait and adaptive performance, no relationships are hypothesized for this aspect. Instead, the focus of the remainder of this section is on the Intellect aspect.

Before developing specific hypotheses pertaining to Intellect, it may prove fruitful to discuss the relationship between Intellect and GMA as the pattern of hypothesized relationships is not identical. The relationship between Intelligence and Openness (or the elusive "factor V" of the FFM) has long been debated (DeYoung et al., 2007). Some early work in the personality arena essentially equated the two concepts, referring to this factor explicitly as "Intelligence" (e.g., Borgatta, 1964; Goldberg, 1981). More recently, important differences between these constructs have been identified and even for those who prefer a more intellectual trait, words like

"Intellect" and "Imagination" (Goldberg, 1993) have supplanted earlier references to an "Intelligence" factor of the FFM. This shift has been driven by empirical and theoretical advances.

For example, work investigating the relationship between "Intelligence" the fifth factor of the FFM and Intelligence as measured by more traditional measures revealed a low correlation between the two constructs and an analysis of the scale items resulted in the emergence of two separate factors (McCrae, 1994). Today, the magnitude of the relationship between Factor V and Intelligence is generally in the vicinity of 0.2-0.3 (Ackerman & Heggestad, 1997; DeYoung, Cicchetti, Rogosch, Gray, & Grigorenko, 2011; DeYoung, Shamosh, Green, Braver, & Gray, 2009). While this is a moderate correlation, it is far from unity, representing less than 10% shared variance, indicating the uniqueness of these two constructs. In addition, many of the more recent studies reporting correlations of this magnitude rely on single-source, single-method, and single-occasion research designs (e.g., Chamorro-Premuzic, Moutafi, & Furnham, 2005; Gignac, Stough, & Loukomitis, 2004; Harris, 2004; Moutafi, Furnham, & Crump, 2006), which may inflate the magnitude of reported relationships due to common method variance (P. M. Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In addition, investigations utilizing a intelligence test commonly employed in organizational contexts, the Wonderlic Personnel Test, have demonstrated relatively modest relationships with Openness (0.08-0.14) compared to other intelligence measures (Furnham & Chamorro-Premuzic, 2006).

Estimation issues aside, there are conceptual reasons to expect some sort of positive relationship between Intellect and Intelligence, and the foundation underlying this relationship has often been conceptualized in terms of an investment model (Chamorro-Premuzic et al., 2005). Specifically, Cattell (1971) and later Ackerman (1996) proposed that an interest in learning and intellectual pursuits associated with Intellect would tend to result in the accumulation of additional experience and knowledge over time that would be reflected in measures of intelligence and crystalized intelligence in particular. Empirical results have generally supported this supposition from the perspective that factor V has generally been more strongly related to crystalized than to fluid intelligence (Ackerman, 1996; Ashton, Lee, Vernon, & Jang, 2000).

Consistent with the current conceptualization as laid out by DeYoung et al. (2007), McCrae and Costa (1997) depict the nature of this relationship using a Venn diagram that shows Intellect overlapping somewhat with Intelligence while being largely encapsulated within an Openness personality factor. McCrae (1994, p. 258) notes that this factor "refers not to the contents of consciousness so much as to the organization of the contents in a particularly fluid and permeable structure." Further arguing for a related by unique relationship, Ashton et al. (2000, p. 205) found evidence to "suggest that Openness/Intellect is essentially orthogonal to the ability to process information of an abstract spatial or quantitative nature", the latter of which is generally considered to be an important component of Intelligence.

More recently, DeYoung et al. (2009, p. 885) note that while "measures of Intellect reflect perceived intelligence as well as intellectual engagement. Neither perceived intelligence nor intellectual engagement can be considered identical, or even strongly related, to intelligence as measured by ability tests." Further, "Intellectual engagement reflects motivation, interest, and enjoyment in intellectual pursuits, without necessarily reflecting cognitive ability" (DeYoung et al., 2009, p. 885). Regardless of the underlying cognitive ability, DeYoung, Grazioplene, and Peterson (2012, p. 64) note that "Individuals high in Openness/Intellect display the ability and tendency to seek, detect, comprehend, and utilize more information than those low in Openness/Intellect."

This proposed distinction between Intellect and Intelligence has recently been validated biologically using fMRI technology as well. In particular, while Intellect and Intelligence were both associated with increased activity in the anterior prefrontal cortex (consistent with some degree of conceptual overlap), Intellect was uniquely (independent of either general Intelligence or Working Memory Capacity) related to activity in the posterior medial frontal cortex (pMFC) region of the brain (DeYoung et al., 2009). This finding could be particularly applicable to the investigation of adaptive performance because this area of the brain is associated with goal striving activities in general (Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004, October 15) and is specifically related to the resolution of uncertainty and response conflicts (J. W. Brown & Braver, 2005, February 18) which are likely to occur when conflicting information (feedback) is processed (Braver et al., 2007).

In addition, the pMFC is thought to be active in a wide variety of tasks, ranging from very complex to relatively simple (Ridderinkhof et al., 2004, October 15). DeYoung et al. (2009, p. 891) conclude that "the (cognitive monitoring) functions of pMFC may be an important substrate of Intellect that is distinct from cognitive ability and is perhaps driven by the motivation to engage with intellectual activities." Thus, while Intellect and Intelligence are related, they are unique constructs and may exhibit different relational patterns with Adaptive performance. This is consistent with the work of Pulakos et al. (2002) who found opposite effects for Openness and GMA when predicting adaptive performance using in a combined regression analysis (that included several personality measures along with a measure of GMA). Specifically, GMA was significantly and positively related to Adaptive Performance while

Openness was significantly and negatively related. Building on the theoretical and empirical evidence presented above, hypotheses related to Intellect emphasize the unique characteristics of this personality aspect compared to GMA.

First the motivational aspects of Intellect, including an interest in learning about new situations and solving problems (DeYoung et al., 2007) may underlie many theoretical explanations linking general Openness to outcomes that may bear on the relationship between Openness and adaptive performance. For example, these desires can help individuals learn new material (Blickle, 1996; Busato, Prins, Elshout, & Hamaker, 1999), and may help explain the finding that Openness is significantly and positively related to training performance (Ellis et al., 2003), a relationship that was not necessarily expected to emerge (Barrick & Mount, 1991). Because adaptive performance generally requires individuals to unlearn and relearn new ways of doing things, often in a manner that is not immediately obvious (LePine et al., 2000), previous researchers have often hypothesized that Openness would be positively related to adaptive performance (Griffin et al., 2007; LePine, 2003; LePine et al., 2000; Pulakos et al., 2002).

By focusing on transition and reacquisition adaptation individually, control theory can be utilized to highlight potential mechanisms that further explain and subsequently deepen understanding of this relationship. As previously discussed, transition adaptation requires timely recognition that a change has occurred and rapid application of corrective action to minimize performance decrements. An increase in monitoring and conflict resolution driven by increased activation of the pMFC which is associated with the Intellect aspect of Openness (DeYoung et al., 2009) may contribute to the successful accomplishment of both of these activities.

First, consistent with these functions, Intellect is associated with a general affinity for pursuing and incorporating new information during life's pursuits (DeYoung et al., 2007; J. A.

Johnson, 1994). In order to satisfy goals of this nature within an individual's goal hierarchy, task-accomplishment programs are likely to be more broad and exploratory in nature. This type of approach would enable individuals to quickly notice feedback that others with more focused programs may not, which is likely to increase adaptive performance (LePine et al., 2000). Thus, Intellect is likely to be associated with a relatively rapid discovery of environmental change because more diverse feedback information is incorporated into the input signal, increasing the likelihood that a performance discrepancy will be noticed and addressed in a timely manner, creating the opportunity for effective transition adaptation.

However, this broad-based approach to novel information search and incorporation may not be universally beneficial. Environmental scanning activities and subsequent incorporation of additional information into programs consumes additional cognitive resources (Braver et al., 2007; Kane & Engle, 2000; Sheridan, 2004), limiting the ability to fully exploit past experience to maximize program efficiency by narrowly focusing on a relatively small subset of the available information. To the extent that the a particular work environment is stable, this may help explain the general lack of a strong relationship between Openness and performance in the performance literature (Barrick & Mount, 1991; Barrick et al., 2001), especially when one considers the span of time when the primary studies underlying these results were conducted in light of more recent increases in workplace dynamism (Pearlman & Barney, 2000).

While potentially not universally advantageous, in a post-change setting, Intellect may not only enable rapid recognition that a change has occurred, but it may also facilitate the development of effective methods of adapting programs to address the change in the immediate aftermath of the change occurrence, further facilitating effective adaptive performance. Openness is associated with an ability to maintain and access numerous ideas simultaneously (Busato et al., 1999; McCrae & Costa, 1997). This may enable individuals high in Intellect to be able to quickly select a suitable alternative program from their repertoire or modify the current program to address the perceived change by effectively incorporating the feedback indicating the presence of a change. In addition to having access to more alternatives, Intellect is associated with the ability to creatively combine information (DeYoung et al., 2007). This can help keep individuals from getting hung up on pre-conceived notions and previous ways of accomplishing the task (LePine et al., 2000; Pulakos et al., 2002), allowing them to more quickly build effective programs for task completion in a post-change environment.

The presence of higher level goals associated with a desire to uncover truth is consistent with this personality aspect and may help explain the tendency to continue improving performance over time as the relevant aspect of adaptive performance shifts to reacquisition performance. When a change is recognized, this is likely to lead to the presence of a discrepancy between the desired and actual levels of performance, leading to activity aimed at redressing this undesirable imbalance (Carver & Scheier, 1998; Powers, 1973). In this context, these activities are likely to include search activities aimed at identifying a suitable program that leads to successful performance in a novel context (March & Simon, 1958). The activation of this search program may actually contribute to a sense of progress regarding attainment of a higher-level desire to uncover truth. Control theorists have long posited that the activation of a program, rather than its completion or the associated accomplishment is the relevant quantity for judging progress toward the accomplishment of higher level goals (Carver & Scheier, 1981, 1982). In this manner, the presence of a change event may actually be enabling for high Intellect individuals, allowing them an opportunity to make progress on a high level goal in their hierarchy associated with truth discovery.

Progress made toward high-level goal attainment can result in particularly strong positive reactions for individuals (Carver & Scheier, 1990), potentially mitigating some of the negative aspects associated with the initial performance decrement. This may help explain why Openness is associated with reductions in stress when dealing with novel situations (Pulakos et al., 2002). Further, those high on Openness are also more apt to judge organizational change positively and to experience more positive and fewer negative attitudes towards their job in general when dealing with a climate of change (Wanberg & Banas, 2000).

Over time, intellect and its associated preference for change may have detrimental effects. Once high intellect individuals begin making perceived progress toward truth discovery as a result of being exposed to multiple change events, the output of this higher level goal is apt to result in the modification of lower level goal states with the hierarchy (Carver & Scheier, 1981). Specifically, these goal states are apt to be increasingly focused on truth discovery and as a result, task programs may become too exploration focused. This may lead to the perception that a change has occurred when in fact one has not (confirmation bias), resulting in an overabundance of search activity. Because multiple programs must often be executed sequentially (Carver & Scheier, 1998) and search programs and execution programs in particular fall into this category (March & Simon, 1958), the execution of additional search activity can hinder task performance. This is also consistent with the notion that exploration and exploitation activities must be balanced in order to achieve high levels of performance; an overreliance on either approach can be detrimental (Weick, 1995).

In sum, Intellect may influence both the adaptive and reacquisition aspects of adaptive performance. Due to a preference for incorporating novel information, broad task-programs are likely to be employed, leading to earlier recognition of change events. In addition, Intellect is apt to lead to the generation of more options for adopting a program that leads to a successful response to a change event. Past research has demonstrated that Intellect is associated with a willingness to quickly abandon previously held notions (LePine et al., 2000), allowing for new programs to be implemented quickly. However, over time, Intellect may result in the premature abandonment of adequate programs in response to an imagined change, consistent with the observed positive relationship between Intellect and a general inability to discern reality from fantasy (DeYoung et al., 2012). The high level interest in understanding situations and solving complex problems associated with this personality aspect (DeYoung et al., 2007; J. A. Johnson, 1994) may inhibit negative responses to change and motivate individuals to persist in identifying programs that are effective for performing in post-change situations. However, their ability to actually do so may be hindered by an inability to balance the demands of exploration and exploitation over time.

Hypothesis 8: Intellect will be positively related to (a) initial and (b) subsequent transition adaptation episodes.

Hypothesis 9: Intellect will be (a) positively related to initial and (b) negatively related to subsequent reacquisition adaptation episodes.

Proposed Effect of Neuroticism on Adaptive Performance

Aside from Conscientiousness, research has shown Neuroticism (or its opposite Emotional Stability) to be the personality trait with the most generalized relationship with performance; specifically, Neuroticism is generally negatively related to performance (Barrick & Mount, 1991; Salgado, 1997; Tett et al., 1991). Understanding of this relationship in the domain of adaptive performance is hindered by the small number of studies that have investigated this relationship. The limited results to date have found a non-significant (Allworth & Hesketh, 1999) and a negative relationship (Pulakos et al., 2002), providing some preliminary evidence that the relationship between Neuroticism and adaptive performance might mirror the one between Neuroticism and performance in general.

At first blush, this would seem reasonable; listing descriptors associated with neuroticism, Barrick et al. (2001, p. 11) noted that "being anxious, hostile, personally insecure and depressed (low emotional stability) is unlikely to lead to high performance in any job". While this seems entirely reasonable, more recent work has identified two aspects of Neuroticism, a trait that historically been viewed as being relatively homogeneous (DeYoung et al., 2007). While both aspects share a common root built on an inability (for those high on Neuroticism) to cope effectively with negative affect, they differ in the manner in which these ineffective mechanisms manifest. Specifically, Volatility incorporates externally focused manifestations, including concepts like anger, hostility, and impulse control issues while the Withdrawal aspect is focused on internal manifestations including depression, anxiety and vulnerability (DeYoung et al., 2007). By and large, it is expected that Neuroticism will negatively impact adaptive performance, but by considering the two aspects for both constructs, a more nuanced view may emerge.

As a trait, Neuroticism has long been associated with trait negative affect, a general disposition to view the world in a negative manner (Costa & McCrae, 1980; Watson, 2000; Watson & Clark, 1992) and an associated increase in threat perception in the environment (Spector, Zapf, Chen, & Frese, 2000). This situation may be self-reinforcing since confirmation bias often leads people to find what they are looking for (Nickerson, 1998), implying that in situations where threats are expected, ambiguous stimuli are more likely to appear threatening, potentially increasing the perceived threat-level of the environment. In environments perceived as being threatening, individuals are likely to include more background scanning of the environment in their performance programs, causing them to distribute their limited attentional resources more broadly (Braver et al., 2007; M. W. Eysenck et al., 2007). In addition, Neuroticism is associated with an increase in the intensity of the negative affective reactions that are felt in response to perceived threats in the environment (Ilies & Judge, 2002; Larsen & Ketelaar, 1991). Collectively, these sorts of arguments support the generally negative relationship between neuroticism and performance generally found in the literature (Barrick et al., 2001). In terms of exhibiting increased performance after a change has occurred, these predispositions are likely to be similarly problematic.

Negative affect has long been viewed as being evolutionarily beneficial, signaling that there is an issue that needs immediate attention, (Fredrickson, 1998; Fredrickson & Levenson, 1998). As such, negative affect may shift attention to a higher order self-preservation goal as a result of our evolutionary past. This may cause individuals to focus on the threat itself, reducing the amount of resources available to complete the actual task (M. W. Eysenck et al., 2007; Nibbeling, Oeudejans, & Daanen, 2012). This can lead to poor task performance as individuals focus on the threat and how to extricate themselves from the unpleasant situation (Beilock & Carr, 2001; Mesagno, Harvey, & Janelle, 2012). In control theory terms, low-level goals tend to be useful to the extent they facilitate accomplishing high level goals (R. E. Johnson et al., 2013). The activation of a high level threat avoidance goal within an individual's hierarchy can diminish the importance of performing well. Instead, performing quickly (or carefully) comes to be seen as an important lower level goal in order to expedite progress toward attaining the desired state of threat avoidance at the higher level.

Negative affect also acts to narrow available response tendencies to facilitate a quick and decisive response in order to avoid serious harm (Frijda, 1986; Lazarus, 1991; Levenson, 1994). While this narrowing of thought may be beneficial for self-preservation when the threat is physical and immediate, in terms of dealing with more mundane changes in the workplace, it can be obstructing. Considering limited options can make it more difficult to come up with the novel, sometimes counterintuitive programs necessary for successful adaptive performance (LePine et al., 2000). In addition, the experience of negative affect can itself consume additional cognitive resources, limiting further limiting the resources available to be applied toward task performance (Beal et al., 2005; Gray, 2001; Gray, Braver, & Raichle, 2002). As a result, the presence of elevated levels of negative affect (associated with both aspects of Neuroticism) may make it not only less important but also more difficult to develop and execute the programs necessary to increase performance after a change has occurred, regardless of whether that affect is internally or externally directed.

Hypothesis 10: Volatility will be negatively related to (a) initial and (b) subsequent reacquisition adaptation episodes.

Hypothesis 11: Withdrawal will be negatively related to (a) initial and (b) subsequent reacquisition adaptation episodes.

While Neuroticism may be detrimental to reacquisition adaptation, the increased environmental scanning could in some cases be beneficial for detecting the presence of a change. This is consistent with the work of Thoresen et al. (2004) who unexpectedly found that neuroticism was positively related to job performance for employees learning a new job role. Drawing on control theory for a brief post-hoc discussion, they posited that this might have been due at least in part to increased environmental monitoring and subsequent action directed at reducing discrepancies that might have been recognized as a result. However, due to the counter-intuitive nature of their findings, they concluded their discussion with a call for additional investigation of this phenomenon to improve understanding of the nature of this relationship (Thoresen et al., 2004). In order to further this cause, potential effects of both aspects of Neuroticism on transition adaptation are discussed below.

First, as previously discussed, both Volatility and Withdrawal should increase environmental scanning. In much the same way that dual methods of control theory (Braver et al., 2007) predicted differences in processing preferences in the context of GMA differences, attentional control theory (M. W. Eysenck et al., 2007) posits a similar difference based on the predisposition to perceive environmental threats. Specifically, attentional control theory posits that a predisposition to perceive environmental threats is likely to increase reliance on reactive, stimulus driven processing and accordingly inhibit proactive processing (M. W. Eysenck et al., 2007). While the underlying mechanism driving activation of the different processing approaches differs from that posited by dual methods of control theory, attentional control theory similarly predicts that when stimulus based processing is utilized, the scope of information processed is generally broader due to less program centric focus and the accompanying bias in information processing (Braver et al., 2007; M. W. Eysenck et al., 2007). Thus Neuroticism should increase the likelihood of noticing when a change has occurred because a predisposition to rely on stimulus based processing should increase the breadth of feedback incorporated into the input signal.

However, the response to this noticed change can be different for each aspect of Neuroticism. Beyond simply modifying the information processing process, attentional control theory also posits that individuals can focus either externally or internally after having been confronted with a perceived threat (M. W. Eysenck et al., 2007). This is consistent with the primary difference in the two aspects of Neuroticism proposed by DeYoung et al. (2007). Specifically, they characterize Volatility in terms of externally focused responses while Withdrawal is conceptualized in terms of internally focused responses to experienced negative affect.

This differential focus is consistent with the activation of programs with different foci. Specifically, drawing on its evolutionary foundations, negative affect has long been proposed to activate different programs in order to facilitate effective responses to a variety of experienced threats (Frijda, 1986; Lazarus, 1991; Levenson, 1994). For example, anger, an externally focused response, is associated with a predisposition to directly confront the threatening stimulus. In contrast, fear, an internally focused response, tends to be associated with programs focused on escaping from the threating situation in a rapid and expedient manner.

While the realization that an environmental change has occurred is generally not profoundly life threatening, exposure to even a relatively innocuous stimulus can elicit a significant emotional response (Weiss & Cropanzano, 1996), and the two aspects of Neuroticism characterize the direction that an individual is apt to take in response (DeYoung et al., 2007). When a change is recognized, a discrepancy between the desired state and the actual state should subsequently be recognized. In turn, Volatility should be associated with the activation of externally focused programs centered on problem confrontation and resolution in order to return the individual to their desired state. Even though affective responses consume personal resources and reduce the amount of resources remaining for problem resolution (Beal et al., 2005; Gray, 2001; Gray et al., 2002), an external focus should result in the application of the remaining resources towards improving performance in an effort to overcome the threat and reduce the discrepancy to an acceptable level (M. W. Eysenck et al., 2007). While the resource costs associated with a negative emotional response and continued environmental monitoring may hinder the ability to maximize performance over time, Volatility may result in a quick and decisive initial response that reduces the negative impact of a change

Hypothesis 12: Volatility will be positively related to (a) initial and (b) subsequent transition adaptation episodes.

In contrast, Withdrawal is apt to be associated with the activation of internally focused programs once a change has been noted and a resulting discrepancy detected. These programs are likely to de-emphasize task performance for the sake of escaping from the threating situation quickly. By focusing attention internally, individuals are generally less effective at addressing the root cause of the perceived threat (Grandey, 2000). While initial attempts may be made to reduce the discrepancy via behavioral means (M. W. Eysenck et al., 2007), over time an inability to effectively address the source of the perceived threat may lead to downward goal revision (Donovan & Williams, 2003; K. J. Williams, Donovan, & Dodge, 2000) or withdrawal from the goal pursuit activities all together (Carver & Scheier, 1998).

The latter avenue is consistent with a goal to focus internally and act to escape (at least mentally) from the external, threatening situation. The decision to effectively withdraw from the goal pursuit activity all together typically begins when ongoing goal pursuit is interrupted, with negative affect serving as a common trigger for this evaluation to occur (Carver & Scheier, 1998). During this interruption, future prospects for success are evaluated and if expectancies for success are low, goal pursuit is likely to be abandoned (Carver & Scheier, 1998). Carver and Scheier (1998) and Howe, Chang, and Johnson (2013) describe several mechanisms by which negative affect may downwardly influence the evaluation of these expectancies, meaning the prospects for success are apt to be low.

As previously discussed negative affect narrows focus (Fredrickson, 1998), which limits the ability to generate potential alternative approaches that could be tried, reducing expectancies of future success (Carver & Scheier, 1998). In addition, affective priming (Forgas & Bower, 1987; Isen, 1984, 1987) is likely to result in the recall of a disproportionately large amount of negatively valenced outcomes from memory, further lowering expectancies based on evaluation of past experience. In addition, consistent with confirmation bias (Evans, 1989), due to increased expectations of threat and failure, individuals experiencing negative affect are apt to subjectively under-evaluate their current level of performance level if feedback is ambiguous, which is quite common in organizational settings. Finally, negative affect is thought to be associated with the use of more intensive and deliberate evaluation approaches, resulting in a small deadband (Howe et al., 2013), which is likely to reduce the prospect of experiencing objective success.

This desire to escape the situation and accept lower performance is consistent with the meta-analytic finding that trait anxiety, a central component of Withdrawal (DeYoung et al., 2007), is negatively associated with motivation to learn in a training context (Colquitt et al., 2000). Anxiety seems to cause people to want to withdraw from the situation, preferring not to engage in a task that they judge to be anxiety inducing. Further, anxiety is also associated with increased worrisome thoughts, which consume additional cognitive resources that are then unavailable for improving task performance (Beilock & Carr, 2005; M. W. Eysenck et al., 2007). In addition, continued experience of these thoughts may lead to increased feelings of anxiety (Watkins, 2008), which may compound these effects and provide even more motivation to reduce performance expectations in response to an inability to achieve the initial goal state. Thus, while Withdrawal may increase awareness that a change has occurred, the increasing internal focus in response to the perceived discrepancy is likely to increasingly impair the ability to improve performance as time passes.

Hypothesis 13: Withdrawal will be (a) positively related to initial and (b) negatively related to subsequent transition adaptation episodes.

Proposed Effect of Extraversion on Adaptive Performance

Extraversion is generally viewed in terms of social attributes including sociability, gregariousness, talkativeness, etc. (Barrick & Mount, 1991); although some researchers have also argued for an ambition aspect for this trait (e.g., R. Hogan, 1986). The conceptualization of Extraversion put forth by DeYoung et al. (2007) falls into the latter camp, proposing Enthusiasm and Assertiveness aspects to capture the social and ambition components respectively. Specifically, DeYoung et al. (2007) conceptualize Enthusiasm as including social descriptors including being friendly, outgoing, and gregarious along with markers for the experience of positive affect that may be the impetus for these socially outgoing manifestations (Lucas & Diener, 2001). In contrast, Assertiveness includes notions of dominance, which are generally thought of as being applicable to social settings, although they embody a more general sense of agency as well (DeYoung et al., 2007).

In general, Extraversion is not related to job performance across occupations, appearing to be beneficial for performance only for occupations that have a significant social component to them (Barrick & Mount, 1991; Barrick et al., 2001). This is consistent with the social focus inherently tied to conceptualizations of Extraversion. Further, explanations for the unexpected meta-analytic findings generally linking Extraversion to training performance (Barrick & Mount, 1991; Barrick et al., 2001) have generally fallen back to the social aspect of the trait, noting that in many cases training takes place in group contexts where Extraversion may be associated with an increased desire to interact and actively participate in the training activity (Barrick & Mount, 1991; Barrick et al., 2001).

The core social component for this trait would seem to draw into question the relevancy of Extraversion for predicting adaptive performance in many instances. Conceptually, both aspects proposed by DeYoung et al. (2007) predictably incorporate this overarching sociability focus as well. Even though components that extend beyond social settings are also included, a social context is important for both aspects. As a result, at least half of the items comprising each aspect measure are inherently socially focused. The presence of other-focused items across aspects is not unique to this particular view of Extraversion. R. Hogan (1986) proposed an alternative conceptualization of Extraversion that separated ambition from more social components of the trait, but when operationalized the ambition measure also included other-focused items. As a result of the mismatch between this social focus and the current theoretical frame, neither Enthusiasm nor Assertiveness is considered further.

Proposed Effect of Agreeableness on Adaptive Performance

DeYoung et al. (2007) propose Compassion and Politeness aspects for Agreeableness. Compassion captures the tendency to form affiliative, emotionally laden connections with others while Politeness refers to a more cognitively intensive awareness of and respect for the needs of others (DeYoung et al., 2007). Even more so than Extraversion, both aspects of Agreeableness are fundamentally social in nature, and correspondingly all items used in the evaluation of the aspects refer to interactions with others (DeYoung et al., 2007). Because the conceptualization of adaptive performance adopted here along with common conceptualizations employed elsewhere (e.g., Pulakos et al., 2000) are not likewise constrained by the necessity of involving social interactions, it is hard to see how to advance robust propositions involving either aspect of Agreeableness.

This is consistent with previous theorizing that Agreeableness should only be relevant for job performance in situations involving high levels of interpersonal interaction and helping in particular (Barrick et al., 2001). Despite this conceptual connection, in their seminal work, Barrick and Mount (1991, p. 21) went so far as to note that Agreeableness was "not an important predictor of job performance, even in those jobs containing a large social component."
More recent opinions may have mellowed somewhat, and while there may be more support for the validity of Agreeableness in some limited contexts, among the big five traits, it still generally exhibits the lowest validities with performance in a more general sense (Barrick et al., 2001). In light of the lack of a conceptual match between Agreeableness and adaptive performance and the overall underwhelming nature of the empirical work attempting to link Agreeableness with performance in general, no hypotheses pertaining to either Compassion or Politeness are forwarded.

The Role of External Goals in Adaptive Performance

As discussed previously, the establishment of goals, or goal-setting, plays a critical role in self-regulation. Goals enable the focus of attention, effort, and action by highlighting the presence of a discrepancy between a current state and a more desirable potential state (Carver & Scheier, 1998). The goal setting process, along with the subsequent goal striving process, wherein people to modify their behavior or cognition in an effort to attain this desirable outcome, is universally important for understanding and predicting human behavior (Lord et al., 2010). In addition, effective management of the goal-setting process plays an important role in determining organizational performance, and organizations that are able to effectively manage this process tend to realize higher levels of performance than those that don't (Locke & Latham, 1990; Rodgers & Hunter, 1991; Tubbs, 1986). However, in practice, managers may be disinclined to use goal setting techniques due to a fear that unforeseen changes may make them ineffective (O'Reilly & Pfeffer, 2000), and exploring this possibility in the context of adaptive performance would seem to hold practical significance for organizations, in addition to its theoretical importance for researchers (Dorsey et al., 2010).

Given the importance of goals for individual and organizational performance, it is not surprising that a substantial amount of research investigating the effects of goals in a wide variety of settings has been conducted (Austin & Vancouver, 1996; R. E. Johnson et al., 2006; Locke & Latham, 2002). Researchers have identified several universal attributes that are critical to linking the use of goals with increased performance. For example, goals that are difficult and specific, rather than easy or vague, are generally more effective in increasing employee performance (Locke & Latham, 1990). In addition, goal effectiveness is enhanced when people are committed to achieving the goal (Hollenbeck & Klein, 1987; H. J. Klein, Wesson, Hollenbeck, & Alge, 1999), and when they have both the cognitive ability (Kanfer & Ackerman, 1989) and self-efficacy (Albert Bandura, 1986) to achieve the goal.

While organizational use of specific, difficult goals is generally thought to lead to increased individual performance (Locke & Latham, 2002), little is known about how the use of goals may impact the adaptive performance aspect. First, the general positive association between goals and performance is largely based on research that focused on how to best use goals to enhance task performance (Locke & Latham, 2002), which is a deficient measure of individual performance in modern organizations (Campbell, 1999; Campbell et al., 1996; Hoffman et al., 2007; Pearlman & Barney, 2000). In addition, the process of recognizing and responding to a change that is at the heart of adaptive performance is a complex one (Dorsey et al., 2010). In particular, the unplanned, reactive nature of adaptive performance inherently increases the dynamic complexity of this process, increasing the data processing requirements that must go on in parallel with task performance (Wood, 1986).

Complexity has long been known to moderate the effectiveness of goals for improving performance (e.g., Wood & Locke, 1990; Wood, Mento, & Locke, 1987), and counter to the general positive association, the use of difficult, specific goals may actually hinder performance in some complex situations (Earley, Connolly, & Ekegren, 1989; Locke & Latham, 2002). This has led researchers to make a distinction between outcome (or performance goals) and learning goals. Performance goals are outcome based (e.g. a specific quantity produced per unit time), and tend to be more exploitation centric, focusing on achieving some level of output with respect to a known valuable outcome. In contrast, learning goals boost exploration by focusing on the acquisition of information, often pertaining to enhancing understanding of a previously perplexing situation; for example, learning goals may be used to encourage the development of a suitable strategy by asking individuals to report a specific quantity of useful heuristics that they developed (Winters & Latham, 1996). Moreover, the use of difficult, specific goals focused on learning outcomes has been found to be positively related performance in complex situations while similarly specific, difficult outcome goals exhibited a negative relationship (Latham & Locke, 2006; Winters & Latham, 1996).

As a result, some researchers have encouraged organizations to use learning goals rather than performance goals in complex situations (Latham & Locke, 2006) or perhaps even to go so far as to replace performance goals with learning goals all-together (Ordóñez, Schweitzer, Galinsky, & Bazerman, 2009). However promising, the use of learning goals is associated with its own drawbacks. For example, the use of learning goals when the strategy for problem solution is known (or is relatively easy to discern) can actually decrease performance (Winters & Latham, 1996). In addition, while learning goals may encourage knowledge acquisition, that knowledge may not be applied to improve task performance unless an appropriate outcome goal motivates such activity (Earley & Perry, 1987). Developing appropriate and timely learning goals may be particularly difficult for managers compared to developing outcome goals, and balancing the use of the two goal types effectively for each individual is likewise apt to be exceedingly difficult since individual differences are likely to influence both the pre-existence and subsequent development rate of appropriate strategies (Ordóñez et al., 2009).

These challenges likely contribute to the longstanding predominance of outcome goals in organizations (Latham & Locke, 2006; Ordóñez et al., 2009; Winters & Latham, 1996). In this context, the dynamic complexity associated with adaptive performance is likely to make the challenge of effectively managing learning and performance goals particularly acute. In addition, little is known about how goals actually influence adaptive performance in general, and further investigations of the role of specific, difficult outcome goals in enhancing or hindering adaptive performance have recently been encouraged as an interesting and warranted effort (Dorsey et al., 2010). Thus, in order to answer this call, maintain organizational relevancy given the current organizational preference for outcome goals, and in light of the shortcomings of learning goals that are apt to be particularly problematic in the context of adaptive performance, the remainder of this section focuses on outcome goals. It is hoped that this approach will build a foundation consistent with previous work on goal setting that future investigators can build on by exploring the relationship between learning goals and adaptive performance.

Proposed Direct Effect of Difficult, Specific Goals on Transition Adaptation

The major premise of goal theory is that difficult, specific goals lead to superior performance compared to easy or vague goal formulations (Chesney & Locke, 1991; Locke & Latham, 1990). One of the primary mechanisms by which such goals improve performance is via increased attention to the focal task (Locke & Latham, 1990). This effect can be understood directly in terms of control theory. The establishment of a difficult, specific task-focused goal is likely to increase the detection of a discrepancy between actual and desired task performance, leading to an increase in activity aimed at resolving this shortcoming (Carver & Scheier, 1998; Powers, 1973). In the absence of an external goal, idiosyncratic personal goals are likely to not only exist but also to drive behavior (Locke & Latham, 1990). The difficult, specific nature of an effective external goal is apt to differ from these personal goals in many important ways.

First, if assigned properly the external goal should direct attention to increasing performance on the focal task. As previously discussed, certain individual differences can lead to a preference for the adoption of goals that are not directly beneficial for task performance (e.g. Orderliness's association with a desire to maintain order and routine). In such settings, individuals may be pursuing a goal, but it may or may not lead to the desired increase in performance. Because the presence of a current – desired state discrepancy is an important driver for activity, the goal striving efforts associated with the adoption of personal goals will focus attention such that feedback thought to be relevant for the goal being pursued will be attended to and interpreted in that frame (Carver & Scheier, 1981, 1998). Feedback thought to be irrelevant for improving performance may be attended to in a diminished capacity (or reinterpreted in support of another goal) as a result.

In a similar manner, the difficult nature of an effective goal is likely to be associated with an increase in the duration of attention devoted to processing performance relevant feedback. Difficult to obtain goals are by definition hard to realize (Locke & Latham, 1990) with the majority of individuals unable to accomplish them (Chesney & Locke, 1991; Wood & Bandura, 1989a). As compared to easier goals that may be achieved relatively quickly, freeing attentional resources for other pursuits, the continued discrepancy between a difficult goal and the current level of performance will act as a force to keep attention focused on feedback deemed relevant for gaging and improving performance on the focal task based on the performance program adopted by the individual (Carver & Scheier, 1981, 1998). Unfortunately, when this program is misspecified, this increased focus can actually work to the detriment of the actually realized level of performance because attentional resources are incorrectly deployed and important feedback information can be disregarded or downplayed as a result (Carver & Scheier, 1981, 1982, 1998). Immediately after a change has occurred, individual performance programs are inherently likely to be more misspecified than prior to the change occurrence.

This is consistent with the argument for the importance of goal specificity put forth by goal setting theory (Locke & Latham, 1990). Specifically, individuals attend more intently to information pertaining to the evaluation of progress towards and completion of the specific aspects of a task explicitly specified in goal statements, to the detriment of additional potential performance avenues not included in the goal specification (Organ, 1977a; Staw & Boettger, 1990). Established conceptualizations of control theory make similar predictions, noting that the presence of desired-actual discrepancies can enable effective self-regulation by limiting attention to a subset of the available feedback in order to allow for effective and ongoing work aimed at accomplishing a focal task (Carver & Scheier, 1981; Lord & Levy, 1994). By defining what aspects of the task are most important for evaluating overall performance, specific goals act to narrow program specification and increase focus on feedback judged to be pertinent to accomplishing those task aspects specified as opposed to other idiosyncratic performance definitions that are apt to exist naturally (Uggerslev & Sulsky, 2008).

Finally, the adoption of a specific goal makes it more difficult to reduce a noted discrepancy via the cognitive route – i.e. adopting a lower goal. People have a tendency to reduce goals when goal progress stagnates (Donovan & Williams, 2003; K. J. Williams et al., 2000), and a vague goal that could be easily operationalized as entailing the current level of performance would seem to facilitate such a tendency. When presented with vague, "do your best" goals, it is easier to give oneself the benefit of the doubt and lower expectations for what that entails in order to reduce performance deficiencies (Locke & Latham, 1990, 2002). In other words, one can accept the current level of performance as being satisfactory without having to either endure a lasting performance discrepancy or fully confront the negative ramifications of having explicitly lowered a goal within one's goal hierarchy. Specific goals encourage task persistence in part by hindering this process of inconsequential downward goal revision, encouraging additional effort and focus necessary to meet the specified performance outcomes (Locke & Latham, 1990, 2002).

In sum, because difficult, specific goals increase the intensity and duration of attention paid to improving a certain aspect of performance, narrow programs focused on maximizing that outcome should be constructed and activated. Feedback containing information with relevance to this program should be preferentially attended to while other information is de-emphasized (Carver & Scheier, 1981, 1998). In the context of adaptive performance, this focus may decrease the likelihood of noticing and effectively responding to a change event because of an increase in program misspecification that is likely to accompany a change. The presence of a specific, difficult goal motivates people to take steps to increase performance in an attempt to achieve the focal performance goal (Locke & Latham, 1990, 2002). However, when the means of achieving this desired level of performance (i.e. programs) are unclear or misspecified, this motivation can result in increased adoption of ineffective or even counterproductive behaviors driven in part by attending to a suboptimal subset of available feedback (Carver & Scheier, 1981, 1982, 1998).

Hypothesis 14: Compared with a do-your-best goal, the presence of a difficult, specific performance goal will be negatively related to (a) initial and (b) subsequent transition adaptation episodes.

Proposed Direct Effect of Difficult, Specific Goals on Reacquisition Adaptation

In addition to increased attention, difficult specific goals improve performance by increasing effort and task persistence (Locke & Latham, 1990, 2002). While these outcomes are generally beneficial for increasing performance, this is not universally the case, and the benefits tend to be particularly weak when the correct program for enabling performance is unknown. For example, compared to do your best goals, Kanfer and Ackerman (1989) found that the assignment of difficult, specific goals during the early stages of novel task performance can be detrimental to performance. They contend that novel situations are cognitively intensive and that the presence of a difficult, specific goal increases self-regulation, diverting a portion of much needed attentional resources that would be better applied to developing appropriate performance programs to the self-regulation process (Kanfer & Ackerman, 1989).

Subsequent work by DeShon, Brown, and Greenis (1996) has since challenged the assertion that self-regulation consumes a significant quantity of attentional resources. This is consistent with the control theory refinements put forth by Lord and Levy (1994), who propose that the self-regulation process is largely automated and not cognitively intensive, relying instead on other systems to monitor progress (e.g. affect). However, in a cognitively demanding situation that individuals likely had not experienced before, the presence of difficult, specific goals did not increase performance (DeShon et al., 1996). Thus, even if suboptimal allocation of limited attentional resources does not play a primary role in limiting the effectiveness of difficult, specific goals in novel situations, other mechanisms would still seem to be hindering the link in novel, cognitively demanding situations.

DeShon and Alexander (1996) investigated one such alternative. Specifically, they considered two types of learning that can occur when confronted with a novel situation: implicit and explicit. Implicit or heuristic programs rely on tacit knowledge to improve performance and even though performance may improve over repeated exposure to related situations, the specific steps taken in the program may be unknown to the individual performing the task (Holyoak & Spellman, 1993). In contrast, explicit learning is much more closely related to declarative and procedural knowledge, requiring significantly more cognitive resources to ascertain, develop and organize the steps involved in program execution, including relevant boundary conditions (Newell & Simon, 1972). Because the relevant program inputs, let alone the exact nature of the relationships among them, can be difficult to identify in novel situations, the demands of explicit learning can exceed available cognitive resources, making implicit learning a superior strategy (DeShon & Alexander, 1996). In novel situations, the presence of difficult, specific goals tends to activate suboptimal explicit learning programs, which can lead to diminished performance (DeShon & Alexander, 1996).

These results are consistent with the previous findings that the effectiveness of goal setting theory may depend in part on the type of task program that is most appropriate for increasing performance. Specifically, Huber (1985) found that the adoption of difficult, specific goals can increase perceptions of task complexity and increase arousal. This combination can diminish cognitive flexibility and dramatically increase reliance on existing performance programs, even when these programs are ineffective. As a result, difficult, specific goals diminished performance compared with assignment of do your best goals on tasks that were better performed using heuristic processing strategies (Huber, 1985).

Huber (1985) also found that the arousal associated with adoption of difficult, specific goals was associated with an increased desire to realize progress towards achieving the goal. In her study this desire led to a short-term focus and an associated increase in the frequency with which feedback on performance was sought, even when doing so was expressly detrimental to task performance in the long-run. In related work by Earley, Connolly, and Ekegren (1989) adoption of difficult, specific goals was likewise associated with a short term focus and a desire to see immediate goal progress. This led to rapid and relatively haphazard switching between alternative performance programs during the initial stages of task performance, which had lasting detrimental effects on performance over the long-term compared with do your best goals (Earley, Connolly, & Ekegren, 1989).

This desire to find evidence of goal progress may also explain why explicit processing was associated with excessive evaluation of each of the various aspects of the program during program development reported by DeShon and Alexander (1996). While this extensive evaluation may provide additional opportunities to realize goal progress, it also dramatically increased the cycle time of goal striving activities, slowing long-term goal progress (DeShon & Alexander, 1996). Collectively, these effects can be viewed in terms of suboptimal control system functioning. Specifically, the inability to achieve the desired rate of progress toward the performance goal can lead to arousal and negative affect (Carver & Scheier, 1990; R. E. Johnson et al., 2013), which in turn leads to a narrowed focus on addressing perceived threats to goal accomplishment (Frijda, 1986; Lazarus, 1991; Levenson, 1994). Increasing the sensitivity of the system to threats is akin to adopting a narrow deadband. In this way, even minor disturbances are recognized quickly, which enables the desired rapid response capability (Sheridan, 2004).

