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TESTING A DYNAMIC PERSPECTIVE OF GOAL ORIENTATION DURING COMPLEX SKILL ACQUISITION AND ADAPTATION TO UNFORESEEN CHANGE

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TESTING A DYNAMIC PERSPECTIVE OF GOAL ORIENTATION DURING COMPLEX SKILL ACQUISITION AND ADAPTATION TO UNFORESEEN CHANGE

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Abstract

In the context of learning a dynamic task involving cognitive and perceptual-motor demands, this laboratory study contributed to a multilevel perspective of goal orientation and performance by examining adaptation to a novel and unforeseen change. Repeated measures and discontinuous mixed-effects growth modeling were used to disentangle within- from between-person effects of mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goal orientation dimensions on performance. At the within-person level, this study failed to replicate previous findings of goal orientation effects corresponding to resource allocation theory. At the between-person level, results were consistent with prior research such that mastery-approach and performance-approach facilitated performance, whereas performance-avoidance hindered it. A positive effect of mastery-avoidance on performance was also found. There were no interactions between goal orientation and adaptation trajectories, suggesting that main effects of goal orientation are stable across changes in task demand. This research contributes toward theories of self-regulation and active learning, and questions the extent to which a dynamic approach for understanding the effects of goal orientation is necessary.

Introduction

The nature of work is becoming increasingly complex due to accelerated technological, economic, and social change (Baard, Rench, & Kozlowski, 2014; Pulakos, Arad, Donovan, & Plamondon, 2000). To compete in increasingly volatile environments, organizations need to continuously adapt—a challenge often delegated to its human resources (Reeves & Deimler, 2011). Now more than ever, people are expected to adapt their knowledge and skills to unforeseen changes in the workplace. The time and costs of developing formal training make it difficult for organizations to implement programs that keep pace with the rate of change (LePine, Colquitt, & Erez, 2000). As such, it often falls on the individual to be responsible for their own learning and development (Noe, Clarke, & Klein, 2014). For these reasons, research has moved beyond traditional approaches of training toward those that emphasize the generalization and adaptation of skills and knowledge (Bell & Kozlowski, 2008).

Traditionally, research on skill acquisition and training has emphasized the proceduralization of routine tasks. This is effective for stable, low variability conditions, but often ineffective or even detrimental in dynamic environments (Paas & van Merriënboer, 1994). One proposed solution is active learning, an approach to instructional design in which learners are proactively engaged in the learning process rather than receiving information passively (Bell & Kozlowski, 2008). Its fundamental tenets are (1) that individuals possess significant control over their learning and (2) that learning is an inductive process. Learners are responsible for developing self-regulatory strategies that accompany the skill being learned. What separates active learning from other constructivist approaches (e.g., discovery learning) is its emphasis on formal training elements that support learners' self-regulation as they engage training materials and practice to-be-learned skills.

Self-regulation refers to how individuals modulate their cognition, behavior, and affect toward accomplishing goals (Karoly, 1993). There are several theories of self-regulated learning (e.g., Carver & Scheier, 1981; Pintrich, 2000; Zimmerman, 1990), but one principle shared by all of them is that goals initiate self-regulatory processes (Sitzmann & Ely, 2011). Goals focus attention on relevant activities, which result in increased effort, persistence, and discovery and use of task-relevant knowledge and strategies (Locke & Latham, 2002). Goal orientation (GO) theory has been offered as a potentially useful overarching framework for understanding self-regulated learning in terms of how individuals might simultaneously pursue a variety of goals.

Theoretical frameworks of GO distinguish between motivation toward mastering a task and demonstrating competence (Payne, Youngcourt, & Beaubien, 2007). Research suggests that GO dimensions lead to relatively unique, adaptive or maladaptive outcomes, but there is disagreement regarding what those effects are and under which contingencies they operate (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). Part of the challenge in understanding these effects is that research on GO has predominantly taken a trait-based approach and has not adequately examined the state-based nature of GO. Self-regulated learning is a within-person phenomenon, such that cognition, motivation, and affect are subject to within-person fluctuations as individuals engage a task. Accordingly, it is vital that research specify and empirically disentangle such within- and between-person effects.

Indeed, recent research that has disentangled between- and within-person GO effects has not only demonstrated that within-person GO-performance relationships meaningfully differ from between-person relationships (Beck & Schmidt, 2013; Yeo, Loft, Xiao, & Kiewitz, 2009), but also that within-person effects can be dynamic over the course of skill acquisition in relation to the effective allocation of cognitive resources (Converse et al., 2013; Yeo et al., 2009).

Given the scarcity of research that has disentangled within- from between-person GO effects, the purpose of the following study was to (1) replicate findings of this nascent empirical literature, particularly Yeo et al. (2009) in the context of skill acquisition, and (2) extend this line of research by examining relationships with adaptation to unforeseen changes in task demands. Specifically, this research used a task-change paradigm in which participants learned a complex task prior to being confronted with unforeseen changes in task demands that required adaptive behavior (Lang & Bliese, 2009). Repeated measures of objective performance and self-reports of GO were taken during both skill acquisition and adaptation. Discontinuous mixed-effects growth modeling was used to test hypotheses based on resource allocation theory (Kanfer & Ackerman, 1989) that distinguish within- from between-person GO effects and adaptation from acquisition. In this vein, the following research clarifies the effects of GO in a manner that can inform the practice of training that better supports self-regulated learning and performance adaptability.

Adaptation and the Task-change Paradigm

Given the increased need for individuals who can adjust to changing environments, there has been a surge of research on adaptation in recent years.

Adaptation is generally described as the modification of cognition and behavior in response to change, though its precise conceptualization and operationalization has varied across studies (Baard, Rench, & Kozlowski, 2014; Jundt, Schoss, & Huang, 2015). In the context of skill acquisition, adaptation is best conceptualized as a process that unfolds over time. Individuals who encounter an unexpected change in task demands employ self-regulatory mechanisms for effectively allocating attention toward meeting achievement goals. These processes can either hinder or facilitate performance depending on the cognitive demands of the task at a given moment (Kanfer & Ackerman, 1989). Relationships between self-regulation and performance across acquisition and adaptation can be modeled using a repeated measures design with a task-change manipulation (Lang & Bliese, 2009).

Given that acquisition and adaptation are both operationalized in terms of task performance, it is necessary to distinguish between the two processes. Research on the former suggests that skill acquisition consists of three stages (Kanfer & Ackerman, 1989; Tenison & Anderson, 2016). In the first (i.e., cognitive) stage, learners devote most, if not all their attention to understanding the task. It is during this phase that the task imposes the highest cognitive load on the learner, given a lack of prior experience from which to draw strategies. As effort is allocated toward encoding task elements and relationships between them, the learner enters a second (i.e., associative) stage in which specific procedures are consolidated into a smaller set of task strategies. Attentional demands imposed by the task decrease as strategies are further consolidated via repeated retrieval and revision in response to errors. With continued practice, task strategies become automated, thus indicating transition into the third (i.e., autonomous) stage of skill acquisition. It is at this point that task strategies become routine and can be executed with minimum demands imposed on the learner's cognitive resources.

The process of skill acquisition is illustrated by modeling performance over time and across individuals. Following a logarithmic growth curve, initial gains in task performance are represented by a steeper slope at the beginning, whereas automated processing of the task occurs as the curve approaches an asymptote (Fitts & Posner, 1967; Newell & Rosenbloom, 1981). The observation that performance gains diminish rather than steadily increasing is due to limits imposed by task and learner characteristics (Kanfer & Ackerman, 1989). In instances where the task is either too difficult or easy, increasing effort has no additional effect on the level of performance. Otherwise, performance gains are constrained by differences in ability (i.e., cognitive resource capacity) and willingness to exert effort. Thus, complete automation of a task beyond a subset of strategies is unlikely for complex tasks due to a confluence of task and learner characteristics. Individuals often settle on reasonably effective, but suboptimal solutions in complex environments (Dörner, 1980). This contrasts with continually monitoring performance, exploring alternatives, and deciding on whether to use existing strategies, modify them, or adopt new ones. These actions are important for attaining exceptional levels of skill in complex domains, and especially for adapting to change.

Typically, an event that demands adaptation involves a shift in the complexity of the task environment. Complexity in this sense consists of the number of task elements, the relationships among the elements, and variation in these quantities and interrelations over time (Wood, 1986). In a laboratory setting where participants are learning and performing a task over multiple trials, such a shift can be implemented by changing the task characteristics mid-protocol (Lang & Bliese, 2009). Strategies used prior to the change are likely to be less effective in the post-change environment, leading to an immediate decrease in performance. This is accounted for in a model of skill acquisition by adding a spline for discontinuous growth, allowing for the intercepts and slopes of performance over time to be compared relative to the task-change (Bliese & Lang, 2016). In the trial immediately following the manipulation—a phase termed transition adaptation—a lower value represents a lesser decrement in performance, thus indicating more successful generalization of skill to the novel environment. Adaptation is not an isolated event, however. Much of the self-regulation and cognitive processing that constitutes adaptation is observed in reacquisition of pre-change performance levels in the trials that follow.

Reacquisition adaptation is like initial acquisition in that it is also modeled as a logarithmic growth curve of performance over time (Lang & Bliese, 2009). It is thought to follow a similar trajectory as well, with cognitive demands being highest at the intercept (i.e., immediately following a change), and diminishing across repeated trials. The key difference between adaptation and initial acquisition is the possession of preexisting routines at the intercept change. Once a change is detected, an individual must identify task strategies that are no longer as effective and modify their representations of the task to compile new or modified strategies. Diagnosing discrepancies may involve unlearning one's mental model of the task characteristics (Klein & Baxter, 2006). Adaptation in this sense can be described as the rate of performance gains over time, with higher slopes demonstrating faster reacquisition and automatization of effective routines in the post-change environment.

While the aggregate models of acquisition and adaptation follow a stable growth curve, a single individual's trajectory is much more variable (Donner & Hardy, 2015). Performance may fluctuate from one trial to another as learners explore new strategies, diagnose errors, or become distracted by off-task thoughts. The advantage of a longitudinal design is that fluctuations in self-regulatory variables can be analyzed alongside trial-to-trial increases and decreases in performance relative to the average change over time. Previous research has used this approach to make inferences about the causal effects of motivation on the process of skill acquisition (Yeo et al., 2009; Yeo & Neal, 2004), but this it yet to be done in the context of adaptation. The following study utilizes a repeated measures design to test effects of a set of motivational states—goal orientations—on both skill acquisition and adaptation, and discontinuous mixed-effects growth modeling to distinguish how these effects differ across the two processes.

Goal Orientation

Goal orientation (GO) refers to the mindsets of individuals in achievement contexts such as school, sports, or work (Elliot, 2005). Since its original conceptualization, GO has been demonstrated to account for variability in self-regulated learning (Pintrich, 2000) and performance (Payne, Youngcourt, & Beauben, 2007). Although scholars tend to agree on the importance of GO for understanding motivation in achievement settings, there are several inconsistencies regarding its conceptualization and operationalization (DeShon & Gillespie, 2005; Hulleman, Schrager, Bodmann, &

Harackiewicz, 2010). The 2 × 2 framework (Elliot & McGregor, 2001) serves as a foundation for distinguishing between GO dimensions via the definition and valence of competence (Elliot, 2005). Research has also begun to resolve conceptual discrepancies by addressing the stability of GO dimension across contexts.

Historically, most of the research on GO has emphasized the distinction between mastery and performance goals (Ames & Archer, 1988; Dweck, 1986; Nicholls, 1984). Mastery GO is striving toward learning a given task, whereas performance GO is striving toward demonstrating competence (Elliot, 2005). Both have been shown to have differential effects on the allocation of cognitive resources during learning (e.g., Fisher & Ford, 1998). Learners with a high mastery GO are inclined to exert effort toward exploration and learning task strategies. Learners with high performance GO might also devote attention to on-task activities, but are likely preoccupied with off-task thoughts concerning how their competence compares to others. Although older conceptualizations of GO described the mastery and performance dimensions as opposite ends on the same continuum, current research distinguishes them as relatively independent constructs (Button, Mathieu, & Zajac, 1996; Hulleman et al., 2010; Payne et al., 2007).

Greater conceptual clarity was provided by incorporating approach and avoidance motivation into GO theory (Elliot & MacGregor 2001; Day, Yeo, & Radosevich, 2003). To account for mixed empirical findings regarding performance GO, it was bifurcated into approach and avoidance dimensions (Elliot & Harackiewicz, 1994; VandeWalle, 1997). Performance-approach (PAp) refers to striving toward higher levels of competence relative to others, whereas performance-avoidance (PAv) refers to the desire to avoid appearing incompetent. PAv is associated with fear of failure and distraction, in addition to off-task thoughts regarding interpersonal comparison, which are also associated with PAp. Approach and avoidance were eventually incorporated in mastery GO, thus renaming mastery GO to mastery-approach (MAp) and adding mastery-avoidance (MAv) to the framework (Elliot & McGregor, 2001). Described as "avoiding task-based or intrapersonal incompetence" (Elliot & Murayama, 2008, p. 614), it is unclear whether MAv is a useful addition to GO theory (Baranik, Stanley, Bynym, & Lance, 2010; DeShon & Gillespie, 2005).

Scholars have also debated on whether GO is better defined as a stable disposition or domain-specific state (DeShon & Gillespie, 2005). Button et al. (1996) described it as a "somewhat stable individual difference factor that may be influenced by situational characteristics" (p. 28). The malleability of GO is apparent given that studies have effectively manipulated it (Van Yperen, Blaga, & Postmes, 2015). In addition, research comparing GO measures has revealed stronger relationships of GO with criteria when it was operationalized as a task-specific construct versus a disposition (e.g., Day, Stokes, & Fein, 2002). Although individuals can maintain general GO tendencies (Payne et al., 2007), the unique effects of variability in GO across time and situations should not be ignored.

With GO being thought to influence the allocation of cognitive resources, the magnitude and direction of its effects are expected to vary across different stages of skill acquisition and adaptation. Throughout both processes, multiple fluctuations in performance occur (Lang & Bliese, 2009). Although some of these fluctuations are due to practice errors, some of the variability is likely reflected by the learner's motivational state. Shifts in attention between on- and off-task thoughts influence performance, such as when learners decide to explore the task environment, focus more on outperforming others, or consider more carefully how to avoid making mistakes. Determining how fluctuations in learner states relate to performance across multiple trials can be examined by statistically disentangling within- and between-person effects of GO on performance.

Goal Orientation and Performance

Only recently has research begun to disentangle the between- and within-person effects of GO on performance (e.g., Beck & Schmidt, 2013; Converse et al., 2013; Yeo et al., 2009). Yeo et al.'s (2009) Study 1 using an air traffic control simulation is especially relevant, being the only one that investigated both levels of GO during complex skill acquisition. Distinct effects of GO were found at the between- and within-person levels, indicating that both individual differences in GO and deviations from an individual's average GO level matter. In addition, Yeo et al. (2009) found that effects were moderated by task practice, such that the magnitude and direction of GO effects change over the duration of skill acquisition. These results were explained via resource allocation theory, which states that goals influence the allocation of limited cognitive resources (Kanfer & Ackerman, 1989). MAp, PAp, and PAv are thought to differentially influence attention to self-regulatory activities and off-task thoughts, which in turn influence task performance. Drawing on resource allocation theory, I expected to replicate Yeo and colleagues' (2009) findings and further apply this reasoning to the effects of GO during adaptation to unforeseen change.

Mastery-approach

MAp reflects striving toward learning and developing competence relative to a self-relevant or task-relevant standard (Elliot, 2005). Due to its positive associations with variables that facilitate performance (e.g., effort, persistence, and feedback seeking; Elliot, Shell, Henry, & Maier, 2005; Payne et al., 2007), MAp is often considered to be ubiquitously beneficial. However, its observed relationships with performance have been mixed between positive (e.g., Fisher & Ford, 1998; Grant & Dweck, 2003) and null (e.g., Cury, Elliot, Da Fonseca, & Moller, 2006; Payne et al., 2007). One explanation for this discrepancy is that past studies have confounded effects at the within- and between-person levels (Yeo et al., 2009). MAp might be expected to operate differently with respect to variation in one's own performance compared to performance relative to others.

When disentangling the multilevel effects of MAp on performance, Yeo et al. (2009) found a positive effect at the within-person level, but a negligible effect at the between-person level. Moreover, they found the within-person effect to be consistent across skill acquisition. These findings support the argument that GO effects on performance vary at different levels of analysis, and corroborate explanations of how MAp is theorized to direct attention. High levels of striving toward mastery are associated with acquiring more advanced task strategies and raising intrapersonal standards. This is expected to translate into increased performance relative to one's previous performance over time, but not necessarily relative to that of others. As such, I expected to replicate the findings of Yeo et al. (2009) regarding the within- and between-person effects of MAp on performance.

Hypothesis 1: At the within-person level, there will be a positive relationship between MAp and performance.

Following a change in task demands, the interaction between the learner and task environment resembles that at the beginning of skill acquisition. However, given that new task demands must be learned, task strategies developed prior to the change are no longer as effective (Bröder & Schiffer, 2006). Due to having constructed a mental model of the task prior to the change, the benefits of having automated routines are no longer as apparent (Betsch, Haberstroh, Glöckner, Haar, & Fiedler, 2001). Learners need to undergo fundamental shifts in their understanding of the task toward more complex mental models. To achieve performance gains, one must direct cognitive resources toward exploring the post-change environment with objectives of modifying existing strategies and discovering new ones. By focusing attention on these objectives, MAp is expected to buffer the increased cognitive demands imposed on the learner by changes in task demands. I expected that striving toward mastery would be especially important following change. Thus, I expected to find a moderating effect of transition adaptation on the positive relationship between MAp and performance at the within-person level.

Hypothesis 2: At the within-person level, there will be an interaction between MAp and transition adaptation, such that the positive effect of MAp on performance will be stronger during post-change versus pre-change trials.