In addition, this narrow deadband explains some of the maladaptive consequences discussed above. For example, an inability to discern which specific parts of the program were truly problematic compared to those that led to only very minor decrements could have led to the long cycle time described by DeShon and Alexander (1996). An overly narrow deadband can make it hard to distinguish noise from actual problems that require attention (Sheridan, 2004). This would also result in the pattern of insufficient testing and premature program abandonment due to minor environmental fluctuations reported by Earley, Connolly, and Ekegren (1989). In addition, the tendency to frequently follow up on short-term goal progress and associated inability to stay focused on long-term task performance reported by Huber (1985) is indicative of a narrow deadband that introduces frequent interruptions to the system as a result of an overly sensitive comparator rapidly identifying potential problems that require attention (Sheridan, 2004).

However, over time identification of effective goal striving programs many diminish many of these effects. For example, Kanfer and Ackerman (1989) found that once participants had the opportunity to develop effective performance programs, the subsequent assignment of a specific, difficult goal was associated with increased performance. Likewise, difficult specific, goals only were only associated with increased performance after participants had the opportunity to get feedback on their initial performance strategy when performing a business simulation game (Chesney & Locke, 1991).

Earley, Connolly, and Lee (1989) investigated an intervention for improving the effectiveness of specific goals in novel situations and identified two successful interventions. First, when individuals exposed to a novel situation were also assigned difficult, specific goals, limiting the number of potential strategies that could be adopted led to increased performance. Alternatively, a similarly positive relationship between difficult, specific goals and performance on a novel task was realized when participants were trained on how to implement an effective search program. Thus, limiting the range of performance programs considered seems to be beneficial for enhancing performance in novel situations when also adopting a difficult, specific goal (Earley, Connolly, & Lee, 1989).

The detrimental effects of goal-setting theory are likely to be particularly acute when there are many potential strategies, the proper strategy is not readily apparent, and it is not possible to ascertain how well a developed strategy would have performed in the past (Earley & Perry, 1987). When attempting to respond to an initial change, these conditions are likely to prevail. However, over time and repeated exposures to similar change events, individuals may develop increasingly effective search programs (March & Simon, 1958).

These search programs may help narrow the number of problem focused programs that are tested, allowing for a more rapid identification of one that is appropriate. In addition, over time, it may be possible to get a feel for how a program would have worked over repeated change events. Earley, Connolly, and Lee (1989) note that the existence of a difficult, specific goal is associated with increased performance after a change has occurred if people have been trained on the development of effective search programs. Presumably, this substitutes for experience and similarly leads to more timely and effective problem-program selection after the change has occurred. Thus, while the research pertaining to differential effects for goal theory over time has primarily been conducted in the paradigm of exposure to a single novel situation, there is reason to believe that a similar pattern may emerge over time with respect to subsequent reacquisition adaptation episodes.

> *Hypothesis 15:* Compared to a do-your-best goal, the presence of a difficult, specific performance goal will be (a) negatively related to initial and (b) positively related to subsequent reacquisition adaptation episodes.

Contextual Effects of Difficult, Specific Goals on Adaptive Performance

To date, relatively little work has been done to investigate the impact of goals on adaptive performance and our theoretical understanding in this area is lacking. As a result, Dorsey et al. (2010) contend that this is an important avenue for future exploration, for both theoretical and practical reasons. Specifically, due to the prevalence of difficult, specific performance goals in modern organizations (Latham & Locke, 2006; Locke & Latham, 2002), explorations of this nature are apt to be particularly relevant for organizations in general and selection system design and evaluation in particular. In order to more fully explicate this area, it is important to consider how the presence (or absence) of difficult, specific goals may affect some of the proposed relations between individual differences and adaptive performance already proposed, beyond the direct effects put forth.

This line of inquiry is consistent with general notions concerning the importance of context for determining individual behavior (Johns, 2006). In particular, it has long been recognized that the inclusion of situational characteristics is important for understanding the behavioral manifestations of personality (e.g., Mischel, 1968). While the well-known concept of situation strength (Mischel, 1977) that many associate with this notion may be overly simplistic (Cooper & Withey, 2009; Mischel, 2004), situations may nevertheless convey important cues that are differentially recognized and interpreted, alternatively intensifying or constraining expression of expected patterns of action as predicted by a particular characteristic (Mischel & Shoda, 1995). In other words, these situational aspects can modify the strength of the relationship between individual differences and exhibited behavior. One way to capture this situation is through the inclusion of a situational moderator. The balance of this section considers how changes in one situational moderator, namely the nature of the goal utilized (or goal condition), may influence how individual differences are related to adaptive performance.

Proposed Interaction between Goal Condition and Intelligence

It was previously argued that the positive relationship between intelligence and proactive control (Braver et al., 2007) would result in a negative relationship between intelligence and initial transition adaptation due to increased exclusion of information deemed irrelevant for the program being executed. However, over time intelligence would motivate and enable individuals to effectively modify their programs to incorporate future change relevant information, leading to an increase in subsequent transition and reacquisition adaptation. The presence of difficult, specific goals is likely to intensify both of these effects.

For example, goals that are specific tend to reduce the breadth of task focus (Organ, 1977a; Staw & Boettger, 1990), likely sharpening the focus of the initial performance programs and narrowing the scope of information considered in a proactive control mode. Any reduction in the number of feedback signals considered makes it more likely that signals of a change will be missed. As previously discussed, the driver of action for control theory is a discrepancy between the goal level and the input signal. When appropriate feedback doesn't get incorporated accurately into the input signal, a discrepancy may go undetected, hindering the impetuous for corrective action (Carver & Scheier, 1981, 1982, 1998). This would act to further hinder initial transition adaptation beyond what would be expected in a more general do-your-best context.

In addition, a specific and difficult goal motivates prolonged goal striving, and encourages extensive program generation and eventual adoption of a program suitable for meeting the goal (Locke & Latham, 1990, 2002). This may be beneficial in the long-term as individuals seek to modify programs so that they are able to regain the specified level of performance. GMA is positively associated with a general preference to utilize complex programs (Beilock & Carr, 2005; Beilock & DeCaro, 2007), consistent with the presence of a high-level goal (in a control theory, goal hierarchy sense) for adoption of the same. By adding an additional goal to the hierarchy, the presence of a difficult, specific goal may provide further motivation to identify and adopt a program that is not only complex, but also meets the specified level of performance. Conversely, consistent with goal theory's suppositions that goals act to focus available resources (Locke & Latham, 1990, 2002), GMA better equips individuals to develop and execute the complex programs necessary to perform well enough to meet the goal level of performance while still recognizing and reacting effectively to subsequent change events.

> *Hypothesis 16*: GMA and Goal Condition will interact to predict adaptive performance such that the effect of GMA on (a) initial and (b) subsequent transition adaptation as well as (c) subsequent reacquisition adaptation will be stronger in the specific, difficult goal condition than in the do-your-best goal condition.

Proposed Interaction between Goal Condition and Cognitive Personality Aspects

As previously mentioned, Conscientiousness and Openness are more cognitively focused personality traits while Neuroticism is more closely tied to affect (DeYoung et al., 2007). Because the arguments for both traits are similar, the interaction of goal condition with the aspects of the first two traits is discussed in this section. The discussion pertaining to the impact on Neuroticism is somewhat unique and is presented in its own section below.

As previously discussed, the Industriousness aspect of Conscientiousness is associated with an increase in the spontaneous setting of difficult goals and subsequent pursuit efforts (Barrick et al., 1993; Hollenbeck & Klein, 1987). Specifically, by self-selecting a difficult goal, a discrepancy between the current and desired level of performance is created, driving activity aimed at resolving that situation (Carver & Scheier, 1998; Powers, 1973), often resulting in higher levels of performance. These are the same mechanisms that goal setting theory draws on to explain the positive benefits of externally imposing difficult, specific goals (e.g., Locke & Latham, 1990). In a more general sense, when individuals have less discretion, the effects of conscientiousness on performance are diminished (Barrick & Mount, 1993) and by diminishing choice associated with goal specification by providing individuals with a difficult, specific goal a similar pattern may result.

For example, in the case of do-your-best goals, Industriousness may be positively associated with the establishment of more challenging goals (Barrick et al., 1993; Hollenbeck & Klein, 1987) because of an increased desire to achieve associated with this aspect (DeYoung et al., 2007; Roberts et al., 2005). However, when the externally imposed goal is comparatively difficult with what Industriousness would have led individuals to choose spontaneously, the difference associated with this aspect fades. In other words, individuals tend to have the same active goal, regardless of their level of Industriousness.

Similarly, when coupled with adequate difficulty, a goal that is specific tends to lead to increased persistence (Locke & Latham, 1990). As previously mentioned, abandoning pursuit of a specific goal or revising it downward via the cognitive route generally has negative ramifications for an individual due to the negative impact that these decisions are likely to have on other, higher-level goals within their goal hierarchy (Carver & Scheier, 1998; Lord & Levy, 1994). In contrast, a nonspecific goal makes it easier to accept a lower level of performance as being satisfactory for meeting the lower level task performance goal (Locke & Latham, 1990), preventing the need to reconcile the ramifications of poor performance for higher level goal attainment. Thus, when confronted with a goal-performance discrepancy that demands attention to redress (Carver & Scheier, 1998; Powers, 1973), compared to a general do-your-best goal, goal specificity makes it more difficult to revise a goal downward, limiting the effectiveness of the cognitive route and pushing individuals to persist with behavioral means of accomplishing the desired level of performance. This increased persistence is driven by the presence of a difficult, specific goal, regardless of whether it was internally or externally imposed. Again, external imposition decreases differences across individuals in the goal being pursued, weakening the impact of Industriousness on adaptive performance.

Hypothesis 17: Industriousness and Goal Condition will interact to predict adaptive performance such that the effect of Industriousness on (a) initial and (b) subsequent transition adaptation as well as (c) initial and (d) subsequent reacquisition adaptation will be weaker in the specific, difficult goal condition than in the do-your-best goal condition.

In contrast to Industriousness, the imposition of a difficult, specific goal has a competing (rather than analogous) effect compared with the natural tendencies associated with Orderliness and Intellect. Specifically, Orderliness is positively associated with a preference for order (Costa & McCrae, 1992) and routine (DeYoung et al., 2007; Roberts et al., 2005) while Intellect is positively associated with an interest in truth discovery (DeYoung et al., 2007). When provided only with a vague or general goal, these sorts of tendencies can result in the generation and adoption of personally derived, idiosyncratic goals that can be heavily influenced by these tendencies (Locke & Latham, 1990). In other words, left to their own devices, individuals are likely to notice situational cues that are consistent with their prevailing preferences (Nickerson, 1998) and set idiosyncratic goals for their performance (Locke & Latham, 1990) that are influenced by individual response tendencies, commonly indexed by personality traits (Mischel & Shoda, 1995).

However, in the presence of a specific, difficult goal these inherent tendencies become less important driving forces for action. In addition to personal goals concerned with routine and stability that characterize Orderliness (DeYoung et al., 2007; Roberts et al., 2005), the presence of a performance goal creates an alternative impetus for action. For example, focusing exclusively on maintaining order and emphasizing routine may contribute to the accomplishment of one goal in an individual's hierarchy, but it may not be an effective means of attaining high levels of performance (as hypothesized previously in regards to all aspects of adaptive performance). The presence of a performance goal is a necessary (but not sufficient) condition for the detection of a performance discrepancy (see Figure 2), and once this discrepancy is detected, the individual will be motivated to mitigate this shortcoming (Carver & Scheier, 1998; Powers, 1973). While individual preferences for stability may still influence the nature of the programs employed in the attempt, the increased focus on achieving a specified level of performance is a function of the goal state and serves to diminish the influence of Orderliness by activating an alternative goal across individuals.

Hypothesis 18: Orderliness and Goal Condition will interact to predict adaptive performance such that the effect of Orderliness on (a) initial and (b) subsequent transition adaptation as well as (c) initial and (d) subsequent reacquisition adaptation will be weaker in the specific, difficult goal condition than in the do-your-best goal condition.

Similarly, Intellect tends to be associated with a preference for truth realization (DeYoung et al., 2007), and the presence of high level goals within an individual's hierarchy focused on the same may impact adaptive performance (as outlined previously). The presence of a difficult, specific performance goal constrains the extent to which these pursuits can be followed. For example, simply activating a search routine aimed at uncovering the true structure of the problem may no longer be good enough. This action may contribute to goals related to discovery of the truth on its own, but unless performance also improves in a timely manner that goal will remain unrealized and increase negative reactions to the situation (Carver & Scheier, 1990). As before, the presence of a common performance goal across individuals weakens the differential volitional force arising from different truth seeking preferences across those same individuals.

Hypothesis 19: Intellect and Goal Condition will interact to predict adaptive performance such that the effect of Intellect on (a) initial and (b) subsequent transition adaptation as well as (c) initial and (d) subsequent reacquisition adaptation will be weaker in the specific, difficult goal condition than in the do-your-best goal condition.

Proposed Interaction between Goal Condition and Affective Personality Aspects

Thus far, the proposed interaction relationships between performance goals and personality are consistent with the view of some researchers that goals represent a strong situation that minimizes the impact of personality variables (e.g., Adler & Weiss, 1988). However, this may not universally be the case (e.g., Dossett, Latham, & Mitchell, 1979). For example, Beaty Jr., Cleveland, and Murphy (2001) found that Neuroticism was related to multiple aspects of performance even when the condition could be labeled strong.

As such, in contrast to the previously discussed situations where the presence of a difficult, specific goal attenuated the relationship between a personality aspect and adaptive performance, the presence of such a performance goal may enhance the effect of Neuroticism. While goal setting is heavily cognitive in nature, both aspects of Neuroticism, Volatility and Withdrawal, are primarily affectively focused (DeYoung et al., 2007). Before, the presence of a performance goal provided a substitute or alternative to a personal goal tendency. In this instance, it may provide a ready means of confirming the existence of a presumed threat and strengthen the resulting response tendencies. Such a distinction between the cognitive and broader effects of goal-theory is well established (e.g., Gellatly & Meyer, 1992; Organ, 1977a).

For example, Gellatly and Meyer (1992) went beyond the basic cognitive mechanisms proposed for goal theory and considered physiological arousal that can also be induced, proposing that in situations where the task itself is viewed as being important and taxing the addition of a difficult, specific goal can result in over-arousal and hinder performance. This is consistent with the findings of Drach-Zahavy and Erez (2002) who manipulated stressor perceptions to be either primarily threatening or challenging. The presence of a difficult, specific performance goal interacted with heightened threat perceptions when predicting adaptive performance such that the relationship between threat perceptions and performance was stronger (and negative) in the presence of a performance goal. Thus, while assigning a performance goal adds another goal to an individual's hierarchy just in the previous examples, the affective response to perceived threat may dominate the pattern of performance.

This is consistent with aspects of goal theory in that propose the possibility of an interactive effect between personality and goals when predicting performance. Specifically, because Neuroticism is likely to impact both the personal goals adopted and the subjective prospect of success in the goal striving activity, an interactive effect is apt to occur (Dossett et al., 1979; Locke, 2001). In addition, under certain circumstances, this interaction can reasonably be expected to enhance the strength of the primary relationship (Locke, 2001), as is proposed here.

Specifically, in order to enable an effective response to a threat, negative affect narrows the focus of attention and initiates physiological changes aimed at supporting self-preservation goals (Fredrickson, 1998; Fredrickson & Levenson, 1998; Frijda, 1986; Lazarus, 1991; Levenson, 1994). Due to the importance of self-preservation, it is likely to be near the apex of an individual's goal hierarchy and by virtue of its position, dominate competing low level performance goals in terms of importance (R. E. Johnson et al., 2013; Lord & Levy, 1994). In such situations, there is a desire to extricate oneself from the unpleasant situation rapidly, with relatively little concern for the level of performance attained (Beilock & Carr, 2001; Mesagno et al., 2012).

This disregard of the task performance aspects of the situation may be facilitated by a lack of commitment to the performance goal. In goal theory, goal commitment is an established and important moderator of the relationship between difficult, specific goals and performance

(Locke & Latham, 1990, 2002). When the assigned goal does not mesh with an individual's disposition, goal commitment is likely to be diminished (Locke, 2001). This is consistent with the work of Kernan and Lord (1988) who proposed that alternative, self-derived goals are likely to be more important in dynamic performance episodes that extend over time because the effect of the initial imposed goal may fade (consistent with the previously discussed aspects of control theory) as individuals focus on their own idiosyncratic goals.

At the trait level, meta-analysis has shown Neuroticism to be negatively related to performance-goal driven motivation, which encompassed the effective use of goals to facilitate task performance (Judge & Ilies, 2002). In addition, certain facets of Neuroticism tend to be negatively related to goal orientation, an individual difference defined in terms of a preference for setting and striving towards specific goals (Malouff et al., 1990). As such, it seems that Neuroticism is not conducive to the incorporation of difficult, specific goals, and as predicted by goal theory (Locke, 2001) this may result in less task-focused effort due to low levels of goal commitment. In a negotiation context, a mismatch between an individual's disposition and the situation has been shown to have a negative effect on both the relative importance of the focal performance task and subsequently task performance itself; specifically, individuals experiencing a mismatch are more likely to downplay the importance of the focal task and forgo high levels of task performance, relying instead on dispositionally consistent action preferences in order to extricate themselves from the unpleasant situation (Dimotakis, Conlon, & Ilies, 2012).

In a similar manner, high levels of Neuroticism are likely to make the presence of a difficult specific goal seem unpleasant. Neuroticism is generally associated with an overall tendency to view the world in a negative manner (Costa & McCrae, 1992) and an associated increase in threat perception (Spector, Zapf, et al., 2000), and both Withdrawal and Volatility aspects share these tendencies (DeYoung et al., 2007). The presence of a specific performance goal (rather than a directive to do your best) has long been thought to induce similar increases in the prospect of failure and this effect is likely to be compounded for individuals who already have a tendency to view the world in a threatening manner (Fiske & Maddi, 1961; Organ, 1977a; Spielberger, 1966). First, this goal condition increases the specter of failure because of one of the primary benefits of using a specific goal: it is relatively straightforward to ascertain whether the displayed level of performance met the desired level (Locke & Latham, 1990). Further, as generally defined, a difficult goal even makes the prospect of failure probable in the majority of cases (e.g., Chesney & Locke, 1991; Drach-Zahavy & Erez, 2002; Earley, Northcraft, Lee, & Lituchy, 1990; Winters & Latham, 1996), which may further enhance threat perceptions related to the focal task and diminish the importance of attaining performance goals.

In summary, by compounding the dispositional tendency to focus on the prospect of threat and failure that is an integral component of Neuroticism (Costa & McCrae, 1992; Spector, Chen, & O'Connell, 2000), the presence of a difficult, specific performance goal is likely to be particularly unpleasant for individuals who score high on either aspect of Neuroticism. This mismatch between the individual and the goal condition is apt to reduce the prospect of incorporating performance goals into the individual's goal hierarchy (which would potentially weaken the previously presented relationships in much the same was as was discussed for Conscientiousness and Openness). Instead, the increased threat perceptions brought on by exposure to a difficult, specific goal are likely to intensify the previously discussed, internally driven affective response tendencies arising due to a change, increasing the strength of the previously presented relationships. This effect is independent of whether the affectively laden response is directed internally or externally. As this is the main difference between the aspects of

Volatility and Withdrawal, the mechanisms discussed above would seem to be applicable for both, and in light of this assertion, analogous interaction hypotheses are put forth for both aspects.

Hypothesis 20: Volatility and Goal Condition will interact to predict adaptive performance such that the effect of Volatility on (a) initial and (b) subsequent transition adaptation as well as (c) initial and (d) subsequent reacquisition adaptation will be stronger in the specific, difficult goal condition than in the do-your-best goal condition.

Hypothesis 21: Withdrawal and Goal Condition will interact to predict adaptive performance such that the effect of Withdrawal on (a) initial and (b) subsequent transition adaptation as well as (c) initial and (d) subsequent reacquisition adaptation will be stronger in the specific, difficult goal condition than in the do-your-best goal condition.

METHODS

In the past, investigations concerning the nature of adaptive performance have utilized inconsistent and often inappropriate operationalizations of adaptation (LePine et al., 2000). In addition, the domain has historically faced a dearth of appropriate techniques for analyzing change data (Cronbach & Furby, 1970; Thoresen et al., 2004), which further compounded the challenges associated with conducting rigorous research in this area. The present study attempts to overcome these challenges by employing an appropriate research design coupled with a contemporary data analysis approach appropriate for evaluating change data. The specifics of this approach are discussed in the remainder of this section, which begins with a discussion of the research paradigm selected.

Procedure

Paradigm

Early work in this domain was hindered by muddled operationalizations of adaptive performance that often did not make a clear distinction between performance in any novel situation and actual adaptive performance (LePine et al., 2000). This led LePine et al. (2000, p. 566) to concede that, "adaptability has been conceptualized and operationalized haphazardly." Since this admonishment, adaptive performance researchers have largely coalesced around the task-change paradigm as a preferable means of studying adaptive performance, and today it is the most frequently employed means of conducting inquiries in this domain (Lang & Bliese, 2009). Due to its suitability and prevalence, it is the paradigm adopted here to test the previously derived hypotheses.

The task change paradigm allows researchers to study how individuals or teams respond to a simulated environmental change, something that is particularly difficult to capture in the field (LePine et al., 2000). Specifically, this paradigm is characterized by the introduction of an unexpected and unannounced (e.g., LePine, 2003, 2005; LePine et al., 2000) or unspecified (e.g., Chen et al., 2005) change during the performance episode. In other words, while individuals (or teams) work to develop effective representations of a novel situation and create performance programs that enable effective performance, a change is introduced that renders some portion of the representation inaccurate, reducing the effectiveness of the associated program. Performance in the post-change time periods, when controlling for pre-change performance, is indicative of adaptive performance (LePine et al., 2000). In particular, transition adaptation indexes the ability to recognize that a change has occurred and take immediate steps to reduce the resulting performance decrement immediately after the change is introduced while reacquisition adaptation focuses on the ability to build effective performance programs to perform well in the post-change environment (Lang & Bliese, 2009).

Drawing on an extensive list of research in this domain, Lang and Bliese (2009) note that in addition to the introduction of an unexpected change during the performance episode, the task change paradigm is also characterized by an attendant increase in the complexity of the program required to perform well on the focal task in the post-change period. Mirroring the increasingly complex environment in which organizations operate (Pearlman & Barney, 2000), the need to successfully adapt to situations of increasing complexity is a common source of change faced by organizational employees (LePine, 2005). Utilizing a change event that incrementally increases the complexity of the task in the post-change period is an attempt to more closely align the task-change paradigm with actual field conditions by capturing this frequently encountered aspect of adaptive performance (Dorsey et al., 2010).

As highlighted above, from a conceptual standpoint the task-change paradigm is generally well suited for evaluating adaptive performance. However, as implemented in previous research, it has failed to fully capture the theorized nature of adaptive performance. Specifically, spanning the duration of work in this area, the need to adapt has consistently been proposed as a frequent and ongoing part of organizational life for modern employees (e.g., Cortina & Luchman, 2013; Lang & Bliese, 2009; LePine, 2005; Pulakos et al., 2000). Despite the proposed need to adapt frequently, most previous work employing the task-change paradigm has only examined one change event (e.g., Chen et al., 2005; Drach-Zahavy & Erez, 2002; Lang & Bliese, 2009; LePine, 2003; LePine, 2005; Mumford et al., 1993); however, for a notable exception see LePine et al. (2000).

It has long been proposed that the search routines employed to identify and construct suitable performance programs may evolve with repeated exposure to similar novel stimuli (e.g., March & Simon, 1958). This has important implications for the study of adaptive performance because in when faced with repeated change events, "individuals might learn how to adapt" (LePine et al., 2000, p. 573). To the extent that this occurs, across multiple change events, a different pattern of relationships between adaptive performance and individual differences may be expected to emerge (LePine et al., 2000), as hypothesized above. In order to investigate this possibility empirically, the present study investigates multiple adaptive performance episodes by utilizing two sequential change events, extending the typical task-change paradigm deployment in a theoretically relevant direction.

Performance Task

In order to effectively utilize the task-change paradigm to investigate adaptive performance, a suitable performance task is required. Past investigations have relied heavily on combat simulation scenarios (e.g., Lang & Bliese, 2009; LePine, 2003, 2005; LePine et al., 2000) to fill this role. While these types of scenarios have face validity for a limited range of occupations, their applicability seems less than universal. In an effort to extend the face validity of the focal task to a wider audience and investigate adaptive performance in a different context, an alternative performance task was chosen for this study.

Specifically, a stock pricing simulation was utilized as the focal performance task. This task has been used previously to investigate individual performance in a novel and complex situation and specifically to test the generalizability of goal setting theory (DeShon & Alexander, 1996; Drach-Zahavy & Erez, 2002; Earley, Connolly, & Ekegren, 1989). Further, it focuses on the important "dealing with uncertainty" component of adaptive performance (Dorsey et al., 2010; Griffin et al., 2007; J. W. Johnson, 2003) and can be readily configured exact the necessary shifts in complexity and associated ambiguity and/or novelty that are characteristic of changes necessitating an adaptive response (Baard et al., 2014). Specifically, this task falls squarely within the conceptual architecture for adaptation (Baard et al., 2014) focusing on the foundational individual level and evaluating behavioral responses to dynamic shifts in complexity.

This exercise asks individuals to estimate the price of a hypothetical company's stock, given multiple potential indicators of firm performance. Such a task would be potentially important for employees in a variety of financial sectors, and using focal tasks in lab settings that are relevant for organizational behavior can help increase the generalizability of the results (Latham & Lee, 1986). In addition, stock valuation is potentially important to a broader range of employees as it is important driver of merger and acquisition activity (Rhodes-Kropf & Viswanathan, 2004). This task may also hold personal relevance because as employees increasingly bear a higher burden for managing their own retirement savings (Hacker, 2006), accurately valuing stocks considered for part of an investment portfolio is becoming a more common experience, further increasing the applicability of the task. Given the face validity of a stock-pricing exercise for a wide range of individuals and its previously established use in contexts where a complex and novel task was desired, it would seem to be a suitable performance task for investigating adaptive performance.

Creation of the base stock-pricing task proceeded in accordance with previous instantiations of this exercise (cf. DeShon & Alexander, 1996; Drach-Zahavy & Erez, 2002; Earley, Connolly, & Ekegren, 1989). The "correct" or target price for each stock was determined by using a linear regression equation incorporating multiple, hypothetical organizational characteristics along with an error term. Consistent with DeShon and Alexander (1996), the magnitude of the error term was specified such that on average, the deterministic portion of the regression equation accounted for a nominal 90% of the variation in the stock price. For a given trial, performance can be indexed by the difference between the individual's estimate of the stock price and the "correct" price obtained using this regression equation.

Participants performing the stock pricing exercise are asked to use the organization's performance on a number of performance metrics to estimate what the firm's stock price should be. In this instance, to add additional realism to the exercise, all of the performance metrics provided for each organization have been meta-analytically related to firm financial performance. Specifically, several strategic factors including Growth, Advertising and Market Share (Capon, Farley, & Hoenig, 1990) have been shown to be positively related to firm financial performance in some situations and are used to index organizational performance in this exercise.

As in previous work employing this technique (e.g., DeShon & Alexander, 1996; Drach-Zahavy & Erez, 2002; Earley, Connolly, & Ekegren, 1989), all performance metrics were presented in terms of an index score to put them on a common scale and simplify information processing requirements. Specifically, each organizational measure was represented by an index score drawn from a discrete uniform distribution with a mean of 100, a range of 20 to 180, and a step size of 10. Compared to a normal distribution, the use of a uniform distribution reduces the number of values clustered near the mean, resulting in a greater prevalence of values near the ends of the range and increasing the effective variation in the index values. Using a discrete uniform distribution with a step size of 10 (rather than a continuous one) further reduces unnecessary computational complexity (Earley, Connolly, & Ekegren, 1989).

Across all of the trials, the performance of each hypothetical organization was summarized using the same three metrics. As in Earley, Connolly, and Ekegren (1989), each metric was not equally important in determining the correct stock price, and not all of the organizational parameters were relevant for the determination of the stock price at all (i.e. had a regression weight equal to zero). In this manner, individuals could attempt to exploit past pricing experience to generate a more accurate estimate of the correct stock price by honing in and focusing their efforts on those parameters that they judged to be the most important, downplaying or ignoring organizational information pertaining to parameters judged to be unimportant. Consistent with the discussion presented earlier in the paper, this type of approach may facilitate high performance so long as the evaluation program emphasizes the correct parameters; however, such focused programs may make detection of a change more difficult to detect, hindering adaptive performance.

In order to investigate this issue using the stock pricing exercise, it was adapted to comply with the tenants of the task-change paradigm by building on the procedure used by Drach-Zahavy and Erez (2002). While there were many similarities (e.g. different equations for each period), there were also substantial differences (e.g. number of periods, relative length of periods, scoring system, etc.). Specifically, in this instance the overall performance episode was divided into three equal length segments and a unique regression equation was employed to generate the "correct" stock price in each. Further, this change was transparent as it was automatically and seamlessly integrated into the software used to generate the correct price, occurring at pre-programmed intervals that did not require a restart of the system or any other form of intervention. In this manner, performance could be evaluated in an initial, pre-change condition and compared with adaptive performance after two distinct, unannounced change events.

In particular, each performance episode was divided into 6 measurement occasions, the reasons for which are discussed in more detail during the discussion of the model parameterization. In turn, each measurement occasion represents the average performance for 15 individual decision trials. Blocking trials in such a manner helps reduce noise in the outcome metric and is commonly employed by researchers using the stock-pricing task (e.g., DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989) in general as well as in other studies employing random coefficient growth modeling techniques to detect performance changes over time (e.g., Lang & Bliese, 2009; Thoresen et al., 2004). Thus, each participant was presented with 270 individual decision trials which were subsequently aggregated down to 18 measurement occasions (using the average performance in each block of 15 individual decision trials) to track performance over repeated trials. Further, in order to mitigate any potential order effects, the individual decision trials within each period were presented to every participant in random order (DeShon & Alexander, 1996).

Because the different combinations of predictors chosen across periods did not result in equal variance for the outcome variable across conditions, the raw "correct" scores were rescaled. Specifically, the correct prices provided to participants (and used to index performance) were scaled such that the mean value in each period was a consistent 100 with a consistent standard deviation of 40. This resulted in "correct" prices that spanned from approximately $5 to $200 in each period. Further, choosing a constant estimate for the stock price across all three performance periods resulted in the same average performance level. In other words, guessing a value of "100" for each of the 270 trials would result in the same level of performance across all three performance periods. If the values were not rescaled to have constant variance across periods, a constant response resulted in an apparent and completely artifactual increase in performance across the periods (since the variance in raw scores decreased across periods).

The specific regression weights used to generate the correct stock price in each period are summarized in Table 4. In keeping with previous deployments of the stock-pricing exercise, for the initial time period, the correct price was determined by two unequally weighted organizational outcomes differing in their importance by a factor of approximately 2:1. Previous work has demonstrated that task performance when using such a weighting scheme improves over the number of trials slated for each performance period (e.g., DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989).

In the initial adaptive performance period, the previously dominant predictor (market share) becomes only marginally important while revenue growth increases significantly in importance. In addition, an additional predictor (advertising spend) also contributes to the determination of the correct stock price. This change requires participants to unlearn the previously established strong relationship between market share and performance and relearn which outcome is now the main driver of performance. Unlearning and relearning are both key hallmarks of adaptive performance (LePine et al., 2000). In addition, including a third predictor increases the complexity of this scenario compared with the pre-change period.

For the second adaptive performance period, additional changes are made that require unlearning and relearning. Specifically, there is no dominant predictor in this period as there was in the previous two performance periods. Search programs focusing on identification of a single dominant predictor that may have proved useful for the first and second periods would now be of limited utility. In a similar vein, the inclusion of multiple, equally valid predictors requires individuals to attend to and process a wider range of information in the same amount of time in order to achieve the same level of performance, increasing the cognitive complexity of the task (Carver & Scheier, 1981). Therefore, across change episodes, both core aspects of the task-change paradigm (i.e. introduction of an unexpected change and an attendant increase in task complexity) are maintained in this implementation of the stock-pricing exercise.

Table 4: Regression Coefficients for Stock-Pricing Exercise by Performance Period

Metric	Initial (Pre-change) Performance Period	Initial Adaptive Performance Period	Secondary Adaptive Performance Period
Advertising Spend	0.0	0.15	0.33
Market Share	0.7	0.15	0.33
Revenue Growth	0.3	0.7	0.33

Notes: Numbers represent regression weights used to generate "correct" stock prices in each performance period.

Implementation

Participants were recruited and voluntarily agreed to participate (a description of the sample characteristics appears on pg. 175). When signing up for the study, participants were directed to an online survey where they completed an informed consent and the personality, intelligence, and additional measures. These measures were completed at least a day prior to completing the focal stock-pricing task to increase temporal and contextual separation between the collection of the trait measures and the performance data.

In order to complete the stock-pricing task, participants reported to a classroom equipped with several computers, each of which was pre-configured to run custom software created to implement the stock-pricing exercise as previously described. In order to allow participants to focus on the focal task without being straddled with overly complex tools, the software was designed to be easy to use, requiring only the use of a keyboard to interact with it. In addition, this software utilized a command prompt interface, mimicking the feel of internally developed, "legacy" software that is prevalent in many organizations (Beheshti, 2006).

The software was configured so that the top portion of the screen provided the participant with performance feedback by displaying participant performance over the previous 4 decision trials (roughly corresponding to performance over the past month). Specifically, the organizational performance metrics for each trial were provided along with the correct price, the participant's estimate of the price, and the difference between those two values. In order to facilitate comparisons, the rightmost column of this display contained the organizational metrics for the current trial (obviously, without the correct price). Participants could then decide which pieces of this feedback information to focus on when estimating the price for the current decision trial. They could choose to focus differentially across the different organizational predictors, deciding to rely primarily on a subset to predict the price for the next trial. They could also chose to focus to varying degrees on the performance feedback provided over time. For example, a participant could choose to modify their pricing model as a reaction to one bad performance trial (which may have been caused by a wayward error term) instead of relying on feedback over time to "smooth" out noise inherent in any one trial, or vice-versa.

Below the feedback, participants were asked to enter their estimate of the price for the current trial. The software was configured so that participants had up to 20[1] seconds to complete each individual decision trial. The cycle time was chosen to coincide with the interval utilized by DeShon and Alexander (1996). This amount of time allows for additional evaluation of the provided feedback, and important consideration given feedback's central role in control theory (Erez, 1977; Neubert, 1998). Previous work in this domain utilizing a shorter cycle time has not always provided detailed feedback at all (e.g., Earley, Connolly, & Ekegren, 1989), or has separated the feedback information from the decision point, such that they could not be viewed simultaneously (e.g., DeShon & Alexander, 1996). While the response time allotted varied from previous work, in order to help keep participants engaged in the task, the response requirement was consistent: participants were forced to answer within the time allotted (e.g., DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989). In other words, late responses were not allowed and if no response was entered within the 20 second window, that trial was treated as missing. Participants were briefed of the importance of entering their response during the provided time during the initial training.

Following the lead of DeShon and Alexander (1996), in order to further encourage participants to utilize the provided feedback, this time was divided into two sections. Specifically, the first 5 seconds were "read only" in the sense that while feedback on past performance was provided, participants could not enter their next price prediction during this time. This provided them with an explicit opportunity to utilize the provided feedback about their past performance. Participants then had up to an additional 15 seconds to enter their prediction

[1] This time period was chosen to be consistent with previous implementations of the stock pricing exercise. However, a pilot test (n=28) was also conducted to verify that this amount of time was sufficient. Across all trials in the study, the full amount of time was utilized infrequently (less than 4% of trials) with the majority (60%) of responses entered within the first 10 seconds of the round.

for the next decision trial. The feedback from the previous trial was displayed for the entirety of the answer period, allowing participants to continue to refer to previous feedback while processing their present response, if they were so inclined. Compared to the design chosen by DeShon and Alexander (1996), the current design provided participants with a better opportunity to incorporate past feedback by providing both more detailed information and at the same time, presenting it for the total duration of the answer sequence, making comparisons across previous trials less cognitively taxing.

Because a fundamental change in market valuation drivers over the course of a few hours would not be particularly reasonable, each individual decision trial was purported to mark the passage of one week. In this manner, the performance portion of the task pricing exercise (270 trials) spanned a hypothetical duration of just over 5 years, making the occurrence of changes to underlying market valuation drivers more plausible. In order to frame this occurrence, participants were told that the task could be thought of in the same way as many course projects they had worked on as part of their course work in the past: an attempt to simulate a work environment in the confines of a classroom. Specifically, they were told that they would be asked to provide their best guess on the value of a stock over a series of trials. They were instructed that each trial was important and that they could consider it analogous to an organization that used a work sampling technique for performance evaluation. Specifically, each week, of their decisions would be scrutinized in order to determine their overall job performance, which would be a prime determinant of future compensation, promotion prospects, and even continued employment. Even though, in actuality this decision would be chosen at random to prevent over-emphasis on a single activity, each trial in today's task would simulate the chosen work sample for a given week, and thus they should take each trial seriously.

In this manner, participants were encouraged to meet their goal for each and every performance trial. Two goal conditions were established. In the baseline condition, participants were told to "do their best" on each trial. In the difficult, specific goal condition, participants were told that successful performance was defined as estimating a stock price within $7[2], and that as a result, their goal was to achieve this level of accuracy on each decision trial. In keeping with previous goal operationalizations (DeShon & Alexander, 1996), and to prevent participants from getting discouraged and giving up due to early failures (or coasting in response to early success), goals were established on a per trial basis, rather than an alternative "percentage of trials within a specified error band" formulation employed by Drach-Zahavy and Erez (2002). In order to further simulate an organizational context, each session of participants was randomly assigned to one of the goal conditions prior to their arrival in the laboratory so that the appropriate goal information could be incorporated into the orientation and training.

While the software functioned identically across goal conditions, the information displayed differed slightly to correspond with the goal manipulation. In both goal conditions, the participant's goal for the current trial was stated just above the data entry point, but the content of this information varied to match the assigned goal condition (i.e. either "do your best" or "to be within +/- $7"). In addition, because the ability to know objectively whether the current level of performance satisfies the focal goal is an integral part of what makes specific goals effective (Locke & Latham, 1990), participants in the difficult, specific goal condition were provided with a binary flag indicating whether or not they met their goal on each of the previous trials in the results portion of the screen. This was intended to reduce computational fatigue and further reinforce the presence of a specific and difficult (as evidenced by infrequent attainment) goal.

[2] The results of a pilot study (n=28) in which participants were instructed to do their best when estimating the stock price for each trial indicated that this level of performance was attainable on approximately 20% of the trials, consistent with previous operationalizations of the "difficult" aspect of performance goals.

Figure 4 shows what the input screen looked like for the do-your-best goal condition while Figure 5 shows an example input screen for a participant in the difficult, specific goal condition.

Before they began the initial performance trials, participants were briefed on the nature of the task that they were about to perform, provided with an overview of each outcome metric, and introduced to the software used to conduct the task-pricing exercise. In order to bound the scope of the exercise, participants were told that the outcome metrics would not be detrimental to the stock price (in essence placing a lower bound of zero on the regression coefficients) and that stock prices would have a mean of $100 and could vary from $5 to $200. The importance of each trial in the task was emphasized and their goal for each trial was specified. After the scripted orientation was complete, questions were elicited and answered and then participants completed 6 practice trials in order to gain first-hand experience working on the focal task and interacting with the software. This amount of practice was chosen to be comparable to the amount afforded to participants in previous work utilizing a computer-based stock-pricing task (e.g., DeShon & Alexander, 1996). In order to further emphasize that software familiarization was the sole role for the training trials, unique organizational characteristics not included in the performance task were utilized; specifically, the actual price was determined by equally weighting the Social Reputation, R&D, and Sales indexes.

After completing the hands-on training, participants were told that the training trials were independent from the performance trials and that they should not expect the same performance drivers to carry over. In addition, they were told that while this exercise was predicated on the performance of a hypothetical stock market, they should not expect it to coincide with their experiences pertaining to the performance of the actual stock market or guiding principles they may have learned about in other classes. After reinforcing their goal for each trial, participants were allowed to begin working on the performance trials. After completing the stock pricing exercise, participants completed a measure of goal specificity and goal difficulty, were debriefed and then dismissed.

Exploratory Learning Goal Condition

Despite the limitations of learning goals previously discussed (e.g., Earley & Perry, 1987; Ordóñez et al., 2009; Winters & Latham, 1996) and the specific call by Dorsey et al. (2010) to investigate the effect of performance goals on adaptive performance, there are reasons to believe that learning goals might uniquely influence adaptive performance because they have previously proven beneficial in complex situations (e.g., Seijts & Latham, 2001; Seijts, Latham, Tasa, & Latham, 2004; Winters & Latham, 1996). As a result, a third "learning goal" condition was operationalized to investigate this possibility. However, due to the exploratory nature of this analysis, no formal hypotheses are forwarded regarding potential direct or interactive effects of learning goals on adaptive performance.

Specifically, learning goals pertaining to the identification and implementation of effective strategies for task performance were investigated. Operationalizing learning goals in this manner is not only consistent with goal theory (Locke & Latham, 2002) but is also consistent with past research investigating the utility of imposing learning goals (e.g., Seijts & Latham, 2001; Seijts et al., 2004; Winters & Latham, 1996). Further, just as is the case with performance goals, goal difficulty and specificity are important learning goal characteristics, with difficult, specific learning goals generally proving to be more effective for enhancing performance in novel situations than vague learning goals (Seijts & Latham, 2001; Seijts et al., 2004).

Past research in this domain has demonstrated that the identification and implementation of 4-6 performance enhancing strategies is an effective way to operationalize a difficult specific learning goal (e.g., Seijts & Latham, 2001; Seijts et al., 2004; Winters & Latham, 1996). In line with these findings, participants in this condition were tasked with the identification and implementation of 7[3] performance enhancing strategies. Adopting the presentation used by Seijts et al. (2004), participants were told to "identify and implement 7 effective strategies to maximize your performance" as shown in the software screen capture presented in Figure 6.

[3] Consistent with past work utilizing relatively simple decision tasks, 7 strategies was chosen to operationalize a difficult, specific learning goal. To help ensure this goal was difficult, this level of performance was chosen to be slightly higher than typical (i.e. 4-6) because the task allowed for a variety of potential strategies that could be listed. The results of a pilot study (n=28) indicated that on average when participants were asked to list any strategies they used (akin to a do-your-best formulation), the mean number of strategies reported was two. The maximum number of strategies reported was four and 75% of participants reported three or fewer even though they were presented with 12 blanks in which to report their strategies.

Summary of Past Performance (Last 4 weeks)

	4 Weeks Ago (Week 1)	3 Weeks Ago (Week 2)	2 Weeks Ago (Week 3)	1 Week Ago (Week 4)	Current Week (Week 5)
Advertising	20	150	160	40	50
Market Share	130	130	60	150	30
Revenue Growth	130	30	80	50	150
Stock Price	$120	$119	$78	$138	$?
Your Estimate	$80	$120	$60	$78	$?
Difference	$-40	$1	$-18	$-60	$?

Remember, this task is an important determinant of your performance evaluation.
You should do your best when estimating the price of this week's stock.

Do not enter anything until prompted.
Based on the performance information above, what is your estimated stock price for this organization? (6 s remaining):

Figure 4: Screen Capture of Stock Pricing Exercise Software: Do Your Best Goal Condition

Summary of Past Performance (Last 4 weeks)

	4 Weeks Ago (Week 1)	3 Weeks Ago (Week 2)	2 Weeks Ago (Week 3)	1 Week Ago (Week 4)	Current Week (Week 5)
Advertising	20	150	160	40	50
Market Share	130	130	60	150	30
Revenue Growth	130	30	80	50	150
Stock Price	$120	$119	$78	$138	$?
Your Estimate	$80	$120	$60	$78	$?
Difference	$-40	$1	$-18	$-60	$?
Achieved Goal	NO	YES	NO	NO	

Remember, this task is an important determinant of your performance evaluation.
Your goal is to be within +/- $7 of the actual stock price for this week's estimate.

Do not enter anything until prompted.
Based on the performance information above, what is your estimated stock price for this organization? (5 s remaining):

Figure 5: Screen Capture of Stock Pricing Exercise Software: Difficult, Specific Performance Goal Condition

Summary of Past Performance (Last 4 weeks)

	4 Weeks Ago (Week 1)	3 Weeks Ago (Week 2)	2 Weeks Ago (Week 3)	1 Week Ago (Week 4)	Current Week (Week 5)
Advertising	20	150	160	40	50
Market Share	130	130	60	150	30
Revenue Growth	130	30	80	50	150
Stock Price	$120	$119	$78	$138	$?
Your Estimate	$80	$120	$60	$78	$?
Difference	$-40	$1	$-18	$-60	$?

Remember, this task is an important determinant of your performance evaluation.
You should identify and implement 7 effective strategies to maximize your performance on this task.

Do not enter anything until prompted.
Based on the performance information above, what is your estimated stock price for this organization? (1 s remaining):

Figure 6: Screen Capture of Stock Pricing Exercise Software: Difficult, Specific Learning Goal Condition

Analytic Approach

Model Parameterization

Despite longstanding notions that performance is dynamic (e.g., Bass, 1962; Ghiselli, 1956; Henry & Hulin, 1987) and may be getting more so (e.g., Hesketh & Neal, 1999; Pearlman & Barney, 2000; Pulakos et al., 2000), much work in the performance domain has utilized cross-sectional research designs that imply a static conceptualization of performance (Thoresen et al., 2004). A lack of appropriate methods for analyzing change has long hindered psychological inquiry in general (Cronbach & Furby, 1970) and may partially underlie this apparent disconnect. In fact, the analysis of the longitudinal data structures necessary for investigating the dynamic aspect of performance is among the most analytically challenging data structure that organizational researchers encounter (Bliese & Ployhart, 2002). Fortunately, recent methodological advances have enabled courses of inquiry into intraindividual performance changes over time (Thoresen et al., 2004). Specifically, approaches using random coefficient modeling (RCM: Bliese & Ployhart, 2002) approaches have been developed to study this phenomenon.

RCM or hierarchical linear modeling (HLM: Bryk & Raudenbush, 1992) techniques generally allow researchers to account for non-independence in their data. This is an important consideration since assumptions of independence underlie most other data analytic techniques commonly employed by organizational researchers, including ordinary regression analysis (Kenny & Judd, 1986). While the specifics of these techniques have been discussed in great detail in the references above, they essentially allow for the consideration of multi-level data structures such that data at one level are nested within groups at a higher level. This structure enables investigations concerning the effects of variables and both levels and the partitioning of variance across levels as well.

Depending on the context, what constitutes a given level may vary. For example, in the case of n employees working for N < n companies, the lower level unit of analysis, or level-1, could be conceptualized as an individual employee while the higher level, or level-2 unit of analysis could be the company that the employee works for (Bryk & Raudenbush, 1992). Alternatively, for longitudinal research designs in which multiple responses are obtained from the same individuals over time, the individual becomes the level-2 unit of analysis and the individual response occasions comprise level-1. While data of this nature presents unique challenges, including probable non-independence of the level-1 errors, robust RCM techniques can be effective in evaluating data with this structure (Bliese & Ployhart, 2002), and this type of data structure forms the basis for the analysis conducted here.

Specifically, a discontinuous random coefficient growth modeling (DRCGM) approach (Singer & Willett, 2003) was utilized to evaluate both transition and reacquisition adaptive performance. While similar to HLM in that it employs two types of equations to account for non-independence in the data, this approach is somewhat unique as well. In particular, it is more similar to general mixed-effects growth modeling (Pinheiro & Bates, 2000) in that time is a key level-1 variable rather than within individual, state variables typically used in repeated measure HLM frameworks. In addition, DRCGM employs additional time-based variables beyond a single time measure to capture the occurrence of underlying events that may impact performance over time, effectively creating pre and post-change performance segments with the possibility of different performance slopes and intercepts in each (Singer & Willett, 2003). The conceptual and methodological appropriateness of this approach for evaluating the impact of individual differences on adaptive performance in a task-change paradigm has been discussed extensively in Lang and Bliese (2009), so the following discussion focuses primarily on the application of DRCGM to this particular study rather than a general overview of the suitability of this technique for adaptive performance research in general.

Drawing on the methodology laid out by Singer and Willett (2003) and assuming a linear model, five time-based level-1 variables were created to characterize the dynamic structure of events underlying the overall performance episode. During this discussion, it is worth keeping in mind that due to the research design, there is no between individual variation in these variables. That is, because performance is evaluated at the same time points for each individual, the values that these variables take on are the same across all study participants. This is a permissible but not necessary data structure for employing DRCGM (Singer & Willett, 2003). These time-dependent variables are summarized in Table 5 and each is discussed in more depth below.

Table 5: Linear Model Time-Based Level-1 Variables

	Measurement Occasion (Period)																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Variable	*(Pre-Change)*						*(Initial Adaptive)*						*(Secondary Adaptive)*					
SA	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
TA1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
RA1	0	0	0	0	0	0	0	1	2	3	4	5	6	7	8	9	10	11
TA2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
RA2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	3	4	5

Notes: SA = skill acquisition (linear change in performance over time); TA1 = initial transition adaptation (immediate change in performance following initial change event); RA1 = initial reacquisition adaptation (change in linear performance slope after initial change event); TA2 = subsequent transition adaptation (immediate change in performance following secondary change event); RA2 = subsequent reacquisition adaptation (change in linear performance slope after secondary change event).

As outlined above, overall performance was broken down into 18 measurement occasions with the first 6 characterizing pre-change performance, the next 6 capturing performance after the first change and the final 6 capturing change after the subsequent change event. This quantity of measurement occasions exceeds the three necessary to characterize the shape of each performance period (Singer & Willett, 2003), meets the recommended minimum number or repeated measures in order to provide reasonable parameter standard error estimates (Snijders & Bosker, 1993), and is consistent with previous research using DRCGM to evaluate adaptive performance (Lang & Bliese, 2009).

In this model, baseline performance is characterized by the skill acquisition (SA) variable. It indexes time and varies from 0 to 17. Initial transition adaptation is captured by the TA1 variable. Initially, in the pre-change condition it is set to zero. Immediately after the first change occurs, it assumes the value of one, which is maintained for the remainder of the measurement occasions. Subsequent transition adaptation is indexed by the TA2 variable, which is set to zero for both the pre-change and initial change periods.

Initial reacquisition adaptation is reflected by RA1. This variable is initially zero in the pre-change period. Because slope reflects a change over time, it remains set to zero during the initial post-change period at which point it begins to increase linearly with each subsequent measurement occasion. Similarly, RA2 remains at zero until the measurement occasion following the subsequent post-change event. When studying adaptive performance, it is important to differentiate it from general task performance (LePine et al., 2000). By utilizing the coding scheme discussed above, both transition and reacquisition adaptation aspects can be effectively differentiated from both common task performance characteristics, namely mean performance as well as performance change over time (Lang & Bliese, 2009). The functioning of these parameters is discussed in the context of the proposed level-1 equation presented below.

$$Y_{it} = \pi_{0i} + \pi_{1i}SA_{it} + \pi_{2i}TA1_{it} + \pi_{3i}RA1_{it} + \pi_{4i}TA2_{it} + \pi_{5i}RA2_{it} + e_{it} \qquad (1)$$

In this equation, the performance of individual *i* at time *t* is represented by Y_{it}, and a linear relationship between performance and the level-1 predictor variables is proposed (with an error term, e_{it}, to account for unexplained within individual variation at each measurement occasion). In this context, the operationalization of performance must be chosen judiciously to in order to satisfy an equation so structured. Due to the foundational nature of this equation for the subsequent analysis, the operationalization chosen for the dependent variable is described below.

As a result of the nature of the stock pricing task chosen for this investigation, performance is generally indexed in the form of a deviation score; specifically, the deviation of the predicted price from the actual price for each trial (DeShon & Alexander, 1996; Drach-Zahavy & Erez, 2002; Earley, Connolly, & Ekegren, 1989). In such a context, better performance is indexed by smaller deviation scores, such that a decreasing trend over time is indicative of increasing performance. In addition, while the data from past studies using this task have not exhibited strong indications of curvilinearity (e.g., DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989), in general, because of learning effects, a non-linear relationship between performance and experience is not unusual and past analyses have incorporated curvilinear effects (e.g., Lang & Bliese, 2009), so deviations from the above proposed linear model were investigated.

In general, when conducting DRCGM, linear models are preferable to curvilinear models due to their relative simplicity and increased interpretability, and whenever possible, variable transformations should be attempted in order to linearize the response with respect to the independent variables (Singer & Willett, 2003). While either the independent variable or the dependent variable can be transformed to achieve a linear relationship, preference should be given to transforming the variable measured on an arbitrary scale (Singer & Willett, 2003). In this instance, the passage of time is indexed in terms of trials, which are intuitively meaningful when evaluating changes in performance. In contrast, the metric for evaluating performance, an arbitrarily indexed deviation score, would seem to be less intuitively appealing, and therefore a better candidate for transformation.

Due to the negative association between the original performance metric and performance, the presence of a curvilinear effect is likely to manifest as downward sloped curve with a diminishing slope over time. The "rule of the bulge" and associated "ladder of powers" technique developed by Mosteller and Tukey (1977) indicates that using a transformation obtained by using the reciprocal of the square of the original performance metric is appropriate for linearizing such a relationship. Beyond serving to linearize the relationship, this transformation has an additional interpretative benefit as well.

When the inverse of the deviation score is taken, large deviation scores that indicate poor performance become small transformed values while high levels of performance and associated small deviation values manifest as larger transformed values. As a result, taking the inverse results in the more familiar pattern in which higher performance is positively related to higher (transformed) performance values. Transformations that have resulted in a similar positive association have been used previously to aid interpretability of results in this domain (e.g., Drach-Zahavy & Erez, 2002). Therefore, when successful, this transformation is useful to aiding interpretability of the findings on its own, and doubly so when one considers the simplicity of the familiar linear regression equation, which is used to motivate the discussion of the level-1 parameters below.

As in any linear regression equation, it can be characterized in terms of an intercept (b) and a slope (m), in terms of the familiar $Y = mX + b$ regression model. In this case, the intercept is comprised of the components of the performance equation that do not index the passage of time, namely π_{0i}, π_{2i}, π_{4i}. Similarly, the slope parameter is a composite of the coefficients that apply to components that index the passage of time. For this equation, π_{1i}, π_{3i}, and π_{5i} impact the effective performance slope. Thus, the transition and reacquisition aspects of adaptive performance are related to the intercept and slope of the performance line respectively. The evaluation of each of these parameters in the various performance segments is discussed in more detail below. A more in-depth discussion (along with an analogous discussion of the yet to be introduced level-2 equation) can be found in Appendix B.

In terms of the slope of the performance line, during the pre-change period, the rate at which performance changes (i.e. slope) is reflected exclusively in the value of π_{1i} because all of the other time-dependent variables have a constant zero value during this period. However, this model allows for this slope to change after the initial change event. Starting with the seventh measurement observation, RA1 begins to increase in lockstep with SA such that the change in performance across adjacent measurement intervals becomes ($\pi_{1i} + \pi_{3i}$). The parameter characterizing the magnitude of the initial reacquisition adaptation, $\pi_{3i,}$ thus manifests as a change in slope for the post-change period (compared to the pre-change timeframe). Similarly, after the second change occurs, RA2 likewise begins to increase and the change in performance across adjacent measurement intervals becomes ($\pi_{1i} + \pi_{3i} + \pi_{5i}$). Thus, the magnitude of subsequent reacquisition adaptation, π_{5i}, results in a change in the performance slope after the second change has occurred, compared to the slope in the first post-change period.

Building on the slope information just presented, the intercept components of the equation can also be discussed. Because all of the level-1 variables take on a value of zero at the first measurement occasion, π_{0i} represents the intercept or the initial level of performance (i.e. at the first measurement occasion). The intercept characterizing the performance line remains unchanged during the pre-change period. However, for the measurement occasions following the initial change event, TA1 takes on the value of one. After this occurs, and prior to the occurrence of the secondary change event (i.e. measurement occasions 7-12), the intercept for the performance equation characterizing the initial post change period becomes ($\pi_{0i} + \pi_{2i} + 6\pi_{1i}$), and as expected, the magnitude of the initial transition adaptation, π_{2i} indexes the magnitude of the immediate vertical shift in an individual's performance trajectory resulting from the initial environmental change. Similarly, after the second change occurs, both TA1 and TA2 have a value of one resulting in an effective intercept for the performance curve characterizing this portion of the performance episode of ($\pi_{0i} + \pi_{2i} + 12\pi_{1i} + 6\pi_{3i} + \pi_{4i}$). Thus, the magnitude of the subsequent transition adaptation, π_{4i}, represents the change in intercept driven by the immediate vertical shift in performance associated with the second change event.

Figure 7 presents hypothetical effects of these parameters graphically. Every coefficient in the performance equation is shown as being positive only to simplify the illustration. They are not indicative of any predicted valences in the present context.

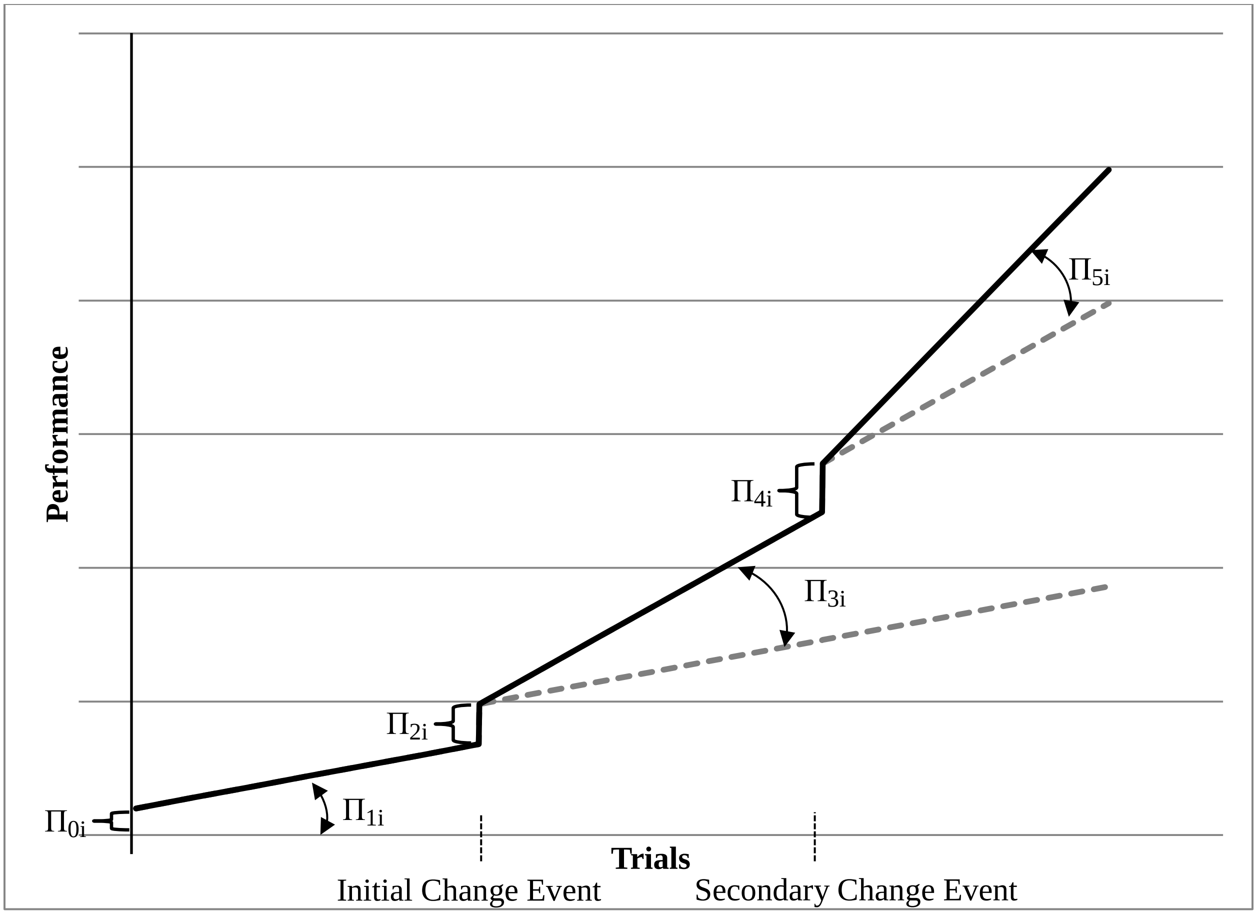

Figure 7: Hypothetical Illustration of Level-1 DRCGM Parameters

While this method of parameterization is conceptually similar to a typical two-way interaction with a binary "condition" variable, there are some important differences that make the two approaches fundamentally different (Singer & Willett, 2003). First, the magnitude of the vertical shift in the outcome that accompanies an underlying change is indexed to the initial time-point in an interaction model, rather than to the point at which the change occurs. In this instance, the magnitude at the point of occurrence is more relevant. In addition, the magnitude of the vertical shift in an interaction model is dependent on the value of time. This is not conceptually consistent with the present model and would make direct comparisons of the initial and subsequent transition adaptation events complex. Finally, by specifying each variable separately, rather than as an interaction between two existing variables, the DRCGM approach appropriately highlights the importance of each time varying predictor, both conceptually and methodologically during construction of the level-2 equations, as outlined below (Singer & Willett, 2003).

Just as in ordinary HLM, once the level-1 equation has been specified, level-2 equations can be postulated to predict each of the level-1 coefficients. Generically, each within-individual, time varying coefficient (π_{ki}) can be predicted as the dependent variable for a linear, level-2 regression equation. Each level-2 equation may contain its own intercept, denoted γ_{k0}, as well as one or more level-2 predictor variables, each with its own coefficient, γ_{kn} with n going from 1 to the number of level-2 predictor variables included. In addition, an error term, ζ_{ki}, which allows the effects of the level-2 predictors to vary randomly across individuals, can be included as well. An example level-2 equation is shown below for a case involving two predictors as well as their interaction.

$$\pi_{ki} = \gamma_{k0} + \gamma_{k1}*X_1 + \gamma_{k2}*X_2 + \gamma_{k3}*(X_1*X_2) + \zeta_{ki} \tag{2}$$

Before concluding this section, the centering strategy adopted is discussed because centering is an important consideration when conducting multi-level analyses (Enders & Tofighi, 2007). In particular, between individual differences in mean levels of the level-1 predictors can be problematic when evaluating cross-level moderation effects (like those proposed here) because within and between group differences can be confounded (Enders & Tofighi, 2007). However, because the values of the level-1 predictors are exclusively related to indexing the passage of time, this approach varies somewhat from typical HLM implementations in organizational research, even within subjects, repeated measures designs. One consequence of this difference is the lack of between individual differences in the magnitude of the level-1 predictors in the raw data to be concerned with when choosing a centering strategy. Therefore, as suggested by Singer and Willett (2003), in order to facilitate interpretability, the level-1 predictors were operationalized to begin at zero, effectively centering them around the temporal origin, rather than centering on the group-means. As a result, the intercept reflects a meaningful quantity, namely performance on the initial measurement occasion. Similarly, the level-2 individual difference variables were grand-mean centered to aid in interpretability by focusing on values relative to the sample average rather than the endpoints of the arbitrary measurement scales employed. Standardized coefficients are obtained by scaling variables to have unit variance without additional recentering.

Model Evaluation

The models described in the preceding section were evaluated in R (R Core Team, 2012) using the 'NLME' package (Pinheiro, Bates, DebRoy, Sarkar, & the R Development Core Team, 2012). The methods employed to conduct the analysis are consistent with the conceptual and methodological framework laid out by Singer and Willett (2003). In addition, the results of the analysis are organized according to the systematic model evaluation guidelines laid out in Bliese and Ployhart (2002). The specifics of this approach are discussed as in integral part of the results section.

In keeping with these recommendations as well as previous work in this area (e.g., Lang & Bliese, 2009), unless stated otherwise, models are evaluated using restricted maximum likelihood (RML) estimation algorithms. While the use of RML allows for evaluation of the statistical significance of any individual parameter estimate, it precludes the comparison of models that differ in terms of their fixed effects by means of goodness of fit statistics (Singer &

Willett, 2003). This can be overcome either by switching to full information maximum likelihood (ML) estimation or by considering the statistical significance of each individual fixed effect estimate individually. Even though the use of single-parameter significance tests can be problematic for evaluating the significance of variance components, it is the preferred means of evaluating fixed effects (Pinheiro & Bates, 2000). In fact, evaluating the statistical significance of the individual fixed effects by "examining *t* values is always the preferred means of significance testing when one is focusing on new fixed effects" (Bliese & Ployhart, 2002, p. 381).

In contrast, multiple models can be compared using goodness of fit comparisons based on RML solutions when they differ only in their stochastic (i.e. random effect) portions. In fact, such a method of evaluation is not only permissible but actually recommended as the primary means of evaluating the significance of stochastic portions of a proposed model (Singer & Willett, 2003). Therefore, in order to evaluate the statistical significance of model parameters appropriately, the method of evaluation varies depending on the nature of the parameter. Specifically, the significance of all fixed effect estimates is determined by evaluating the statistical significance of each individual coefficient (by comparing the magnitude of the effect size estimate to the provided *t* value). Conversely, the significance of all random effects is evaluated by comparing the goodness of fit statistics (e.g. deviance for nested models) across models.

Power

Determining the power level to detect a particular effect for studies utilizing a RCM approach is a challenging undertaking (Thoresen et al., 2004). While relatively straightforward formulae can be used to estimate sample size for multilevel models containing only one predictor (or multiple uncorrelated predictors) for each level, these formulae are generally unsuitable for more typical models including multiple, correlated predictors (Snijders, 2005). In this case, general, exact solutions have not been developed (Thoresen et al., 2004), and the models and formulae used to estimate power in such situations become particularly complex and unwieldy (Snijders & Bosker, 1993). Snijders, Bosker, and Guldemond (2007) developed a software program, PinT (Power in Two-level designs), to make the process more tractable, but numerous assumptions on are still required in order to estimate the power of the design. Further, because relatively little work on adaptive performance has been conducted, there are limited sources of guidance to draw upon when making these assumptions. While the existent literature was used where applicable, as is typical for this technique, it was necessary to utilize "guesses" as part of the power analysis (Snijders & Bosker, 1993).

Because power is dependent in part on effect size (Cohen, 1992), in order to gage the power of a research design a-priori, an estimate of the anticipated effect size must be made. In this case, an effect size (in terms of standardized regression coefficient) of 0.30 was assumed, corresponding to a medium effect size (Cohen, 1992). This is in line with previous work that investigated the role of GMA on adaptive performance (Lang & Bliese, 2009) and is conservative based on previous meta-analytic findings that indicate the potential existence of a stronger relationship between GMA and performance (F. L. Schmidt & Hunter, 1998), which may itself be conservative given the restricted nature of the samples employed in the primary studies (Chernyshenko, Stark, & Drasgow, 2011).

In the context of personality, Thoresen et al. (2004) note that this is a practically meaningful effect size, and one that is in line with previous meta-analytic findings relating personality and aspects of performance. Further, this estimate may be considered conservative since it was based on trait levels of personality that should exhibit lower effect sizes with specific components of performance than that found with a more granular conceptualization of personality like the one employed here (Mount & Barrick, 1995; Stewart, 1999). Finally, Locke and Latham (1990) reported that the meta-analytic effect sizes linking the use of difficult goals to task performance were medium to large in magnitude. Hence, a medium effect size was adopted in this instance in order to remain on the conservative end of that range.

Because the output of PinT is in terms of expected standard errors, this assumed effect size must be related to a standard error in order to utilize the output of PinT for a-priori power analysis. Snijders (2005) provides an approximation for this relationship based on a two-tailed t-test (for testing parameter significance) that is appropriate for reasonable effect sizes (or equivalently power levels greater than 0.3). Assuming a desired power level of 0.80 (Cohen, 1992) and a standard 95% confidence interval (corresponding to a nominal type one error rate of 5%) along with a standardized effect size of 0.30 results in an estimated maximum allowable standard error of 0.11.

Several iterations of PinT were conducted using estimated relational assumptions consistent with the discussion in Snijders and Bosker (1993) and the PinT user manual (Bosker, Snijders, & Guldemond, 2003). The resulting analysis of the specified research design discussed below and a sample size of 240 (approximately evenly distributed across the do-your-best, performance and learning goal conditions) indicated that the estimated standard errors remained at or below the critical level of 0.11, indicating an estimated power level of at least 0.80 to detect a standardized effect size of magnitude 0.30. Some indication of the plausibility of this outcome can be obtained by comparing this design to other recent work utilizing a similar design. For example, this study incorporates some additional level two observations (i.e. individuals) and

50% more level one observations (i.e. repeated measures) than the recent work by Lang and Bliese (2009) that employed a similar analysis strategy. Further, this study utilizes twice the respondents (level-2) and four times the number of repeated measures (level-1) as Thoresen et al. (2004), who reported sufficient power to detect a 0.30 standardized effect size for personality when predicting performance using RCM modeling techniques, albeit directed at answering a slightly different question.

Participants

Participants were primarily upper level undergraduate students (96% juniors and seniors) enrolled at a large Midwestern university who received course credit for participating in the study. In addition to course credit for participating, students also had the opportunity to earn $50 based on their performance during the stock pricing exercise. Specifically, the top 10% of performers in each goal condition were paid $50 in cash at the end of the data collection. In order to keep participants motivated throughout the exercise, they did not know what level of performance was necessary to receive the payment during or immediately after the exercise. A total of 261 students participated in the exercise with 82 in the do-your-best condition, 86 in the performance goal condition and 93 in the learning goal condition. The sample was 51% female and race was reported as 76% White and 22% Asian. The average age was 21 years.

Measures

GMA

General mental ability was assessed using the Wonderlic Personnel Test – Quicktest (WPT-Q). This is a timed test, and respondents have 8 minutes to answer a battery of 30 questions. This well-established and reliable test of general mental ability was developed to mirror the results that would be obtained using the previously deployed Wonderlic Personnel

Test, (Wonderlic, 2004), which has itself been successfully used in a wide variety of field and lab contexts and generally demonstrates a high level of internal reliability (LePine et al., 2000). The WPT-Q was developed to maintain the desirable psychometric properties of the previously established Wonderlic Personnel Test (WPT) while being more suitable for administration in modern organizational settings, particularly during the selection process (Wonderlic, 2004). As evidence of the success of these endeavors, the WPT-Q has demonstrated internal reliability of around 0.8 (similar to that demonstrated by the WPT) and a corrected correlation with the WPT in excess of 0.9 (Wonderlic, 2004). In this instance, the test was administered in an online format, in a manner consistent with its recommended use in a selection context, and the data was obtained at the same time that the personality information was collected (i.e. at least a day prior to completing the focal performance task).

Personality

The aspect level personality scales developed by DeYoung et al. (2007) were used to measure both aspects of Conscientiousness and Neuroticism along with the Intellect aspect of Openness. In addition, even though no hypothesized relationships were derived for the remaining five aspects (i.e. Extraversion: Enthusiasm and Assertiveness; Agreeableness: Politeness and Compassion; Openness: Openness), these measures were obtained as well in order to maintain the prescribed data collection approach of interspersing the items from all 10 scales during data collection (DeYoung et al., 2007). Specifically, the interspersion was accomplished by randomizing the order that each of the 100 statements was displayed for each participant. Further following the recommendations of the scale's developers, items were measured on a 5-point Likert scale, with standard endpoints ranging from "Very Inaccurate" to "Very Accurate", as suggested by the International Personality Item Pool (IPIP) project (Goldberg et al., 2006). In order to reduce within-person inconsistency, the items were contextualized at the scale (i.e. instruction) level per the recommendations of Lievens, De Corte, and Schollaert (2008). The specific items and instructions provided to participants are provided in Table 30 of Appendix A. The reliability for each scale appears on the diagonal of the correlation matrix, presented in Table 6.

Goal Condition: Manipulation Check

As previously mentioned, each section of participants was randomly assigned to either a do-your-best or a difficult, specific goal condition. In the latter case, the goal level of performance was operationalized as estimating the stock price for each trial within +/- $7 of the "correct" stock price generated by using the appropriate regression equation discussed previously. Due to the error present in the estimating equations, this level of performance would be attainable approximately 36% of the time with perfect prediction, and would only be attained 13% of the time if the mean value of the outcome was selected for each trial. This is in contrast with a moderate goal, which was operationalized by DeShon and Alexander (1996) as a level of performance attainable 55% of the time by selecting the mean value of the outcome (corresponding to a goal level of +/- $33 in this case). The level of difficulty associated with a +/- $7 goal is also consistent with longstanding contentions that the level of performance denoted by difficult goals should be unattainable for the vast majority (on the order of 75% to 90%) of participants (e.g., Chesney & Locke, 1991; Earley et al., 1990; Winters & Latham, 1996; Wood & Bandura, 1989b).

The effectiveness of this goal manipulation was assessed by four items used by Earley et al. (1990) to evaluate a similar design that compared the efficacy of do-your-best and difficult, specific goals. Specifically, two items addressed reported differences in difficulty across conditions while the remaining two items evaluated differences in specificity. Responses to all four items were collected after completion of the stock-pricing exercise, and the specific questions are presented in Table 31 in Appendix A. To arrive at indices of goal difficulty and specificity, each individual's responses were averaged across each pair of questions.

Dependent Variable: Performance

As previously discussed, the dependent variable used in the analysis represents a transformation of the deviation score between the "correct" and estimated stock price for each trial. First, previous work in this area has consistently relied on the use of the absolute values of deviation scores to allow for the aggregation of individual trial-level responses in a meaningful way (e.g., DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989). If raw deviation scores were used instead, large deviations of opposite signs could cancel one another out, resulting in a low average deviation score (i.e. high performance) despite consistently poor performance on each individual trial. To avoid that problem, the absolute value function is employed in the first step of the performance calculation here as well.

Specifically, the magnitude of the deviation score for each trial was calculated by taking the absolute value of the difference between the correct and user estimated stock price values. Then, the average magnitude of this value for each block of 15 trials (corresponding to a particular measurement occasion), was inverted and squared to linearize the performance curves and simplify the model, as suggested by Singer and Willett (2003). As mentioned before, in addition to linearizing the model, this transformation results in a more intuitively appealing measure such that higher levels of performance (i.e. guessing closer to the actual stock price) are represented by higher levels of the outcome measure (Drach-Zahavy & Erez, 2002). Summary statistics pertaining to the average performance (as indexed by this transformed metric) for all individuals for each of the 3 performance periods (i.e. initial performance, initial adaptive performance, and secondary adaptive performance) are presented as part of the correlation matrix in Table 6.

Additional Measures

In addition to the measures described above, two additional scales were administered during the online data collection. Because affect may play a role in the self-regulatory process (Howe et al., 2013), trait positive and negative affect were assessed to capture individual tendencies to view the world in a generally positive or negative manner (Watson, 2000). Trait affect was evaluated using the Positive and Negative Affect Scales (PANAS) developed by Watson, Clark, and Tellegen (1988) using the general temporal instructions. The specific indicators and instructions are provided in Table 32 of Appendix A. For administration, the items for both affective traits were interspersed and presented in random order.

Another individual difference that is related to the goal striving aspect of self-regulation (Diefendorff, Hall, Lord, & Strean, 2000) is Action-State Orientation (Kuhl, 1985, 1994b; Kuhl & Beckmänn, 1994). Action orientation is associated with an increased ability to devote available resources toward goal accomplishment while state orientation is characterized by an inability to block out recurrent thoughts about competing goals and affective states, reducing the availability of cognitive resources for the task at hand (Diefendorff et al., 2000; Kuhl, 1994b). Further, Kuhl (e.g., Kuhl, 1994b; Kuhl & Beckmänn, 1994) has proposed 3 sub-dimensions of this trait.

The first, preoccupation, is focused on the extent to which individuals are able to disengage from (indicative of action orientation) or become preoccupied (indicative of state orientation) with thoughts about negative event occurrences. The second, hesitation, is concerned with individual differences in the tendency to initiate (indicative of action orientation) or hesitate (indicative of state orientation) goal striving activities. The final dimension, volatility, captures the ability to persevere (indicative of action orientation) with the pursuit of a particular goal compared with an inability to maintain goal focus and an associated rapid switching between goals, termed volatility (indicative of state orientation).

All three components were assessed using the updated version of the Action Control Scale (ACS-90) originally put forth by Kuhl (1994a). Due to issues with the factor structure of the original measure, the updated measure proposed and validated by Diefendorff et al. (2000) is adopted. While the original ACS-90 had 12 items per sub dimension (36 total), the revised scale has 22 items (8 items each for the preoccupation and hesitation sub-components and 6 items for the volatility measure). Following the scoring guidelines laid out by Kuhl (1994a), measures indicative of action orientation were constructed by summing the number of action-oriented choices selected for each subscale (scores could range from 0-8 for preoccupation and hesitation and 0-6 for volatility). Due to the differences in the length of the subscales of the revised measure but in keeping with the initial implementation of interspersed items, the items for all three subscales were combined and presented to participants in random order.

RESULTS

Before aggregating the simulation data into groups of 15 responses necessary to begin the focal analysis, the simulation data was screened for uninterpretable and unreasonable responses. For example, approximately 1.6% of the raw responses were missing (i.e., no response was entered during the 20 seconds allotted for a particular trial) or contained non-numeric price estimates (e.g. 17\) that were discarded because it was unclear what the respondent intended to enter (e.g. $17, $170, or $179, etc.). In addition, a few responses appeared to be the result of participant data entry errors. During the training, it was repeatedly emphasized to participants that the actual stock price could only vary between $5 and $200 and as such, there was no reason to ever guess a value outside of this range.

In order to avoid skewing the results for a given data point due to an outlier (particularly on the high end, e.g., $7075), responses falling outside of the range of $5-$200 (inclusive) were recoded as missing. This resulted in the removal of an additional 1.5% of raw responses. To clarify, this data removal procedure did not introduce any missing data at the measurement occasion level that was used to test the hypothesized relationships. Due to the low proportion of missing data and the aggregation process associated with each data point, each data point could be estimated. Less than 0.5% of aggregated performance values are based on fewer than 10 responses due to missing data of any sort, and over 70% were based on the maximum number of trials (i.e. 15).

A summary of the measures included in this study, along with the correlations between measures is presented in Table 6. Means and standard deviations are provided for the raw data (before rescaling) with the exception of performance, which is presented in its transformed state so the correlation coefficients have easier to interpret signs. Specifically, a *positive* sign indicates that *increasing (decreasing)* values on that independent variable are associated with *increasing* *(decreasing)* performance. Where applicable, an indication of internal reliability, Cronbach's alpha (1951), is shown on the diagonal of the correlation matrix. The reliability is consistent with previous data collections using these measures, and in all cases, at an acceptable level (Nunnally & Bernstein, 1994).

In terms of the personality aspects, the mean and variance of the scales is consistent with expectations. Previous work has reported means of approximately 2.5 for both Neuroticism aspects and approximately 3.5 for the other aspects, and standard deviation values of 0.4 to 0.7 are typical (DeYoung et al., 2007). In addition, the pattern of relationships is in line with previous work utilizing this scale. For example, across multiple samples, a correlation between the two aspects of Neuroticism was reported as being nearly 0.6 and both Volatility and Withdrawal were negatively related to Industriousness exhibited moderate negative correlations on the order of -0.3 to -0.4 (DeYoung et al., 2007).

In terms of GMA, the mean score on the WPT-Q was slightly above the normative average value of 21.9 while the standard deviation of the scores was slightly lower than the reported 5.0 (Wonderlic, 2004). This is consistent with the collegiate sample in the current study, which might be expected to exhibit higher than average intelligence with reduced dispersion. Further, as expected the relationship between GMA and the Intellect aspect of Openness is positive, but quite modest in magnitude.

Given the random assignment of participants to goal conditions, no substantive relations with individual difference variables would be expected. As previously mentioned, 82 participants were assigned to the DYB condition, 86 performed in the PG condition, and 93 were in the LG condition. In general, this pattern is present in the data in Table 6 as the magnitudes of the correlations are small (Cohen, 1992) and the majority are not significantly different from zero.

The average inter-individual performance levels are largely the same across the three performance phases (i.e., initial performance, adaptive performance after the first change event, and adaptive performance after the second change event) as was the variance in performance across individuals. Given the nature of the performance task, this is not unexpected. In each time period, participants had to ascertain a unique relationship between the organizational performance measures and the outcome (stock price). In addition, as the trials went on, the nature of the relationship exhibited increasing component complexity in addition to the dynamic complexity associated with the changing coordinative aspects of the relationship. As such, correlations on the order of 0.5 across performance periods seem reasonable. In addition, given the volume of literature devoted to the relationship between GMA and performance, it is not unexpected that there is a modest positive relationship between GMA and performance in each period.

In addition to investigating potential performance changes over time, the relationship between overall performance and goal condition was investigated. Much as before, performance was largely consistent, regardless of goal condition. Specifically, the average performance in the DYB goal condition was 175.8, which did not differ significantly from either the average performance level of 174.6 in the PG condition ($t=1.47$, $p=0.14$, ns) or the average in the LG condition of 175.2 ($t=0.82$, $p=0.41$, ns). Further, as would be expected from these values, the PG & LG conditions did not differ in terms of average performance either ($t=0.71$, $p=0.48$, ns). The average performance for the three performance periods is likewise similar across goal conditions with no significant differences, as shown in Table 7.

Table 6: Means, Standard Deviations and Correlations

	Mean	sd	1	2	3	4	5	6	7	8	9	10	11
1. GMA	25.27	3.90	-*										
2. Industriousness	3.55	0.62	.04	(0.84)									
3. Orderliness	3.70	0.54	.17	.49	(0.74)								
4. Intellect	3.58	0.55	.21	.53	.23	(0.78)							
5. Volatility	2.62	0.74	-.08	-.39	-.13	-.20	(0.88)						
6. Withdrawal	2.73	0.65	-.08	-.57	-.18	-.44	.64	(0.83)					
7. PG Condition	-	-	-.06	.14	.03	-.01	-.22	-.12	-				
8. LG Condition	-	-	-.18	.13	-.02	.01	-.21	-.05	-	-			
9. Initial Perf.	175.8	6.58	.21	.05	.00	.14	-.12	-.09	-.09	.00	-		
10. Adapt. Perf. I	175.0	6.30	.23	.05	.04	.11	-.09	-.02	-.09	-.09	.50	-	
11. Adapt. Perf. II	174.8	6.32	.29	.03	.14	.14	.03	.03	-.11	-.07	.55	.54	-

Notes: n = 261 except for correlations involving PG Condition (n=168) or LG condition (n=175). sd = standard deviation. Numbers in parentheses denote reliability. Correlations greater than 0.12 in absolute magnitude are significant at p = 0.05 for the majority of the table. For those correlations involving PG Condition and LG Condition, correlations greater than 0.15 in absolute magnitude are significant at p = 0.05. PG Condition = Performance Goal Condition (compared to DYB condition). LG Condition = Learning Goal Condition (compared to DYB condition). Initial Perf. = Average performance in the initial performance (pre-change) period. Adapt. Perf. I = Average performance in the period following the first change and prior to the second change (i.e. initial adaptive performance). Adapt. Perf. II = Average performance in the period following the second change (i.e. secondary adaptive performance). *The published reliability for the WPT-Q is 0.81 (Wonderlic, 2004).