Performance-approach

PAp is composed of elements that are both facilitative and detrimental to learning, which has made it a topic of debate among scholars (Senko, Hulleman, & Harackiewicz, 2011). While the element of approach motivation links PAp to greater effort and persistence (Elliot & McGregor, 2001), performance orientation is also associated with off-task thoughts about demonstrating competence relative to others. Some argue that the interaction of these elements is beneficial to performance (Elliot & McGregor, 2001; Senko et al., 2011), while others posit that consequences outweigh any benefits (Brophy 2005; Midgley, Kaplan, & Middleton, 2001). Evidence is mixed, with meta-analyses reporting both null (Payne et al., 2007) and positive effects of PAp on performance (Day et al., 2003; Hulleman et al., 2010). Yeo et al. (2009) found that the relationship at the between-person level was positive, suggesting that on average, those who attend more to demonstrating competence tend to perform better. Furthermore, Yeo et al. (2009) found a dynamic within-person effect throughout skill acquisition, suggesting that the relationship between PAp and performance is rather nuanced.

The complicated relationship between PAp and performance can be understood in terms of how cognitive demands change across the stages of skill acquisition. In the beginning of skill acquisition, cognitive demands imposed on the learner are high. The learner must devote the entirety of their attention toward understanding task elements and their relationships. Focusing on interpersonal comparison during this phase steals from limited cognitive resources that are needed to understand task fundamentals. As task strategies become automated with practice, tasks can then be performed with a reserve of attention (Kanfer & Ackerman, 1989). Striving toward outperforming others becomes beneficial by focusing attention on sustaining high levels of performance. Indeed, Yeo et al. (2009) found an interaction with the linear trajectory of skill acquisition, such that PAp had a negative effect on performance in early trials, but a positive effect in later trials. In contrast to the positive effect of PAp at the between-person level, within-person effects of PAp correspond to demands placed on the learner's cognitive resources. Accordingly, I expected to replicate the findings of Yeo et al. (2009) at both levels.

> *Hypothesis 3:* At the between-person level, there will be a positive relationship between PAp and performance.

> *Hypothesis 4:* At the within-person level, the effect of PAp on performance will be dynamic, such that it will be negative early in skill acquisition, but become positive in later trials.

Following an unforeseen change in task demands, PAp can hinder performance by directing attention toward off-task thoughts related to demonstrating competence. This consumes cognitive resources that are needed for modifying and discovering task strategies (Avery & Simille, 2013; Avery, Simille, & de Fockert, 2013). In addition, reliance on pre-existing routines can interfere with learning (Betsch et al., 2001; Bröder & Schiffer, 2006). Learners focused on interpersonal comparison may be more likely to rely on existing strategies and their underlying mental models. Attention to changed task demands is vital for appropriately unlearning old ways and modifying existing schemas. As such, PAp was expected to be detrimental in adaptation compared to skill acquisition.

> *Hypothesis 5:* At the between-person level, there will be an interaction between PAp and transition adaptation, such that individuals with higher PAp will experience a larger decrement in performance following change in task demand.

> *Hypothesis 6:* At the within-person level, there will be an interaction between PAp and transition adaptation, such that the effect of PAp on performance will be more negative during post-change versus pre-change trials.

As with the initial skill acquisition process, however, cognitive resources become increasingly available as individuals compile new or modified task strategies for the post-change environment. With a reserve of cognitive resources becoming available as new and modified task strategies become automated, PAp goals become less distracting and more facilitative of reaching higher levels of performance. Although the within-person PAp effect has been shown to shift from negative to positive during skill acquisition (Yeo et al., 2009), an interaction of this degree will probably not occur during adaptation due to the increased cognitive demands associated with the interference of previously automated task strategies to discovering and understanding changes in the task environment.

> *Hypothesis 7:* At the within-person level, the relationship between PAp and performance will be dynamic, such that it will be negative early in reacquisition adaptation, but will be less negative in later trials.

Performance-avoidance

Defined as avoiding demonstrations of incompetence (Elliot & McGregor, 2001), PAv is generally thought to hinder performance (Payne et al. 2007). This negative relationship is primarily driven by the avoidance dimension, which is related to anxiety and self-doubt (Elliot et al., 2005; Eysenck & Calvo, 1992). Meta-analytic reviews have shown that PAv yields negative effects on performance (Payne et al., 2007, Van Yperen et al., 2015). Indeed, Yeo et al. (2009) found a negative between-person effect of PAv on performance, but not at the within-person level. Their explanation for this finding was based on how self-regulatory processes are hierarchically organized (see Carver and Scheier, 1998), and specifically that within-person effects of PAv can be overridden by those for PAp such that striving to outperform others subsumes avoiding demonstrations of incompetence. This could partially explain why PAp and PAv are so closely related (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2012). Parsing out the relationship likely involves additional moderators (e.g., Law et al., 2012) and is beyond the scope of this study. As such, I expected to replicate the finding of Yeo et al. (2009).

> *Hypothesis 8:* At the between-person level, there is a negative relationship between PAv and performance.

Like what is expected from PAp, the effects of PAv are expected to be stronger during adaptation compared to skill acquisition. Cognitive resources consumed by interpersonal comparison and negative affect interfere with the ability to make sense of new task demands and modify existing task strategies (Crouzevialle & Butera, 2012; Eysenck & Calvo, 1992). Learners occupied with off-task thoughts are less likely to devote the attention required to revise their mental models. As such, they may rely on routines developed prior to the change, which are suboptimal for meeting post-change task demands. Thus, I expected that PAv is more detrimental to performance during adaptation when aggregated across trials.

> *Hypothesis 9:* At the between-person level, there will be an interaction between PAv and transition adaptation, such that individuals with higher PAv will experience a larger decrement in performance following a change in task demand.

Mastery-avoidance

Despite Elliot and McGregor's (2001) assertion to include MAv in frameworks of GO, many scholars choose to exclude it (DeShon & Gillespie, 2009). Even Elliot and McGregor (2001) acknowledge the counterintuitive nature of MAv, which corresponds to striving toward avoiding incompetence. The conflicting combination of absolute/intrapersonal standards and negative valence makes it difficult to anticipate how MAv is associated with performance. Furthermore, the little research on MAv and performance has produced mixed results (Baranik, Lau, Stanley, Barron, & Lance, 2013; Elliot & Murayama, 2008). MAv might possess limited relevance for specific contexts, such as among experts (DeShon & Gillespie, 2009) or individuals with declining skill via aging (Senko & Freund, 2015). Baranik, Stanley, Bynum and Lance (2010) suggested that it might be especially relevant for dynamic environments. Individuals who are challenged to frequently acquire new skills in novel situations might adopt MAv just to “get by” (Baranik et al., 2010, p. 267).

Whereas MAv is expected to facilitate skill acquisition via on-task attention directed toward meeting intrapersonal standards, it is also expected to hinder it via negative affect. Like PAv, individuals with high MAv might struggle with effectively allocating cognitive resources. MAv is associated with increased anxiety (Elliot & McGregor, 2001), maladaptive task strategies (Howell & Watson, 2007), and disinterest (Baranik et al., 2010). MAv is also thought to reflect perfectionism, which can either facilitate or hinder performance via perfectionistic strivings or concerns (Kaye, Conroy, & Fifer, 2008; Stoeber, Stoll, Pescheck, & Otto, 2008). Whereas MAv is self-referent at a within-person level, avoidance motivation is thought to propagate at the between-person level (Yeo et al., 2009). To investigate these contrasts, I tested effects of MAv on performance at within- and between-person levels during skill acquisition and adaptation.

> *Research question:* How does MAv relate to performance during skill acquisition and adaptation to change?

Method

Participants

288 undergraduate students at the University of Oklahoma completed the present study in exchange for credit toward a psychology course and entries into a gift card drawing contingent on task performance. Data were excluded for 12 participants

who experienced technical difficulties and 6 who failed to follow instructions. An additional 17 participants were removed for careless responding, which was detected via long string analysis (Meade & Craig, 2012). The final sample consisted of 253 participants, 85 of whom were female (M_{age} = 19, SD_{age} = 1.55, *Range* = 18–30). 169 reported their ethnicity as White, 14 as Black, 25 as Asian, 16 as Hispanic, 8 as Native American, 4 as Middle Eastern, 11 as Multiple, and 6 as Other.

Performance Task

The performance task used in this study was Unreal Tournament 2004 (UT2004; Epic Games, 2004), a commercially available first-person shooter computer game used in previous research on complex skill acquisition (e.g., Hardy et al., 2014; Hughes et al., 2013). The objective of UT2004 was to destroy computer-controlled opponents while minimizing the destruction of one's own character. Participants had opportunities to collect weapons or resources (i.e., power-ups) during each trial to increase their character's offensive and defensive capabilities. When a participant's character or opponent was destroyed, it reappeared in a random location with the default weapons and capabilities. The game was "every character for him- or herself," meaning that the computer-controlled characters were in competition with each other as well as the participant. Performance on UT2004 involves a high degree of cognitive and psychomotor demands. Participants simultaneously used a mouse and keyboard to control their character, all the while learning the strengths and weaknesses of different weapons and strategies, and quickly deciding which to use given the situation.

Procedure

Participants were told that the purpose of the study was to investigate how people learn to play a dynamic and complex videogame. They completed an informed consent document followed by a battery of individual difference measures to serve as control variables. Participants were told that they were entered in a lottery to win one of five, $25 gift cards for each trial in which their score was in the top 50% of all study participants for that given trial. Participants watched a 15 min presentation on UT2004 explaining the basic game controls, rules, and power-ups, followed by a 1 min practice trial for becoming familiar with the controls, display, and game environment without any opponents.