Table 7: Task Performance by Period & Goal Condition

Goal Condition	Initial Performance	Initial Adaptive Performance	Subsequent Adaptive Performance
Do-your-best	176.18	175.76	175.56
Performance	174.97	174.72	174.17
Learning	176.24	174.62	174.66

Manipulation Checks

The effectiveness of this goal manipulation was assessed by four items used by Earley et al. (1990). These items are reproduced in Table 31 in Appendix A and assess the perceived difficulty and specificity of the goal assigned to participants. The results are summarized in Table 8 and discussed below.

Table 8: Goal Condition Manipulation Check Results

	DYB mean	PG mean	LG mean	DYB-PG |t|	DYB-LG |t|	PG-LG |t|
Difficulty	3.2	3.8	3.3	**4.0***	0.1	**4.0***
Specificity	1.6	2.4	2.0	**6.6***	**3.8***	**3.2***
# Strategies	2.5	2.4	6.1	0.0	**11.4***	**10.9***

Goal difficulty is evaluated using two items assessing perceived difficulty and challenge of the assigned goal. The results indicate that the performance goal (PG) was perceived as being more difficult than the do-your-best (DYB) goal (3.8 vs. 3.2; $t=4.0$, $p<0.001$) and the learning goal (LG) as well (3.8 vs. 3.3; $t=4.0$, $p<0.001$). In contrast, the DYB and LG conditions did not differ significantly in terms of perceived goal difficulty (3.2 vs. 3.3; $t=0.1$, $p<0.95$). As expected, participants in the PG condition met their goal (of being within +/- $7) on 23% of the trials.

Similarly, goal specificity is evaluated using two items that assess the specificity of the assigned and internalized goal. The results indicate that the PG was perceived as being more specific than the DYB goal (2.4 vs. 1.6; $t=6.6$, $p<0.001$) as well as the LG (2.4 vs. 2.0; $t=3.2$, $p<0.01$). In addition, the LG was perceived as being more specific than the DYB goal (2.0 vs. 1.6; $t=3.8$, $p<0.001$).

To further characterize the effectiveness of the LG condition, the number of strategies participants reported identifying and implementing across conditions was evaluated. Across the DYB and PG goal conditions, only five individuals (3% of participants) listed seven or more strategies that they identified and implemented in order to maximize their performance (i.e., the goal for the LG condition) on the stock pricing exercise. Further, these five individuals were roughly evenly distributed with two in the DYB condition and three in the PG condition. In contrast, 55 individuals (59% of participants) in the LG condition reported seven or more strategies that they identified and implemented in order to maximize their performance. The mean number of strategies reported in the DYB condition was 2.5 compared with 2.4 in the PG condition. As expected a t-test indicated that there was no significant difference ($t=0.03$, $p=0.97$). In contrast, the mean number of strategies in the LG condition was 6.1, which was significantly more than either the DYB ($t=11.4$, $p<0.001$) or PG conditions ($t=10.9$, $p<0.001$) indicating that the learning goal manipulation was successful in increasing the number of reported strategies.

Because of the complexity and relative novelty of DRCGM for organizational researchers, the structure of the balance of this section is aligned with the recommended analytical roadmap laid out by Bliese and Ployhart (2002). This roadmap begins by constructing and fitting simple models to the data in order to test the validity of underlying methodological assumptions and build a foundation for the more complex models necessary to test the proposed hypotheses. Utilizing this established framework should reduce the possibility of unintentional oversights and lead to a more rigorous evaluation of the data. In addition, by presenting the results in a logical manner consistent with previous work utilizing this technique (e.g., Lang & Bliese, 2009), it is easier interpret parameter estimates and compare results across studies.

Level 1 Results

Before presenting the specifics of the developed Level 1 model, it should be pointed out that the proposed inverse and square data transformation recommended by Mosteller and Tukey (1977) and endorsed by Singer and Willett (2003) to linearize the model did not achieve the desired outcome. Prior to the transformation, significant curvilinear effects were present in both the baseline performance as well as the initial adaptive performance time periods. While the transformation lessened the curvilinear effects, it did not succeed in eliminating them (i.e. the coefficient associated with the quadratic time effect in the initial performance period was significant at $p < 0.05$ while the quadratic effect in the initial adaptive performance period was significant at the $p < 0.01$ level, even after transformation).

In order to address this shortcoming, Mosteller and Tukey (1977) recommend increasing the power that the original metric is raised to. That is, instead of taking the reciprocal of the difference score and squaring it (as was done here), the reciprocal could be raised to the third, fourth, or higher levels as necessary to arrive at a linear function. For example, the quadratic time effect is no longer significant when the difference score is inverted and raised to the third power. However, even though the difference score is measured on somewhat of an arbitrary metric (i.e., hypothetical dollars), it does have some basis in the simulation task itself, limiting the degree to which it can be transformed without losing its meaningfulness. Specifically, participants were told that the magnitude of the raw difference score indexed their performance on a specific trial and were further instructed to minimize this difference. Taking steps that result in a dependent variable that is too far removed from the focal outcome of the stock pricing task risks a loss of conceptual clarity. For example, the reciprocal of the difference score is correlated at –0.90 with the raw difference metric across time points. When the difference score is inverted and squared (as was proposed here), the two scores are correlated at –0.78. Raising the power to the third reduces the correlation to –0.65 while a fourth-power transformation results in a correlation of –0.53.

In light of these persistent curvilinear effects and conceptual issues associated with adopting more aggressive data transformations, an alternative (and more benign) data transformation strategy was adopted. Following the work of Drach-Zahavy and Erez (2002), the difference score for each trial was simply subtracted from 200. Because 200 is greater than the maximum difference score observed, like the previously discussed transformations, this data manipulation inverts the direction of the performance curve so that greater performance is indexed by higher values, but unlike the previously discussed transformations, this transformation maintains a perfect (negative) correlation with the original outcome metric. In order to account for the curvilinearity associated with the first two time periods using this transformation, quadratic time variable coding proposed by Snijders and Bosker (1999) and adopted for DRCGM by Lang and Bliese (2009) was utilized. The specific variable parameterization is indicated below in Table 9. The handling of these parameters is discussed in more detail below.

Table 9: Curvilinear Model Time-Based Level-1 Variables

	Measurement Occasion (Period)																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Variable	*(Pre-Change)*						*(Initial Adaptive)*						*(Secondary Adaptive)*					
SA	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
TA1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
RA1	0	0	0	0	0	0	0	1	2	3	4	5	6	7	8	9	10	11
TA2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
RA2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	3	4	5
SA^2	0	1	4	9	16	25	25	25	25	25	25	25	25	25	25	25	25	25
$RA1^2$	0	0	0	0	0	0	0	1	4	9	16	25	25	25	25	25	25	25

Notes: SA = skill acquisition (linear change in performance over time); TA1 = initial transition adaptation (immediate change in performance following initial change event); RA1 = initial reacquisition adaptation (change in linear performance slope after initial change event); TA2 = subsequent transition adaptation (immediate change in performance following secondary change event); RA2 = subsequent reacquisition adaptation (change in linear performance slope after secondary change event). SA^2 = Quadratic change in pre-change performance over time. $RA1^2$ = Quadratic change in initial adaptive performance over time.

The detection of curvilinear effects is an important aspect of systematically building an appropriate Level 1 model, the specifics of which will be outlined below. Consistent with the recommendations of Bliese and Ployhart (2002) as well as Pinheiro and Bates (2000), data analysis begins with an evaluation of the Level 1 model because it is important to construct this portion of the model properly before testing the Level 2 hypotheses. Given the level 2 hypotheses were relevant to the DYB and PG conditions, data from those participants was used to construct the model discussed below. By their nature, Level 1 models contain only time varying predictors (i.e. no individual difference variables), but they can still provide considerable insight into the nature of the data. In addition, because a properly specified Level 1 model sets the foundation for subsequent hypothesis testing, it is imperative that this portion of the model be constructed in a rigorous manner.

A logical starting point (Bliese & Ployhart, 2002) for model construction is to evaluate how the variance of the dependent variable (performance in this case) is partitioned into differences between individuals as well as within individual variation. This sort of variance decomposition is certainly not novel, and is commonly reported in multilevel research. Specifically, the ICC1 (Bliese, 2000) considers the proportion of variance in the dependent variable that occurs at the between group level compared to the total amount of variation (both between and within groups). In this case because multiple data points are collected for each individual, the generic *between group* label corresponds to differences *between individuals* while the *within group* label corresponds to *within individual* variation. Because the focal predictors are at the between individual level, it is important to demonstrate the presence of substantial between individual performance variation over time prior to testing the hypothesized relations.

This desired variance partitioning can be accomplished by fitting a random intercept null model (Bliese & Ployhart, 2002) also known as an unconditional means model to the data. This model is so fundamental that it "is the first model you should always run" (Singer & Willett, 2003, p. 92) when evaluating longitudinal data. This model is focused on the average performance of individuals over time, including no substantive predictors at either Level 1 or Level 2. In addition, by including a random intercept, the average performance of each individual is allowed to vary around the overall average level of performance. After fitting the model, the variance in intercepts (i.e. individual average performance over time) can be compared to the total amount of variance, allowing for the calculation of the ICC1. In this instance, the ICC1 was 0.35, indicating a viable degree of between individual variance with which to proceed with the rest of the analysis.

Further analysis showed that each of the proposed linear model time-varying predictors (as shown in Table 5) were significantly related to performance with the exception of initial reacquisition adaptation (i.e., RA1). As expected, the coefficient for RA1 indicated that the slope change between the pre-change and the initial change periods was negative; however, the magnitude of the coefficient did not reach statistical significance. As expected for the other linear time terms, significant negative coefficients for each transition adaptation term (i.e., TA1 & TA2) indicated that performance significantly decreased in the immediate aftermath of each change event. Similarly, the significant negative coefficient for subsequent reacquisition adaptation (i.e. RA2) indicates that the slope in the second change period was significantly less than the slope in the initial change period. These coefficients are presented in more detail in Table 10, which summarizes the final Level 1 model, arrived at by carrying out the analysis laid out below.

After specifying the linear change model, the next step in the analysis is to evaluate the nature of any curvilinear performance effects over time (Bliese & Ployhart, 2002). This investigation begins with the inclusion of a quadratic time term in each of the three performance periods (i.e. pre-change, after initial change, after secondary change) to accommodate a non-linear slope in each performance segment. As alluded to previously, two of the terms were significantly different from zero (p values for the coefficients in the pre-change and after initial change period are presented in Table 10; the p value in the secondary change period was 0.73), and as such fixed quadratic effects for the first two time periods were included in subsequent models. Finally, since the quadratic terms were significant in the first two time periods, an investigation into potential higher order terms was conducted by including cubic time parameters in the first two time periods; neither coefficient for the cubic terms was significant, indicating that a quadratic model was sufficient (Bliese & Ployhart, 2002).

Once the overall order of the Level 1 model has been determined, it is important to ascertain the structure of the stochastic portion of the model (Bliese & Ployhart, 2002). Random components allow each individual's performance trajectory to vary from the overall trajectory of the group (Singer & Willett, 2003). While this is an important aspect to include in growth models, the inclusion of unnecessary random effects consumes considerable degrees of freedom associated with estimating the model and should generally be avoided. In particular, only random effects that significantly improve model fit (based on log-likelihood tests) are included in the final Level 1 model (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000; Singer & Willett, 2003; Snijders & Bosker, 1999).

As mentioned previously, the stochastic portion of the model should be evaluated by comparing deviance statistics between nested models using likelihood ratio tests (Bliese & Ployhart, 2002; Singer & Willett, 2003). As such, allowing individual performance (i.e. SA in Table 5) in the pre-change period to vary randomly improved model fit (likelihood ratio 92.9 on 2 df, $p < 0.001$). Likewise, allowing both initial transition adaptation and secondary transition adaptation (i.e. TA1 & TA2 in Table 5 respectively) to vary randomly significantly improved model fit (likelihood ratio: 88.9 & 93.1 respectively on 3 df, $p <0.001$). The inter-individual variation in initial and secondary reacquisition adaptation (i.e., RA1 & RA2 in Table 5 respectively) was mixed. Allowing the slope in the initial adaptive performance period to vary significantly improved model fit (likelihood ratio: 27.5 on 5 df, $p < 0.001$). In the second adaptive period, model fit was not significantly increased when the slope was allowed to vary (likelihood ratio: 10.2 on 5 df, $p =0.07$), indicating that there was limited variation across people in the slope changes observed in the second change period after controlling for the passage of time. The impact on model fit of allowing the quadratic time terms in both time periods (SA^2 & $RA1^2$ in Table 9 respectively) to vary randomly was mixed as well. The fit was significantly improved when the curvilinear effect in the pre-change period was allowed to vary randomly (likelihood ratio: 21.1 on 5 df, $p < 0.001$), but model fit was not significantly improved by assuming a random effect in the initial adaptive performance period (likelihood ratio: 5.9 on 5 df, $p = 0.32$). As a result of these findings, RA2 and $RA1^2$ were treated as fixed effects moving forward (however, for the sake of completeness, hypothesis tests involving RA2 were still conducted), while SA, TA1, TA2, RA1, and SA^2 were allowed to vary randomly.

The final area of the Level 1 model to be scrutinized is the assumed error structure. This is an important area of consideration since an improperly specified error structure may influence the validity of statistical tests of parameter estimates and longitudinal data often does not conform to standard assumptions regarding the independence and homoscedasticity of the error terms (Bliese & Ployhart, 2002; DeShon, Ployhart, & Sacco, 1998). As above, the suitability of both alternative error structures was assessed by comparing competing models using log-likelihood tests.

Specifically, in line with previous work in this area (e.g., Lang & Bliese, 2009), autocorrelation was characterized using a first-order autocorrelation model which assumes that the errors between any two subsequent time points are correlated at some value, ρ, with the degree of relation decaying as a power function of ρ. For example, errors separated by two measurement occasions are assumed to be related at ρ-squared while those separated by three would be related at ρ-cubed. Even though the value estimated for ρ was relatively modest at

0.05, allowing for an autocorrelated error structure significantly improved model fit (likelihood ratio: 3.9 on 1 df, $p < 0.05$).

Heteroscedasticity was modeled using an exponential function (the varExp function in nlme) suitable for time series that include a zero point (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000), as is the case in the present model. The estimated exponent was -0.008, indicating that the variance of the errors tended to decrease somewhat over time. This pattern is consistent with the notion that as performance increases over time and individuals become more likely to get closer to the actual value, the variance of the residuals is apt to decrease. Finally, combining this error structure with the previously discussed autocorrelation specification was found to significantly improve model fit (likelihood ratio: 4.3 on 1 df, $p < 0.05$).

The individual model parameters for the final Level 1 model, accounting for both autocorrelation and heroscedasticity, are summarized below. In addition, following the methodology of Singer and Willett (2003) a pseudo-R-squared value can be estimated for the Level 1 model by correlating the fitted performance values with the observed performance for each occasion. In this case, the correlation is 0.78, indicating that the Level 1 model accounts for approximately 61% of the variance in performance.

In addition to the fixed effects, a summary of the random component of the model is presented as well, as is typical for work employing this type of model (e.g., Lang & Bliese, 2009). In addition to the variance of the various error terms, correlations between the random effects are also presented. However, substantive interpretation of the correlations presented is generally not recommended (Bliese & Ployhart, 2002) because the results are highly dependent on several arbitrary aspects of the data including the centering strategy utilized (Hofmann &

Gavin, 1998). Thus, while these results are provided for completeness, the reader is strongly cautioned against drawing conclusions from this portion of the results.

Table 10: Summary of Level 1 Model

Variable	Coef.	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.3**	**0.70**	**245.0**
Skill Acquisition (SA)	**2.49**	**0.44**	**5.67**
Initial Transition Adaptation (TA1)	**–6.32**	**0.83**	**7.60**
Initial Reacquisition Adaptation (RA1)	–0.71	0.59	1.21
Secondary Transition Adaptation (TA2)	**–3.87**	**0.76**	**5.08**
Secondary Reacquisition Adaptation (RA2)	**–1.51**	**0.42**	**3.61**
Quadratic Skill Acquisition (SA^2)	**–0.33**	**0.08**	**4.02**
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	**–0.22**	**0.08**	**2.81**

		Correlations					
	Variance	1	2	3	4	5	6
Random Effects							
1. Intercept	47.71	–					
2. Skill Acquisition	2.37	–0.35	–				
3. Initial Transition Adaptation	45.82	–0.05	–0.55	–			
4. Initial Reacquisition Adaptation	1.85	0.41	–0.93	0.48	–		
5. Secondary Transition Adaptation	43.48	0.02	–0.57	–0.07	0.38	–	
6. Quadratic Skill Acquisition	0.04	0.01	–0.64	0.06	0.52	0.90	–
Residual	41.88	–	–	–	–	–	–

Notes: Coef. = Coefficient. SE = Standard Error.

Hypothesized Level 2 Results

Now that the Level 1 model has been specified, the hypothesized relationships can be tested using a series of Level 2 models. As stated earlier, the statistical significance of fixed effects (such as those being tested here) are evaluated using the magnitude of the individual parameter estimates along with their associated standard errors (as in evaluating the significance of a coefficient from a normal regression using a t-value). The results pertaining to the tests of the hypotheses associated with each individual difference variable (e.g. GMA, Industriousness) are reviewed in turn. In addition to the descriptive text, the model parameters are summarized in tabular form, with a separate table presented for each focal, Level 2 variable. In order to conserve space, results presented are for models incorporating both the hypothesized main and interactive (i.e., individual difference and goal condition) variables. For example, Table 12 presents information pertaining to the main effects of GMA (pertinent for testing *Hypothesis 1* through *Hypothesis 3*) and the interaction between GMA and goal condition (*Hypothesis 16*). The specified main effects were also evaluated in separate models not including the individual difference-goal condition interactions, but as the results were substantively equivalent to those presented below, a detailed accounting of the specific results is omitted.

Across tables, each Level 2 individual difference variable was grand-mean centered prior to being entered in the analysis. This allows for slopes and intercepts to be interpreted in terms of deviations from the sample average, rather than zero (which is not a valid value for these measures). In addition, normalized coefficients are presented as well. Following Lang and Bliese (2009), while the time variables were normalized to have a variance of one, no additional centering was done (such that zero still corresponds to the beginning of time). Finally, the previously stated caution pertaining to the interpretation of the random component correlations remains applicable for the Level 2 models as well.

In order to provide additional context for interpreting the specific parameter estimates for each hypothesized model, Figure 8 presents a pictoral representation of average performance over time, delineated by goal condition. Specifically, the three lines represent the performance curve generated from the fixed effects of the DRCGM for each goal condition. The individual data points represent the average observed level of performance for each measurement occasion (again, broken down by goal condition). Essentially, this is conceptually equivalent to reviewing a scatter plot of observed data with a superimposed best-fit regression line.

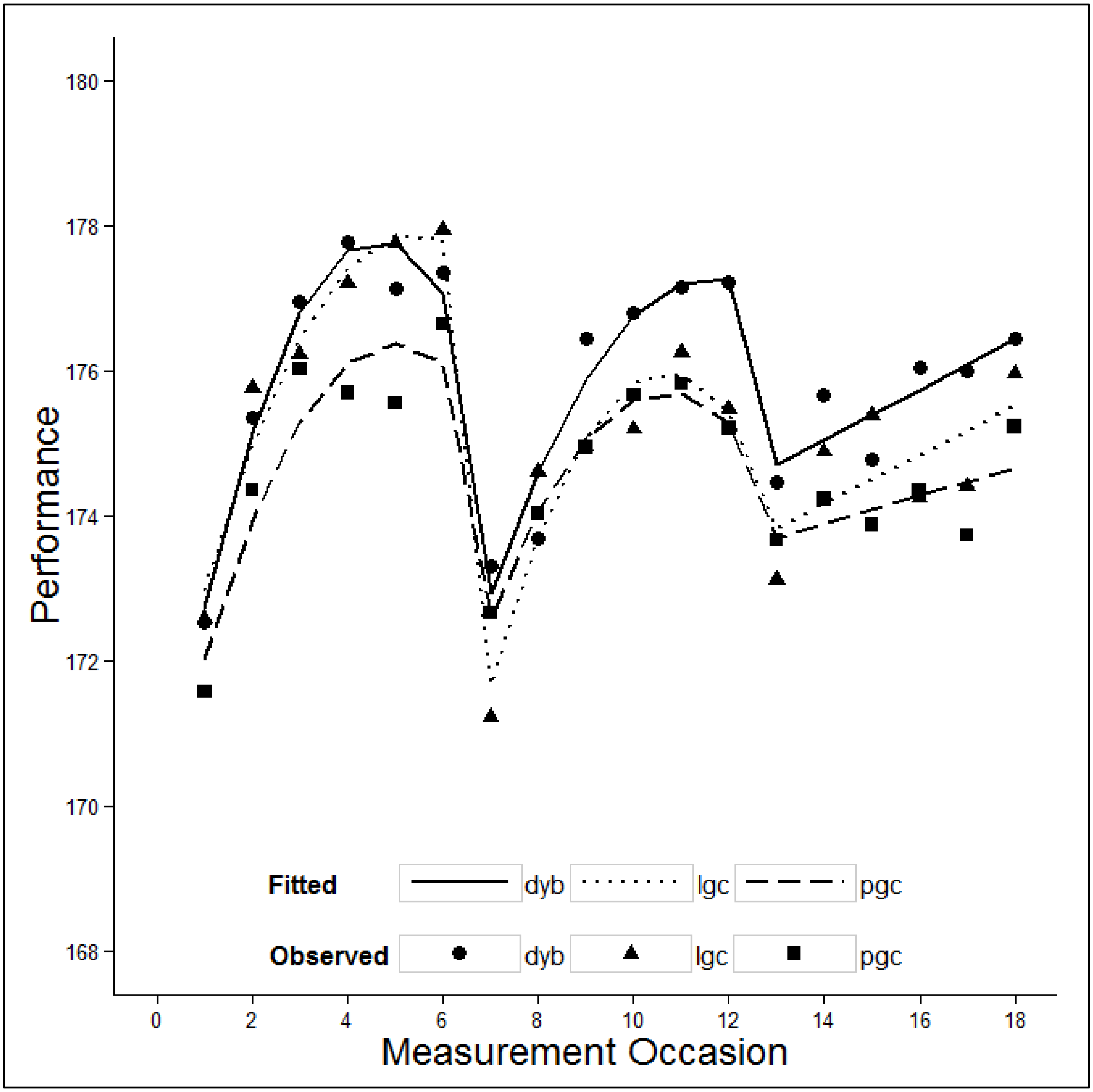

Figure 8: DRCGM Results by Goal Condition

Table 11: Example DRCGM Results by Goal Condition

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	**1.04**	**166.25**
Skill Acquisition (SA)	**2.81 (1.67)**	**0.67**	**4.22**
Initial Transition Adaptation (TA1)	**-6.93 (-0.37)**	**1.27**	**5.47**
Initial Reacquisition Adaptation (RA1)	-0.93 (-0.41)	0.87	1.08
Secondary Transition Adaptation (TA2)	**-4.45 (-0.24)**	**1.06**	**4.20**
Secondary Reacquisition Adaptation (RA2)	**-1.53 (-0.27)**	**0.61**	**2.52**
Quadratic Skill Acquisition (SA^2)	**-0.39 (-0.40)**	**0.12**	**3.28**
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.20 (-0.27)	0.11	1.82
Level 2			
Performance Goal Condition (PGC)			
PGC	-0.71 (-0.08)	1.45	0.49
SA x PGC	-0.62 (-0.37)	0.93	0.67
TA1 x PGC	1.25 (0.07)	1.77	0.71
RA1 x PGC	0.44 (0.19)	1.21	0.36
TA2 x PGC	1.14 (0.06)	1.48	0.77
RA2 x PGC	0.03 (0.01)	0.85	0.04
SA^2 x PGC	0.11 (0.12)	0.17	0.69
$RA1^2$ x PGC	-0.03 (-0.04)	0.15	0.19
Learning Goal Condition (LGC)			
LGC	0.24 (0.03)	1.43	0.17
SA x LGC	-0.55 (-0.33)	0.91	0.60
TA1 x LGC	-1.44 (-0.08)	1.74	0.83
RA1 x LGC	1.02 (0.45)	1.19	0.86
TA2 x LGC	0.49 (0.03)	1.45	0.34
RA2 x LGC	-0.48 (-0.08)	0.83	0.57
SA^2 x LGC	0.13 (0.13)	0.16	0.80
$RA1^2$ x LGC	-0.12 (-0.15)	0.15	0.76

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 4413, except for the time invariant predictor (i.e., PGC) which has 258 degrees of freedom.

In order to further aid interpretation, the fixed effects corresponding to the results illustrated in Figure 8 are presented in Table 11. While the Level-2 (and two of the Level-1) parameters do not reach statistically significant levels, they are discussed qualitatively nonetheless with the sole purpose of facilitating conceptual mapping between the graphical results shown in Figure 8 and the tabular results appearing in Table 11 (and subsequently throughout the remainder or the results section). To further help the reader focus on parameter mapping and interpretation in general rather than on the specific outcomes of this model, the significance levels for parameters discussed below have been suppressed. In the more substantive analyses to follow, significance values are presented in addition to point estimates. Finally, in both Figure 8 and Table 11 the DYB goal condition is treated as the baseline and the PG and LG conditions are each compared back to the DYB condition.

Specifically, the intercept, or average level of performance in the first measurement occasion for those in the DYB goal condition is 172.7. In addition, as reflected in Figure 8, on average those in the PG condition had a lower estimated intercept (as indicated by the PGC term in Table 11: -0.71) while those in the LG condition had a slightly higher intercept (as indicated by the LGC term in Table 11: 0.24). In other words, the effective intercept for those in the PG condition was 171.99 (172.7-.71) while it was 172.94 (172.7+0.24) for those in the LG condition. As discussed previously, transition adaptation is reflected by the magnitude of the decline in performance immediately after the change event has occurred, which smaller decrements reflecting higher levels of transition adaptation. In this instance, on average, performance for those in the DYB goal condition decreased by 6.93 immediately after the first change event. Further, the decline was less for those in the PG condition (the magnitude of the decline was reduced by the magnitude of the TA1 x PGC coefficient: +1.25). Conversely, those in the LG condition experienced a larger decline on average, as reflected by the TA1 x LGC coefficient (-1.44).

In terms of slope, for both the skill acquisition and initial reacquisition adaptation periods the linear slope was positive (e.g. 2.81 in the skill acquisition period for those in the DYB condition) while the quadratic time effect was negative (e.g. -0.39 in the skill acquisition period for those in the DYB condition). This combination of effects is indicative of performance that improved over time, but at a declining rate (i.e. positive velocity and negative acceleration). This is consistent with well-known learning curve effects that are characterized by diminishing returns over time as performance asymptotically approaches some maximum level (e.g., Thurstone, 1919). Further, the parameters that characterize this curvilinear relationship can vary by goal condition. For example, the "SA x PGC" and "SA^2 x PGC" terms indicate how the linear and quadratic slope components (respectively) for the skill acquisition phase vary for those in the PG condition compared to the DYB condition. In general, significant Level-2 coefficients are indicative of significant effects, either for individual level or contextual characteristics, the latter of which would be relevant for this example.

As previously discussed, reacquisition adaptation is indexed by the change in slope across performance periods. While performance slope will generally decline after the change event has occurred (compared to the pre-change slope), the size of this decrement may vary across individuals and conditions. Smaller slope reductions are indicative of higher levels of reacquisition adaptation. Similar to the effects discussed previously, the effects of goal condition on reacquisition adaptation are reflected in the "RA" parameters presented in Table 11.

Building on this foundation, the results pertaining to the hypothesized relationships are presented. As previously mentioned, Hypothesis 1 through Hypothesis 3 concern the relationship between GMA and the various components of adaptive performance. Specifically, Hypothesis 1 stated that GMA would be negatively related to initial transition adaptation while Hypothesis 2 and Hypothesis 3 proposed that GMA would be positively related to secondary transition and reacquisition adaptation respectively. As indicated in Table 12, GMA was significantly related to initial transition adaptation, but in the opposite direction of that stated in Hypothesis 1, such that GMA was positively associated with initial transition adaptation. In addition, Table 12 indicates that GMA was not significantly related to either subsequent transition or reacquisition adaptation. Therefore, Hypotheses 1, *Hypothesis 2*, and Hypothesis ***3*** were not supported. Further, Hypothesis 16 proposed that the presence of a difficult, specific performance goal would strengthen the previously proposed effects. As shown in Table 12, there was not a significant interaction between GMA and goal condition when predicting adaptive performance; thus Hypothesis 16 was not supported either.

The results for the aspects of Conscientiousness, Industriousness and Orderliness, are presented in Table 13 and Table 14 respectively. Neither Hypotheses Hypothesis *4* through Hypothesis *7* which predicted main effects nor Hypothesis 17 and Hypothesis *18* which proposed interactive effects with the performance goal condition were supported. Similar results for the Intellect aspect of Openness can be seen in Table 15: Performance Change Over Time – DCGM Results for Intellect; neither the main effect hypotheses (Hypothesis *8* and Hypothesis *9*) nor the interaction hypothesis (Hypothesis *19*) received support. Parallel results for the Volatility and Withdrawal aspects of Neuroticism appear in Table 16 and Table 17 respectively. As indicated in the tables, Hypothesis 10 through Hypothesis *13* predicted main effects while Hypothesis 20 and Hypothesis 21 predicted interactive effects and none were supported. Finally, Table 18 provides results germane to the proposed main effects of the performance goal condition (Hypothesis 14 and Hypothesis *15*). Again, neither hypotheses received support.

Table 12: Performance Change Over Time – DCGM Results for GMA

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.1 (-0.33)**	0.99	173.86
Skill Acquisition (SA)	**3.16 (1.88)**	0.63	4.99
Initial Transition Adaptation (TA1)	**-7.55 (-0.41)**	1.20	6.28
Initial Reacquisition Adaptation (RA1)	-1.14 (-0.50)	0.86	1.33
Secondary Transition Adaptation (TA2)	**-4.61 (-0.25)**	1.12	4.11
Secondary Reacquisition Adaptation (RA2)	**-1.71 (-0.30)**	0.61	2.80
Quadratic Skill Acquisition (SA^2)	**-0.44 (-0.46)**	0.12	3.70
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	**-0.23 (-0.30)**	0.11	2.04
Level 2			
General Mental Ability (GMA)			
GMA	**0.88 (0.40)**	0.30	2.92
SA x GMA	**-0.53 (-1.23)**	0.19	2.72
TA1 x GMA (H1)	**0.95 (0.20)**	0.37	2.60
RA1 x GMA	0.27 (0.46)	0.26	1.03
TA2 x GMA (H2)	0.25 (0.05)	0.34	0.74
RA2 x GMA (H3)	0.31 (0.21)	0.19	1.65
SA^2 x GMA	**0.08 (0.32)**	0.04	2.17
$RA1^2$ x GMA	0.05 (0.25)	0.03	1.42
Performance Goal Condition (PGC)			
PGC	-0.27 (-0.03)	1.37	0.20
SA x PGC	-0.97 (-0.58)	0.88	1.11
TA1 x PGC	1.79 (0.10)	1.67	1.08
RA1 x PGC	0.66 (0.29)	1.19	0.55
TA2 x PGC	1.30 (0.07)	1.56	0.83
RA2 x PGC	0.20 (0.04)	0.84	0.24
SA^2 x PGC	0.17 (0.18)	0.17	1.04
$RA1^2$ x PGC	-0.00 (-0.01)	0.16	0.02
General Mental Ability x Performance Goal Condition			
GMA x PGC	-0.37 (-0.17)	0.39	0.97
SA x GMA x PGC	**0.54 (1.25)**	0.25	2.16
TA1 x GMA x PGC (H16a)	-0.88 (-0.19)	0.47	1.87
RA1 x GMA x PGC	-0.28 (-0.48)	0.34	0.84
TA2 x GMA x PGC (H16b)	-0.29 (-0.06)	0.44	0.66
RA2 x GMA x PGC (H16c)	-0.33 (-0.23)	0.24	1.38
SA^2 x GMA x PGC	-0.09 (-0.37)	0.05	1.95
$RA1^2$ x GMA x PGC	-0.05 (-0.27)	0.04	1.19

Table 12 (cont'd)

	Variance	Correlations 1	2	3	4	5	6
Random Effects							
1. Intercept	41.77	-					
2. Skill Acquisition	1.47	-0.24	-				
3. Initial Transition Adaptation	43.66	-0.16	-0.47	-			
4. Initial Reacquisition Adaptation	1.15	0.30	-0.87	0.33	-		
5. Secondary Transition Adaptation	45.01	-0.02	-0.57	-0.10	0.28	-	
6. Quadratic Skill Acquisition	0.03	-0.16	-0.45	-0.18	0.29	0.85	-
Residual	41.73	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., GMA, PGC & GMA x PGC) which have 164 degrees of freedom.

Table 13: Performance Change Over Time – DCGM Results for Industriousness

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	1.03	167.86
Skill Acquisition (SA)	**2.92 (1.73)**	0.64	4.57
Initial Transition Adaptation (TA1)	**-6.91 (-0.37)**	1.21	5.71
Initial Reacquisition Adaptation (RA1)	-1.12 (-0.49)	0.86	1.31
Secondary Transition Adaptation (TA2)	**-4.36 (-0.24)**	1.09	4.00
Secondary Reacquisition Adaptation (RA2)	**-1.46 (-0.26)**	0.60	2.41
Quadratic Skill Acquisition (SA^2)	**-0.41 (-0.43)**	0.12	3.47
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.19 (-0.25)	0.11	1.70
Level 2			
Conscientiousness: Industriousness (C_IND)			
C_IND	-0.17 (-0.01)	1.55	0.11
SA x C_IND	0.92 (0.33)	0.96	0.96
TA1 x C_IND (H4a)	0.07 (0.00)	1.82	0.04
RA1 x C_IND (H5a)	-1.43 (-0.38)	1.29	1.11
TA2 x C_IND (H4b)	0.76 (0.03)	1.64	0.47
RA2 x C_IND (H5b)	0.44 (0.05)	0.91	0.49
SA^2 x C_IND	-0.22 (-0.14)	0.18	1.22
$RA1^2$ x C_IND	0.08 (0.06)	0.17	0.45
Performance Goal Condition (PGC)			
PGC	-0.70 (-0.08)	1.43	0.49
SA x PGC	-0.78 (-0.46)	0.89	0.88
TA1 x PGC	1.19 (0.06)	1.68	0.71
RA1 x PGC	0.73 (0.32)	1.19	0.61
TA2 x PGC	0.75 (0.04)	1.52	0.49
RA2 x PGC	-0.08 (-0.01)	0.84	0.09
SA^2 x PGC	0.15 (0.16)	0.17	0.91
$RA1^2$ x PGC	-0.05 (-0.06)	0.15	0.30
Conscientiousness: Industriousness x Performance Goal Condition			
C_IND x PGC	0.13 (0.01)	2.25	0.06
SA x C_IND x PGC	-0.05 (-0.02)	1.39	0.04
TA1 x C_IND x PGC (H17a)	-0.38 (-0.01)	2.64	0.14
RA1 x C_IND x PGC (H17c)	-0.11 (-0.03)	1.87	0.06
TA2 x C_IND x PGC (H17b)	3.78 (0.12)	2.38	1.59
RA2 x C_IND x PGC (H17d)	-0.03 (0.00)	1.32	0.02
SA^2 x C_IND x PGC	0.05 (0.03)	0.26	0.19
$RA1^2$ x C_IND x PGC	-0.05 (-0.04)	0.24	0.19

Table 13 (cont'd)

	Variance	Correlations 1	2	3	4	5	6
Random Effects							
1. Intercept	49.34	-					
2. Skill Acquisition	2.64	-0.38	-				
3. Initial Transition Adaptation	47.20	-0.05	-0.48	-			
4. Initial Reacquisition Adaptation	2.12	0.44	-0.94	0.39	-		
5. Secondary Transition Adaptation	40.86	0.02	-0.65	-0.05	0.48	-	
6. Quadratic Skill Acquisition	0.05	0.04	-0.66	-0.04	0.58	0.91	-
Residual	41.32	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., C_IND, PGC & C_IND x PGC) which have 164 degrees of freedom.

Table 14: Performance Change Over Time – DCGM Results for Orderliness

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	1.01	170.33
Skill Acquisition (SA)	**2.81 (1.67)**	0.62	4.50
Initial Transition Adaptation (TA1)	**-6.92 (-0.37)**	1.19	5.80
Initial Reacquisition Adaptation (RA1)	-0.96 (-0.42)	0.84	1.14
Secondary Transition Adaptation (TA2)	**-4.43 (-0.24)**	1.09	4.07
Secondary Reacquisition Adaptation (RA2)	**-1.50 (-0.26)**	0.60	2.53
Quadratic Skill Acquisition (SA^2)	**-0.39 (-0.40)**	0.12	3.33
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.20 (-0.26)	0.11	1.80
Level 2			
Conscientiousness: Orderliness (C_ORD)			
C_ORD	0.99 (0.06)	1.65	0.60
SA x C_ORD	-0.44 (-0.14)	1.02	0.43
TA1 x C_ORD (H6a)	0.73 (0.02)	1.94	0.37
RA1 x C_ORD (H7a)	0.22 (0.05)	1.37	0.16
TA2 x C_ORD (H6b)	2.67 (0.08)	1.77	1.51
RA2 x C_ORD (H7b)	0.51 (0.05)	0.97	0.53
SA^2 x C_ORD	0.01 (0.01)	0.19	0.05
$RA1^2$ x C_ORD	0.02 (0.01)	0.18	0.09
Performance Goal Condition (PGC)			
PGC	-0.71 (-0.08)	1.42	0.50
SA x PGC	-0.67 (-0.40)	0.87	0.76
TA1 x PGC	1.17 (0.06)	1.67	0.70
RA1 x PGC	0.50 (0.22)	1.18	0.42
TA2 x PGC	1.10 (0.06)	1.52	0.72
RA2 x PGC	0.02 (0.00)	0.83	0.02
SA^2 x PGC	0.13 (0.13)	0.16	0.77
$RA1^2$ x PGC	-0.03 (-0.04)	0.15	0.21
Conscientiousness: Orderliness x Performance Goal Condition			
C_ORD x PGC	-1.79 (-0.11)	2.59	0.69
SA x C_ORD x PGC	2.29 (0.73)	1.59	1.44
TA1 x C_ORD x PGC (H18a)	-0.46 (-0.01)	3.04	0.15
RA1 x C_ORD x PGC (H18c)	-1.20 (-0.28)	2.15	0.56
TA2 x C_ORD x PGC (H18b)	-2.28 (-0.07)	2.77	0.82
RA2 x C_ORD x PGC (H18d)	-1.42 (-0.13)	1.52	0.93
SA^2 x C_ORD x PGC	-0.41 (-0.23)	0.30	1.39
$RA1^2$ x C_ORD x PGC	-0.19 (-0.13)	0.28	0.67

Table 14 (cont'd)

	Variance	Correlations					
		1	2	3	4	5	6
Random Effects							
1. Intercept	49.33	-					
2. Skill Acquisition	2.12	-0.39	-				
3. Initial Transition Adaptation	47.15	-0.05	-0.56	-			
4. Initial Reacquisition Adaptation	1.79	0.45	-0.92	0.47	-		
5. Secondary Transition Adaptation	43.21	-0.01	-0.49	-0.10	0.25	-	
6. Quadratic Skill Acquisition	0.03	0.01	-0.55	-0.00	0.46	0.80	-
Residual	41.41	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., C_ORD, PGC & C_ORD x PGC) which have 164 degrees of freedom.

Table 15: Performance Change Over Time – DCGM Results for Intellect

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	1.00	172.61
Skill Acquisition (SA)	**2.81 (1.67)**	0.62	4.51
Initial Transition Adaptation (TA1)	**-6.89 (-0.37)**	1.19	5.79
Initial Reacquisition Adaptation (RA1)	-0.98 (-0.43)	0.84	1.17
Secondary Transition Adaptation (TA2)	**-4.42 (-0.24)**	1.08	4.08
Secondary Reacquisition Adaptation (RA2)	**-1.48 (-0.26)**	0.59	2.50
Quadratic Skill Acquisition (SA^2)	**-0.39 (-0.40)**	0.12	3.35
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.19 (-0.26)	0.11	1.77
Level 2			
Openness: Intellect (O_INT)			
O_INT	2.71 (0.17)	1.95	1.39
SA x O_INT	0.09 (0.03)	1.21	0.08
TA1 x O_INT (H8a)	2.72 (0.08)	2.32	1.17
RA1 x O_INT (H9a)	-2.19 (-0.52)	1.64	1.34
TA2 x O_INT (H8b)	2.49 (0.07)	2.11	1.18
RA2 x O_INT (H9b)	2.15 (0.21)	1.16	1.86
SA^2 x O_INT	-0.14 (-0.08)	0.23	0.62
$RA1^2$ x O_INT	0.33 (0.24)	0.21	1.55
Performance Goal Condition (PGC)			
PGC	-0.72 (-0.08)	1.40	0.51
SA x PGC	-0.62 (-0.37)	0.87	0.71
TA1 x PGC	1.16 (0.06)	1.67	0.70
RA1 x PGC	0.48 (0.22)	1.18	0.41
TA2 x PGC	1.19 (0.06)	1.51	0.79
RA2 x PGC	-0.02 (0.00)	0.83	0.02
SA^2 x PGC	0.12 (0.12)	0.16	0.71
$RA1^2$ x PGC	-0.04 (-0.05)	0.15	0.26
Openness: Intellect x Performance Goal Condition			
O_INT x PGC	-1.24 (-0.08)	2.61	0.47
SA x O_INT x PGC	0.07 (0.02)	1.63	0.04
TA1 x O_INT x PGC (H19a)	-2.44 (-0.07)	3.11	0.79
RA1 x O_INT x PGC (H19c)	1.64 (0.39)	2.19	0.75
TA2 x O_INT x PGC (H19b)	1.30 (0.04)	2.82	0.46
RA2 x O_INT x PGC (H19d)	-1.91 (-0.18)	1.55	1.23
SA^2 x O_INT x PGC	0.11 (0.06)	0.30	0.36
$RA1^2$ x O_INT x PGC	-0.36 (-0.26)	0.29	1.25

Table 15 (cont'd)

	Variance	Correlations 1	2	3	4	5	6
Random Effects							
1. Intercept	47.41	-					
2. Skill Acquisition	2.28	-0.38	-				
3. Initial Transition Adaptation	47.16	-0.06	-0.52	-			
4. Initial Reacquisition Adaptation	1.96	0.43	-0.92	0.41	-		
5. Secondary Transition Adaptation	42.27	-0.02	-0.53	-0.08	0.31	-	
6. Quadratic Skill Acquisition	0.04	0.03	-0.58	-0.03	0.49	0.85	-
Residual	41.05	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., O_INT, PGC & O_INT x PGC) which have 164 degrees of freedom.

Table 16: Performance Change Over Time – DCGM Results for Volatility

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.9 (-0.24)**	1.05	164.07
Skill Acquisition (SA)	**3.00 (1.78)**	0.65	4.60
Initial Transition Adaptation (TA1)	**-7.22 (-0.39)**	1.23	5.87
Initial Reacquisition Adaptation (RA1)	-1.13 (-0.50)	0.88	1.29
Secondary Transition Adaptation (TA2)	**-4.76 (-0.26)**	1.14	4.18
Secondary Reacquisition Adaptation (RA2)	**-1.48 (-0.26)**	0.62	2.37
Quadratic Skill Acquisition (SA^2)	**-0.43 (-0.45)**	0.12	3.52
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.19 (-0.26)	0.11	1.70
Level 2			
Neuroticism: Volatility (N_VOL)			
N_VOL	-0.59 (-0.05)	1.29	0.45
SA x N_VOL	-0.81 (-0.35)	0.80	1.01
TA1 x N_VOL (H12a)	1.29 (0.05)	1.51	0.86
RA1 x N_VOL (H10a)	0.74 (0.23)	1.08	0.69
TA2 x N_VOL (H12b)	1.34 (0.05)	1.39	0.96
RA2 x N_VOL (H10b)	-0.12 (-0.02)	0.76	0.16
SA^2 x N_VOL	0.17 (0.13)	0.15	1.17
$RA1^2$ x N_VOL	-0.01 (-0.01)	0.14	0.08
Performance Goal Condition (PGC)			
PGC	-0.97 (-0.11)	1.45	0.67
SA x PGC	-0.87 (-0.52)	0.90	0.97
TA1 x PGC	1.78 (0.10)	1.69	1.05
RA1 x PGC	0.68 (0.30)	1.21	0.56
TA2 x PGC	1.52 (0.08)	1.57	0.97
RA2 x PGC	-0.00 (0.00)	0.86	0.00
SA^2 x PGC	0.16 (0.17)	0.17	0.97
$RA1^2$ x PGC	-0.03 (-0.04)	0.16	0.21
Neuroticism: Volatility x Performance Goal Condition			
N_VOL x PGC	-0.54 (-0.04)	1.91	0.28
SA x N_VOL x PGC	0.16 (0.07)	1.18	0.14
TA1 x N_VOL x PGC (H20a)	1.69 (0.07)	2.23	0.76
RA1 x N_VOL x PGC (H20c)	-0.43 (-0.13)	1.60	0.27
TA2 x N_VOL x PGC (H20b)	-0.48 (-0.02)	2.07	0.23
RA2 x N_VOL x PGC (H20d)	0.43 (0.05)	1.13	0.38
SA^2 x N_VOL x PGC	-0.11 (-0.08)	0.22	0.48
$RA1^2$ x N_VOL x PGC	0.08 (0.07)	0.21	0.36

Table 16 (cont'd)

	Variance	Correlations 1	2	3	4	5	6
Random Effects							
1. Intercept	48.36	-					
2. Skill Acquisition	1.99	-0.42	-				
3. Initial Transition Adaptation	43.92	-0.04	-0.50	-			
4. Initial Reacquisition Adaptation	1.68	0.47	-0.91	0.39	-		
5. Secondary Transition Adaptation	43.57	0.02	-0.53	-0.11	0.30	-	
6. Quadratic Skill Acquisition	0.03	0.04	-0.54	-0.11	0.45	0.83	-
Residual	41.67	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., N_VOL, PGC & N_VOL x PGC) which have 164 degrees of freedom.

Table 17: Performance Change Over Time – DCGM Results for Withdrawal

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	1.01	170.52
Skill Acquisition (SA)	**2.81 (1.67)**	0.63	4.47
Initial Transition Adaptation (TA1)	**-6.93 (-0.37)**	1.19	5.85
Initial Reacquisition Adaptation (RA1)	-0.97 (-0.43)	0.85	1.15
Secondary Transition Adaptation (TA2)	**-4.59 (-0.25)**	1.10	4.18
Secondary Reacquisition Adaptation (RA2)	**-1.46 (-0.26)**	0.60	2.43
Quadratic Skill Acquisition (SA^2)	**-0.39 (-0.40)**	0.12	3.32
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.19 (-0.25)	0.11	1.73
Level 2			
Neuroticism: Withdrawal (N_WTH)			
N_WTH	-0.41 (-0.03)	1.59	0.26
SA x N_WTH	0.08 (0.03)	0.99	0.08
TA1 x N_WTH (H13a)	0.11 (0.00)	1.86	0.06
RA1 x N_WTH (H11a)	0.19 (0.05)	1.33	0.14
TA2 x N_WTH (H13b)	1.68 (0.06)	1.73	0.97
RA2 x N_WTH (H11b)	-0.59 (-0.07)	0.94	0.63
SA^2 x N_WTH	0.01 (0.01)	0.18	0.06
$RA1^2$ x N_WTH	-0.08 (-0.07)	0.17	0.45
Performance Goal Condition (PGC)			
PGC	-0.69 (-0.08)	1.41	0.49
SA x PGC	-0.70 (-0.42)	0.88	0.80
TA1 x PGC	1.40 (0.08)	1.65	0.85
RA1 x PGC	0.57 (0.25)	1.18	0.49
TA2 x PGC	1.14 (0.06)	1.53	0.75
RA2 x PGC	-0.05 (-0.01)	0.84	0.06
SA^2 x PGC	0.13 (0.13)	0.16	0.78
$RA1^2$ x PGC	-0.03 (-0.05)	0.15	0.22
Neuroticism: Withdrawal x Performance Goal Condition			
N_WTH x PGC	1.42 (0.11)	2.14	0.66
SA x N_WTH x PGC	-1.41 (-0.54)	1.32	1.06
TA1 x N_WTH x PGC (H21a)	2.83 (0.10)	2.50	1.13
RA1 x N_WTH x PGC (H21c)	1.07 (0.31)	1.79	0.60
TA2 x N_WTH x PGC (H21b)	-3.47 (-0.12)	2.32	1.49
RA2 x N_WTH x PGC (H21d)	0.58 (0.07)	1.27	0.46
SA^2 x N_WTH x PGC	0.16 (0.11)	0.25	0.65
$RA1^2$ x N_WTH x PGC	0.19 (0.17)	0.23	0.83

Table 17 (cont'd)

		Correlations					
	Variance	1	2	3	4	5	6
Random Effects							
1. Intercept	47.83	-					
2. Skill Acquisition	1.98	-0.36	-				
3. Initial Transition Adaptation	43.93	-0.08	-0.48	-			
4. Initial Reacquisition Adaptation	1.61	0.41	-0.91	0.35	-		
5. Secondary Transition Adaptation	43.65	0.02	-0.59	-0.07	0.37	-	
6. Quadratic Skill Acquisition	0.03	-0.02	-0.54	-0.12	0.43	0.86	-
Residual	41.27	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2828, except for the three time invariant predictors (i.e., N_WTH, PGC & N_WTH x PGC) which have 164 degrees of freedom.

Table 18: Performance Change Over Time – DCGM Results for Goal Condition

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.7 (-0.26)**	1.00	172.32
Skill Acquisition (SA)	**2.81 (1.67)**	0.62	4.52
Initial Transition Adaptation (TA1)	**-6.92 (-0.37)**	1.18	5.86
Initial Reacquisition Adaptation (RA1)	-0.96 (-0.42)	0.84	1.14
Secondary Transition Adaptation (TA2)	**-4.45 (-0.24)**	1.09	4.08
Secondary Reacquisition Adaptation (RA2)	**-1.51 (-0.26)**	0.59	2.54
Quadratic Skill Acquisition (SA^2)	**-0.39 (-0.40)**	0.12	3.34
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	-0.20 (-0.26)	0.11	1.80
Level 2			
Performance Goal Condition (PGC)			
PGC	-0.72 (-0.08)	1.40	0.52
SA x PGC	-0.62 (-0.37)	0.87	0.71
TA1 x PGC (H14a)	1.19 (0.06)	1.65	0.72
RA1 x PGC (H15a)	0.47 (0.21)	1.17	0.40
TA2 x PGC (H14b)	1.12 (0.06)	1.52	0.74
RA2 x PGC (H15b)	-0.00 (-0.00)	0.83	0.00
SA^2 x PGC	0.12 (0.12)	0.16	0.71
$RA1^2$ x PGC	-0.04 (-0.05)	0.15	0.23

	Variance	Correlations 1	2	3	4	5	6
Random Effects							
1. Intercept	47.57	-					
2. Skill Acquisition	2.06	-0.36	-				
3. Initial Transition Adaptation	45.08	-0.07	-0.51	-			
4. Initial Reacquisition Adaptation	1.79	0.40	-0.91	0.41	-		
5. Secondary Transition Adaptation	43.47	0.01	-0.53	-0.10	0.29	-	
6. Quadratic Skill Acquisition	0.03	-0.01	-0.55	-0.05	0.45	0.84	-
Residual	41.21	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient. Fixed effect degrees of freedom = 2842, except for the time invariant predictor (i.e., PGC) which has 166 degrees of freedom.

Exploratory Level 2 Results

Learning Goal Condition

In order to begin investigating the impact of having a learning goal, a parallel analysis to that just described for the hypothesized effects was conducted. Specifically, the analysis began by testing the proposed hypotheses using data from the baseline do-your-best goal condition and the learning goal condition. To generate results comparable to those just discussed, data from the performance goal condition was not included in this initial analysis. In the interest of brevity, the full panel of results (akin to those previously displayed in Table 12 through Table 18) is not presented because of the sparseness of significant effects. Rather, the individual effects that reached significance are described below in order to summarize the analyses. Each reported effect corresponds to one line item in the previously presented tables. That is, the standardized effect size, standard error and t-value are presented for each significant effect.

There was only one individual difference by learning goal condition cross level interaction (i.e., the learning goal analog of Hypothesis 16c in Table 12: GMAxLGC had a standardized effect size of -0.340 with a standard error of 0.152, $|t| = 2.2$ when predicting secondary reacquisition adaptation) and no main effect for the learning goal condition (vs. the do-your-best condition). However, GMA was positively related to both ITA and IRA across goal conditions (standardized effect sizes of 0.14 and 0.84 with standard errors of 0.05 and 0.26 and t-values of 3.0 and 3.2, respectively).

To further explore the learning goal condition, DRCGM was utilized to compare the performance and learning goal conditions. In this analysis, those in the do-your-best condition were excluded. Again, there were no main effects for the learning vs. performance goal condition for any aspect of adaptive performance; however, there were some significant effects to discuss.

Specifically, three individual difference-goal condition interactions were significant across models. For this analysis, the learning goal condition was taken as the baseline because learning goals have been hypothesized to be more suitable for complex tasks (Ordóñez et al., 2009). This allows for an investigation of the effects of a potentially misspecified performance oriented goal type. First, the Intellect aspect of Openness interacted with PG condition to predict secondary transition adaptation, although the effect fell just short of statistical significance (standardized effect size: 0.15, standard error: 0.08, $t = 1.92$). However, the paucity of significant results (either in terms of main or interactive effects) across the remaining additional aspects of adaptive performance makes interpretation of this effect difficult, and the detailed results of this model are omitted.

Before presenting the results of the two remaining effects, it should be noted that the Level 1 structure for the combined learning goal and performance goal data differed slightly from that presented previously for the combined do-your-best and performance goal data. Specifically, with this data, the slope of the secondary adaptive performance change period (secondary reacquisition adaptation) varied significantly across individuals. As such, it was modeled as a random effect when evaluating the Level-2 results. Accordingly, this term is also included in the random effect section of the following tables (Table 19 and Table 20) as well.

The summaries of the models corresponding to the two remaining interactions are presented below. First, as shown in Table 19, while overall GMA was positively related to initial reacquisition adaptation (standardized effect size: 1.12, standard error: 0.19, $t = 3.4$), this effect varied by goal condition. Specifically, GMA and goal condition interacted (standardized effect size: -1.15, standard error: 0.51, $t = 2.3$) such that the effect of GMA on initial reacquisition was dependent on goal condition and on average, those in the PG condition improved significantly slower than those in the LG condition.

Further, the goal condition interacted with the Industriousness aspect of Conscientiousness (standardized effect size: 0.25, standard error: 0.08, $t = 3.0$). Table 20 summarizes remaining parameters for this model. While there were no statistically significant main effects for Industriousness, there was some indication that it may be related to both secondary transition and reacquisition adaptation as these coefficients were both significant at the $p = 0.1$ level.

Table 19: DRCGM Effects of GMA: Learning vs. Performance Goal Conditions

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**173.7 (-0.15)**	0.91	189.89
Skill Acquisition (SA)	**1.92 (1.14)**	0.66	2.91
Initial Transition Adaptation (TA1)	**-8.08 (-0.44)**	1.22	6.64
Initial Reacquisition Adaptation (RA1)	0.57 (0.25)	0.84	0.68
Secondary Transition Adaptation (TA2)	**-3.86 (-0.21)**	1.07	3.62
Secondary Reacquisition Adaptation (RA2)	**-2.14 (-0.38)**	0.57	3.77
Quadratic Skill Acquisition (SA^2)	-0.21 (-0.22)	0.12	1.78
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	**-0.35 (-0.46)**	0.10	3.34
Level 2			
General Mental Ability (GMA)			
GMA	**0.95 (0.43)**	0.21	4.52
SA x GMA	**-0.47 (-1.10)**	0.15	3.12
TA1 x GMA	0.46 (0.10)	0.28	1.66
RA1 x GMA	**0.65 (1.12)**	0.19	3.37
TA2 x GMA	0.20 (0.04)	0.24	0.84
RA2 x GMA	-0.18 (-0.13)	0.13	1.40
SA^2 x GMA	**0.07 (0.28)**	0.03	2.51
$RA1^2$ x GMA	-0.04 (-0.19)	0.02	1.53
Performance Goal Condition (PGC)			
PGC	-1.78 (-0.20)	1.31	1.35
SA x PGC	0.26 (0.15)	0.94	0.28
TA1 x PGC	2.34 (0.13)	1.74	1.34
RA1 x PGC	-1.04 (-0.46)	1.20	0.87
TA2 x PGC	0.55 (0.03)	1.53	0.36
RA2 x PGC	0.64 (0.11)	0.81	0.79
SA^2 x PGC	-0.06 (-0.06)	0.17	0.35
$RA1^2$ x PGC	0.11 (0.15)	0.15	0.77
General Mental Ability x Performance Goal Condition			
GMA x PGC	-0.45 (-0.20)	0.32	1.39
SA x GMA x PGC	**0.48 (1.13)**	0.23	2.10
TA1 x GMA x PGC	-0.39 (-0.08)	0.43	0.92
RA1 x GMA x PGC	**-0.67 (-1.15)**	0.29	2.28
TA2 x GMA x PGC	-0.24 (-0.05)	0.37	0.64
RA2 x GMA x PGC	0.16 (0.11)	0.20	0.81
SA^2 x GMA x PGC	-0.08 (-0.33)	0.04	1.94
$RA1^2$ x GMA x PGC	0.03 (0.17)	0.04	0.92

Table 19 (cont'd)

	Variance	Correlations 1	2	3	4	5	6	7
Random Effects								
1. Intercept	39.41	-						
2. SA	8.46	-0.39	-					
3. TA1	63.76	0.03	-0.72	-				
4. RA1	6.21	0.47	-0.96	0.70	-			
5. TA2	50.74	0.12	-0.45	-0.03	0.25	-		
6. RA2	0.59	-0.28	-0.52	0.36	0.28	0.77	-	
7. SA^2	0.14	0.23	-0.96	0.66	0.85	0.63	0.71	-
Residual	43.29	-	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient.. Fixed effect degrees of freedom = 3026, except for the three time invariant predictors (i.e., GMA, PGC & GMA x PGC) which have 177 degrees of freedom.

Table 20: DRCGM Effects for Industriousness: Learning vs. Performance Goal Conditions

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**172.9 (-0.24)**	0.96	180.30
Skill Acquisition (SA)	**2.27 (1.35)**	0.67	3.40
Initial Transition Adaptation (TA1)	**-8.56 (-0.46)**	1.22	7.02
Initial Reacquisition Adaptation (RA1)	0.15 (0.07)	0.84	0.18
Secondary Transition Adaptation (TA2)	**-3.87 (-0.21)**	1.03	3.77
Secondary Reacquisition Adaptation (RA2)	**-2.09 (-0.37)**	0.56	3.74
Quadratic Skill Acquisition (SA^2)	**-0.26 (-0.27)**	0.12	2.20
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	**-0.33 (-0.44)**	0.10	3.25
Level 2			
Conscientiousness: Industriousness (C_IND)			
C_IND	1.44 (0.10)	1.61	0.89
SA x C_IND	-0.14 (-0.05)	1.12	0.13
TA1 x C_IND	3.19 (0.11)	2.05	1.56
RA1 x C_IND	-1.28 (-0.34)	1.41	0.91
TA2 x C_IND	-2.88 (-0.09)	1.73	1.67
RA2 x C_IND	1.79 (0.19)	0.94	1.90
SA^2 x C_IND	0.01 (0.01)	0.20	0.05
$RA1^2$ x C_IND	0.28 (0.23)	0.17	1.65
Performance Goal Condition (PGC)			
PGC	-0.88 (-0.10)	1.39	0.63
SA x PGC	-0.15 (-0.09)	0.97	0.15
TA1 x PGC	2.87 (0.15)	1.76	1.63
RA1 x PGC	-0.53 (-0.23)	1.21	0.44
TA2 x PGC	0.26 (0.01)	1.48	0.18
RA2 x PGC	0.56 (0.10)	0.81	0.70
SA^2 x PGC	-0.00 (0.00)	0.17	0.01
$RA1^2$ x PGC	0.10 (0.13)	0.15	0.66
Conscientiousness: Industriousness x Performance Goal Condition			
C_IND x PGC	-1.49 (-0.10)	2.30	0.65
SA x C_IND x PGC	1.03 (0.37)	1.60	0.65
TA1 x C_IND x PGC	-3.50 (-0.12)	2.92	1.20
RA1 x C_IND x PGC	-0.29 (-0.08)	2.01	0.14
TA2 x C_IND x PGC	**7.46 (0.25)**	2.46	3.03
RA2 x C_IND x PGC	-1.37 (-0.15)	1.34	1.02
SA^2 x C_IND x PGC	-0.18 (-0.12)	0.28	0.65
$RA1^2$ x C_IND x PGC	-0.25 (-0.20)	0.24	1.03

Table 20 (cont'd)

	Variance	Correlations 1	2	3	4	5	6	7
Random Effects								
1. Intercept	49.16	-						
2. SA	10.82	-0.50	-					
3. TA1	68.02	0.13	-0.74	-				
4. RA1	8.19	0.58	-0.97	0.73	-			
5. TA2	46.04	0.20	-0.51	0.03	0.36	-		
6. RA2	0.59	-0.25	-0.50	0.33	0.29	0.77	-	
7. SA^2	0.19	0.38	-0.96	0.68	0.89	0.68	0.66	-
Residual	43.04	-	-	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient.. Fixed effect degrees of freedom = 3012, except for the three time invariant predictors (i.e.,C_IND, PGC & GMA x PGC) which have 175 degrees of freedom.

Event History Analysis

Due to the centrality of event recognition for hypothesis development, additional analysis was done in an effort to further validate systematic, between-individual differences in event recognition. Specifically, in addition to the primary analyses already presented, robustness checks for the hypothesized cross-level relationships with transition adaptation were attempted using event history (aka survival) analysis. In this supplemental analysis, the level two variables were used to predict the number of iterations required to realize that a change had occurred, as indexed by an increase in response latency.

Recognition that a change has occurred is precipitated by the evaluation of unexpected feedback. The interpretation of unexpected feedback signals that the current schema or program is in need of revision or replacement via the selection of a more appropriate program (D. Norman & Shallice, 1986). While the temporal performance costs of switching tasks have long been known (e.g., Jersild, 1927), more recent theorizing and investigation has revealed that the integration of unexpected feedback, regardless of valence has a similar slowing effect on subsequent performance to accommodate the feedback evaluation and program update tasks that subsequently result (Alexander & Brown, 2010; Ferdinand, Mecklinger, Kray, & Gehring, 2012).

Conducting an event history analysis requires the occurrence of an "event". Common events for this technique include death (hence the term "survival" analysis), marriage, and job loss. In this case, the relevant event is the recognition that a change has occurred, and because integration of unexpected feedback temporarily slows subsequent processing, a substantial increase response latency is used in order to gage when this event has occurred. The data generated by the simulation program included the time remaining for each trial when the participant submitted their estimate of the stock price. This time excluded the initial five-second "read only" period and as such varied from 14 seconds (i.e., the participant entered their response within 1 second of being able to respond) to 0 (i.e., the participant entered their response during the last second available for that trial).

In order to translate this data into a format suitable for signaling the occurrence of event recognition, it was converted to a series of zeros and ones. As is typical for event analysis, 1 indicated that the event had occurred while 0 indicated the lack of an event. More specifically, the 15 trials immediately preceding and the 15 trials immediately following each change event (for a total of 30 trials for both the initial and subsequent change events) were analyzed. This corresponds to the data used to establish the last pre-change data point and the first post-change data point. All 15 pre-change trials[4] were used to establish individual-level localized estimates of mean response latency and response latency variability.

The 15 remaining post-change trials for each individual were then examined to identify the trial when the response latency first exceeded the one-tailed 95% confidence interval in the pre-change trials established for each individual. In other words, the lower bound of the anticipated time remaining for "expected" feedback was defined to be the mean of the 15 previous trials minus 1.64 times the standard deviation across those trials for each individual. Subsequently, the first trial (out of the 15 post-change trials) with a time remaining less than the lower bound of the expected feedback response latency range for each individual was coded as being indicative of recognition that a change had occurred (i.e. coded as 1). If a participant did not have a response latency falling outside of the expected range for the 15 trials comprising the first post-change time point, their data was treated as right censored (i.e., while the event may potentially have occurred, it did not occur during the period of observation).

Table 21 provides the breakdown of recognition events obtained via this coding scheme for the trials surrounding each change event. As can be seen, approximately 59% of participants (155 out of 261) recognized the first change event sometime within the subsequent 15 trials. Similarly, just over 61% of participants (160 out of 261) recognized the second change event sometime within the subsequent 15 trials.

[4] Because the response latency is measured before participants receive feedback for a given trial, it lags the trial wherein the feedback was recognized, so they could not know that an event had occurred for the first trial following each change event. For example, trial 91 was the first post-change trial for the initial change event; however, participants did not get feedback indicating a potential shift until after they had responded to trial 91. Thus, if they recognized that a change event had occurred after only one trial (trial 91), then this would be reflected in an increased response latency for trial 92, so response latencies were adjusted accordingly to correspond to the proper number of trials before and after the change event.

Table 21: Event Table for Initial and Subsequent Event Recognition

Post Change Trial Number	Initial Change Recognition	Subsequent Change Recognition
1	19 (261)	28 (261)
2	16 (242)	14 (233)
3	17 (226)	15 (219)
4	20 (209)	19 (204)
5	13 (189)	23 (185)
6	10 (176)	12 (162)
7	10 (166)	6 (150)
8	10 (156)	10 (144)
9	5 (146)	7 (134)
10	14 (141)	10 (127)
11	5 (127)	4 (117)
12	7 (122)	4 (113)
13	5 (115)	3 (109)
14	3 (110)	1 (106)
15	1 (107)	4 (105)
TOTAL	**154 (106)**	**155 (101)**

Notes: Numbers represent the number of participants in each time period who were coded as having recognized a change occurred for the first time. Numbers in parentheses represent the risk set (those at risk to experience the event at the beginning of each trial). Data is pooled across all three goal conditions (i.e., do-your-best, performance and learning goal conditions.

Because there were a finite number of opportunities to recognize that a change occurred and the independent variables are assumed constant over the period of observation, event history techniques suitable for invariant predictors and discrete time were employed. Discrete time models are particularly appropriate when the underlying time process is either inherently discrete or when numerous individuals experience the event at the same point in time, or "tie" (Allison, 1984; Yamaguchi, 1991), both of which are the case in this situation. In addition, because the focus of the analysis was on investigating the effect of the individual difference and contextual variables on the rate of event recognition, proportional hazard methods initially proposed by Cox (1972) are preferred (Allison, 1984; Yamaguchi, 1991). Specifically, discrete time Cox regression methods were applied by using the "coxreg" function in the "eha" package in R and setting the method equal to "ml" as instructed by Broström (2012, p. 205).

For robustness, a sample of models was evaluated multiple times. First, they were evaluated using the Efron approximation suitable for resolving numerous ties in continuous data, which can also be applied to discrete data (Hosmer Jr. & Lemeshow, 1999). In addition, a logistic regression with a complementary log-log link function, which is also suitable for the evaluation of discrete time models with time invariant predictors as the proportional odds evaluated by this technique approach the proportional rates of a proportional hazard event history model (Hosmer Jr. & Lemeshow, 1999; Yamaguchi, 1991) was also applied. As expected, across the sample of models, the results were nearly identical between the discrete Cox methods and Efron approximation approach and substantively the same for the logistic regression approach.

The results of the event history analysis for the hypothesized effects are presented in Table 22 through Table 28. Consistent with the results presented previously, there were no significant effects for the hypothesized individual difference variables when predicting either initial or secondary change event recognition. The specific results for GMA appear in Table 22 while the results for the Industriousness and Orderliness aspects of Conscientiousness are presented in Table 23 and Table 24 respectively. The results for the Intellect aspect of Openness appear in Table 25 while the results for the Volatility and Withdrawal aspects of Neuroticism are in Table 26 and Table 27 respectively.

Table 22: Event History Results for GMA and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
GMA	-0.203	0.174	0.244	0.125	0.193	0.520
PGC	-0.155	0.193	0.423	0.255	0.203	0.209
LGC	**-0.526**	**0.204**	**0.010**	0.223	0.200	0.265
GMAxPGC	0.265	0.223	0.236	-0.165	0.239	0.492
GMAxLGC	0.068	0.212	0.749	-0.137	0.228	0.548

Notes: GMA = General Mental Ability. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 8.59 on 5 df, p = 0.13. Secondary Change Model Deviance Statistic: 2.15 on 5 df, p=0.83.

Table 23: Event History Results for Industriousness and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
C_IND	-0.017	0.122	0.892	-0.142	0.135	0.292
PGC	-0.123	0.192	0.523	0.263	0.202	0.194
LGC	**-0.448**	**0.198**	**0.024**	0.241	0.199	0.226
C_INDxPGC	0.099	0.179	0.579	0.083	0.187	0.657
C_INDxLGC	0.021	0.194	0.915	0.032	0.187	0.866

Notes: C_IND = Conscientiousness: Industriousness. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 6.21 on 5 df, p = 0.29. Secondary Change Model Deviance Statistic: 3.68 on 5 df, p=0.60.

Table 24: Event History Results for Orderliness and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
C_ORD	0.073	0.117	0.532	-0.131	0.128	0.308
PGC	-0.133	0.194	0.491	0.234	0.199	0.240
LGC	**-0.459**	**0.200**	**0.022**	0.217	0.196	0.268
C_ORDxPGC	0.171	0.182	0.348	0.111	0.191	0.560
C_ORDxLGC	-0.054	0.201	0.789	0.296	0.197	0.134

Notes: C_ORD = Conscientiousness: Orderliness. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 9.29 on 5 df, p = 0.10. Secondary Change Model Deviance Statistic: 3.9 on 5 df, p=0.56.

Table 25: Event History Results for Intellect and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
O_INT	-0.158	0.154	0.303	-0.084	0.154	0.584
PGC	-0.114	0.192	0.553	0.221	0.201	0.273
LGC	**-0.472**	**0.201**	**0.019**	0.209	0.197	0.289
O_INTxPGC	0.196	0.205	0.338	-0.108	0.194	0.577
O_INTxLGC	-0.076	0.208	0.716	0.044	0.192	0.819

Notes: O_INT = Openness: Intellect. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 9.7 on 5 df, p = 0.08. Secondary Change Model Deviance Statistic: 4.68 on 5 df, p=0.46.

Table 26: Event History Results for Volatility and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
N_VOL	-0.005	0.125	0.965	-0.195	0.146	0.181
PGC	-0.143	0.195	0.464	0.142	0.204	0.489
LGC	**-0.467**	**0.201**	**0.020**	0.154	0.199	0.440
N_VOLxPGC	-0.149	0.186	0.424	0.012	0.209	0.955
N_VOLxLGC	-0.138	0.201	0.492	0.292	0.200	0.146

Notes: N_VOL = Neuroticism: Volatility. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 7.93 on 5 df, p = 0.16. Secondary Change Model Deviance Statistic: 5.49 on 5 df, p=0.36.

Table 27: Event History Results for Withdrawal and Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
N_WTH	0.072	0.131	0.585	-0.031	0.157	0.844
PGC	-0.123	0.192	0.524	0.240	0.200	0.230
LGC	**-0.437**	**0.197**	**0.027**	0.200	0.197	0.311
N_WTHxPGC	-0.172	0.180	0.337	0.161	0.205	0.431
N_WTHxLGC	-0.194	0.198	0.328	0.067	0.203	0.740

Notes: N_WTH = Neuroticism: Withdrawal. PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. "x" denotes the interaction between the two listed variables. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 7.45 on 5 df, p = 0.19. Secondary Change Model Deviance Statistic: 2.72 on 5 df, p=0.74.

The results for goal condition appear in Table 28. While there was no effect for performance goal condition, consistent with the results presented above, there was a persistent and relatively consistent effect for the learning goal condition relative to the baseline, do-your-best goal condition for recognition of the initial change event. In particular, the negative coefficient associated with the learning goal condition implies that for any given point in time, those in the learning goal condition were less likely to have recognized the occurrence of the initial change event. As indicated in Table 28 the coefficient of -0.450 implies that this group had a relative "risk" of change event recognition of 63.7% (calculated by raising the natural log base e to -0.450) compared to those in the baseline do-your-best goal condition.

Table 28: Event History Results for Goal Condition

	Initial Change			Secondary Change		
Variable	**Coef.**	**S.E.**	**Wald p**	**Coef.**	**S.E.**	**Wald p**
PGC	-0.114	0.190	0.549	0.232	0.199	0.245
LGC	**-0.450**	**0.197**	**0.022**	0.205	0.196	0.295

Notes: PGC = Performance Goal Condition. LGC = Learning Goal Condition. Do-your-best goal condition is the baseline. Coef= Coefficient. S.E. = Standard Error. Wald p = Wald estimate of p value. Bold indicates that a coefficient is significant at p = 0.05. Overall model significance: Initial Change Model Deviance Statistic 5.79 on 2 df, p = 0.06. Secondary Change Model Deviance Statistic: 1.64 on 2 df, p=0.44.

This effect can be seen graphically in Figure 9 which presents the survivor function by goal condition. As would be expected from the name, the survivor function shows the proportion of individuals who have not experienced the focal event (historically death or system failure) at a particular point in time. In this case, it is the proportion of individuals who have not yet recognized that a change event has occurred. As is expected, it begins at 1, indicating that no one has recognized the change event prior to receiving the necessary feedback and decreases stepwise with each new trial, bottoming out at the proportion of individuals who never recognized the change and "survived" for the duration of observation (15 post-change trials). Consistent with the results in Table 28, the learning goal condition consistently lags behind in event recognition compared to the other two goal conditions. Although, while not shown in Table 28, the coefficient differentiating the learning goal condition from the performance goal condition of -0.336 is only marginally significant, p=0.09.

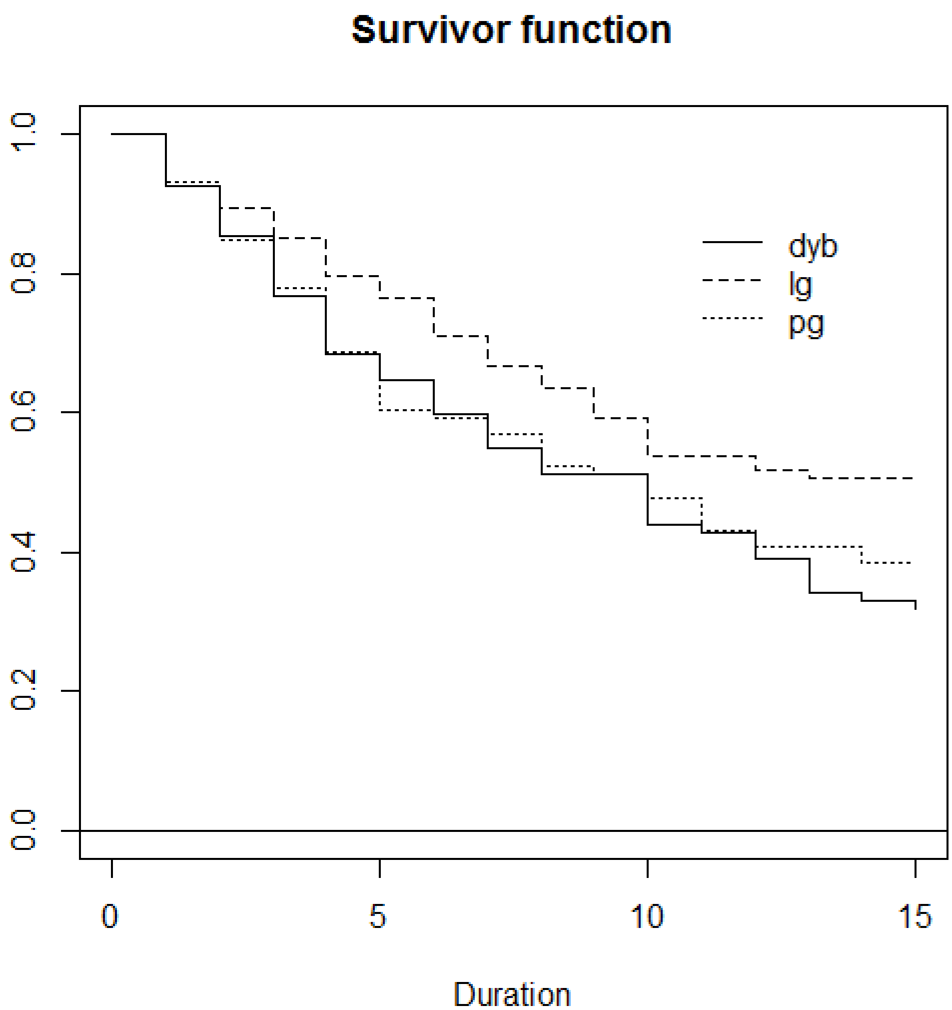

Figure 9: Survivor Function by Goal Condition

Supplemental Analysis

In order to further investigate the phenomenon of interest, an additional analysis was conducted to build on the results presented in Table 19 pertaining to the combined effect of GMA and Learning vs. Performance goal conditions. Specifically, because of the general lack of results for either of the secondary aspects of adaptive performance in either the primary or the event history analyses, this analysis focuses on performance after the initial change event (i.e., initial transition and reacquisition adaptation). These are the same aspects of adaptive performance recently studied by Lang and Bliese (2009) where the authors report that GMA was negatively related to (initial) transition adaptation and unrelated to (initial) reacquisition adaptation, indicating an overall net negative relationship between GMA and adaptive performance.

Table 29 presents the results for an analogous investigation in the current paradigm. Before discussing the parts of the model relevant to evaluating the effect of GMA on initial adaptive performance in detail, differences in the Level 1 model from those previously presented are discussed. In terms of fixed effects, both secondary aspects of transition adaptation have been removed to align with this subset of the data. In addition, in terms of random effects, there are several changes (in addition to removing the secondary aspects of adaptive performance). First, comparative deviance statistics indicated no significant increase in model fit when the quadratic aspect of Initial Reacquisition Adaptation was treated as a random variable; therefore, it was treated as fixed in order to preserve model degrees of freedom (Singer & Willett, 2003). In addition, there was no increase in model fit associated with adopting either an autocorrelated or a heteroscedastic error structure so neither was included in the final Level 1 model.

Contrary to the results reported by Lang and Bliese (2009), in this context, GMA was positively related to initial transition adaptation (standardized effect size 0.12, standard error = 0 .06, $t = 2.1$). In addition, GMA was significantly related to initial reacquisition adaptation (standardized effect size 0.88, standard error = 0.27, $t = 3.3$) in the learning goal condition. Further, the effect of GMA on reacquisition adaptation was dependent on the goal condition that participants were working under; specifically, the relationship between GMA and reacquisition adaptation was significantly lower for those in the PG condition compared with those in the LG condition (standardized effect size –0.95, standard error = 0.04, |t| = 2.4). Finally, similar analyses were run for each hypothesized aspect of personality and no significant main or interactive effects were found.

Table 29: Effect of GMA and Goal Condition on Initial Adaptive Performance

Variable	Coef.(Std.)	SE	|t|
Fixed Effects			
Level 1			
Intercept	**173.7 (-0.15)**	0.92	187.85
Skill Acquisition (SA)	**1.93 (1.14)**	0.65	2.98
Initial Transition Adaptation (TA1)	**-5.83 (-0.31)**	1.13	5.15
Initial Reacquisition Adaptation (RA1)	**-1.79 (-0.79)**	0.66	2.71
Quadratic Skill Acquisition (SA^2)	-0.21 (-0.22)	0.11	1.85
Quadratic Initial Reacquisition Adaptation ($RA1^2$)	0.01 (0.02)	0.04	0.30
Level 2			
General Mental Ability (GMA)			
GMA	**0.95 (0.43)**	0.21	4.46
SA x GMA	**-0.47 (-1.10)**	0.15	3.16
TA1 x GMA	**0.55 (0.12)**	0.26	2.11
RA1 x GMA	**0.51 (0.88)**	0.15	3.34
SA^2 x GMA	**0.07 (0.27)**	0.03	2.55
$RA1^2$ x GMA	-0.00 (-0.02)	0.01	0.51
Performance Goal Condition (PGC)			
PGC	-1.79 (-0.20)	1.33	1.35
SA x PGC	0.28 (0.17)	0.93	0.31
TA1 x PGC	1.78 (0.10)	1.62	1.10
RA1 x PGC	-0.44 (-0.19)	0.95	0.46
SA^2 x PGC	-0.06 (-0.07)	0.16	0.39
$RA1^2$ x PGC	0.01 (0.01)	0.06	0.11
General Mental Ability x Performance Goal Condition			
GMA x PGC	-0.44 (-0.20)	0.32	1.38
SA x GMA x PGC	**0.48 (1.13)**	0.23	2.14
TA1 x GMA x PGC	-0.45 (-0.10)	0.40	1.15
RA1 x GMA x PGC	**-0.55 (-0.95)**	0.23	2.38
SA^2 x GMA x PGC	**-0.08 (-0.32)**	0.04	1.99
$RA1^2$ x GMA x PGC	0.00 (0.03)	0.01	0.34

Table 29 (cont'd)

	Variance	Correlations 1	2	3	4	5
Random Effects						
1. Intercept	45.49	-				
2. SA	9.65	-0.45	-			
3. TA1	66.58	0.09	-0.60	-		
4. RA1	10.33	0.45	-0.98	0.47	-	
5. SA^2	0.15	0.30	-0.97	0.50	0.98	-
Residual	38.60	-	-	-	-	-

Notes: Coef. = Coefficient. Std = Standardized Coefficient. Bolded values correspond to a p-value of <0.05. SE = Standard Error for unstandardized coefficient.. Fixed effect degrees of freedom = 3020, except for the three time invariant predictors (i.e., GMA, PGC & GMA x PGC) which have 175 degrees of freedom.

These results are depicted graphically in Figure 10 for the learning goal condition and Figure 11 for the performance goal condition. Specifically, projected performance for someone possessing an average level of GMA is presented. In addition, analogous curves representing a level of GMA one standard deviation above and below that observed in the sample are plotted. Consistent with the results presented above, regardless of goal condition, GMA was positively associated with initial transition adaptation. Graphically, this manifests as a smaller performance decrement immediately after the change event has occurred for those above average in GMA compared with those below average in GMA.