Participants completed 14 sessions, each consisting of two 4 min trials. Prior to each session, participants completed self-report measures of state GO. For the first seven sessions, participants competed against two computer-controlled opponents at a difficulty setting of 5 on a 1-to-8 scale. Following the 7th session (i.e., 14th pre-change trial), several task elements changed without warning, corresponding to an increase in task complexity (Hughes et al., 2013). Players then competed against nine computer-controlled opponents at a difficulty setting of 6 on a 1-to-8 scale. The game environment (i.e., map) was much larger, with open spaces, multiple levels of platforms, and edges over which characters could fall to their destruction. Task characteristics for the pre- and post-change trials were the same as those used by Jorgensen (2017). Participants were debriefed following the 14th session (i.e., 28th post-change trial).

Measures

Control variables. Self-reported ACT scores (*M* = 26.91, *SD* = 4.25) were used as a proxy of general mental ability (GMA). A 4-item scale was used to measure prior video game experience, which served as an index of pre-training videogame knowledge (Hardy et al., 2014; Jorgensen, 2017). For the first two items, participants responded using a 5-point Likert scale (1 = not at all, 2 = rarely, just a few times, 3 = monthly, 4 = weekly, 5 = daily) to the following questions: "*Over the last 12 months, how frequently have you typically played video games?*" (*M* = 2.97, *SD* = 1.40) and "*Over the last 12 months, how frequently have you typically played first-person shooter video games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament)?*" (*M* = 2.26, *SD* = 1.25). For the second two items, participants indicated how many hours per week they typically play video games (*M* = 4.37, *SD* = 6.89) and more specifically, first-person shooter video games (*M* = 1.74, *SD* = 3.76). Scores for these items were standardized and then averaged into a prior videogame experience score (α = .86).

Goal orientation. Task-specific MAp, PAp, and PAv were measured using items adapted from Yeo et al. (2009). These were modified to refer to UT2004 instead of air traffic control. Participants responded to each item using a 7-point scale (1 = strongly disagree, 7 = strongly agree), and each item was prefixed with "*At the moment*." The MAp items were "*The opportunity to extend the range of my abilities during this game is important to me*," and "*The opportunity to learn new things during this game is important to me*." The PAp items were "*It is important for me to perform better at UT2004 than others*," and "*I want others to recognize that I am one of the best at this game*." The PAv items were "*I want to hide from others that they are better than* *me at this game*,” and “*I aim to avoid discovering that others are better than me at this game*.” MAv was measured using 2 items adapted from Elliot & Murayama’s (2008) Achievement Goal Questionnaire–Revised: “*My aim is to avoid learning less than I possibly could in this game*,” and “*My goal is to avoid learning less than it is possible to learn in this game*.” Across the 14 sessions, the average Cronbach’s alpha was .90 (min. = .85, max. = .94) for MAp, .87 (min. = .82, max. = .90) for PAp, .75 (min. = .69, max. = .79) for PAv, and .91 (min. = .78, max. = .94) for MAv.

Task performance. Task performance scores for each trial were calculated using the index described in Hardy et al. (2014): player kills (i.e., number of times a participant destroyed an opponent) divided by the quantity of kills plus deaths (i.e., number of kills plus the number of times a participant’s own character was destroyed) plus player rank (i.e., the participant’s rank relative to the computer opponents in that trial). Scores were multiplied by one-hundred to aid interpretability. Performance for each session was calculated to be the average score for both trials in that session.

Analysis

Performance and GO trajectories were modeled as discontinuous mixed-effects growth models, which take advantage of multiple time variables to model change across measurement occasions and in relation to the task change (Lang & Bliese, 2009). This allowed for the modeling of skill acquisition, transition adaptation, and reacquisition adaptation, each of which were coded following the relative coding scheme described by Bliese and Lang (2016; Table 1). The slope of the linear trend (SA) represents the rate of skill acquisition prior to the task change. Transition adaptation is modeled using a dummy coded variable (TA), which accounts for discontinuity by marking time before and after the task change. Reacquisition adaptation (RA) is the slope of the linear trend for the post-change trials relative to that of the pre-change trials. In addition, a quadratic term for skill acquisition (SA^2) was included in the model to account for curvilinear change (Lang & Bliese, 2009). Analyses were conducted using restricted maximum likelihood (REML) estimation and the nlme package in R (Pinheiro, Bates, DebRoy, & Sarkar, 2016; R Development Core Team, 2016).

Results

Means, standard deviations, and correlations between study variables are reported in Table 2. The intraclass correlation coefficient (ICC1; Bliese, 2000) was computed for performance and each GO to determine the relative proportion of variance at the between- and within-person levels. Analyses revealed that ICC1 = .71 for performance, indicating that 71% of the variability in performance was at the between-person level. The ICC1s for MAp, MAv, PAp, and PAv were .58, .53, .71, and .67 respectively, indicating substantial proportions of GO variability within and between individuals.

Trends in self-reported GO across the performance sessions are displayed in Figure 1. Discontinuous mixed-effects growth models were tested to analyze GO trends across time and following the task manipulation. Parameters for the mastery GO dimensions are displayed in Table 3, and parameters for the performance GO dimensions in Table 4. MAp decreased over time ($\beta_{10} = -0.09$, $t(3286) = -5.49$, $p < .001$), the rate of which remained the same following the task change ($\beta_{30} = 0.03$, $t(3286) = 1.18$, $p = .238$). In contrast, MAv remained constant during pre-change trials ($\beta_{10} = 0.02$, $t(3286) = 1.25$, $p = .213$), but decreased during post-change trials ($\beta_{30} = –$

0.10, $t(3286) = –3.54$, $p < .001$). Neither levels of MAp ($\beta_{20} = 0.00$, $t(3286) = 0.01$, $p = .992$) nor MAv ($\beta_{20} = 0.00$, $t(3286) = –0.05$, $p = .959$) changed immediately after the task change. Both PAp ($\beta_{10} = –0.13$, $t(3286) = –7.62$, $p < .001$) and PAv ($\beta_{10} = –0.03$, $t(3286) = –2.29$, $p = .022$) decreased over time. The rate of change of PAp decreased following the task change ($\beta_{30} = 0.09$, $t(3286) = 4.02$, $p < .001$), whereas that of PAv remained the same ($\beta_{30} = 0.02$, $t(3286) = 0.84$, $p = .399$). Neither PAp ($\beta_{20} = 0.09$, $t(3286) = 1.49$, $p = .137$) nor PAv ($\beta_{20} = 0.00$, $t(3286) = 0.05$, $p = .959$) changed immediately after the task change (Table 4).

Modeling Performance Change

An unconditional model of performance change was built using the series of steps recommended by Bliese and Lang (2016). The coefficient for skill acquisition was positive ($\beta_{10} = 5.22$, $t(3285) = 14.76$, $p < .001$), indicating that performance increased over time. Transition and reacquisition adaptation were coded such that coefficients were interpreted relative to the skill acquisition trajectory. The coefficient for transition adaptation ($\beta_{20} = –17.91$, $t(3285) = –22.36$, $p < .001$) indicated a decrease in performance relative to the value predicted by skill acquisition immediately following the task change. The coefficient for reacquisition acquisition ($\beta_{30} = –4.64$, $t(3285) = –12.34$, $p < .001$) indicated a decrease in the rate of performance change during the post-change trials relative to the pre-change trials. A quadratic trend was observed for skill acquisition ($\beta_{40} = –0.53$, $t(3285) = –9.60$, $p < .001$), but not for reacquisition adaptation ($\beta_{50} = –0.08$, $t(3284) = –1.25$, $p = .209$). Analyses revealed significant variability in skill acquisition: $\chi^2_{diff}(2) = 229.23$, $p < .001$, transition adaptation: $\chi^2_{diff}(4) = 137.90$, $p < .001$, and reacquisition adaptation: $\chi^2_{diff}(4) = 70.59$, $p < .001$, but not quadratic skill acquisition: $\chi^2_{diff}(5) = 4.92$, $p = .426$. Table 5 displays the results for the unconditional model, which was specified by the following set of equations:

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

Level 2: $\pi_{0i} = \beta_{00} + r_{0i}$

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

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

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

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

Gender, GMA, and videogame experience were grand-mean centered and added to the model as control variables. GMA ($\beta_{02} = 0.52$, $t(249) = 3.51$, $p < .001$) and videogame experience ($\beta_{03} = 8.08$, $t(249) = 10.03$, $p < .001$) were positively related to performance, and males tended to outperform females ($\beta_{01} = –14.42$, $t(249) = –8.33$, $p < .001$). Building on this model, I simultaneously tested interaction effects for each of these variables with skill acquisition, transition adaptation, and reacquisition. Significant interaction effects were only found for gender with transition adaptation ($\beta_{21} = 3.20$, $t(3283) = 2.61$, $p = .008$) and videogame experience with transition adaptation ($\beta_{22} = –1.40$, $t(3283) = –2.45$, $p = .014$). Males and individuals with more videogame experience had larger decrements in performance following the task change. Only statistically significant effects were retained in the conditional model (Table 5), which was specified by the following set of equations:

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

Level 2: $\pi_{0i} = \beta_{00} + \beta_{01}(SEX_i - \overline{SEX}) + \beta_{02}(GMA_i - \overline{GMA}) + \beta_{03}(VGE_i - \overline{VGE}) + r_{0i}$

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

$\pi_{2i} = \beta_{20} + \beta_{21}(SEX_i - \overline{SEX}) + \beta_{22}(VGE_i - \overline{VGE}) + r_{2i}$

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

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

Testing Goal Orientation Effects

Following specification of the conditional model of performance change, I tested a series of models that added effects of within- and between-person GO. Due to limited degrees of freedom via the 14 repeated measures (i.e., sessions), it was not possible to add main effects of the within-person GO dimensions and their interactions with each of the performance trajectories simultaneously. Therefore, the following model building steps were carried out for each GO independently. Model 1 tested the main effect of person-mean centered GO at the within-person level, which is the relationship between within-person fluctuations of GO and task performance across all sessions on average. Within-person GO interactions with SA, TA, and RA were added in Model 2. Between-person GO, operationalized as the mean of within-person GO scores across trials, was grand-mean centered and included in Model 3. Between-person GO interactions with SA, TA, and RA were added in Model 4. Each step in the model building process maintained the coefficients in the previous model.

Model parameters for MAp are displayed in Table 6. There was no statistically significant effect of within-person MAp (β_{50} = 0.05, $t(3282) = 0.30$, $p = .762$), which failed to support Hypothesis 1. Hypothesis 2 predicted an interaction between MAp and TA, in which the effect of MAp on performance would be stronger following the task change. Model 2 indicated no evidence for the interaction with TA (β_{70} = –0.25, $t(3279)$ = –0.40, $p = .690$), nor for interactions between MAp and SA (β_{60} = 0.02, $t(3282)$ =

0.14, p = .886) or RA (β_{80} = 0.07, $t(3282)$ = 0.48, p = .628). At the between-person level, there was a positive main effect of MAp (β_{04} = 1.76, $t(248)$ = 3.88, p < .001), but no statistically significant interactions with SA (β_{60} = 0.11, $t(3276)$ = 1.19, p = .234), TA (β_{70} = –0.09, $t(3276)$ = –0.16, p = .873), or RA (β_{80} = 0.03, $t(3276)$ = 0.21, p = .833).

Model parameters for PAp are displayed in Table 7. There was a significant positive effect of between-person PAp (β_{04} = 0.88, $t(248)$ = 2.17, p = .031), which supported Hypothesis 3. Hypothesis 5 predicted an interaction between PAp and TA at the between-person level, such that learners with higher PAp experience a larger decrement in performance following the task change. This was not supported (β_{70} = –0.31, $t(3276)$ = –0.65, p = .514). Hypothesis 4 predicted a dynamic effect of PAp, such that its effect switches from negative to positive during later trials of skill acquisition. However, there was no main effect of within-person PAp (β_{50} = –0.02, $t(3282)$ = –0.12, p = .904), nor was there an interaction with SA (β_{60} = –0.07, $t(3279)$ = –0.65, p = .517). There was also no interaction between PAp and TA at the within-person level (β_{70} = 0.01, $t(3279)$ = 0.01, p = .990), which failed to support Hypothesis 6. There was an interaction between PAp and RA (β_{80} = 0.41, $t(3279)$ = 2.42, p = .016), supporting Hypothesis 7, such that the effect of PAp became less negative throughout the post-change trials.

Model parameters for PAv are displayed in Table 8. In support of Hypothesis 8, a negative effect of PAv on performance was found at the between-person level (β_{04} = –1.31, $t(248)$ = –2.66, p = .008). Hypothesis 9 proposed an interaction between PAv and transition adaptation at the between-person level, such that the negative effect of PAv would be stronger during the post-change trials. This was not supported (β_{70} = 0.92, $t(3276) = 1.50$, $p = .134$).

Model parameters for MAv are displayed in Table 9. The extent to which MAv was related to performance during skill acquisition and adaptation was investigated as a research question. There was no effect of MAv at the within-person level (β_{50} = –0.11, $t(3282) = –0.89$, $p = .375$), or for its interactions with SA (β_{60} = –0.09, $t(3279) = –1.04$, $p = .297$), TA(β_{70} = 0.16, $t(3279) = 0.30$, $p = .767$) or RA (β_{80} = 0.18, $t(3279) = 1.42$, $p = .157$). As with MAp, there was a positive effect of MAv at the between-person level (β_{04} = 1.36, $t(248) = 2.96$, $p = .003$), but no interactions with SA (β_{60} = 0.00, $t(3276) = 0.00$, $p = .999$), TA (β_{70} = –0.14, $t(3276) = –0.25$, $p = .801$), or RA (β_{80} = 0.23, $t(3276) = 1.74$, $p = .083$).

Ancillary Analysis

A substantial proportion of variance is shared between GO dimensions, particularly within each of the mastery and performance dimensions (Elliot & MacGregor, 2001; Payne et al., 2007). A series of post-hoc analyses compared the relative effects of multiple GO dimensions on performance when included in the same model (Table 10). When both mastery GO dimensions were modeled together, there was a significant main effect of MAp (β = 1.44, $t(247) = 2.66$, $p = .008$), but not MAv (β = 0.55, $t(247) = 1.01$, $p = .312$). When the performance GO dimensions were modeled together, PAp (β = 1.42, $t(247) = 3.44$, $p < .001$) and PAv (β = –1.94, $t(247) = –3.77$, $p < .001$) had significant positive and negative effects on performance respectively. Lastly, I tested a third model that simultaneously included all four GO dimensions. There was a significant, negative effect of PAv (β = –1.94, $t(245) = –3.81$,

p = .009), but no significant effects of MAp (β = 1.11, t(245) = 1.85, p = .066), MAv (β = 0.79, t(245) = 1.48, p = .141), or PAp (β = 0.74, t(245) = 1.53, p = .127).

Discussion

The present study contributed toward a dynamic process perspective of skill acquisition and adaptation by disentangling the within- and between-person effects of GO on performance. Guided by Yeo et al. (2009) and resource allocation theory (Kanfer & Ackerman 1989), I hypothesized differential effects of MAp, PAp, and PAv corresponding to their relationships with self-regulatory activities. Discontinuous mixed-effects growth modeling was used to further distinguish between phases of skill acquisition and adaptation. Overall, the present study failed to replicate the within-person effects reported by Yeo et al. (2009). Individuals' deviations from their average level of GO were unrelated to changes in performance. However, significant GO effects were identified at the between-person level, which were consistent with patterns of results commonly reported in prior research (see Payne et al., 2007). Individuals with higher levels of MAp, MAv, PAp, and lower levels of PAv tended to achieve higher levels of performance relative to others. There were no interactions with skill acquisition or adaptation trajectories, indicating GO effects are consistent across phases of learning. These findings have several implications for theory and practice, which are discussed in the following sections.

On the Multilevel Perspective of Goal Orientation

Testing the effects of GO on performance at multiple levels of analysis has been proposed for resolving discrepancies in the GO literature (DeShon & Gillespie, 2009). Among these discrepancies are mixed results corresponding to the relationship between

MAp and performance (Hulleman et al., 2010; Payne et al., 2007). Yeo et al. (2009) offered a multilevel perspective as an explanation by demonstrating MAp effects to be positive at the within-person level, yet null at the between-person level. Because MAp reflects the motivation to develop competence relative to oneself, it makes sense for it to relate to gains in performance relative to oneself instead of others. However, the present study found the opposite pattern: MAp effects were null at the within-person level, yet positive at the between-person level. This relationship between MAp and performance appears to depend on more than just the level of analysis.

Although MAp is expected to facilitate performance via increased focus on developing practicing task-relevant strategies, there are reasons why this might not be reflected at the within-person level. MAp states correspond to exploratory behavior, which enables learners to discover new and alternative ways of performing the task. Exploration can lead to immediate performance gains (Hardy et al., 2014), but its effects might be more distal in dynamic environments (Hardy, Day, & Arthur, 2018). Exploration might involve a greater number of errors, leading to momentary decreases in performance. Learning from error and building a diverse repertoire of task strategies is expected to pay off over extended periods of time, which might explain the positive effect of MAp at the between-person level. It is worth noting that between-person MAp was operationalized as individuals' average levels of MAp throughout the study, as opposed to a trait inventory. Interestingly, between-person MAv was also positively related to performance. However, this effect of MAv disappeared when including both mastery GO dimensions in the ancillary analysis, which indicates that it can be attributed to variance in MAv reflecting MAp.

In contrast to Yeo et al. (2009), the present study lacked support for dynamic, within-person effects of PAp. These predictions were based resource allocation theory, which suggests that limited cognitive resources become increasingly available with task practice (Kanfer & Ackerman, 1989). Given that PAp directs attention toward off-task thoughts (Avery & Simille, 2013; Avery, Simille, & de Fockert, 2013), it was expected to be detrimental in the beginning of skill acquisition and immediately following change. As individuals became familiar with the task environment, off-task thoughts were expected to be less detrimental. Instead, focusing on outperforming others was expected to facilitate performance via increased engagement. The latter prediction was supported in part, such that effect of PAp became positive in later trials of reacquisition adaptation. However, this was the only statistically significant interaction involving within-person GO out of the twelve that were tested, thus this interaction may be spurious. The present evidence suggests that PAp is consistently facilitative of performance, but at the between-person level. This finding is consistent with Yeo et al., (2009), who wrote that motivation to outperform others should relate to higher task engagement, and thus higher performance on average.