In addition, for those in the LG condition, GMA was positively related to initial reacquisition adaptation. Graphically, initial reacquisition adaptation corresponds to the difference in slope between the skill acquisition and initial adaptive performance portions of the performance episode. As shown in Figure 10, a participant one standard deviation above average in GMA is predicted to have a performance slope that is roughly equal across the two performance periods, indicating relatively high initial reacquisition adaptation. Conversely, performance in the post-change period for a participant one standard deviation below average in

GMA increases more slowly compared to the pre-change period, which is indicative of a lower level of reacquisition adaptation. In contrast, the three performance curves depicted in Figure 11 are roughly parallel. That is, on average, the change in slope between the initial performance period and the post-change performance period did not vary with participant GMA. This is consistent with the finding that GMA was not substantially related to initial reacquisition adaptation for those in the PG condition.

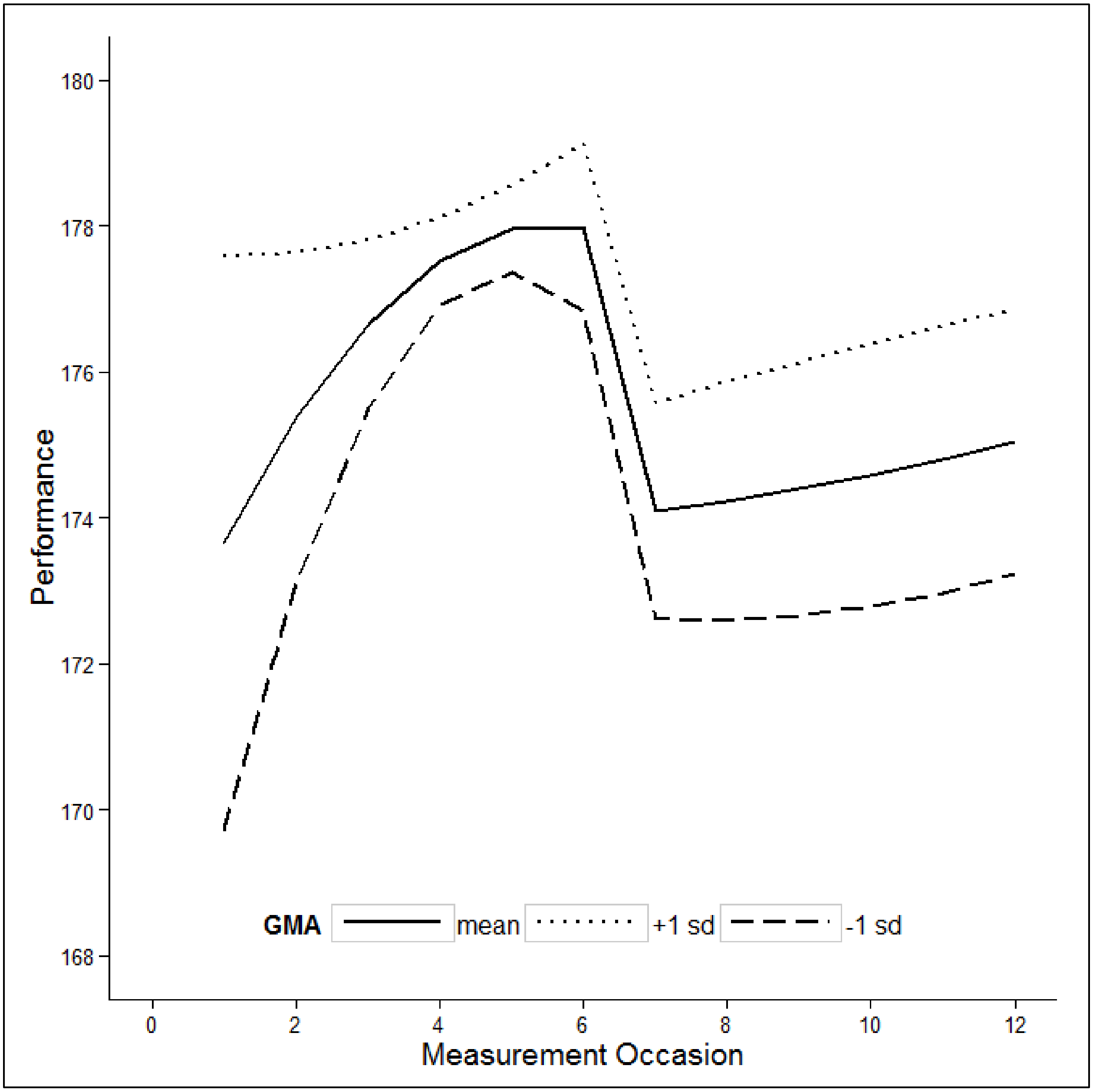

Figure 10: GMA & Initial Adaptive Performance in Learning Goal Condition

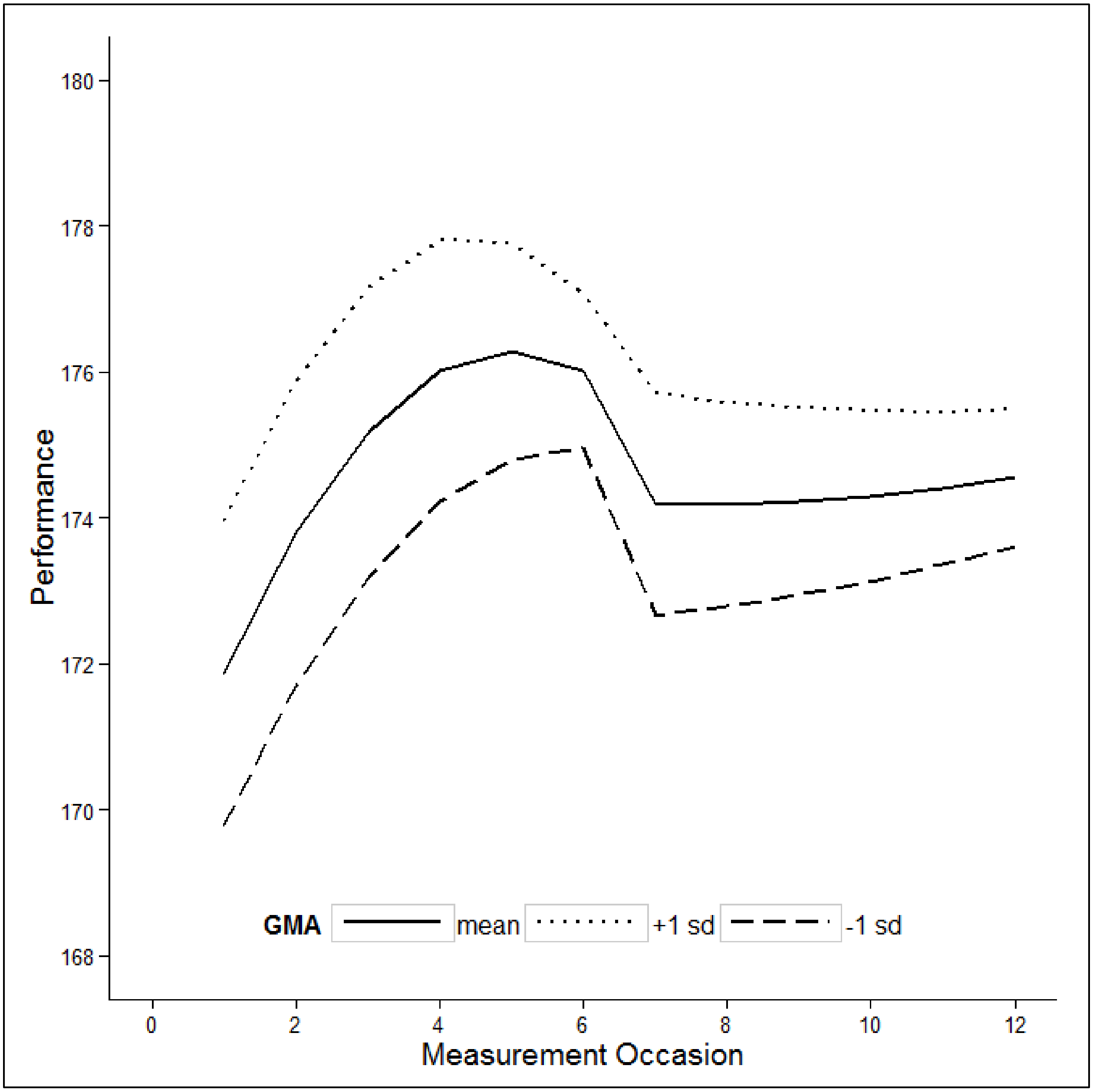

Figure 11: GMA & Initial Adaptive Performance in Performance Goal Condition

DISCUSSION

This study attempted to contribute to the adaptive performance literature in several ways. First, in an effort to answer the call to increase the theoretical rigor of adaptive performance research (Baard et al., 2014), control theory was put forth as a potentially useful framework to guide investigations of adaptive performance. In addition, past research and theory would suggest that adaptive performance may vary with repeated exposure to a change stimulus (Ackerman, 1988; LePine et al., 2000; March & Simon, 1958). Specifically, control theory was used to guide development of hypotheses related to the relationships between key individual differences including general mental ability and various personality aspects might be related to different components of adaptive performance, answering a call in the literature to consider the role of personality (Lang & Bliese, 2009; Thoresen et al., 2004). In addition, the importance of goal type was investigated as a potentially important contextual moderator (Dorsey et al., 2010) and participants were assigned to either a do-your-best condition, or a difficult, specific performance or learning goal condition. These hypotheses were evaluated using a novel simulation program created to implement an adapted version of the stock-pricing exercise.

The experimental task seemed to generate a data-structure that was conducive to being evaluated using the proposed discontinuous random coefficient growth modeling paradigm that is particularly suitable to evaluating adaptive performance occurring in the task-change paradigm (Lang & Bliese, 2009). As shown in Table 10 (and augmented by Table 11, Figure 8, and the associated discussion) performance initially increased over time, declined significantly in the aftermath of the first change event, increased again, and then declined immediately after the second change event, and then rebounded again. In addition, the proposed Level 1 model accounted for approximately 61% of the variance in performance. Further, there was substantial (Bliese & Ployhart, 2002) between individual variation in performance that could conceivably be predicted by individual and contextual differences. However, the data seemed to exhibit a persistent curvilinear nature that was resistant to recommended transformations, which has the tendency to make interpreting the results of the model more difficult (Singer & Willett, 2003).

While the descriptives and reliability indicators seem to indicate that the individual difference variables were assessed adequately, the results for the goal condition manipulation were more ambiguous. Difficult and specific are two key aspects of effective goals, rather they are focused on performance or learning outcomes (Locke & Latham, 2002). Based on the manipulation checks, the performance goal manipulation seemed to be effective on both counts. However, the learning goal manipulation did not seem to be quite as effective. While the learning goal condition was seen as being more specific than the do-your-best condition, it wasn't as specific as the performance goal condition. Further, the learning goal condition was not seen as being more difficult than the do-your-best condition and nearly 60% of participants achieved their goal in the learning goal condition, validating the perceived lack of difficulty. In contrast, the stock price was only estimated with a level of accuracy laid out by the performance goal 23% of the time, consistent with previous operationalizations of difficult goals (e.g., Winters & Latham, 1996).

The perceived and observed difference in goal difficulty may have been in part related to how the performance and learning goal conditions were operationalized. Specifically, the performance goal condition asked participants to achieve a particular level of performance (i.e. get within +/- $7 of the actual stock price) on each trial. This sort of operationalization is consistent with past work in this domain (e.g., DeShon & Alexander, 1996) and was adopted in order to help prevent participants from giving up (coasting) if their level of performance in the early trials was poor (exemplary), which is a concern in these sorts of learning tasks (Lang &

Bliese, 2009). In comparison, difficult, specific learning goal operationalizations typically involve developing a certain number of strategies (in this case 7 vs. a typical 4-6) that were effective across the whole performance episode because the intention is to have participants identify strategies that are applicable across individual trials (Seijts & Latham, 2001; Seijts et al., 2004), which precludes an analogous by-trial learning goal formulation.

This difference in focus (i.e. within vs. across trials) between the performance and learning goal conditions may have created somewhat asymmetric goal conditions due to the temporal difference in goal specification across conditions. Performance in tasks like the stock pricing exercise is influenced by whether implicit or explicit learning is employed, and performance goals tend to encourage explicit learning due to their focus on short-term, objective performance outcomes that encourage rapid development and evaluation of explicit mental models of the task environment (DeShon & Alexander, 1996). Conversely, while the learning goal condition was seemingly effective in influencing participant behavior regarding the number of strategies reported (59% achievement rate in-condition vs. 3% out-of-condition), this reporting was done after the simulation task was complete. This leaves open the possibility that participants in this situation were able to utilize implicit learning strategies during the task and then used sensemaking processes to retrospectively describe strategies that seemed plausible at the end of the exercise (Weick, 1979).

While not entirely analogous, the method of specifying the performance and learning goal specifications was deemed necessary to capture differences in the operational mechanisms of each goal type. As a result, the combination of being able to employ a learning approach well matched to the exercise (i.e. implicit learning) and the temporal separation between completion of the focal task and the reporting of any beneficial strategies may have diminished the cognitive resources required, reducing perceptions of goal difficulty and enabling higher goal accomplishment rates compared to the performance goal condition. In other words, the reported goal difficulty and specificity for each condition may reflect meaningful differences in how the two types of goals function when influencing behavior, not solely the relative effectiveness of the manipulations across conditions.

Further, while the Level-1 model seemed plausible, as presented in the results section, the hypothesized results (which relied on cross-level interactions) largely failed to materialize. There are several reasons why this may have occurred. First, theories of both cognitive (Dual Methods of Control Theory; Braver et al., 2007) and emotional (Attentional Control Theory; M. W. Eysenck et al., 2007) processing posit that resource allocation is a fundamental driver of the processing of feedback, which is a key process in control theory. Specifically, attention allocation can be biased towards executing the currently active program or towards environmental scanning and stimulus investigation. While the first allocation strategy can be beneficial for performance in some settings (e.g. Stroop task; Kane & Engle, 2003), it can be detrimental in others because potentially valuable information is marginalized or excluded, and the ways in which individual differences and situational cues influence the processing or exclusion of this information formed a key conceptual foundation for this study.

In order to create tension between program retention and program revision driven by the incorporation of inconsistent feedback, the simulation task included an error term that caused the "correct" stock price shown to participants for each trial to vary randomly from the price that the organizational performance parameters would justify (using the loadings presented in Table 4). Without such an error term, participants could more easily ascertain the nature of the underlying relationship and thus change events would be more immediately obvious. By including an error term, after each trial participants had to decide whether the result indicated a fundamental problem with their selected program (potentially caused by an underlying shift in the complexity of the situation) which would require substantial revision or whether the bad outcome was the result of a wayward error term.

While the inclusion of the error term is consistent with the task change paradigm (DeShon & Alexander, 1996; Earley, Connolly, & Ekegren, 1989), it may present an overly conservative test of the proposed hypotheses if individuals are unable to ascertain a satisfactory strategy and reach the automatic, autonomous phase of performance (Ackerman, 1988) during the initial performance phase. This level of proficiency is consistent with the development and execution of a suitable program that may in turn lead to the exclusion of inconsistent information. The hypotheses inherently assumed that participants would be able to reach this state and thus future information processing would be substantially influenced by the content of enacted program (which was proposed to be a function of individual and contextual considerations). Further, temporary performance costs associated with the activation of search programs were proposed to be an important consideration for the various aspects of adaptive performance. If participants remained in the developmental cognitive or associative performance phases (Ackerman, 1988), the proposed effects are likely to be subdued.

The error term only accounted for about 11% of the variance in the stock price across trials, and the overall net effect when averaged across trials was less than 2% of the average stock price. While the average effects of the error term were in the vicinity of the expected 11%, for some trials, the effects were much more drastic. In particular, when a small expected stock price was combined with an excessive error term, the reported "correct" stock price seen by participants could be off by more than 85% of the nominal value. This may have unintentionally confounded participants and prevented them from establishing acceptable performance programs. In contrast to the current study, many other task-change evaluations of adaptive performance used more deterministic input-outcome linkages within each performance episode (e.g., Lang & Bliese, 2009; LePine et al., 2000).

The strategies participants reported employing provide some further insight into how participants perceived the change events, and as hypothesized, there seemed to be variability across individuals. Some participants seemed to adjust, for example: "I tried to figure out the numbers that seemed to control the stock price the most (I think this varied as time went on)", "If a current strategy falters; reevaluate", and "The most useful historical data is the data from last week. Data from weeks that are more distant is not as helpful." However, consistent with the discussion above, others were seemingly more confounded by the pattern of results: "I used the same formula for determining the answer once I figured out one that was getting me close to the correct price", "It changed, didn't find one that worked", and "I felt like I was guessing and I could not find a correlation between the numbers. At first I thought I was doing well and then it seemed to change. My accuracy was very poor." Thus, while there was seemingly some inter-individual variation as predicted, the noise in the feedback signal may have obscured the intended change pattern.

This supposition is consistent with the overall lack of effects for the individual difference variables when predicting response time shifts with the previously presented event history analysis. In addition, on average, when response time was aggregated to the measurement occasion level, there was no significant difference in response time immediately before and after the first (mean time remaining for measurement occasion 6 = 9.06; mean time remaining for measurement occasion 7 = 9.16) or second change event (mean time remaining for measurement occasion 12 = 10.18; mean time remaining for measurement occasion 13 = 10.33). This pattern is consistent with the supposition that the change events may not have caused a disruptive shift between performance and search programs as intended.

If participants had a tendency to remain in an exploratory-oriented state, this situation would conceivably be exacerbated by the presence of a learning goal, which overtly encourages this sort of focus (Ordóñez et al., 2009). The results of the event history analysis are supportive of this type of situation as there was a contextual effect in terms of response latency after the first change event. Specifically, those in the learning goal condition were generally slower to recognize the occurrence of the initial change event.

Further, the impact of a noisy feedback signal may have been compounded by the lack of extensive, explicit strategy recommendations provided during the training. The information provided was purposely brief to create a weaker situation and induce variation in the programs participants devised to predict the stock price (e.g., GMA is generally positively related to program complexity; Beilock & DeCaro, 2007). Even though participants were not left to devise a strategy completely from scratch as they were provided with some instructive examples and other useful information it may not have been sufficiently narrowing.

Specifically, during the training, the participants were provided with an example situation that walked them through 3 trials in order to see how the process unfolded. During that example, the first demonstrated strategy relied exclusively on one aspect of organizational performance (equivalent to a 0-1-0 weighting scheme for the organizational variables in Table 4). When this strategy performed poorly based on the feedback received in the subsequent trial, the demonstrated strategy conveyed to participants was switched to an evenly weighted average (equivalent to a 0-0.5-0.5 scheme weighting scheme). In addition, participants were told that none of the organizational parameters would be negatively related to the stock price.

It seems as though some people were able to pick up on these cues effectively as some form of averaging (either all three variables or some subset) was listed relatively frequently in the strategies reported by participants. Others reported focusing on market share (sometimes with revenue growth) which were the key drivers in the first two periods (as reported Table 4). However, others were less successful, listing strategies as: "it's almost random" or "I found no patterns to follow and generally did better with a random guess somewhere between the three numbers". Others used rather esoteric strategies including: "using the second highest number in a set for my entry", "Raise[ing] price if Revenue was above Advertising" or "If bottom two input values were the same, the stock price was that value plus the number in the top input value divided by 10."

To the extent that the number of potential strategies was overwhelming, systematic differences in performance may not have materialized due to a lack of ability. The availability of too many potential strategies can be detrimental to performance in novel situations (Earley, Connolly, & Lee, 1989), but aside from the arguments pertaining to GMA, the theory presented largely assumed that participants had the ability to effectively enhance their performance. If this ability is lacking, the theorized dispositional differences in feedback perceptions and responses indexed by the evaluated personality aspects may not have been strongly associated with adaptive performance. If performance was more heavily reliant on ability rather than the discrepancy detection and improvement motivation processes relied upon to develop the proposed hypotheses, the proposed effects may not have materialized. In many ways, this is akin to the established finding that ability is generally associated with maximum performance while dispositional variables are more strongly related to typical performance (Klehe & Anderson, 2007) and would be consistent with the assertion of Dorsey et al. (2010) that adaptive performance is more akin to maximal rather than typical performance. These authors further go on to note that as such, ability is a key determinant of adaptive performance (along with motivation).

This would be consistent with the findings reported in the supplemental analysis. Specifically, GMA, an ability index, seems more relevant for predicting adaptive performance in this context than personality aspects that speak more to motivation. Initially, it was proposed that GMA would be negatively related to initial transition adaptation due to the feedback screening effects associated with more focused performance programs and proactive control. However, in light of the above discussion, it may be that having a more complex program to deal with noisy information allowed high GMA individuals to better differentiate the occurrence of a change event from the omnipresent error present in the feedback signal. In other words, in this environment, the complex programs possible for and generally preferred by high GMA individuals may have been more effective (Beilock & DeCaro, 2007; Ricks et al., 2007). Further, these individuals may have been more adept at extracting appropriate model prototypes from the initial training, enabling them to more quickly and appropriately respond to the change event. This is consistent with the prevailing wisdom that GMA is moderately and positively related to training transfer (Colquitt et al., 2000).

Initially, no hypothesis was put forward for the relationship between GMA and initial reacquisition adaptation. Even though GMA is generally positively related to performance (Morgeson et al., 2007b), it was thought that this relationship may not hold for this aspect of adaptive performance. Previous work in multiple areas has demonstrated a lack of a relationship in situations characterized by either the presence of a sufficiently taxing secondary task (e.g., Kane & Engle, 2000) or anxiety (e.g., Beilock & Carr, 2005). Based on the nature of adaptive performance, it seemed reasonable to expect one or both of these conditions to prevail during the initial reacquisition phase (e.g., Lang & Bliese, 2009).

While these mechanisms have been proposed as being relevant for some aspects of adaptive performance (Lang & Bliese, 2009), there is no strong theory pertaining to when they are likely to manifest in the context of multiple change events. As such, these effects could have become more pronounced later on during the performance series, contributing to the lack of significant results for GMA after the subsequent change event. Specifically, the occurrence of a secondary change event may have added additional complexity to the situation that overwhelmed the ability of high GMA individuals to maintain a high level of performance. Further, there was no dominant driver of stock price in the third performance period, with all three organizational performance parameters contributing equally (Table 4). In addition, because participants were told ahead of time how many trials they would be completing for the exercise, they may have felt additional anxiety regarding the likelihood of goal attainment. Past research has demonstrated that differences in discrepancy reduction efforts are likely to manifest as the time remaining to achieve a goal diminishes (K. J. Williams et al., 2000). In addition, when goal progress rates (i.e. velocity) are below desired levels, negative emotional responses (akin to anxiety) are likely to result (Chang et al., 2010).

Conversely, in the initial change period participants may have felt less anxiety or need to change their goal state because a substantial proportion of the available trials were still remaining. When faced with challenges and shortcomings, people initially tend to remain dedicated to achieving their goals and modify their behavior to accomplish their desired state, generally by some combination of working harder and/or smarter (Campion & Lord, 1982; Carver & Scheier, 1998; Donovan & Williams, 2003). Specifically, for those in the learning goal condition there was a positive relationship between GMA and initial reacquisition adaptation. Presumably, in this condition, participants higher in GMA were motivated and able to successfully employ the complex programs that generally serve them well (Beilock & DeCaro, 2007; Ricks et al., 2007) in this portion of the performance task to good effect.

As reported in Table 29, this relationship was not universal as there was a significant effect for goal condition. Specifically, the negative effect associated with the performance goal condition negated the positive relationship between GMA and initial reacquisition adaptation observed in the learning goal condition. This outcome is consistent with the current theoretical framework and previous empirical findings. In contrast to learning goals which encourage exploration and development (Ordóñez et al., 2009; Seijts & Latham, 2001), performance goals encourage focus on the desired distal outcome (Locke & Latham, 2002). As previously discussed, this focus has been shown to be detrimental to performance in certain circumstances, including those that incorporate many potential strategies for success best suited for an implicit learning approach (DeShon & Alexander, 1996).

Specifically, in situations like this, the presence of a performance goal can increase perceptions of task complexity, and the desire to realize goal progress can result in overly frequent comparisons of an individual's current state compared to the goal state, even when such investigations are expressly detrimental to performance on the focal task (Huber, 1985). Further, performance goals can induce rapid and haphazard strategy selection, evaluation, and retain versus reject decisions, which tends to be detrimental to performance (Earley, Connolly, & Ekegren, 1989; Wood & Locke, 1990). Performance goals can also encourage explicit modes of learning characterized by the creation of accurate mental models of the underlying characteristics and relationships that govern the situation, which can be exceedingly complex and difficult to ascertain for tasks better suited to implicit strategies (DeShon & Alexander, 1996). Thus, performance goals may encourage suboptimal allocation of cognitive resources and attenuate the relationship between GMA and initial reacquisition adaptation, akin to the previously discussed examples from the dual-task paradigm. Finally, the lack of a significant moderating effect for do-your-best goals versus either learning or performance goals provides some evidence that this condition may be intermediate in terms of influencing initial reacquisition adaptation compared to the two other conditions.

CONCLUSION

While support for the chosen hypotheses from the proposed model was far from universal, there are still potential contributions to be realized. First, theories relevant to strategy selection and task complexity seem to be relevant for adaptive performance. In particular, as presently implemented, due to the complexity of the stock-pricing task, adaptive performance seemed better suited to prediction with indexes of ability (i.e., GMA) compared with motivation (i.e., personality). This pattern of results is consistent with the assertion of Dorsey et al. (2010) who proposed viewing adaptive performance in the light of maximal rather than typical performance.

Based on their results, Lang and Bliese (2009) recently pointed out that GMA might be negatively related to transition adaptation and unrelated to reacquisition adaptation, casting some doubt on the utility of GMA in modern workplaces, which are increasingly characterized by a need to adapt (Ployhart & Bliese, 2006; Pulakos et al., 2000). However, this study provides evidence to countermand this assertion. First, the negative relationship between GMA and (initial) transition adaptation recently reported by Lang and Bliese (2009) was not replicated. Rather, a positive relationship was generally obtained, and this finding was fairly robust across goal conditions, with a significant main effect when collapsing across all three conditions. In addition, the effect was significant when comparing the learning goal to the do-your-best goal condition and was marginally significant ($t = 1.76$; $p < 0.1$) when comparing the performance and do-your-best goal conditions individually.

As previously discussed, the task employed in the current study was relatively complex and noisy. In contrast, based on the description provided, the tank-combat scenario employed by Lang and Bliese (2009) did not seem to share these traits. Rather, participants completed 300 decision trials (split into three episodes) that took place on the same, restricted size game-grid prior to the occurrence of the change event (after which an additional 300 trials were performed). In addition, the rules governing the game and participant scoring were deterministic and unchanging across trials, and participants did not face any time pressure as they were allowed unlimited time to make each decision. Collectively, a relatively stable, deterministic performance task environment coupled with a much larger number of decision trials may have allowed participants to reach more autonomous levels of task processing than they were able to attain in the current study. As previously discussed, the theoretical arguments put forward in support of a negative relationship between GMA and initial transition adaptation were predicated on the assumption that stable performance programs would be implemented, effectively screening pertinent information. For the reasons just discussed, the simulation employed by Lang and Bliese (2009) may have elicited these effects to a higher degree than the stock-pricing exercise as implemented in the current investigation, highlighting a potential consideration for future researchers to consider.

Further, in the current study, GMA was positively related to initial reacquisition adaptation across the learning goal condition (when compared to either the performance or do-your-best condition, or both). However, the relationship between GMA and (initial) reacquisition adaptation was dependent on the goal condition under which the task was performed. Specifically, while the relationship was positive in the learning goal condition, this relationship was nullified in the performance goal condition. While Lang and Bliese (2009) do not provide any information pertaining to what goals, if any, participants were provided with as part of their study, this may account for the difference in the relationship between GMA and (initial) reacquisition adaptation between their study (i.e. no relation) and the current one.

Regardless, the current study highlights the importance of considering goal condition when studying adaptive performance.

Limitations

No study is without its limitations, and this one is no exception. First, even though attempts were made to make the stock-pricing task relevant to participants by emphasizing how it might be related to critical job tasks, it was still a simulated task performed by students in a computer lab. This could potentially impact the generalizability of these findings; although there is nothing particular to adaptive performance that would indicate specific issues, and lab findings have a general tendency to generalize despite their potential shortcomings (Locke, 1986). Further, lab studies can be powerful to the extent they enable the understanding of the phenomena of interest (Highhouse, 2009).

This study considered the adaptive performance of individuals working independently. Because team and individual level adaptive performance are distinct phenomena (Pulakos et al., 2006), the results of this study should not necessarily be expected to extend to team contexts. While teams are commonly used in organizations (Morgeson et al., 2005), not all jobs (e.g. college professor) are primarily team based. Further, some aspects of most jobs are performed individually, providing a potentially important context for the results of this study. However, the lack of a social context could be argued to be a deficiency and work exploring the drivers of the diffusion and adoption of adaptive responses would seem to be a natural extension to the existing body of work in this domain.

In addition, due to a desire to present participants with a single, uninterrupted performance episode in which to evaluate their adaptive performance, no "in-process" measures were collected. While the framework presented focused on individual traits, there are natural ties to more temporal constructs (e.g. neuroticism to the more frequent experience of negative affect). Further, temporally variant affective states can influence self-regulatory processes (R. E. Johnson et al., 2013). Thus, this research design presented limited opportunities to investigate these potentially important intra-individual processes and gain additional insight into the adaptive performance process (and the suitability of utilizing a self-regulatory framework).

Future Directions

There are numerous opportunities for future investigations to build on these findings and further our understanding of adaptive performance. In particular, as previously discussed, the complexity of the task environment may have been a substantial contributor to the pattern of results obtained, and future work could attempt to validate and understand this issue in more detail. Specifically, the impact of the noise in the feedback signal could be further evaluated by comparing predictors of adaptive performance in low and high noise environments.

The impact of the overall level of noise could be evaluated by varying the proportion of the variation in the stock price presented to participants for each trial that was explained by the organizational performance parameters. In addition, the impact of variation in the noise signal could be explored by manipulating the maximum size of the error term. This would seem to be potentially relevant for adaptive performance due to the similarity in the initial appearance of the signal presented by a large error term compared with an underlying change event. While distinct, this is consistent with recent work proposing that variance in performance evaluations over time (akin to a noisy feedback signal) may be a consideration in overall performance evaluations (Reb & Cropanzano, 2007).

In addition to noise in the feedback signal, the sheer number of potential (and manifest) strategies for linking the organizational performance attributes may be another fruitful area for future research. The number and saliency of potential strategies have been shown to impact performance in complex situations, especially when it is difficult to evaluate the relative effectiveness of different approaches for previous performance episodes (Earley & Perry, 1987). The extent to which the size of the pool of potential strategies available to participants might influence the relationship between individual differences and adaptive performance could be empirically investigated by varying the specificity of instructions provided to participants.

In particular, participants could be trained to consider only simple linear combinations of the organizational performance parameters (like those used to generate the stock price as delineated in Table 4) in order to substantially reduce the number of potential choices. Instruction on potential search strategies relevant to determining the appropriate weight for each aspect could be provided as well. In addition to providing further insight into the impact that the number of potential goal strategies might have on individual adaptive performance, this program of research would also further our understanding of the benefits of training and examine a mechanism by which organizations may be able to help increase the adaptive performance of their employees.

Finally, due to the potential issues with the task-change paradigm previously highlighted, further research could attempt to determine individual difference predictors of adaptive performance in actual job contexts. While the importance of adaptability is likely to vary in relative importance across jobs, it is likely to play a role in overall performance across a wide variety of contexts (Ployhart & Bliese, 2006). Due to difficulties in manipulating or observing adaptive performance events in field settings, (Dorsey et al., 2010; LePine et al., 2000), it may be beneficial to rely on the evaluation of employees and their coworkers and supervisors, as is widely done for other aspects of performance (e.g., task performance, organizational citizenship behaviors).

While supervisor reports of adaptive performance have been collected in the past (Pulakos et al., 2002), the lack of a readily available, easy to administer measure makes this type of investigation difficult to implement at the present. Future research aimed at developing and validating such a measure would seem to be a viable path to furthering our understanding of this area. In addition, the existence of this sort of measure would facilitate investigations into the conceptual uniqueness of adaptive performance as well as its importance for overall performance evaluation and organizational performance, relative to more established aspects of performance (e.g, task performance, organizational citizenship behaviors, counterproductive work behaviors). Research of this sort would also answer the call of Cortina and Luchman (2013), who have recently identified the need for investigations of this nature in order to more firmly ground the concept of adaptive performance and strengthen the case for continued future investigation.

APPENDICES

APPENDIX A: Measure Items

Table 30: Items Assessing Personality Aspects (DeYoung et al., 2007)

Trait/Domain	Aspect	Items
Agreeableness		
	Compassion	
		Am not interested in other people's problems. (R)
		Feel others' emotions.
		Inquire about others' well-being.
		Can't be bothered with other's needs. (R)
		Sympathize with others' feelings.
		Am indifferent to the feelings of others. (R)
		Take no time for others. (R)
		Take an interest in other people's lives.
		Don't have a soft side. (R)
		Like to do things for others.
	Politeness	
		Respect authority.
		Insult people. (R)
		Hate to seem pushy.
		Believe that I am better than others. (R)
		Avoid imposing my will on others.
		Rarely put people under pressure.
		Take advantage of others. (R)
		Seek conflict. (R)
		Love a good fight. (R)
		Am out for my own personal gain. (R)
Conscientiousness		
	Industriousness	
		Carry out my plans.
		Waste my time. (R)
		Find it difficult to get down to work. (R)
		Mess things up. (R)
		Finish what I start.
		Don't put my mind on the task at hand. (R)
		Get things done quickly.
		Always know what I am doing.
		Postpone decisions. (R)
		Am easily distracted. (R)

Table 30 (cont'd)

Trait/Domain	Aspect	Items
Conscientiousness		
	Orderliness	
		Leave my belongings around. (R)
		Like order.
		Keep things tidy.
		Follow a schedule.
		Am not bothered by messy people. (R)
		Want everything to be “just right".
		Am not bothered by disorder. (R)
		Dislike routine. (R)
		See that rules are observed.
		Want every detail taken care of.
Extraversion		
	Enthusiasm	
		Make friends easily.
		Am hard to get to know. (R)
		Keep others at a distance. (R)
		Reveal little about myself. (R)
		Warm up quickly to others.
		Rarely get caught up in the excitement. (R)
		Am not a very enthusiastic person. (R)
		Show my feelings when I’m happy.
		Have a lot of fun.
		Laugh a lot.
	Assertiveness	
		Take charge.
		Have a strong personality.
		Lack the talent for influencing people. (R)
		Know how to captivate people.
		Wait for others to lead the way. (R)
		See myself as a good leader.
		Can talk others into doing things.
		Hold back my opinions. (R)
		Am the first to act.
		Do not have an assertive personality. (R)

Table 30 (cont'd)

Trait/Domain	Aspect	Items
Neuroticism		
	Volatility	
		Get angry easily.
		Rarely get irritated. (R)
		Get upset easily.
		Keep my emotions under control. (R)
		Change my mood a lot.
		Rarely lose my composure. (R)
		Am a person whose moods go up and down easily.
		Am not easily annoyed. (R)
		Get easily agitated.
		Can be stirred up easily.
	Withdrawal	
		Seldom feel blue. (R)
		Am filled with doubts about things.
		Feel comfortable with myself. (R)
		Feel threatened easily.
		Rarely feel depressed. (R)
		Worry about things.
		Am easily discouraged.
		Am not embarrassed easily. (R)
		Become overwhelmed by events.
		Am afraid of many things.
Openness		
	Intellect	
		Am quick to understand things.
		Have difficulty understanding abstract ideas. (R)
		Can handle a lot of information.
		Like to solve complex problems.
		Avoid philosophical discussions. (R)
		Avoid difficult reading material. (R)
		Have a rich vocabulary.
		Think quickly.
		Learn things slowly. (R)
		Formulate ideas clearly.

Table 30 (cont'd)

Trait/Domain	Aspect	Items
Openness		
	Openness	
		Enjoy the beauty of nature.
		Believe in the importance of art.
		Love to reflect on things.
		Get deeply immersed in music.
		Do not like poetry. (R)
		See beauty in things that others might not notice.
		Need a creative outlet.
		Seldom get lost in thought. (R)
		Seldom daydream. (R)
		Seldom notice the emotional aspects of paintings and Pictures. (R)

Notes: (R) indicates that the item is reverse-scored when calculating scale score. Items were assessed on a 1 to 5 scale consisting of "Very Inaccurate", "Moderately Inaccurate", "Neither Accurate nor Inaccurate", "Moderately Accurate" and "Very Accurate" respectively. Participant instructions were as follows: "Below, there are several phrases describing people's behaviors. Please use the rating scale provided to describe how accurately each statement describes ***you*** at school. Describe yourself as you generally are at school now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. So that you can describe yourself in an honest manner, you should know that there are no right or wrong answers and that your responses will be kept in absolute confidence."

Table 31: Manipulation Check Items: Goal Difficulty and Specificity (Earley et al., 1990)

Construct	Items	Anchors
Goal Difficulty		
	In today's study, how difficult was your performance goal?	1 = Not at all difficult 5 = Extremely difficult
	How challenging was your assigned stock-pricing goal?	1 = Not at all challenging 5 = Extremely challenging
Goal Specificity		
	How specific was your performance goal in today's study?	1 = Not at all specific 5 = Extremely specific
	What was your accuracy goal for each pricing task, if any?	Open-ended 0 = non-numeric; 1 = numeric

Note: Items were measured after completion of the focal task and an index score for each construct was determined by averaging both items assigned to measure it.

Table 32: PANAS Affect Items (Watson et al., 1988)

Positive Affect	Negative Affect
Active	Afraid
Alert	Ashamed
Attentive	Distressed
Determined	Guilty
Enthusiastic	Hostile
Excited	Irritable
Inspired	Jittery
Interested	Nervous
Proud	Scared
Strong	Upset

Notes: Items were assessed on a 1 to 5 scale consisting of "Very Slightly or Not at All", "A Little", "Moderately", "Quite a bit" and "Extremely" respectively. Participant instructions were as follows: "This scale consists of a number of words that describe different feelings and emotions. Read each item and indicate to what extent you generally feel this way, that is, how you feel on the average. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence."

Table 33: Amended Action-State Orientation Scale (Diefendorff et al., 2000)

Preoccupation (AOF) Subscale:

4. If I've worked for weeks on one project and then everything goes completely wrong with the project:
   A. It takes me a long time to adjust myself to it
   B. If bothers me for a while, but then I don't think about it anymore*
10. **If I had just bought a new piece of equipment (for example a laptop) and it accidentally fell on the floor and was damaged beyond repair:
   A. I would manage to get over it quickly*
   B. It would take me a long time to get over it
13. If I have to talk to someone about something important and, repeatedly, can't find him or her at home:
   A. I can't stop thinking about it, even while I'm doing something else
   B. I easily forget about it until I see the person*
19. When I am told that my work has been completely unsatisfactory:
   A. I don't let it bother me for too long*
   B. I feel paralyzed
22. If I'm stuck in traffic and miss an important appointment:
   A. At first, it's difficult for me to start do anything else at all
   B. I quickly forget about it and do something else*
28. When something really gets me down:
   A. I have trouble doing anything at all
   B. I find it easy to distract myself by doing other things*
31. When several things go wrong on the same day:
   A. I usually don't know how to deal with it
   B. I just keep on going as though nothing had happened*
34. When I have put all my effort into doing a really good job on something and the whole thing doesn't work out:
   A. I don't have too much difficulty starting something else*
   B. I have trouble doing anything else at all

Hesitation (AOD) Subscale:

2. When I know I must finish something soon:
   A. I have to push myself to get started
   B. I find it easy to get it done and over with*
5. When I don't have anything in particular to do and I am getting bored:
   A. I have trouble getting up enough energy to do anything at all
   B. I quickly find something to do*
8. When I am getting ready to tackle a difficult problem:
   A. It feels like I am facing a big mountain that I don't think I can climb
   B. I look for a way that the problem can be approached in a suitable manner*
11. When I have to solve a difficult problem:
   A. I usually don't have a problem getting started on it*
   B. I have trouble sorting things out in my head so that I can get down to working on the problem

Table 33 (cont'd)

20. When I have a lot of important things to do and they must all be done soon:
    A. I often don't know where to begin
    B. I find it easy to make a plan and stick with it*
26. When I have to take care of something important which is also unpleasant:
    A. I do it and get it over with*
    B. It can take a while before I can bring myself to it
29. When I am facing a big project that has to be done:
    A. I often spend too long thinking about where I should begin
    B. I don't have any problems getting started*
35. When I have an obligation to do something that is boring and uninteresting:
    A. I do it and get it over with*
    B. It can take a while before I can bring myself to do it

Volatility (AOP) Subscale:

3. When I have learned a new and interesting game:
    A. I quickly get tired of it and do something else
    B. I can really get into it for a long time*
15. When I read an article in the newspaper that interests me:
    A. I usually remain so interested in the article that I read the entire article*
    B. I still often skip to another article before I've finished the first one
21. When one of my co-workers brings up an interesting topic for discussion:
    A. It can easily develop into a long conversation*
    B. I soon lose interest and want to go do something else
24. When I am busy working on an interesting project:
    A. I need to take frequent breaks and work on other projects
    B. I can keep working on the same project for a long time*
33. When I read something I find interesting:
    A. I sometimes still want to put the article down and do something else
    B. I will sit and read the article for a long time*
36. When I am trying to learn something new that I want to learn:
    A. I'll keep at it for a long time*
    B. I often feel like I need to take a break and go do something else for a while

Notes: * Indicates the answer for each item that corresponds to an action orientation.
** In accordance with the updated scale user's guide (Appelt, Milch, Handgraaf, & Weber, 2011), the wording of this item was modified slightly from the item in Diefendorff et al. (2000); specifically the example was changed from a "tape deck" to a "laptop" order to make the example more timely. Participant instructions were as follows: "The following statements have two different response options. Please read each item and choose the alternative that applies best to you. Please describe yourself in an honest manner: there are no right or wrong answers and your responses will be kept in absolute confidence."