Also consistent with Yeo and colleagues' (2009) findings at the between-person level, the present study found that individuals with higher levels of PAv tended to perform worse on average. This negative effect of PAv is thought to be due to anxiety involving worries about appearing incompetent (Elliot & McGregor, 2001). According to resource allocation theory, off-task thoughts such as worries about incompetence might be expected to become less detrimental with practice. However, neither the present study nor Yeo et al. (2009) found within-person effects of PAv, let alone dynamic effects. Yeo et al. (2009) suggested that formal, computational models may be required to understand how avoidance motivation is related to feedback loops across levels of analysis (see Carver & Scheier, 1989). Given the overall lack of within-person effects in the present study, this might be necessary for GO in general, as opposed to just PAv. Given that GO effects are already quite small at the between-person level (Payne et al., 2007), the within-person effects might also be negligible or dependent on specific boundary conditions.

On the Dynamic Process Perspective of Adaptation

Surprisingly, none of the GO dimensions were shown to be more or less facilitative of performance following an unforeseen change in task demands. This contrasted with the expectation that GO dimensions would be especially relevant for modulating the allocation of cognitive resources in response to increased task complexity. Rather, the main effects of between-person GO were consistent across each phase. These main effects align with recent findings suggesting that adaptation is largely a function of pre-existing knowledge, skills, and abilities (Frank & Kluge, 2017; Huck, Day, Lin, Jorgensen, Westlin, & Hardy, 2018). According to this research, the strongest predictors of performance immediately following change and the subsequent rate of reacquisition are the initial performance and rate of learning prior to the change. For example, Huck et al. (2018) found that GMA and other predictors of skill acquisition had negligible effects on adaptive performance after controlling for the main effect of pre-change performance. If GO does facilitate adaptation, these effects could be largely mediated by its influence on initial learning.

Further research is needed to determine the extent to which self-regulatory processes during adaptation are different from those of skill acquisition. Although the present study suggested off-task attention and affect as mediating variables for justifying the hypothesized effects of GO on performance, these were not explicitly modeled. Differences between self-regulatory processes in skill acquisition and adaptation may require computational modeling of systems of variables (see Hardy, Day, & Arthur, 2018; Weinhardt & Vancouver, 2012). For example, MAp effects during adaptation might be contingent on levels of negative affect, which in turn is a function of an individual's emotion regulation ability. Furthermore, a computational modeling approach might require emphasis on specific task components and problem-solving strategies that differ between pre- and post-change task environments. In doing so, it might be worthwhile to model the effects of specific self-regulation processes in relation to different types of adaptation requirements (Jundt et al., 2015).

Limitations and Future Directions

There are several limitations to be considered while interpreting and generalizing these findings. First, the performance task used in this study differs from those typically encountered in procedural learning environments. UT2004 is a dynamic, fast-paced task involving cognitive and psychomotor demands, which contrasts with classroom-based, instructional settings. Aside from initial training on basic elements, participants learned UT2004 without explicit instructions or guidance. This is representative of technology-based, active-learning environments in which learners are required to develop their own self-regulatory strategies (Bell & Kozlowski, 2008). However, this can also induce stress and high workload perceptions. Given that participants performed for several hours with little time between sessions, there was also little opportunity for reflection (cf. Yang, Zhang, & Yang, 2017). This study contributed toward an understanding of how people learn complex tasks in a dynamic, fast-paced environment, yet more research is needed to generalize across diverse populations and contexts.

Consideration of the task environment is especially important for understanding self-regulated learning, especially given how the present results contradicted those of Yeo et al. (2009). Both UT2004 and air traffic control are complex tasks, yet the former, which was used in the present study, involves greater perceptual-motor demands in a fast-paced environment. One explanation for the lack of within-person GO effects observed in the present study is that UT2004 skills are acquired via a higher ratio of implicit to explicit learning. Research on complex skill acquisition has shown that training design elements, like goal setting, that trigger explicit self-regulatory processes can have negligible or detrimental effects on learning for tasks that better lend themselves to implicit learning (DeShon & Alexander, 1996; DeShon, Brown, & Greenis, 1996). The extent to which within-person GO effects are dependent upon task demands that relate to the implicit-explicit learning distinction is an issue worth future investigation. For instance, it is unclear if within-person fluctuations in GO compete for individuals' limited pool of attentional resources.

Related to the implicit-explicit learning distinction, under conditions of uncertainty, research has shown that heuristic strategies are often superior to explicit processing of optimal decisions (Cokely & Kelley, 2009). Numeracy, defined as the ability to use mathematics in context, is among the best predictors of decision making under uncertainty (Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012; Cokely et al., 2018). Having an intuitive sense of probability and numerical operations is thought to translate into better metacognition. That is, highly numerate learners are better able to discern performance outcomes associated with different decisions and make accurate judgments of confidence (Ghazal, Cokely, & Garcia-Retamero, 2014). As such, it may be that individual differences in numeracy serve as a boundary condition for the effects of motivational aspects of self-regulation like goal setting or GO, especially with respect to the uncertainty in deciding which performance strategies should be abandoned or modified when facing unexpected changes in task demands.

Because this research was in part a replication of Yeo et al. (2009), I adapted the GO measure used in the original study. This strengthens comparisons between Yeo et al. (2009) and the present replication, but neglects recent work on developing more precise measures of GO. Hulleman et al.'s (2010) meta-analysis of GO measures found that relationships between GO and other variables are substantially influenced by item content. For example, measures of performance GO tend to conflate social comparison (e.g., outperforming others) with social validation (e.g., appearing competent to others) motives. Whether PAp is positively or negatively related to performance has been attributed to the relative number of items corresponding to each of these components (Hulleman et al., 2010). Indeed, the PAp measure used in this study contained items tapping social comparison (i.e., *"It is important for me to perform better at this game than others,"*) and social validation (i.e., *"I want others to recognize that I am one of the best at this game."*). Between the MAp and PAv measures, each pair of items were consistent, corresponding to self-improvement (e.g., *"The opportunity to extend the* *range of my abilities during this game is important to me*,") and social validation (e.g., "*I prefer to avoid discovering that others are better than me at this game,*") respectively.

This echoes a broader set of concerns about defining GO and its role among other motivational constructs (DeShon & Gillespie, 2005). Definitions have varied substantially across studies, with scholars referring to GO as goals, reasons, beliefs, or combinations of these (Senko & Tropiano, 2016; Sommet & Elliot, 2017). Adopting the perspective of industrial-organizational psychology, the present study viewed GO as "goal preferences in achievement situations," (Payne et al., 2007, p. 128), which encompass a variety of specific goals (DeShon & Gillespie, 2005). One explanation for the lack within-person GO effects is the higher-order nature of the construct. The 2 × 2 framework effectively categorizes achievement goals into dimensions, but understanding the dynamic, self-regulatory nature of GO may require further unpacking (Elliot, Murayama, & Pekrun, 2011). One approach has been to decompose GO into specific goals and reasons (e.g., "my goal is to learn *because* I find this a challenging goal;" Sommet & Elliot, 2017, p. 1143). Future research ought to investigate the effects of achievement goals when the reasons for pursuing them are intrinsically or extrinsically motivated.

Practical Implications

Despite a lack of support for most hypotheses, these results have implications for training and development in organizations. Individuals working in dynamic environments are likely to benefit from higher MAp and lower PAv, which focuses attention on learning and diverts it from worries about performance relative to others.

PAp is also potentially beneficial, but research suggests that its utility is small compared to MAp (e.g., Brophy, 2005). GO dimensions are indeed malleable (Van Yperen, Blaga, & Postmes, 2015). Practitioners ought to include design elements in training that encourage MAp and discourage PAv. Facilitating GO adoption can be accomplished by prompting self-regulation (e.g., "*Have I spent enough time reviewing to remember the information?*") or setting goals that correspond to desired GO dimensions (Sitzmann & Ely, 2010). In the latter case, it would be important to ensure that goal content is aligned with goal framing and proximity (see Kozlowski & Bell, 2006).

These recommendations are more straightforward than what has previously been suggested in research on active learning, which often assumes technology-based training interventions in which learners' cognitive and motivational states are continuously tracked and manipulated (e.g., Bell & Kozlowski, 2002). If GO states have differential effects on learning throughout the training process, then models could be used to "optimize" goal setting interventions. However, the lack of within-person and dynamic effects in the present study suggests that GO effects are relatively stable across skill acquisition and adaptation. In contrast to prior recommendations to adopt hands-on approaches for optimizing goal interventions across time (e.g., Yeo et al., 2009), consistent endorsement of MAp and discouragement of PAv might be more effective. Further research is required to understand the extent to which GO effects are present under varying task conditions. Until the nuances of self-regulation are better understood, managers ought to be cautious about "pulling the right levers at the right time" (Hackman, 2012, p. 434). Encouraging individuals to achieve mastery and worry less about interpersonal comparison during training can be simple, yet robust means of improving performance.