APPENDIX B: Equation Illustration

In order to more fully explicate the model parameters presented in the main text, this section provides an overview of representative Level 1 and Level 2 models and briefly discusses each parameter thereof. The nomenclature and symbology used is taken from Singer and Willett (2003). To facilitate this discussion, Equation 1, corresponding to the Level 1 equation is reproduced below. A representative Level 2 equation, previously presented as Equation 2, is likewise reintroduced. In addition, to further facilitate explanation, Equation 2 is written out explicitly for k equals 0 through 5 (corresponding to the subscripts in Equation 1), presented as Equation 2a through 2f.

$$Y_{it} = \pi_{0i} + \pi_{1i}SA_{it} + \pi_{2i}TA1_{it} + \pi_{3i}RA1_{it} + \pi_{4i}TA2_{it} + \pi_{5i}RA2_{it} + e_{it} \quad (1)$$

$$\pi_{ki} = \gamma_{k0} + \gamma_{k1}*X_1 + \gamma_{k2}*X_2 + \gamma_{k3}*(X_1*X_2) + \zeta_{ki} \quad (2)$$

$$\pi_{0i} = \gamma_{00} + \gamma_{01}*X_1 + \gamma_{02}*X_2 + \gamma_{03}*(X_1*X_2) + \zeta_{0i} \quad (2a)$$

$$\pi_{1i} = \gamma_{10} + \gamma_{11}*X_1 + \gamma_{12}*X_2 + \gamma_{13}*(X_1*X_2) + \zeta_{1i} \quad (2b)$$

$$\pi_{2i} = \gamma_{20} + \gamma_{21}*X_1 + \gamma_{22}*X_2 + \gamma_{23}*(X_1*X_2) + \zeta_{2i} \quad (2c)$$

$$\pi_{3i} = \gamma_{30} + \gamma_{31}*X_1 + \gamma_{32}*X_2 + \gamma_{33}*(X_1*X_2) + \zeta_{3i} \quad (2d)$$

$$\pi_{4i} = \gamma_{40} + \gamma_{41}*X_1 + \gamma_{42}*X_2 + \gamma_{43}*(X_1*X_2) + \zeta_{4i} \quad (2e)$$

$$\pi_{5i} = \gamma_{50} + \gamma_{51}*X_1 + \gamma_{52}*X_2 + \gamma_{53}*(X_1*X_2) + \zeta_{5i} \quad (2f)$$

As previously discussed, Equation 1 characterizes the performance of individual *i* at time *t*. The coefficients in Equation 1 (π_{0i} through π_{5i}) can in turn each be predicted by an equation of the form of Equation 2. As presented here, Equation 2 is quite general, and not all of the potential terms included in this representation are included in each application of this equation.

For example, ζ_{ki} allows for a particular effect to vary randomly across individuals; that is, the magnitude of the effect for a particular individual can vary appreciably from the group mean effect size. While this may occur with some regularity, it is not always an appropriate or desirable assumption (Singer & Willett, 2003), and the viability of this assumption for each of the Level 1 coefficients was tested during model construction (as outlined in the Results section).

Beyond proper model specification, neither the presence nor the magnitude of these random effects is particularly germane to the hypotheses being evaluated, and in order to maintain the focus of this section on model evaluation in the context of hypothesis evaluation, the random effects are not discussed in depth below. Instead, the notation used by Singer and Willett (2003) to separate fixed and random effects is adopted. Specifically, the fixed and random effects are separated using two sets of square brackets. Pertinent to this discussion, the fixed effects in the first set of brackets are discussed individually while the random effects in the second set of brackets are treated largely en masse.

In addition, as presented Equation 2 includes two Level 2 predictors along with their interaction. This formulation is appropriate for hypotheses that predict a differential effect for an individual characteristic based on the goal condition present. However, such a complex model is not stipulated by hypotheses that don't propose such situational effects. In these situations, X_1 is the sole Level 2 variable, which implies that γ_{k2} and γ_{k3} are both zero.

An expanded example for both scenarios is provided below based on the combined equation (Singer & Willett, 2003) considering the impact of individual differences in GMA. This equation is created by simple algebraic substitution of Equations 2a through 2f back into Equation 1. A hypothetical example representative of the hypotheses related to the main effects of individual differences is presented in Table 34. Table 35 presents the same sort of information relevant for hypotheses that consider the contextual effects of goal condition. In both cases, the equations presented are focused on GMA. The equations associated with the other individual characteristics are constructed and interpreted similarly by simply replacing "GMA" with the individual difference variable of interest.

Table 34: Individual Hypotheses Prototypical Combined Equation with Term Explanation

Term	Interpretation
Combined Equation (Individual Difference Hypotheses): $Y_{it} = [\gamma_{00} + \gamma_{01}*GMA + SA_{it}*(\gamma_{10} + \gamma_{11}*GMA) + TA1_{it}*(\gamma_{20} + \gamma_{21}*GMA) + RA1_{it}*(\gamma_{30} + \gamma_{31}*GMA) + TA2_{it}*(\gamma_{40} + \gamma_{41}*GMA) + RA2_{it}*(\gamma_{50} + \gamma_{51}*GMA)] + [e_{it} + \zeta_{0i} + SA_{it}* \zeta_{1i} + TA1_{it}* \zeta_{2i} + RA1_{it}*\zeta_{3i} + TA2_{it}*\zeta_{4i} + RA2_{it}* \zeta_{5i}]$	
Term	**Interpretation**
γ_{00}	Average initial performance (intercept) for a participant of average intelligence
γ_{01}	Incremental change in initial performance (intercept) due to participant intelligence (deviation from group mean)
γ_{10}	Average rate of change in performance over time (slope) in pre-change condition for a participant of average intelligence
γ_{11}	Incremental change in rate of performance change over time (slope) in pre-change condition due to participant intelligence (deviation from group mean)
γ_{20}	Average magnitude of first discontinuity (Initial Transition Adaptation) for a participant of average intelligence
γ_{21}	Incremental change in magnitude of first discontinuity (Initial Transition Adaptation) due to participant intelligence (deviation from group mean)
γ_{30}	Average change in rate of change in performance over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) for a participant of average intelligence
γ_{31}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) due to participant intelligence (deviation from group mean)
γ_{40}	Average magnitude of second discontinuity (Secondary Transition Adaptation) for a participant of average intelligence
γ_{41}	Incremental change in magnitude of second discontinuity (Secondary Transition Adaptation) due to participant intelligence (deviation from group mean)
γ_{50}	Average change in rate of change in performance over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) for a participant of average intelligence

Table 34 (cont'd)

γ_{51}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) due to participant intelligence (deviation from group mean)
$[e_{ti} + \zeta_{0i} + SA_{it} * \zeta_{1i} + TA1_{it} * \zeta_{2i} + RA1_{it} * \zeta_{3i} + TA2_{it} * \zeta_{4i} + RA2_{it} * \zeta_{5i}]$	Random Effects

Notes: GMA = General Mental Ability. SA = Skill Acquisition. TA1 = Initial Transition Adaptation. RA1 = Initial Reacquisition Adaptation. TA2 = Secondary Transition Adaptation. RA2 = Secondary Reacquisition Adaptation.

Table 35: Contextual Hypotheses Prototypical Combined Equation with Term Explanation

Combined Equation (Contextual Hypotheses):

$Y_{it} = [\gamma_{00} + \gamma_{01}*GMA + \gamma_{02}*GC + \gamma_{03}*(GMA*GC) + SA_{it}*(\gamma_{10} + \gamma_{11}*GMA + \gamma_{12}*GC + \gamma_{13}*(GMA*GC)) + TA1_{it}*(\gamma_{20} + \gamma_{21}*GMA + \gamma_{22}*GC + \gamma_{23}*(GMA*GC)) + RA1_{it}*(\gamma_{30} + \gamma_{31}*GMA + \gamma_{32}*GC + \gamma_{33}*(GMA*GC)) + TA2_{it}*(\gamma_{40} + \gamma_{41}*GMA + \gamma_{42}*GC + \gamma_{43}*(GMA*GC)) + RA2_{it}*(\gamma_{50} + \gamma_{51}*GMA + \gamma_{52}*GC + \gamma_{53}*(GMA*GC))] + [e_{it} + \zeta_{0i} + SA_{it}* \zeta_{1i} + TA1_{it}* \zeta_{2i} + RA1_{it}*\zeta_{3i} + TA2_{it}*\zeta_{4i} + RA2_{it}* \zeta_{5i}]$

Term	Interpretation
γ_{00}	Average initial performance (intercept) for a participant of average intelligence in the do-your-best goal condition
γ_{01}	Incremental change in initial performance (intercept) due to participant intelligence (deviation from group mean)
γ_{02}	Incremental change in initial performance (intercept) due to being in the specific-difficult goal condition
γ_{03}	Incremental change in initial performance (intercept) due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition
γ_{10}	Average rate of change in performance over time (slope) in pre-change condition for a participant of average intelligence in the do-your-best goal condition
γ_{11}	Incremental change in rate of performance change over time (slope) in pre-change condition due to participant intelligence (deviation from group mean)
γ_{12}	Incremental change in rate of performance change over time (slope) in pre-change condition due to due to being in the specific-difficult goal condition
γ_{13}	Incremental change in rate of performance change over time (slope) in pre-change condition due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition
γ_{20}	Average magnitude of first discontinuity (Initial Transition Adaptation) for a participant of average intelligence in the do-your-best goal condition
γ_{21}	Incremental change in magnitude of first discontinuity (Initial Transition Adaptation) due to participant intelligence (deviation from group mean)
γ_{22}	Incremental change in magnitude of first discontinuity (Initial Transition Adaptation) due to being in the specific-difficult goal condition
γ_{23}	Incremental change in magnitude of first discontinuity (Initial Transition Adaptation) due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition
γ_{30}	Average change in rate of change in performance over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) for a participant of average intelligence in the do-your-best goal condition

Table 35 (cont'd)

γ_{31}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) due to participant intelligence (deviation from group mean)
γ_{32}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) due to being in the specific-difficult goal condition
γ_{33}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the initial change event (Initial Reacquisition Adaptation) due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition
γ_{40}	Average magnitude of second discontinuity (Secondary Transition Adaptation) for a participant of average intelligence in the do-your-best goal condition
γ_{41}	Incremental change in magnitude of second discontinuity (Secondary Transition Adaptation) due to participant intelligence (deviation from group mean)
γ_{42}	Incremental change in magnitude of second discontinuity (Secondary Transition Adaptation) due to being in the specific-difficult goal condition
γ_{43}	Incremental change in magnitude of second discontinuity (Secondary Transition Adaptation) due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition
γ_{50}	Average change in rate of change in performance over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) for a participant of average intelligence in the do-your-best goal condition
γ_{51}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) due to participant intelligence (deviation from group mean)
γ_{52}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) due to being in the specific-difficult goal condition
γ_{53}	Incremental rate of change in rate of performance change over time (slope) after the occurrence of the secondary change event (Secondary Reacquisition Adaptation) due to the interaction of participant intelligence (deviation from group mean) and being in the specific-difficult goal condition

Table 35 (cont'd)

[$e_{it} + \zeta_{0i} + SA_{it}* \zeta_{1i} + TA1_{it}* \zeta_{2i} + RA1_{it}*\zeta_{3i} + TA2_{it}*\zeta_{4i} + RA2_{it}* \zeta_{5i}$]	Random Effects

Notes: GMA = General Mental Ability. GC = Goal Condition. SA = Skill Acquisition. TA1 = Initial Transition Adaptation. RA1 = Initial Reacquisition Adaptation. TA2 = Secondary Transition Adaptation. RA2 = Secondary Reacquisition Adaptation.

REFERENCES

REFERENCES

Ackerman, P. L. (1987). Individual differences in skill learning: An integration of psychometric and information processing perspectives. *Psychological Bulletin, 102*, 3-27.

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General, 117,* 288-318.

Ackerman, P. L. (1996). A theory of adult intellectual development: Process, personality, interests, and knowledge. *Intelligence, 22,* 227-257.

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin, 131*, 30-60.

Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin*, *121*, 219-245.

Adler, S., & Weiss, H. M. (1988). Recent developments in the study of personality and organizational behavior. In C. L. Cooper & I. T. Robertson (Eds.), *International review of industrial and organizational psychology*. New York: Wiley.

Alexander, W. H., & Brown, J. W. (2010). Computational models of perfrmance monitoring and cognitive control. *Topics in Cognitive Science, 2,* 658-677. doi: 10.1111/j.1756-8765.2010.01085.x

Allison, P. D. (1984). *Event history analysis: Regression for longitudinal event data*. Newbury Park, CA: Sage.

Allworth, E., & Hesketh, B. (1999). Construct-oriented biodata: Capturing change-related and contextually relevant future performance. *International Journal of Selection and Assessment, 7*, 97-111. doi: 10.1111/1468-2389.00110

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*, 369-406.

Ang, S., Van Dyne, L., & Koh, C. (2006). Personality correlates of the four-factor model of cultural intelligence. *Group & Organization Management, 31*, 100-123.

Appelt, K. C., Milch, K. F., Handgraaf, M. J. J., & Weber, E. U. (2011). The decision making individual differences inventory and guidelines for the study of individual differences in judgment and decision-making research. *.Judgment and Decision Making, 6*, 252-262.

Arthur, W., Bennett, W., Edens, P. S., & Bell, S. T. (2003). Effectiveness of training in organizations: A meta-analysis of design and evaluation features. *Journal of Applied Psychology, 88,* 234-245. doi: 10.1037/0021-9010.88.2.234

Arthur, W., Day, E. A., McNelly, T. L., & Edens, P. S. (2003). A meta-analysis of the criterion-related validity of assessment center dimensions. *Personnel Psychology, 56*, 125-154. doi: 10.1111/j.1744-6570.2003.tb00146.x

Ashcraft, M. H., & Kirk, E. P. (2001). The relationships among working memory, math anxiety, and performance. *Journal of Experimental Psychology: General*, *130*, 224-237.

Ashton, M. C., Jackson, D. N., Paunonen, S. V., Helmes, E., & Rothstein, M. G. (1995). The criterion validity of broad factor scales versus specific facet scales. *Journal of Research in Personality, 29*, 432-442.

Ashton, M. C., Lee, K., Perugini, M., Szarota, P., de Vries, R. E., Di Blas, L., . . . De Raad, B. (2004). A six-factor structure of personality descriptive adjectives: Solutions from psycholexical studies in seven languages. *Journal of Personality and Social Psychology, 86*, 356-366.

Ashton, M. C., Lee, K., Vernon, P. A., & Jang, K. L. (2000). Fluid intelligence, cryistallized intelligence and the openness/intellect factor. *Journal of research in personality, 34*, 198-207.

Austin, J. T., & Vancouver, J. B. (1996). Goal constructs in psychology: Structure, process, and content. *Psychological Bulletin*, *120*, 338-375.

Baard, S. K., Rench, T. A., & Kozlowski, S. W. J. (2014). Performance adaptation: A theoretical integration and review. *Journal of Management, 40*, 48-99.

Baldwin, T. T., & Ford, J. K. (1988). Transfer of training - a review and directions for future research. *Personnel Psychology, 41*, 63-105. doi: 10.1111/j.1744-6570.1988.tb00632.x

Baldwin, T. T., Ford, J. K., & Blume, B. D. (2009). Transfer of training 1988–2008: An updated review and agenda for future research. In G. P. Hodgkinson & J. K. Ford (Eds.), *International review of industrial and organizational psychology* (Vol. 24, pp. 41-70). Padstow, UK: Wiley.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A., & Locke, E. A. (2003). Negative self-efficacy and goal effects revisited. *Journal of Applied Psychology, 88*, 87-99. doi: 10.1037/0021-9010.88.1.87

Barber, J. (2004). Skill upgrading within informal training: Lessons from the indian auto mechanic. *International Journal of Training and Development, 8*, 128-139.

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44*, 1-26.

Barrick, M. R., & Mount, M. K. (1993). Autonomy as a moderator of the relationships between the big five personality dimensions and job performance. *Journal of Applied Psychology, 78,* 111-118.

Barrick, M. R., Mount, M. K., & Judge, T. A. (2001). Personality and performance at the beginning of the new millennium: What do we know and where do we go next? *Personality and Performance, 9,* 9-30.

Barrick, M. R., Mount, M. K., & Strauss, J. P. (1993). Conscientiousness and performance of sales representatives: Test of the mediating effects of goal setting. *Journal of Applied Psychology, 78,* 715-722.

Bass, B. M. (1962). Further evidence of the dynamic nature of criteria. *Personnel Psychology, 15,* 93-97.

Bateman, T. S., & Organ, D. W. (1983). Job satisfaction adn the good soldier: The relationship between affect and employee "citenzenship". *Academy of Management Journal, 26*, 587-595.

Beal, D. J., Weiss, H. M., Barros, E., & MacDermid, S. M. (2005). An episodic process model of affective influences on performance. *Journal of Applied Psychology, 90*, 1054-1068. doi: 10.1037/0021-9010.90.6.1054

Beaty Jr., J. C., Cleveland, J. N., & Murphy, K. R. (2001). The relation between personality and contextual performance in “strong” versus “weak” situations. *Human Performance, 14,* 125-148.

Beheshti, H. M. (2006). What managers should know about erp/erp ii. *Management Research News, 29*, 184-193.

Beilock, S. L., & Carr, T. H. (2001). On the fragility of skilled performance: What governs choking under pressure? *Journal of Experimental Social Psychology: General, 130*, 701-725. doi: 1100..111037//0096-3445.130.4.701

Beilock, S. L., & Carr, T. H. (2005). When high-powered people fail: Working memory and “choking under pressure” in math. *Psychological Science, 16*, 101-105.

Beilock, S. L., & DeCaro, M. S. (2007). From poor performance to success under stress: Working memory, strategy selection, and mathematical problem solving under pressure. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 33*, 983-998.

Beilock, S. L., Kulp, C. A., Holt, L. E., & Carr, T. H. (2004). More on the fragility of performance: Choking under pressure in mathematical problem solving. *Journal of Experimental Psychology: General, 133,* 584-600. doi: 10.1037/0096-3445.133.4.584

Bennett, R. J., & Robinson, S. L. (2000). Development of a measure of workplace deviance. *Journal of Applied Psychology, 85,* 349-360. doi: 10.1037//0021-9010.85.3.349

Blickle, G. (1996). Personality traits, learning strategies and performance. *European Journal of Psychology, 10*, 337-352.

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein & S. W. J. Kozlowski (Eds.), *Mulitlevel theory, research, and methods in organizations: Foundations, extensions and new directions* (pp. 349-381). San Francisco, CA: Jossey-Bass.

Bliese, P. D., & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods, 5*, 362-387. doi: 10.1177/109442802237116

Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin, 117*, 187-215.

Borgatta, E. F. (1964). The structure of personality characteristics. *Behavioral Science*, *9*, 8-17.

Borman, W. C., Bryant, R. H., & Dorio, J. (2010). The measurement of task performance as criteria in selection research. In J. L. Farr & N. T. Tippins (Eds.), *Handbook of employee selection* (pp. 439-461). New York: Taylor Francis.

Borman, W. C., & Motowidlo, S. J. (1993). Expanding the criterion domain to include elements of contextual peformance. In N. Schmitt & W. C. Borman (Eds.), *Personality selection* (pp. 71-98). San Francisco: Jossey-Bass.

Bosker, R. J., Snijders, T. A. B., & Guldemond, H. (Producer). (2003, 15Feb2013). Pint (power in two-level designs) v2.1: Estimating standard errors of regression coefficients in hierarchical linear models for power calculations user's manual. Retrieved from http://www.stats.ox.ac.uk/~snijders/Pint21_UsersManual.pdf

Bouchard, T. J., Jr. (1997). The genetics of personality. In K. Blum & E. P. Noble (Eds.), *Handbook of psychiatric genetics* (pp. 273-296). Boca Raton, FL: Circle Press.

Brand, C. (1996). *The g factor: General intelligence and its implications*. Chichester, England: Wiley.

Braver, T. S., Gray, J. R., & Burgess, G. C. (2007). Explaining the many varieties of working memory variation. In A. Conway, C. Jarrold, M. J. Kane, A. Miyake & J. N. Towse (Eds.), *Variation in working memory* (pp. 76-106). New York: Oxford University Press.

Bridges, W. (1994). *Job shift*. Reading, MA: Addison-Wesley.

Broström, G. (2012). *Event history analysis with r*. Boca Raton, FL: CRC.

Brown, J. W., & Braver, T. S. (2005, February 18). Learned predictions of error likelihood in the anterior cingulate cortex. *Science, 307*, 1118–1121.

Brown, K. G., & Sitzmann, T. (2011). Training and employee development for improved performance. In S. Zedeck (Ed.), *Apa handbook of industrial and organizational psychology: Selecting and developing members for the organization* (Vol. 2, pp. 469-503). Washington, DC: American Psychological Association.

Brown, S. L., & Eisenhardt, K. M. (1995). Product development - past research, present findings, and future-directions. *Academy of Management Review, 20*, 343-378. doi: 10.2307/258850

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchial linear models: Applications and data analysis methods*. Newbury Park, CA: Sage.

Burke, C. S., Pierce, L. G., & Salas, E. (Eds.). (2006). *Understanding adaptability: A prerequisite for effective performance within complex environments*. Oxford, United Kingdom: Elsevier.

Burke, C. S., Stagl, K. C., Salas, E., Pierce, L., & Kendall, D. (2006). Understanding team adaptation: A conceptual analysis and model. *Journal of Applied Psychology, 91*, 1189-1207. doi: 10.1037/0021-9010.91.6.1189

Busato, V. V., Prins, F. J., Elshout, J. J., & Hamaker, C. (1999). The relation between learning styles, the big five personality traits and achievement motivation in higher education. *Personality and individual differences, 26*, 129-140.

Campbell, J. P. (1990). Modeling the performance prediction problem in industrial and organizational psychology. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (2nd ed., pp. 399-429). Palo Alto, CA: Consulting Psychologists Press.

Campbell, J. P. (1999). The definition and measurement of performance in the new age. In D. R. Ilgen & E. Pulakos (Eds.), *The changing nature of work and performance: Implications for staffing, personnel actions, and development* (pp. 399-429). San Francisco: Jossey-Bass.

Campbell, J. P., Gasser, M. B., & Oswald, F. L. (1996). The substantive nature of performance variability. In K. R. Murphy (Ed.), *Individual differences and behavior in organizations* (pp. 258-299). San Francisco: Jossey-Bass.

Campbell, J. P., McCloy, R. A., Oppler, S. H., & Sager, C. E. (1993). A theory of performance. In N. Schmitt & W. C. Borman (Eds.), *Personnel selection in organizations* (pp. 35-70). San Francisco: Jossey-Bass.

Campion, M. A., & Lord, R. G. (1982). A control systems conceptualization of the goal-setting and changing process. *Organizational Behavior and Human Performance, 30*, 265-287. doi: 10.1016/0030-5073(82)90221-5

Cannon-Bowers, J. A., Tannenbaum, S. I., Salas, E., & Volpe, C. E. (1995). Defining competencies and establishing team training requirements. In R. A. Guzzo & E. Salas

(Eds.), *Team effectiveness and decision making in organizations* (pp. 333-380). San Francisco: Jossey-Bass.

Capon, N., Farley, J. U., & Hoenig, S. (1990). Determinants of financial performance: A meta-analysis. *Management Science, 36*, 1143-1159.

Carver, C. S., & Scheier, M. F. (1981). *Attention and self-regulation: A control-theory approach to human behavior*. New York: Springer-Verlag

Carver, C. S., & Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality-social, clinical, and health psychology. *Psychological Bulletin, 92*, 111-135.

Carver, C. S., & Scheier, M. F. (1990). Origins and functions of positive and negative affect: A control-process view. *Psychological Review, 97*, 19-35. doi: 10.1037/0033-295x.97.1.19

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior*. Cambridge, UK: Cambridge University Press.

Cascio, W. F. (1995). Whither industrial and organizational psychology in a changing world of work. *American Psychologist, 50*, 928-939.

Cattell, R. B. (1971). *Abilities: Their structure, growth and action*. Boston: Houghton Mifflin.

Chamorro-Premuzic, T., Moutafi, J., & Furnham, A. (2005). The relationship between personality traits, subjectively-assessed and fluid intelligence. *Personality and Individual Differences, 38*, 1517-1528.

Chan, D. (1998). Functional relations among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology, 83*, 234-246. doi: 10.1037/0021-9010.83.2.234

Chang, C.-H., Johnson, R. E., & Lord, R. G. (2010). Moving beyond discrepancies: The importance of velocity as a predictor of satisfaction and motivation. *Human Performance, 23*, 58-80. doi: 10.1080/08959280903400226

Chen, G., Thomas, B., & Wallace, J. C. (2005). A multilevel examination of the relationships among training outcomes, mediating regulatory processes, and adaptive performance. *Journal of Applied Psychology, 90*, 827-841. doi: 10.1037/0021-9010.90.5.827

Chernyshenko, O. S., Stark, S., & Drasgow, F. (2011). Individual differences: Their measurement and validity. In S. Zedeck (Ed.), *Apa handbook of industrial and organizational psychology. Vol. 2. Selecting and developing members of for the organizatoin* (pp. 117-151). Washington, DC: American Psychological Association.

Chesney, A. A., & Locke, E. A. (1991). Relationships among goal difficulty, business strategies, and performance on a complex managment simulation task. *Academy of Management Journal, 34*, 400-424.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

Cohen, J. (1992). A power primer. *Psychological bulletin, 112,* 155-159.

Colquitt, J. A., LePine, J. A., & Noe, R. A. (2000). Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology, 85,* 678-707. doi: 10.1037//0021-9010.85.5.678

Cooper, W. H., & Withey, M. J. (2009). The strong situation hypothesis. *Personality and Social Psychology Review, 13*, 62-72.

Cortina, J. M., Goldstein, N. B., Payne, S. C., Davison, H. K., & Gilliland, S. W. (2000). The incremental validity of interview scores over and above cognitive ability and conscientiousness scores. *Personnel Psychology, 53,* 325-351. doi: 10.1111/j.1744-6570.2000.tb00204.x

Cortina, J. M., & Luchman, J. N. (2013). Personnel selection and employee performance. In I. B. Weiner, N. W. Schmitt & S. Highhouse (Eds.), *Handbook of psychology: Industrial and organizational psychology* (2nd ed., Vol. 12). Hoboken, NJ: Wiley.

Costa, P. T., Jr., & McCrae, R. R. (1980). Influence of extraversion and neuroticism on subjective well-being: Happy and unhappy people. *Journal of personality and social psychology, 38,* 668-678.

Costa, P. T., Jr., & McCrae, R. R. (1988). Personality in adulthood: A six-year longitudinal study of sel-reports and spouce ratings on the neo personality inventory. *Journal of personality and social psychology, 54*, 853-863.

Costa, P. T., Jr., & McCrae, R. R. (1992). *Revised neo personality inventory (neo pi-r) and neo five-factor inventory (neo-ffi) professional manual*. Odessa, FL: Psychological Assessment Resources.

Cox, D. R. (1972). Regression models and life-tables (with discussion). *Journal of the Royal Statistical Society, Series B, 34*, 187-220.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*, 297-334.

Cronbach, L. J. (1960). *Essentials of psychological testing* (2nd ed.). New York: Harper Row.

Cronbach, L. J., & Furby, L. (1970). How we should measure "change": Or should we? *Psychological Bulletin, 74,* 68-80.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological bulletin, 52,* 281-302.

Depue, R. A., & Collins, P. F. (1999). Neurobiology of the structure of personality: Dopamine, facilitation of incentive motivation, and extraversion. *Behavioral and Brain Sciences, 22*, 491-517.

DeShon, R. P., & Alexander, R. A. (1996). Goal setting effects on implicit and explicit learning of complex tasks. *Organizational Behavior and Human Decision Processes*, *65*, 18-36. doi: 10.1006/obhd.1996.0002

DeShon, R. P., Brown, K. G., & Greenis, J. L. (1996). Does self-regulation require cognitive resources? Evaluation of resource allocation models of goal setting. *Journal of Applied Psychology*, *81,* 595-608. doi: 10.1037//0021-9010.81.5.595

DeShon, R. P., Kozlowski, S. W. J., Schmidt, A. M., Milner, K. R., & Wiechmann, D. (2004). A multiple-goal, multilevel model of feedback effects on the regulation of individual and team performance. *Journal of Applied Psychology*, *89,* 1035-1056. doi: 10.1037/0021-9010.89.6.1035

DeShon, R. P., Ployhart, R. E., & Sacco, J. M. (1998). The estimation of reliability in longitudinal models. *International Journal of Behavioral Development, 22*, 493-515.

Devos, G., Buelens, M., & Bouckenooghe, D. (2007). Contribution of content, context, and process to understanding openness to organizational change: Two experimental simulation studies. *Journal of Social Psychology, 147*, 607-629. doi: 10.3200/socp.147.6.607-630

DeYoung, C. G. (2006). Higher-order factors of the big five in a multi-informant sample. *Journal of personality and social psychology*, *91*, 1138-1151. doi: 10.1037/0022-3514.91.6.1138

DeYoung, C. G., Cicchetti, D., Rogosch, F. A., Gray, J. R., & Grigorenko, E. L. (2011). Sources of cognitive exploration: Genetic variation in the prefrontal dopamine system predicts openness/intellect. . *Journal of Research in Personality, 45,* 364-371.

DeYoung, C. G., Grazioplene, R. G., & Peterson, J. B. (2012). From madness to genius: The openness/intellect trait domain as a paradoxical simplex. *Journal of Research in Personality*, *46,* 63-78.

DeYoung, C. G., Peterson, J. B., & Higgins, D. M. (2002). Higher-order factors of the big five predict conformity: Are there neuroses of health? *Personality and Individual Differences, 33*, 533-552.

DeYoung, C. G., Peterson, J. B., & Higgins, D. M. (2005). Sources of openness/intellect: Cognitive and neuropsychological correlates of the fifth factor of personality. *Journal of Personality, 73,* 825-858.

DeYoung, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between facets and domains: 10 aspects of the big five. *Journal of personality and social psychology, 93*, 880-896. doi: 10.1037/0022-3514.93.5.880

DeYoung, C. G., Shamosh, N. A., Green, A. E., Braver, T. S., & Gray, J. R. (2009). Intellect as distinct from openness: Differences revealed by fmri of working memory. *Journal of Personality and Social Psychology, 97*, 883-892.

Diefendorff, J. M., & Gosserand, R. H. (2003). Understanding the emotional labor process: A control theory perspective. *Journal of Organizational Behavior, 24*, 945-959. doi: 10.1002/job.230

Diefendorff, J. M., Hall, R. J., Lord, R. G., & Strean, M. L. (2000). Action-state orientation: Construct validity of a revised measure and its relationship to work-related variables. *Journal of Applied Psychology, 85*, 250-263. doi: 10.1037/0021-9010.85.2.250

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual review of psychology, 41*, 417-440.

Digman, J. M. (1997). Higher-order factors of the big five. *Journal of personality and social psychology, 73*, 1246-1256.

Digman, J. M., & Shemelyov, A. G. (1996). The structure of temperament and personality in russian children. *Journal of personality and social psychology, 71*, 341-351.

Dimotakis, N., Conlon, D. E., & Ilies, R. (2012). The mind and heart (literally) of the negotiator: Personality and contextual determinants of experiential reactions and economic outcomes in negotiation. *Journal of Applied Psychology;Journal of Applied Psychology, 97*, 183-193. doi: 10.1037/a0025706

Diogenes, L. (c. 300/1925). Lives of eminent philosophers (R. D. Hicks, Trans.) (Vol. 2). Cambridge, MA: Harvard University Press.

Donovan, J. J., & Williams, K. J. (2003). Missing the mark: Effects of time and causal attributions on goal revision in response to goal-performance discrepancies. *Journal of Applied Psychology, 88*, 379-390. doi: 10.1037/0021-9010.88.3.379

Dorsey, D. W., Cortina, J. M., & Luchman, J. (2010). Adaptive and citizenship-related behaviors at work. In J. L. Farr & N. T. Tippins (Eds.), *Handbook of employee selection* (pp. 463-487). New York: Taylor Francis.

Dossett, D. L., Latham, G. P., & Mitchell, T. R. (1979). Effects of assigned versus participatively set goals, knowledge of results, and individual differences on employee behavior when goal difficulty is held constant. *Journal of Applied Psychology, 64*, 291-298.

Drach-Zahavy, A., & Erez, M. (2002). Challenge versus threat effects on the goal-performance relationship. *Organizational Behavior and Human Decision Processes, 88*, 667-682. doi: 10.1016/s0749-5978(02)00004-3

Driskell, J. E., Johnston, J. H., & Salas, E. (2001). Does stress training generalize to novel settings? *Human Factors, 42*, 99-110.

Dudley, N. M., Orvis, K. A., Lebiecki, J. E., & Cortina, J. M. (2006). A meta-analytic investigation of conscientiousness in the prediction of job performance: Examining the intercorrelations and the incremental validity of narrow traits. *Journal of Applied Psychology, 91*, 40-57. doi: 10.1037/0021-9010.91.1.40

Earley, P. C., Connolly, T., & Ekegren, G. (1989). Goals, strategy development, and task performance: Some limits on the efficacy of goal setting. *Journal of Applied Psychology, 74*, 24-33.

Earley, P. C., Connolly, T., & Lee, C. (1989). Task strategy interventions in goal setting: The importance of search in strategy development. *Journal of Management, 15*, 589-602.

Earley, P. C., Northcraft, G. B., Lee, C., & Lituchy, T. R. (1990). Impact of process and outcome feedback on the relation of goal setting to task performance. *Academy of Management Journal, 33*, 87-105.

Earley, P. C., & Perry, B. C. (1987). Work plan availability and performance: An assessment of task strategy priming on subsequent task completion. *Organizational Behavior and Human Decision Processes, 39*, 279-302.

Edwards, J. R. (1992). A cybernetic theory of stress, coping, and well-being organizations. *Academy of Management Review, 17*, 238-274.

Ellis, A. P. J., Hollenbeck, J. R., Ilgen, D. R., Porter, C., West, B. J., & Moon, H. (2003). Team learning: Collectively connecting the dots. *Journal of Applied Psychology, 88*, 821-835. doi: 10.1037/0021-9010.88.5.821

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological methods, 12*, 121-138.

Erez, M. (1977). Feedback - necessary condition for goal setting-performance relationship. *Journal of Applied Psychology, 62*, 624-627. doi: 10.1037//0021-9010.62.5.624

Evans, J. S. B. T. (1989). *Bias in human reasoning: Causes and consequences*. Hillsdale, NJ: Erlbaum.

Eysenck, H. J. (1992). Four ways five factors are not basic. *Personality and Individual Differences, 13*, 667-673.

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion, 7*, 336-353. doi: 10.1037/1528-3542.7.2.336

Ferdinand, N. K., Mecklinger, A., Kray, J., & Gehring, W. J. (2012). The processing of unexpected positive response outcomes in the mediofrontal cortex. *The Journal of Neuroscience, 32*, 12087-12092. doi: 10.1523/JNEUROSCI.1410-12.2012

Fiske, D. W., & Maddi, S. R. E. (1961). *Functions of varied experience*. Homewood, IL: Dorsey Press.

Forgas, J. P., & Bower, G. H. (1987). Mood effects on person perception judgments. *Journal of personality and social psychology, 53*, 53-60.

Fredrickson, B. L. (1998). What good are positive emotions. *Review of General Psychology, 2,* 300-319.

Fredrickson, B. L., & Levenson, R. W. (1998). Positive emotions speed reovery from the cardiovascular sequelae of negative emotions. *Cognition and Emotion, 12*, 191-220.

Frijda, N. H. (1986). *The emotions*. Cambridge: Cambridge University Press.

Furnham, A., & Chamorro-Premuzic, T. (2006). Personality, intelligence and general knowledge. *Learning and Individual Differences, 16*, 79-90.

Gellatly, I. R., & Meyer, J. P. (1992). The effects of goal difficulty on physiological arousal, cognition, and task performance. *Journal of Applied Psychology, 77*, 694-704.

Ghiselli, E. E. (1956). Dimensional problems of criteria. *Journal of Applied Psychology, 40*, 1-4.

Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of Management Journal, 47*, 209-226.

Gignac, G. E., Stough, C., & Loukomitis, S. (2004). Openness, intelligence, and self-report intelligence. *Intelligence, 32*, 133-143.

Goldberg, L. R. (1981). ‘Language and individual differences: The search for universals in personality lexicons. In L. Wheeler (Ed.), *Review of personality and social psychology* (Vol. 2, pp. 141-165). Beverly Hills, CA: Sage.

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist, 48*, 26-34.

Goldberg, L. R. (2001). The comparative validity of adult personality inventories: Applications of a consumer-testing framework. In S. R. Briggs, J. M. Cheek & E. M. Donahue (Eds.), *Handbook of adult personality inventories* (pp. 165-178). New York: Plenum.

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Coloninger, C. R., & Gough, H. C. (2006). The international personality item pool and the future of public-domain personality measures. *Journal of research in personality, 40*, 84-96.

Grandey, A. A. (2000). Emotion regulation in the workplace: A new way to conceptualize emotional labor. *Journal of Occupational Health Psychology, 5*, 95-110.

Gray, J. R. (2001). Emotional modulation of cognitive control: Approach-withdrawal states double-dissociate spatial from verbal two-back task performance. *Journal of Experimental Psychology: General, 130*, 436-452.

Gray, J. R., Braver, T. S., & Raichle, M. E. (2002). Integration of emotion and cognition in the lateral prefrontal cortex. *Proceedings of the National Academy of Sciences, USA, 99*, 4115-4120.

Griffin, M. A., Neal, A., & Parker, S. K. (2007). A new model of work role performance: Positive behavior in uncertain and interdependent contexts. *Academy of Management Journal, 50*, 327-347.

Guion, R. M., & Gottier, R. F. (1965). Validity of personality measures in personnel selection. *Personnel Psychology, 18*, 135-164.

Gwynne, S. C. (1992, September 28). The long haul. *Time,* 34-38.

Hacker, J. S. (2006). *The great risk shift: The new economic insecurity and the decline of the american dream*. New York: Oxford University Press.

Hammer, L. B., & Stone-Romero, E. F. (1996). Effects of mood states and favorability of feedback on reactions to performance feedback. *Perceptual and Motor Skills, 83*, 923-934.

Hampshire, A., Highfield, R. R., Parkin, B. L., & Owen, A. M. (2012). Fractionating human intelligence. *Neuron, 76*, 1225-1237. doi: 10.1016/j.neuron.2012.06.022

Han, T. Y., & Williams, K. J. (2008). Multilevel investigation of adaptive performance : Individual- and team-level relationships. *Group and Organization Management, 33*, 657-684. doi: 10.1177/1059601108326799

Hanisch, K. A. (1995). Behavioral families and multiple causes: Matching the complexity of responses to the complexity of antecedents. *Current Directions in Psychological Science, 4*, 156-162. doi: 10.1111/1467-8721.ep11512268

Harris, J. A. (2004). Measured intelligence, achievement, openness to experience, and creativity. *Personality and Individual Differences, 36,* 913-929.

Hastorf, A. H., & Cantril, H. (1954). They saw a game; a case study *The Journal of Abnormal and Social Psychology, 49*, 129-134. doi: http://dx.doi.org/10.1037/h0057880

Henry, R. A., & Hulin, C. L. (1987). Stability of skilled performance across time: Some generalization and limitations on utilities. *Journal of Applied Psychology, 72*, 457-462.

Hesketh, B., & Feiler, H. (1994). *Using fuzzy rating scales for graphic distributional performance ratings*. Paper presented at the 9th Annual Conference of the Society for Industrial and Organizational Psychology, Nashville, Tennessee.

Hesketh, B., & Neal, A. (1999). Technology and performance. In D. R. Ilgen & E. D. Pulakos (Eds.), *The changing nature of performance: Implications for staffing, motivation, and development* (pp. 21-55). San Francisco: Jossey-Bass.

Highhouse, S. (2009). Designing experiments that generalize. *Organizational Research Methods, 12*, 554-566. doi: 10.1177/1094428107300396

Hoffman, B. J., Blair, C. A., Meriac, J. P., & Woehr, D. J. (2007). Expanding the criterion domain? A quantitative review of the ocb literature. *Journal of Applied Psychology, 92*, 555-566. doi: 10.1037/0021-9010.92.2.555

Hofmann, D. A., & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management, 24*, 623-641. doi: 10.1016/s0149-2063(99)80077-4

Hofstee, W. K. B., de Rand, B., & Goldberg, L. R. (1992). Integration of the big five and circumplex approaches to trait structure. *Journal of personality and social psychology, 63*, 146-163.

Hogan, R. (1986). *Manual for the hogan personality inventory*. Minneaplis, MN: National Computer Systems.

Hogan, R. T., & Hogan, J. (1992). *Hogan personality inventory manual*. Tulsa, OK: Hogan Assessment Systems.

Hollenbeck, J. R. (1989). Control-theory and the perception of work environments - the effects of focus of attention on affective and behavioral reactions to work. *Organizational Behavior and Human Decision Processes, 43*, 406-430. doi: 10.1016/0749-5978(89)90045-9

Hollenbeck, J. R., Ellis, A. P. J., Humphrey, S. E., Garza, A. S., & Ilgen, D. R. (2011). Asymmetry in structural adaptation: The differential impact of centralizing versus decentralizing team decision-making structures preface. *Organizational Behavior and Human Decision Processes, 114*, 64-74. doi: 10.1016/j.obhdp.2010.08.003

Hollenbeck, J. R., & Klein, H. J. (1987). Goal commitment and the goal-setting process - problems, prospects, and proposals for future-research. *Journal of Applied Psychology, 72*, 212-220. doi: 10.1037/0021-9010.72.2.212

Hollenbeck, J. R., LePine, J. A., & Ilgen, D. R. (1996). Adapting to roles in decision making teams. In K. R. Murphy (Ed.), *Individual differences and behavior in organizations* (pp. 946-955). San Francisco: Jossey-Bass.