Conclusion

In summary, this study disentangled the within- and between-person effects of GO on complex skill acquisition and adaptation to unforeseen change. Results indicated that momentary fluctuations in GO are unlikely to correspond to performance dynamics. Rather, GO effects on performance occur primarily at the between-person level. Individuals maintaining higher levels of MAp and PAp tend to perform better, whereas those with higher levels of PAv tend to perform worse. Furthermore, GO effects appear to be consistent whether an individual is learning initially or adapting pre-existing knowledge and skill to unforeseen changes in task demand. Future studies ought to investigate possible moderators of these relationships and elaborate on the multilevel nature of self-regulation. This research provides insight into the self-regulatory processes that facilitate learning in dynamic environments.

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Appendix A: Tables

Table 1

Coding of Change Variables in Discontinuous Multilevel Growth Models

Change variable	Pre-change							Post-change						
Session	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Skill acquisition (SA)	0	1	2	3	4	5	6	7	8	9	10	11	12	13
Quadratic skill acquisition (SA^2)	0	1	4	9	16	25	36	36	36	36	36	36	36	36
Transition adaptation (TA)	0	0	0	0	0	0	0	1	1	1	1	1	1	1
Reacquisition adaptation (RA)	0	0	0	0	0	0	0	0	1	2	3	4	5	6

Note. Relative coding scheme and its alternatives are described in Bliese and Lang (2016).

Table 2

Means, Standard Deviations, and Correlations of Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7
Between-person level									
1. Gender[1]	0.34	0.47	—						
2. General mental ability[2]	26.91	4.25	$-.21^{**}$	—					
3. Videogame experience[3]	0.08	1.02	$-.54^{**}$	$.20^{**}$	.86				
4. MAp	4.47	1.38	$-.21^{**}$	$.15^{*}$	$.24^{**}$	—			
5. MAv	4.01	1.38	$-.14^{*}$	$.20^{**}$	$.21^{**}$	$.58^{**}$	—		
6. PAp	3.38	1.65	$-.34^{**}$	.08	$.35^{**}$	$.57^{**}$	$.31^{**}$	—	
7. PAv	2.55	1.24	.04	–.01	–.08	$.12^{\dagger}$	$.13^{*}$	$.29^{**}$	—
8. Performance	33.83	16.87	$-.66^{**}$	$.31^{**}$	$.69^{**}$	$.35^{**}$	$.30^{**}$	$.38^{**}$	$-.16^{*}$

Variable	ICC	*M*	*SD*	1	2	3	4
Within-person level							
1. MAp	.58	4.47	1.00				
2. MAv	.53	4.01	1.10	$.51^{**}$			
3. PAp	.71	3.38	0.88	$.53^{**}$	$.28^{**}$		
4. PAv	.67	2.55	0.71	$.16^{**}$	$.14^{**}$	$.30^{**}$	
5. Performance[4]	.71	33.83	10.11	$.26^{**}$	$.20^{**}$	$.30^{**}$	$-.11^{**}$

Note. Diagonals are standardized Cronbach's alphas. MAp = mastery-approach; MAv = mastery-avoidance; PAp = performance-approach; PAv = performance-avoidance. [1] Gender was coded as a binary variable where Male = 0 and Female = 1. [2] Self-reported ACT scores were used as a proxy of general mental ability. [3] Videogame experience was a standardized composite index.

† $p < .10$, * $p < .05$, ** $p < .01$.

Table 3

Discontinuous Mixed-Effects Growth Models of Mastery Goal Orientation Trajectories

	Mastery-approach				Mastery-avoidance			
	Coef.	*SE*	*t*	Std. coef.	Coef.	*SE*	*t*	Std. coef.
Fixed effects								
Intercept	5.05	.09	53.84**		4.00	.10	40.84**	
Skill acquisition (SA)	–0.10	.02	–5.50**	–.22	0.02	.02	1.25	.05
Transition adaptation (TA)	0.00	.07	0.01	.00	0.00	.08	–0.05	.00
Reacquisition adaptation (RA)	0.03	.03	1.18	.04	–0.10	.03	–3.54**	–.11

			Correlations					Correlations		
	Variance	*SD*	1	2	3	Variance	*SD*	1	2	3
Random effects										
1. Intercept	1.53	1.24				1.91	1.38			
2. Skill acquisition	0.05	0.23	–.19			0.06	0.24	–.34		
3. Transition adaptation	0.51	0.71	.02	–.61		0.40	0.63	–.18	–.40	
4. Reacquisition adaptation	0.13	0.36	.09	–.83	.63	0.11	0.33	.29	–.87	.41
Residual	0.72	0.85				1.12	1.06			

Note. SA represents the linear trajectory of GO preceding the task manipulation, TA represents the immediate change in GO following the task manipulation, and RA represents the linear trajectory of GO following the task manipulation. $N = 253$. $k = 3542$. $df = 3286$.
** $p < .01$.

Table 4

Discontinuous Mixed-Effects Growth Models of Performance Goal Orientation Trajectories

	Performance-approach				Performance-avoidance			
	Coef.	*SE*	*t*	Std. coef.	Coef.	*SE*	*t*	Std. coef.
Fixed effects								
Intercept	4.05	.10	39.13**		2.72	.08	33.66**	
Skill acquisition (SA)	–0.13	.02	–7.62**	–.27	–0.03	.01	–2.29*	–.08
Transition adaptation (TA)	0.09	.06	1.49	.02	0.00	.06	0.05	.00
Reacquisition adaptation (RA)	0.09	.02	4.02**	.10	0.02	.02	0.84	.02

			Correlations					Correlations		
	Variance	*SD*	1	2	3	Variance	*SD*	1	2	3
Random effects										
1. Intercept	2.47	1.57				1.41	1.19			
2. Skill acquisition	0.06	0.24	–.14			0.03	0.16	–.08		
3. Transition adaptation	0.38	0.62	–.18	–.58		0.22	0.47	–.15	–.73	
4. Reacquisition adaptation	0.10	0.31	–.04	–.81	.52	0.05	0.22	–.12	–.79	.67
Residual	0.51	0.71				0.52	0.72			

Note. SA represents the linear trajectory of GO preceding the task manipulation, TA represents the immediate change in GO following the task manipulation, and RA represents the linear trajectory of GO following the task manipulation. $N = 253$, $k = 3542$, $df = 3286$.

$^{*} p < .05$, $^{**} p < .01$.

Table 5

Discontinuous Mixed-Effects Growth Models of Performance Trajectories

	Unconditional Model				Conditional Model			
	Coef.	*SE*	*t*	Std. coef.	Coef.	*SE*	*t*	Std. coef.
Fixed effects								
Level 1								
Intercept	28.78	1.14	25.32^{**a}		33.42	0.99	33.92^{**b}	
Skill acquisition (SA)	5.22	0.35	14.76^{**a}	1.07	5.40	0.37	14.68^{**b}	1.07
Quadratic skill acquisition (SA^2)	–0.53	0.06	-9.60^{**a}	–0.39	–0.53	0.06	-9.61^{**b}	–0.39
Transition adaptation (TA)	–17.91	0.80	-22.36^{**a}	–0.45	–19.94	0.99	-20.18^{**b}	–0.45
Reacquisition adaptation (RA)	–4.64	0.41	-12.34^{**a}	–0.49	–4.71	0.40	-11.64^{**b}	–0.49
Level 2								
Gender					–13.81	1.82	-7.57^{**c}	–0.33
General mental ability (GMA)					0.58	0.17	3.33^{**c}	0.11
Videogame experience (VGE)					7.61	0.85	8.97^{**c}	0.39
SA × Gender					–0.54	0.31	-1.74^{b}	–0.05
TA × Gender					6.05	1.90	3.18^{**b}	0.07
RA × Gender					0.21	0.45	0.46^{b}	0.01
SA × GMA					–0.02	0.03	-0.62^{b}	–0.01
TA × GMA					0.03	0.18	0.17^{b}	0.00
RA × GMA					0.03	0.04	0.72^{b}	0.01
SA × VGE					0.23	0.14	1.64^{b}	0.05
TA × VGE					–2.27	0.89	-2.57^{*b}	–0.06
RA × VGE					–0.32	0.21	-1.57^{b}	–0.03

			Correlations					Correlations		
	Variance	*SD*	1	2	3	Variance	*SD*	1	2	3
Random effects										
1. Intercept	227.50	16.66				101.49	10.07			
2. Skill acquisition	1.61	1.27	.29			1.61	1.27	.05		
3. Transition adaptation	85.14	9.23	–.61	–.77		69.06	8.31	–.40	–.75	
4. Reacquisition adaptation	3.38	1.84	–.06	–.72	.57	3.38	1.84	.15	-.72	.58
Residual	64.74	8.05				64.74	8.05			

Note. $N = 253$, $k = 3542$.
[a] $df = 3285$, [b] $df = 3276$, [c] $df = 249$.
* $p < .05$, ** $p < .01$.