Holyoak, K. J., & Spellman, B. A. (1993). Thinking. *The Annual Review of Psychology, 44*, 265-315.

Hosmer Jr., D. W., & Lemeshow, S. (1999). *Applied survival analysis: Regression modeling of time to event data*. New York: John Wiley.

Hough, L. M. (1992). The 'big five' personality variables - construct confusion: Description versus prediction. *Human Performance, 5*, 139-155.

Hough, L. M. (2001). I-owes its advances to personality. In B. W. Roberts & R. Hogan (Eds.), *Personality psychology in the workplace* (pp. 19-44). Washington, DC: American Psychological Association.

Hough, L. M., & Dilchert, S. (2010). Personality: Its measurement and validity for employee selection. In J. L. Farr & N. T. Tippins (Eds.), *Handbook of employee selection* (pp. 299-319). New York: Routledge.

Hough, L. M., Eaton, N. K., Dunnette, M. D., Kamp, J. D., & McCloy, R. A. (1990). Criterion-related validities of personality constructs and the effects of response distortion on those validities. *Journal of Applied Psychology, 75*, 581-595.

Howard, A. (1995). *The changing nature of work*. San Francisco: Jossey-Bass.

Howe, M., Chang, C. H., & Johnson, R. E. (2013). Understanding affect, stress, and well-being within a self-regulation framework In P. L. Perrewé, J. Halbesleben & C. C. Rosen (Eds.), *Research in occupational stress and well being : The role of emotion and emotion regulation* (Vol. 11): Emerald Group.

Huber, V. L. (1985). Effects of task difficulty, goal setting, and strategy on performance of a heuristic task. *Journal of Applied Psychology, 70*, 492-504.

Hulin, C. (1991). Adaptation, persistence and commitment in organizations. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (2nd ed., Vol. 2, pp. 445-505). Palo Alto, CA: Consulting Psychologists Press.

Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96*, 72-98.

Hutchinson, K. A. (2011). The interactive effects of listwide control, item-based control, and working memory capacity on stroop performance. *Journal of Experimental Social Psychology: Learning, Memory, and Cognition, 37*, 851-860.

Ilgen, D. R., Fisher, C. D., & Taylor, M. S. (1979). Consequences of individual feeback on behavior in organizations. *Journal of Applied Psychology, 64*, 349-371.

Ilgen, D. R., & Hollenbeck, J. R. (1991). The structure of work: Job design and roles. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (Vol. 2, pp. 165-207). Palo Alto, CA: Consulting Psychologists Press.

Ilgen, D. R., & Pulakos, E. D. (1999). Employee performance in today's organizations. In D. R. Ilgen & E. D. Pulakos (Eds.), *The changing nature of work performance: Implications for staffing, motivation, and development* (pp. 1-18). San Francisco: Jossey-Bass.

Ilies, R., Fulmer, I. S., Spitzmuller, M., & Johnson, M. D. (2009). Personality and citizenship behavior: The mediating role of job satisfaction. *Journal of Applied Psychology, 94*, 945-959. doi: 10.1037/a0013329

Ilies, R., & Judge, T. A. (2002). Understanding the dynamic relationships among personality, mood, and job satisfaction: A field experience sampling study. *Organizational Behavior and Human Decision Processes, 89*, 1119-1139. doi: 10.1016/s0749-5978(02)00018-3

Intelligence and its measurement: A symposium. (1921). *Journal of Educational Psychology, 12*, 123-147, 195-216, 271-275.

Isen, A. (1984). Towards understanding the role of affect in cognition. In R. S. Wyer & T. K. Srull (Eds.), *Handbook of social cognition* (Vol. 3, pp. 179-236). Hillsdale, NJ: Erlbaum.

Isen, A. (1987). Positive affect, cognitive processes and social behaviour. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 20, pp. 203-253). San Diego, CA: Academic Press.

Jang, K. L., Livesley, W. J., Angleitner, A., Reimann, R., & Vernon, P. A. (2002). Genetic and environmental influences on the covariance of facets defining the domains of the five-factor model of personality. *Personality and Individual Differences, 33*, 83-101.

Jensen, A. R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger/Greenwood.

Jersild, A. T. (1927). *Mental set and shift* (Vol. 89). New York.

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review, 31*, 386-408.

Johnson, J. A. (1994). Clarification of factor five with the help of the ab5c model. *European Journal of Psychology, 8*, 311-334.

Johnson, J. W. (2001). The relative importance of task and contextual performance dimensions to supervisor judgments of overall performance. *Journal of Applied Psychology, 86*, 984-996. doi: 10.1037//0021-9010.86.5.984

Johnson, J. W. (2003). Toward a better understanding of the relationship between personality and individual job performance. In M. R. Barrick & A. M. Ryan (Eds.), *Personality and work: Reconsidering the role of personality in organizations* (pp. 83-120). San Francisco, CA: Jossey-Bass.

Johnson, R. E., Chang, C.-H., & Lord, R. G. (2006). Moving from cognition to behavior: What the research says. *Psychological Bulletin, 132*, 381-415. doi: 10.1037/0033-2909.132.3.381

Johnson, R. E., Howe, M., & Chang, C.-H. (2013). The importance of velocity, or why speed may matter more than distance. *Organizational Psychology Review, 3*, 62-85.

Jones, E. E., Rock, L., Shaver, K. G., Goethals, G. R., & Ward, L. M. (1968). Pattern of performance and ability attribution: An unexpected primacy effect. *Journal of Personality and Social Psychology, 10*, 317-340.

Judge, T. A., & Ilies, R. (2002). Relationship of personality to performance motivation: A meta-analytic review. *Journal of Applied Psychology, 87*, 797-807. doi: 10.1037//0021-9010.87.4.797

Kane, M. J., & Engle, E. M. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review of General Psychology, 9*, 637-671.

Kane, M. J., & Engle, R. W. (2000). Working memory capacity, proactive interference, and divided attention: Limits on long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*, 333-358.

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to stroop interference. *Journal of Experimental Psychology: General, 132*, 47-70. doi: 10.1037/0096-3445.132.1.47

Kane, M. J., Hambrick, D. Z., & Conway, A. R. A. (2005). Working memory capacity and fluid intelligence are strongly related constructs: Comment on ackerman, beier, and boyle (2005). *Psychological Bulletin, 131*, 66-71. doi: 10.1037/0033-2909.131.1.66

Kanfer, R. (1991). Motivation theory and industrial/organizational psychology. In M. D. Dunnette & L. Hough (Eds.), *Handbook of industrial and organizational psychology.* (Vol. 1, pp. 75-170). Palo Alto, CA: Consulting Psychologists Press.

Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities; an integrative apptitude-treatment interaction approach to skill acquisition. *Journal of Applied Psychology, 74*, 657-690.

Kanter, R. M. (1988). When a thousand flowers bloom: Structural, collective, and social conditions for innovation in organizations. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 10, pp. 169-211). Greenwich, CT: JAI Press.

Katz, D., & Kahn, R. L. (1978). *The social psychology of organizations* (2nd ed.). New York: Wiley.

Katzell, R. A. (1994). Contemporary meta-trends in industrial and organizational psychology. In H. C. Triandis, M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (2nd ed., Vol. 4, pp. 1-89). Palo Alto, CA: Consulting Psychologists Press.

Keith, N., & Frese, M. (2008). Effectiveness of error management training: A meta-analysis. *Journal of Applied Psychology, 93*, 59-69. doi: 10.1037/0021-9010.93.1.59

Kenny, D. A., & Judd, C. M. (1986). Consequences of violating the independence assumption in analysis of variance. *Psychological Bulletin, 99*, 422-431.

Kernan, M. C., & Lord, R. G. (1988). Effects of participative vs assigned goals and feedback in a muititrial task. *Motivation and Emotion*, *12*, 75-86.

Kiesler, S., & Sproull, L. (1982). Managerial response to changing environments: Perspectives on problem sensing from social cognition. *Administrative Science Quarterly, 27*, 548-570.

Klehe, U. C., & Anderson, N. (2007). Working hard and working smart: Motivation and ability during typical and maximum performance. *Journal of Applied Psychology, 92*, 978-992. doi: 10.1037/0021-9010.92.4.978

Klein, H. J. (1989). An integrated control theory model of work motivation. *Academy of Management Review*, *14*, 150-172.

Klein, H. J., Wesson, M. J., Hollenbeck, J. R., & Alge, B. J. (1999). Goal commitment and the goal-setting process: Conceptual clarification and empirical synthesis. *Journal of Applied Psychology, 84*, 885-896. doi: 10.1037/0021-9010.84.6.885

Klein, K. J., & Kozlowski, S. W. J. (2000). From micro to meso: Critical steps in conceptualizing and conducting multilevel research. *Organizational Research Methods, 3*, 211-236. doi: 10.1177/109442810033001

Kopp, C. B. (1982). Antecedents of self-regulation: A developmental perspective. *Developmental Psychology, 18*, 199-214.

Kozlowski, S. W. J., & Bell, B. S. (2008). Team learning, development and adaptation. In V. I. Sessa & M. London (Eds.), *Team effectiveness in complex organizations: Cross-disciplinary perspectives and approaches* (pp. 15-44). New York: Lawrence Erlbaum.

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

Kozlowski, S. W. J., Toney, R. J., Mullins, M. E., Weissbein, D. A., Brown, K. G., & Bell, B. S. (2001). Developing adaptation: A theory for the design of integrated–embedded training systems. *Advances in Human Performance and Cognitive Engineering Research, 1*, 59-122.

Kozlowski, S. W. J., Watola, D., Jensen, J. M., Kim, B., & Botero, I. (2009). Developing adaptive teams: A theory of dynamic team leadership. In E. Salas, G. F. Goodwin & C. S. Burke (Eds.), *Team effectiveness in complex organizations: Cross-disciplinary perspectives and approaches* (pp. 113-155). New York: Psychology Press.

Kraiger, K. (2003). Perspectives on training and development. In W. C. Borman, D. R. Ilgen & R. J. Klimoski (Eds.), *Handbook of psychology* (Vol. 12, pp. 171-192). Hoboken, NJ:: Wiley.

Krischer, M., & Witt, L. A. (2010). *Achieving adaptive performance in the workplace: The compensatory effects of general mental ability and adaptive leadership*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, Atlanta.

Kuhl, J. (1985). Volitional mediators of cognition-behavior consistency: Self-regulatory processes and action versus state orientation. In J. Kuhl & J. Beckmänn (Eds.), *Action control: From cognition to behavior* (pp. 101-128). New York: Springer-Verlag.

Kuhl, J. (1992). A theory of self-regulation: Action versus state orientation, self-discrimiantion, and some applications. *Applied Psychology-an International Review, 71*, 97-129.

Kuhl, J. (1994a). Action versus state orientation: Psychometric properties of the action control scale (acs-90). In J. Kuhl & J. Beckmänn (Eds.), *Volition and personality: Action versus state orientation* (pp. 47-59). Seattle, WA: Hogrefe & Huber.

Kuhl, J. (1994b). A theory of action and state orientation. In J. Kuhl & J. Beckmänn (Eds.), *Volition and personality: Action versus state orientation* (pp. 9-46). Seattle, WA: Hogrefe & Huber.

Kuhl, J., & Beckmänn, J. E. (1994). *Volition and personality: Action versus state orientation*. Seattle, WA: Hogrefe & Huber.

Lang, J. W. B., & Bliese, P. D. (2009). General mental ability and two types of adaptation to unforeseen change: Applying discontinuous growth models to the task-change paradigm. *Journal of Applied Psychology, 94*, 411-428. doi: 10.1037/a0013803

Larsen, R. J., & Ketelaar, T. (1991). Personality and susceptibility to positive and negative emotional states. *Journal of personality and social psychology, 61*, 132-140.

Latham, G. P., & Lee, T. W. (1986). Goal setting. In E. A. Locke (Ed.), *Generalizing from laboratory to field settings* (pp. 122-146). Lexington, MA: Lexington Books.

Latham, G. P., & Locke, E. A. (2006). Enhancing the benefits and overcoming the pitfalls of goal setting. *Organizational Dynamics, 35*, 332-340. doi: 10.1016/j.orgdyn.2006.08.008

Lawrence, J. W., Carver, C. S., & Scheier, M. F. (2002). Velocity toward goal attainment in immediate experience as a determinant of affect. *Journal of Applied Social Psychology, 32*, 788-802. doi: 10.1111/j.1559-1816.2002.tb00242.x

Lazarus, R. S. (1991). *Emotion and adaptation*. New York: Oxford University Press.

LePine, J. A. (2003). Team adaptation and postchange performance: Effects of team composition in terms of members' cognitive ability and personality. *Journal of Applied Psychology, 88,* 27-39. doi: 10.1037/0021-9010.88.1.27

LePine, J. A. (2005). Adaptation of teams in response to unforeseen change: Effects of goal difficulty and team composition in terms of cognitive ability and goal orientation. *Journal of Applied Psychology, 90*, 1153-1167. doi: 10.1037/0021-9010.90.6.1153

LePine, J. A., Colquitt, J. A., & Erez, A. (2000). Adaptability to changing task contexts: Effects of general cognitive ability conscientiousness, and openness to experience. *Personnel Psychology, 53,* 563-593. doi: 10.1111/j.1744-6570.2000.tb00214.x

Levenson, R. W. (1994). Human emotions: A functional view. In P. Ekman & R. Davidson (Eds.), *The nature of emotion: Fundamental questions* (pp. 123-126). New York: Oxford University Press.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal, 14,* 95-112.

Lievens, F., De Corte, W., & Schollaert, E. (2008). A closer look at the frame-of-reference effect in personality scale scores and validity. *Journal of Applied Psychology, 93*, 268-279. doi: 10.1037/0021-9010.93.2.268

Locke, E. A. (1986). Generalizing from laboratory to field: Ecological validity or abstraction of essential elements. In E. A. Locke (Ed.), *Generalizing from laboratory to field settings* (pp. 3-9). Lexington, MA: Lexington Books.

Locke, E. A. (2001). Self-set goals and self-efficacy as mediators of incentives and personality. In M. Erez, H. U. Kleinbeck & H. Thierry (Eds.), *Work motivation in the context of a globalizing economy* (pp. 13-26). Mahwah, NJ: Erlbaum.

Locke, E. A., & Hulin, C. L. (1962). A review and evaluation of the validity of studies of activity. *Personnel Psychology, 15*, 25-42.

Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting and task performance*. Englewood Cliffs, NJ: Prentice-Hall.

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation - a 35-year odyssey. *American Psychologist, 57*, 705-717. doi: 10.1037//0003-066x.57.9.705

Lord, R. G., Diefendorff, J. M., Schmidt, A. M., & Hall, R. J. (2010). Self-regulation at work. *Annual Review of Psychology, 61*, 543-568. doi: 10.1146/annurev.psych.093008.100314

Lord, R. G., & Levy, P. E. (1994). Moving from cognition to action - a control-theory perspective. *Applied Psychology-an International Review, 43*, 335-398. doi: 10.1111/j.1464-0597.1994.tb00828.x

Lovett, M. C., & Schuun, C. D. (1999). Task representations, strategy variability and base-rate neglect. *Journal of Experimental Psychology: General, 128*, 107-130.

Lucas, R. E., & Diener, E. (2001). Understanding extraverts' enjoyment of social situations: The importance of pleasantness. *journal of personality and social psychology, 81*, 343-356.

Malouff, J., Bauer, M., Mantelli, D., Pierce, B., Cordova, G., Reed, E., & Schutte, N. (1990). Development and evaluation of a measure of the tendency to be goal oriented. *Personality and Individual Differences, 11*, 1191-1200.

Maney, K. (1998). The networked economy changes everything, *USA Today,* p. 1E.

March, J. G., & Simon, H. (1958). *Organizations*. Cambridge, MA: Blackwell.

Matlin, M. W., & Stang, D. J. (1978). *The pollyana principle: Selectivity in language, memory, and thought.* Cambridge, MA: Shenkman.

McCrae, R. R. (1994). Openness to experience: Expanding the boundaries of factor v. *European Journal of Psychology, 8*, 251-272.

McCrae, R. R., & Costa, P. T., Jr. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of personality and social psychology, 52*, 81-90.

McCrae, R. R., & Costa, P. T., Jr. (1997). Conceptions and correlates of openness to experience. In R. Hogan, J. A. Johnson & S. R. Briggs (Eds.), *Handbook of personality psychology* (pp. 825-847). San Diego, CA: Academic Press.

Mednick, S. (1962). The associative basis of the creative problem solving process. *Psychological Review, 69*, 200-232.

Mesagno, C., Harvey, J. T., & Janelle, C. M. (2012). Choking under pressure: The role of fear of negative evaluation. *Psychology of Sport and Exercise, 13*, 60-68.

Miller, V. D., Johnson, J. R., & Grau, J. (1994). Antecedents to willingness to participate in a planned organizational change. *Journal of Applied Communication Research, 22,* 59-80.

Mischel, W. (1968). *Personality and assessment*. New York: Wiley.

Mischel, W. (1977). The interaction of person and situation. In D. Magnusson & N. S. Endler (Eds.), *Personality at the crossroads: Current issues in interactional psychology* (pp. 333-352). Hillsdale, NJ: Lawrence Erlbaum.

Mischel, W. (2004). Toward an integrative science of the person. *Annual Review of Psychology, 55*, 1-22.

Mischel, W., & Shoda, Y. (1995). A cognitive affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Pyschological Review, 102*, 246-268.

Morgeson, F. P., Campion, M. A., Dipboye, R. L., Hollenbeck, J. R., Murphy, K., & Schmitt, N. (2007a). Are we getting fooled again? Coming to terms with limitations in the use of personality tests for personnel selection. *Personnel Psychology, 60*, 1029-1049. doi: 10.1111/j.1744-6570.2007.00100.x

Morgeson, F. P., Campion, M. A., Dipboye, R. L., Hollenbeck, J. R., Murphy, K., & Schmitt, N. (2007b). Reconsidering the use of personality tests in personnel selection contexts. *Personnel Psychology, 60*, 683-729. doi: 10.1111/j.1744-6570.2007.00089.x

Morgeson, F. P., & Dierdorff, E. C. (2011). Work analysis: From technique to theory. In S. Zedeck (Ed.), *Apa handbook of industrial and organizational psychology* (Vol. 2, pp. 3-41). Washington, DC: APA.

Morgeson, F. P., Reider, M. H., & Campion, M. A. (2005). Selecting individuals in team settings: The importance of social skills, personality characteristics, and teamwork knowledge. *Personnel Psychology, 58*, 583-611. doi: 10.1111/j.1744-6570.2005.655.x

Mosteller, F., & Tukey, J. W. (1977). *Data analysis and regression: A second course in statistics*. Reading, MA: Addison-Wesley.

Mount, M. K., & Barrick, M. R. (1995). The big five personality dimensions: Implications for research and practice in human resource management. *Research in Personnel and Human Resources Management, 13*, 153-200.

Mount, M. K., Barrick, M. R., Laffitte, L. J., & Callans, M. C. (1999). *Personal characteristics inventory user's manual*. Libertyville, IL: Wonderlic Consulting.

Moutafi, J., Furnham, A., & Crump, J. (2006). What facets of openness and conscientiousness predict fluid intelligence score? *Learning and Individual Differences, 16*, 31-42.

Mumford, M. D., Baughman, W. A., Threlfall, K. V., Uhlman, C. E., & Costanza, D. P. (1993). Personality, adaptability, and performance: Performance on well-defined and ill-defined problem-solving tasks. *Human Performance, 6*, 241-285.

Mumford, M. D., & Gustafson, S. B. (1988). Creativity syndrome - integration, application, and innovation. *Psychological Bulletin, 103*, 27-43. doi: 10.1037/0033-2909.103.1.27

Murphy, P. R., & Jackson, S. E. (1999). Managing work role performance: Challenges for twenty-first-century organizations and their employees. In D. R. Ilgen & E. D. Pulakos (Eds.), *The changing nature of performance: Implications for staffing, motivation, and development* (pp. 325-365). San Francisco: Jossey-Bass.

Neubert, M. J. (1998). The value of feedback and goal setting over goal setting alone and potential moderators of this effect: A meta-analysis. *Human Performance, 11*, 321-335. doi: 10.1207/s15327043hup1104_2

Newell, A. (1990). *Unified theories of cognition*. Cambridge, MA: Harvard University Press.

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Englewood Cliffs, NJ: Prentice-Hall.

Nibbeling, N., Oeudejans, R. R. D., & Daanen, H. A. M. (2012). Effects of anxiety, a cognitive secondary task, and expertise on gaze behavior and performance in a far aiming task. *Psychology of Sport and Exercise, 13*, 427-435.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology, 2*, 175-220.

Nisbett, R. E., & Ross, L. (1980). *Human inference: Strategies and shortcomings of social judgment*. Englewood Cliffs, NJ: Prentice-Hall.

Norman, D., & Shallice, T. (1986). Attention to action: Willed and automatic control of behavior. In R. Davison, G. Schwartz & D. Shapiro (Eds.), *Consciousness and self regulation: Advances in research and theory* (Vol. 4). New York: Plenum.

Norman, W. T. (1963). Toward an adequate taxonomy of personality attributes: Replicated factor structure in peer nomination personality ratings. *Journal of Abnormal & Social Psychology, 66*, 574-583.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (2nd ed.). New York: McGrawll-Hill.

O'Leary, M. B., Mortensen, M., & Woolley, A. W. (2011). Multiple team membership: A theoretical model of its effects on productivity and learning for individuals and teams. *Academy of Management Review, 36*, 461-478.

O'Reilly, C. A., & Pfeffer, J. (2000). *Hidden value: How great companies achieve extraordinary results with ordinary people*. Boston, MA: Harvard Business School Press.

Oberauer, K., Schulze, R., Wilhelm, O., & Süß, H.-M. (2005). Working memory and intelligence--their correlation and their relation: Comment on ackerman, beier, and boyle (2005). *Psychological Bulletin, 131*, 61-65. doi: 10.1037/0033-2909.131.1.61

Ones, D. S., Dilchert, S., Viswesvaran, C., & Judge, T. A. (2007). In support of personality assessment in organizational settings. *Personnel Psychology, 60*, 995-1027. doi: 10.1111/j.1744-6570.2007.00099.x

Ones, D. S., & Viswesvaran, C. (1996). Bandwidth-fidelity dilemma in personality measurement for personnel selection. *Journal of Organizational Behavior, 17*, 609-626. doi: 10.1002/(sici)1099-1379(199611)17:6<609::aid-job1828>3.0.co;2-k

Ordóñez, L. D., Schweitzer, M. E., Galinsky, A. D., & Bazerman, M. H. (2009). Goals gone wild: The systematic side effects of overprescribing goal setting. *The Academy of Management Perspectives*, *23*, 6-16.

Organ, D. W. (1977a). Intentional vs arousal effects of goal-setting. *Organizational Behavior and Human Decision Processes, 18*, 378-389.

Organ, D. W. (1977b). A reappraisal and reinterpretation of the satisfaction-causes-performance hypothesis. *Academy of Management Review, 2*, 46-53.

Organ, D. W. (1988). *Organizational citizenship behavior: The good soldier syndrome*. Lexington, MA: Lexington books.

Organ, D. W. (1997). Organizational citizenship behavior: It's construct clean-up time. *Human Performance, 10*, 85-97.

Outtz, J. L. (2011). The unique origins of advancement in slection and personnel psychology. In S. Zedeck (Ed.), *Apa handbook of industrial and organizational psychology* (Vol. 2, pp. 445-465). Washington, D.C.: APA.

Pearlman, K., & Barney, M. F. (2000). Selection for a changing workforce. In J. F. Kehoe (Ed.), *Managing selection in changing organizations: Human resource strategies* (pp. 3-72). San Francisco: Jossey-Bass.

Pearlman, K., Schmidt, F. L., & Hunter, J. E. (1980). Validity generalization results for tests used to predict job proficiency and training success in clerical occupations. *Journal of Applied Psychology, 65,* 373-406.

Pennebaker, J. W., & Skelton, J. A. (1978). Psycholgical parameters of physical symptoms. *Personality and Social Psychology Bulletin, 4*, 524-530.

Penney, L. M., David, E., & Witt, L. A. (2011). A review of personality and performance: Identifying boundaries, contingencies, and future research directions. *Human Resource Management Review, 21*, 297-310. doi: 10.1016/j.hrmr.2010.10.005

Perry-Smith, J. E., & Shalley, C. E. (2003). The social side of creativity: A static and dynamic social network perspective. *Academy of Management Review, 28,* 89-106.

Pinheiro, J. C., & Bates, D. M. (2000). *Mixed-effects models in s and s-plus*. New York: Springer.

Pinheiro, J. C., Bates, D. M., DebRoy, S., Sarkar, D., & the R Development Core Team. (2012). Nlme: Linear and nonlinear mixed effects models (Version R package version 3.1-104).

Ployhart, R. E., & Bliese, P. D. (2006). Individual adaptability (i-adapt) theory: Conceptualizing the anteceedents, consequences, and measurement of individual differences in adaptability. In C. S. Burke, L. G. Pierce & E. Salas (Eds.), *Understanding adaptability:*

A prerequisite for effective performance within complex environments (pp. 3-39). Amsterdam: Elsevier.

Podsakoff, N. P., Whiting, S. W., Podsakoff, P. M., & Blume, B. D. (2009). Individual- and organizational-level consequences of organizational citizenship behaviors: A meta-analysis. *Journal of Applied Psychology*, *94*, 122-141. doi: 10.1037/a0013079

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88,* 879-903. doi: 10.1037/0021-9101.88.5.879

Powers, W. T. (1973). *Behavior: The control of perception*. Chicago: Aldine.

Pulakos, E. D., Arad, S., Donovan, M. A., & Plamondon, K. E. (2000). Adaptability in the workplace: Development of a taxonomy of adaptive performance. *Journal of Applied Psychology*, *85*, 612-624. doi: 10.1037/0021-9010.85.4.612

Pulakos, E. D., Dorsey, D. W., & White, S. S. (2006). Adaptability in the workplace: Selecting an adaptive workforce. In C. S. Burke, L. G. Pierce & E. Salas (Eds.), *Understanding adaptability: A prerequsite for effective performance within complex environments* (pp. 41-71). Amsterdam: Elsevier.

Pulakos, E. D., Schmitt, N., Dorsey, D. W., Arad, S., Hedge, J. W., & Borman, W. C. (2002). Predicting adaptive performance: Further tests of a model of adaptability. *Human Performance, 15*, 299-323. doi: 10.1207/s15327043hup1504_01

R Core Team. (2012). R: A language and environment for statistical computing (Version 2.15.1). Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/

Raisch, S., & Birkinshaw, J. (2008). Organizational ambidexterity: Antecedents, outcomes, and moderators. *Journal of Management*, *34*, 375-409. doi: 10.1177/0149206308316058

Randall, K. R., Resick, C. J., & DeChurch, L. A. (2011). Building team adaptive capacity: The roles of sensegiving and team composition. *Journal of Applied Psychology, 96*, 525-540. doi: 10.1037/a0022622

Reb, J., & Cropanzano, R. (2007). Evaluating dynamic performance: The influence of salient gestalt characteristics on performance ratings. *Journal of Applied Psychology, 92*, 490-499. doi: 10.1037/0021-9010.92.2.490

Rhodes-Kropf, M., & Viswanathan, S. (2004). Market valuation and merger waves. *The Journal of Finance, LIX*, 2685-2718.

Ricks, T. R., Turley-Ames, K. J., & Wiley, J. (2007). Effects of working memory capacity on mental set due to domain knowledge. *Memory & Cognition, 35*, 1456-1462.

Ridderinkhof, K. R., Ullsperger, M., Crone, E. A., & Nieuwenhuis, S. (2004, October 15). The role of the medial frontal cortex in cognitive control. *Science, 306*, 443–447.

Roberts, B. W., Chernyshenko, O. S., Stark, S., & Goldberg, L. R. (2005). The structure of conscientiousness: An empirical investigation based on seven major personality questionnaires. *Personnel Psychology, 58*, 103-139. doi: 10.1111/j.1744-6570.2005.00301.x

Robinson, S. L., & Bennett, R. J. (1995). A typology of deviant workplace behaviors - a multidimensional-scaling study. *Academy of Management Journal, 38*, 555-572. doi: 10.2307/256693

Rodgers, R., & Hunter, J. E. (1991). Impact of management by objectives on organizational productivity. *Journal of Applied Psychology, 76*, 322-336. doi: 10.1037/0021-9010.76.2.322

Rosen, M. A., Bedwell, W. L., Wildman, J. L., Fritzsche, B. A., Salas, E., & Burke, C. S. (2011). Managing adaptive performance in teams: Guiding principles and behavioral markers for measurement. *Human Resource Management Review, 21*, 107-122. doi: 10.1016/j.hrmr.2010.09.003

Rosen, V. M., & Engle, R. W. (1997). The role of working memory capacity in retrieval. *Journal of Experimental Psychology: General, 126*, 211-227.

Rotundo, M., & Sackett, P. R. (2002). The relative importance of task, citizenship, and counterproductive performance to global ratings of job performance: A policy-capturing approach. *Journal of Applied Psychology, 87*, 66-80. doi: 10.1037//0021-9010.87.1.66

Salgado, J. F. (1997). The five factor model of personality and job performance in the european community. *Journal of Applied Psychology, 82*, 30-43. doi: 10.1037//0021-9010.82.1.30

Salgado, J. F. (1998). *Criterion validity of personality measures based and non-based on the five factor model*. Paper presented at the 106th Annual Convention of the American Psychological Association, San Francisco, CA.

Salgado, J. F., Anderson, N., Moscoso, S., Bertua, C., & De Fruyt, F. (2003). International validity generalization of gma and cognitive abilities: A european community meta-analysis. *Personnel Psychology, 56*, 573-605. doi: 10.1111/j.1744-6570.2003.tb00751.x

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, Cognition and Personality, 9*, 185-211.

Saucier, G., & Goldberg, L. R. (2001). Lexical studies of indigenous personality factors: Premises, products, and prospects. *Journal of Personality, 69*, 847-879.

Saucier, G., & Ostendorf, F. (1999). Hierarchial subcomponents of the big five personality factors: A cross-language replication. *Journal of personality and social psychology, 76*, 613-627.

Schmidt, A. M., & DeShon, R. P. (2007). What to do? The effects of discrepancies, incentives, and time on dynamic goal prioritization. *Journal of Applied Psychology, 92*, 928-941. doi: 10.1037/0021-9010.92.4.928

Schmidt, A. M., & Dolis, C. M. (2009). Something's got to give: The effects of dual-goal difficulty, goal progress, and expectancies on resource allocation. *Journal of Applied Psychology, 94*, 678-691. doi: 10.1037/a0014945

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124*, 262-274. doi: 10.1037/0033-2909.124.2.262

Schmidt, F. L., Hunter, J. E., & Pearlman, K. (1981). Task differences as moderators of aptitude-test validity in selection - a red herring. *Journal of Applied Psychology, 66*, 166-185. doi: 10.1037//0021-9010.66.2.166

Schmit, M. J., Kihm, J. A., & Robie, C. (2000). Development of a global measure of personality. *Personnel Psychology, 53*, 153-193. doi: 10.1111/j.1744-6570.2000.tb00198.x

Schmitt, N., Cortina, J. M., Ingerick, M. J., & Wiechmann, D. (2003). Personnel selection and employee performance. In W. C. Borman, D. R. Ilgen & R. J. Klimoski (Eds.), *Handbook of psychology* (pp. 77-106). New York: Wiley.

Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior - a path model of individual innovation in the workplace. *Academy of Management Journal, 37*, 580-607. doi: 10.2307/256701

Seijts, G. H., & Latham, G. P. (2001). The effect of distal learning, outcome, and proximal goals on a moderately complex task. *Journal of Organizational Behavior, 22*, 291-307. doi: 10.1002/job.70

Seijts, G. H., Latham, G. P., Tasa, K., & Latham, B. W. (2004). Goal setting and goal orientation: An integration of two different yet related literatures. *Academy of Management Journal, 47*, 227-239.

Sheridan, T. B. (2004). Driver distraction from a control theory perspective. *Human Factors, 46*, 587-599.

Sinclair, R. C. (1988). Mood, categorization breadth, and performance appraisal: The effects of order of information acquisition and affective state on halo, accuracy, information retrieval, and evaluations. *Organizational Behavior and Human Decision Processes, 42*, 22-46.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurence*. New York: Oxford University Press.

Smith, G. M. (1967). Usefulness of peer ratings of personality in educational research. *Educational and Psychological Measurement, 27*, 967-984.

Snijders, T. A. B. (2005). Power and sample size in multilevel linear models. In B. S. Everitt & D. C. Howell (Eds.), *Encyclopeida of statistics in behavioral sciences* (Vol. 3, pp. 1570-1573). Chicester: Wiley.

Snijders, T. A. B., & Bosker, R. J. (1993). Standard errors and sample sizes for two-level research. *Journal of Educational Statistics, 18*, 237-259.

Snijders, T. A. B., & Bosker, R. J. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. London: Sage.

Snijders, T. A. B., Bosker, R. J., & Guldemond, H. (2007). Pint (Version 2.12). Retrieved from http://www.stats.ox.ac.uk/~snijders/Pint_e212.zip

Spector, P. E., Chen, P. Y., & O'Connell, B. J. (2000). A longitudinal study of relations between job stressors and job strains while controlling for prior negative affectivity and strains. *Journal of Applied Psychology, 85*, 211-218. doi: 10.1037//0021-9010.85.2.211

Spector, P. E., Zapf, D., Chen, P. Y., & Frese, M. (2000). Why negative affectivity should not be controlled in job stress research: Don't throw out the baby with the bath water. *Journal of Organizational Behavior, 21*, 79-95. doi: 10.1002/(sici)1099-1379(200002)21:1<79::aid-job964>3.3.co;2-7

Spielberger, C. D. E. (1966). *Anxiety and behavior*. New York: Academic Press.

Staw, B. M., & Boettger, R. D. (1990). Task revision: A neglected form of work performance. *Academy of Management Journal, 33*, 534-559.

Sternberg, R. J. (2003). A broad view of intelligence: The theory of successful intelligence. *Consulting Psychology Journal: Practice and Research, 55*, 139-154. doi: 10.1037/1061-4087.55.3.139

Stewart, G. L. (1999). Trait bandwidth and stages of job performance: Assessing differential effects for conscientiousness and its subtraits. *Journal of Applied Psychology, 84*, 959-968. doi: 10.1037/0021-9010.84.6.959

Stewart, G. L., & Nandkeolyar, A. K. (2006). Adaptation and intraindividual variation in sales outcomes: Exploring the interactive effects of personality and environmental opportunity. *Personnel Psychology, 59*, 307-332. doi: 10.1111/j.1744-6570.2006.00016.x

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology, 18*, 643-662. doi: 10.1037/h0054651

Taylor, P. J., Taylor, H., & Russ-Eft, D. F. (2009). Transfer of management training from alternative perspectives. *Journal of Applied Psychology, 94*, 104-121. doi: 10.1037/a0013006

Tett, R. P., Jackson, D. N., & Rothstein, M. (1991). Personality measures as precitors of job performance: A meta-analytic review. *Personnel Psychology, 44*, 703-742.

Tharenou, P., Saks, A. M., & Moore, C. (2007). A review and critique of research on training and organizational-level outcomes. *Human Resource Management Review, 17*, 251-273.

Thoresen, C. J., Bradley, J. C., Bliese, P. D., & Thoresen, J. D. (2004). The big five personality traits and individual job performance growth trajectories in maintenance and transitional job stages. *Journal of Applied Psychology, 89*, 835-853. doi: 10.1037/0021-9010.89.5.835

Thurstone, L. L. (1919). The learning curve equation. *Psychological Monographs: General and Applied, 26*, i-51.

Thurstone, L. L. (1924). *The nature of intelligence*. London: Routledge & Kegan Paul.

Tubbs, M. E. (1986). Goal-setting - a meta-analytic examination of the empirical-evidence. *Journal of Applied Psychology, 71*, 474-483. doi: 10.1037//0021-9010.71.3.474

Tupes, E. C., & Christal, R. E. (1961). Recurrent personality facts based on trait ratings. Lackland Air Force Base, TX: Aeronautical Systems Division, Personnel Labratory.

Uggerslev, K. L., & Sulsky, L. M. (2008). Using frame-of-reference training to understand the implications of rater idiosyncrasy for rating accuracy. *Journal of Applied Psychology, 93*, 711-719. doi: 10.1037/0021-9010.93.3.711

Vancouver, J. B. (2005). The depth of history and explanation as benefit and bane for psychological control theories. *Journal of Applied Psychology, 90*, 38-52. doi: 10.1037/0021-9010.90.1.38

Vancouver, J. B., Thompson, C. M., Tischner, E. C., & Putka, D. J. (2002). Two studies examining the negative effect of self-efficacy on performance. *Journal of Applied Psychology, 87*, 506-516. doi: 10.1037//0021-9010.87.3.506

Vancouver, J. B., Thompson, C. M., & Williams, A. A. (2001). The changing signs in the relationships among self-efficacy, personal goals, and performance. *Journal of Applied Psychology, 86*, 605-620. doi: 10.1037//0021-9010.86.4.605

Viswesvaran, C. (1993). *Modeling job performance: Is there a general factor?* Unpublished doctoral dissertation, University of Iowa. Iowa City.

Waller, M. J. (1999). The timing of adaptive group responses to nonroutine events. *Academy of Management Journal, 42*, 127-137. doi: 10.2307/257088

Wanberg, C. R., & Banas, J. T. (2000). Predictors and outcomes of openness to changes in a reorganizing workplace. *Journal of Applied Psychology, 85*, 132-142. doi: 10.1037//0021-9010.85.1.132

Wanberg, C. R., Zhu, J., & Van Hooft, E. A. J. (2010). The job search grind: Perceived progress, self-reactions, and self-regulation of search effort. *Academy of Management Journal, 53*, 788-807.

Wang, M., Zhan, Y. J., McCune, E., & Truxillo, D. (2011). Understanding newcomers' adaptability and work-related outcomes: Testing the mediating roles of perceived p-e fit variables. *Personnel Psychology, 64*, 163-189. doi: 10.1111/j.1744-6570.2010.01205.x

Watkins, E. R. (2008). Constructive and unconstructive repetitive thought. *Psychological Bulletin, 134*, 163-206. doi: 10.1037/0033-2909.134.2.163

Watson, D. (2000). *Mood and temperament*. New York: The Guilford Press.

Watson, D., & Clark, L. A. (1992). On traits and temperament: General and specific facotrs of emotional experience and their relation to the five-factor model. *Journal of Personality, 60*, 441-476.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The panas scales. *Journal of Personality and Social Psychology, 54*, 1063-1070. doi: 10.1037/0022-3514.54.6.1063

Weick, K. E. (1979). *The social psychology of organizing*. Reading, Mass: Addison-Wesley.

Weick, K. E. (1995). *Sensemaking in organizations*. Thousand Oaks, CA: Sage Publications, Inc.

Weiss, H. M. (1990). Learning theory and industrial and organizational theory. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (pp. 171-221). Palo Alto, CA: Consulting Psychologists Press.

Weiss, H. M., & Cropanzano, R. (1996). Affective events theory: A theoretical discussion of the structure, causes and consequences of affective experiences at work. *Research in Organizational Behavior, 18*, 1-74.

Weiss, H. M., & Ilgen, D. R. (1985). Routinized behavior in organizations. *Journal of Behavioral Economics*, 57-67.

West, M. A., & Farr, J. L. (1990). Innovation at work. In M. A. West & J. L. Farr (Eds.), *Innovation and creativity at work: Psychological and organizational strategies* (pp. 3-13). New York: Wiley.

Wildman, J. L., Bedwell, W. L., Salas, E., & Smith-Jentsch, K. A. (2011). Performance measurement at work: A multilevel perspective. In S. Zedeck (Ed.), *Apa handbook of industrial and organizational psychology* (Vol. 1, pp. 303-341). Washington, D.C.: American Psychological Association.

Williams, K. J., & Alliger, G. M. (1994). Role stressors, mood spillover, and perceptions of work-family conflict in employed parents. *Academy of Management Journal, 37*, 837-868. doi: 10.2307/256602

Williams, K. J., Donovan, J. J., & Dodge, T. L. (2000). Self-regulation of performance: Goal establishment and goal revision processes in athletes. *Human Performance, 13*, 159-180. doi: 10.1207/s15327043hup1302_3

Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of Management, 17,* 601-617. doi: 10.1177/014920639101700305

Winters, D., & Latham, G. P. (1996). The effect of learning versus outcome goals on a simple versus a complex task. *Group & Organization Management*, *21*, 236-250.

Wonderlic. (2004). The wonderlic quicktest series of tests successfully predicts scores on the wonderlic personnel test (wpt) *Research Note*. Libertyville, IL: Wonderlic.

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

Wood, R. E., & Bandura, A. (1989a). Impact of conceptions of ability on self-regualtory mechanisms and complex decision-making. *Journal of personality and social psychology*, *56*, 407-415.

Wood, R. E., & Bandura, A. (1989b). Social cognitive theory of organizational management. *Academy of Management Review, 14*, 361-384.

Wood, R. E., & Locke, E. A. (1990). Goal setting and strategy effects on complex tasks. *Research in organizational behavior*, *12*, 73-109.

Wood, R. E., Mento, A. J., & Locke, E. A. (1987). Task complexity as a moderator of goal effets: A meta-analysis. *Journal of Applied Psychology, 72*, 416-425.

Yamaguchi, K. (1991). *Event history analysis* (Vol. 28). Newbury Park, CA: Sage.