Table 6

Discontinuous Mixed-Effects Growth Models of Mastery-approach Goal Orientation and Performance

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Level 1								
Intercept	33.60^{**a}	0.97	33.64^{**c}	0.98	33.43^{**c}	0.98	33.57^{**e}	0.98
Skill acquisition (SA)	5.22^{**a}	0.35	5.21^{**c}	0.36	5.23^{**c}	0.36	5.20^{**e}	0.37
Quadratic skill acquisition (SA^2)	–0.53^{**a}	0.06	–0.53^{**c}	0.06	–0.53^{**c}	0.06	–0.53^{**e}	0.06
Transition adaptation (TA)	–18.99^{**a}	0.86	–19.02^{**c}	0.87	–19.06^{**c}	0.87	–19.08^{**e}	0.87
Reacquisition adaptation (RA)	–4.63^{**a}	0.38	–4.59^{**c}	0.39	–4.61^{**c}	0.39	–4.58^{**e}	0.39
Mastery-approach (MAp)	0.05 ^{a}	0.15	–0.03 ^{c}	0.37	0.09 ^{c}	0.38	–0.11 ^{e}	0.39
SA × MAp			0.02 ^{c}	0.11	–0.01 ^{c}	0.11	0.11 ^{e}	0.09
TA × MAp			–0.25 ^{c}	0.63	–0.27 ^{c}	0.63	–0.09 ^{e}	0.56
RA × MAp			0.07 ^{c}	0.15	0.11 ^{c}	0.15	0.03 ^{e}	0.13
Level 2								
Gender	–14.42^{**b}	1.73	–14.42^{**b}	1.73	–13.98^{**d}	1.172	–14.09^{**d}	1.72
General mental ability	0.52^{**b}	0.15	0.52^{**b}	0.15	0.47^{**d}	0.15	0.47^{**d}	0.15
Videogame experience	8.08^{**b}	0.81	8.08^{**b}	0.81	7.67^{**d}	0.80	7.79^{**d}	0.81
TA × Gender	3.21^{**a}	1.22	3.18^{**c}	1.23	3.18^{**c}	1.22	3.35^{**e}	1.13
TA × Videogame experience	–1.40* ^{a}	0.57	–1.41* ^{c}	0.57	–1.41* ^{c}	0.57	–1.57^{**e}	0.58
Average MAp					1.76^{**d}	0.45	1.26* ^{d}	0.55
SA × Average MAp							0.11 ^{e}	0.09
TA × Average MAp							–0.09 ^{e}	0.56
RA × Average MAp							0.03 ^{e}	0.13

Note. $N = 253$. $k = 3542$.

^{a} $df = 3282$, ^{b} $df = 249$, ^{c} $df = 3279$, ^{d} $df = 248$, ^{e} $df = 3276$.

* $p < .05$, ** $p < .01$.

Table 7

Discontinuous Mixed-Effects Growth Models of Performance-approach Goal Orientation and Performance

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Level 1								
Intercept	33.64^{**a}	0.98	33.71^{**c}	1.03	33.45^{**c}	1.01	33.64^{**e}	1.01
Skill acquisition (SA)	5.22^{**a}	0.36	5.23^{**c}	0.38	5.25^{**c}	0.39	5.18^{**e}	0.39
Quadratic skill acquisition (SA^2)	–0.53^{**a}	0.06	–0.53^{**c}	0.06	–0.54^{**c}	0.06	–0.53^{**e}	0.06
Transition adaptation (TA)	–18.98^{**a}	0.86	–19.07^{**c}	0.88	–19.10^{*c}	0.88	–19.13^{**e}	0.88
Reacquisition adaptation (RA)	–4.63^{**a}	0.38	–4.55^{**c}	0.41	–4.57^{**c}	0.41	–4.50^{**e}	0.41
Performance-approach (PAp)	–0.02^{a}	0.18	–0.13^{c}	0.35	–0.07^{c}	0.36	–0.25^{e}	0.37
SA × PAp			–0.07^{c}	0.11	–0.09^{c}	0.11	–0.05^{e}	0.11
TA × PAp			0.01^{c}	0.74	–0.02^{c}	0.74	–0.05^{e}	0.75
RA × PAp			0.41^{*c}	0.17	0.43^{*c}	0.17	0.40^{*e}	0.17
Level 2								
Gender	–14.41^{**b}	1.73	–14.37^{**b}	1.73	–13.73^{**d}	1.76	–13.90^{**d}	1.76
General mental ability	0.52^{**b}	0.15	0.52^{**b}	0.15	0.53^{**d}	0.15	0.52^{**d}	0.15
Videogame experience	8.08^{**b}	0.81	8.10^{**b}	0.81	7.76^{**d}	0.82	7.87^{**d}	0.82
TA × Gender	3.20^{**a}	1.23	3.13^{*c}	1.22	3.13^{*c}	1.22	3.40^{*e}	1.25
TA × Videogame experience	–1.40^{*a}	0.57	–1.43^{*c}	0.57	–1.43^{*c}	0.57	–1.40^{*e}	0.57
Average PAp					0.88^{*d}	0.40	0.48^{d}	0.48
SA × Average PAp							0.13^{e}	0.08
TA × Average PAp							–0.31^{e}	0.48
RA × Average PAp							–0.04^{e}	0.10

Note. $N = 253$. $k = 3542$.

^{a} $df = 3282$, ^{b} $df = 249$, ^{c} $df = 3279$, ^{d} $df = 248$, ^{e} $df = 3276$.

* $p < .05$, ** $p < .01$.

Table 8

Discontinuous Mixed-Effects Growth Models of Performance-avoidance Goal Orientation and Performance

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Level 1								
Intercept	33.62^{**a}	0.97	33.57^{**c}	0.97	33.58^{**c}	0.95	33.59^{**e}	0.95
Skill acquisition (SA)	5.22^{**a}	0.35	5.26^{**c}	0.36	5.25^{**c}	0.36	5.25^{**e}	0.36
Quadratic skill acquisition (SA^2)	–0.53^{**a}	0.06	–0.53^{**c}	0.06	–0.53^{**c}	0.06	–0.53^{**e}	0.06
Transition adaptation (TA)	–18.98^{**a}	0.86	–19.03^{**c}	0.87	–19.02^{**c}	0.87	–19.02^{**e}	0.87
Reacquisition adaptation (RA)	–4.64^{**a}	0.38	–4.66^{**c}	0.38	–4.66^{**c}	0.38	–4.66^{**e}	0.38
Performance-avoidance (PAv)	0.03^{a}	0.19	0.35^{c}	0.43	0.29^{c}	0.44	0.23^{e}	0.44
SA × PAv			–0.12^{c}	0.13	–0.11^{c}	0.13	–0.09^{e}	0.13
TA × PAv			0.35^{c}	0.80	0.34^{c}	0.80	0.24^{e}	0.80
RA × PAv			0.18^{c}	0.19	0.17^{c}	0.19	0.14^{e}	0.19
Level 2								
Gender	–14.42^{**b}	1.73	–14.45^{**b}	1.73	–14.41^{**d}	1.72	–14.44^{**d}	1.70
General mental ability	0.52^{**b}	0.15	0.52^{**b}	0.15	0.53^{**d}	0.15	0.53^{**d}	0.15
Videogame experience	8.08^{**b}	0.81	8.09^{**b}	0.80	7.95^{**d}	0.79	7.90^{**d}	0.79
TA × Gender	3.20^{**a}	1.23	3.22^{**c}	1.23	3.22^{**c}	1.22	3.22^{**e}	1.23
TA × Videogame experience	–1.40^{*a}	0.57	–1.40^{*c}	0.57	–1.41^{*c}	0.57	–1.47^{*e}	0.58
Average PAv					–1.31^{**d}	0.49	–1.85^{**d}	0.58
SA × Average PAv							0.00^{e}	0.10
TA × Average PAv							0.92^{e}	0.61
RA × Average PAv							–0.07^{e}	0.14

Note. $N = 253$. $k = 3542$.

[a] $df = 3282$, [b] $df = 249$, [c] $df = 3279$, [d] $df = 248$, [e] $df = 3276$.

$^{*}p < .05$, $^{**}p < .01$.

Table 9

Discontinuous Mixed-Effects Growth Models of Mastery-avoidance Goal Orientation and Performance

	Model 1		Model 2		Model 3		Model 4	
	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Level 1								
Intercept	33.60** [a]	0.97	33.65** [c]	0.97	33.64** [c]	0.96	33.65** [e]	0.96
Skill acquisition (SA)	5.25** [a]	0.35	5.22** [c]	0.36	5.21** [c]	0.36	5.22** [e]	0.36
Quadratic skill acquisition (SA^2)	–0.53** [a]	0.06	–0.53** [c]	0.06	–0.53** [c]	0.06	–0.53** [e]	0.06
Transition adaptation (TA)	–18.98** [a]	0.86	–18.98** [c]	0.87	–18.97** [c]	0.87	–18.98** [e]	0.87
Reacquisition adaptation (RA)	–4.67** [a]	0.38	–4.59** [c]	0.38	–4.63** [c]	0.38	–4.64** [e]	0.38
Mastery-avoidance (MAv)	–0.11 [a]	0.12	0.12 [c]	0.30	0.17 [c]	0.29	0.15 [e]	0.30
SA × MAv			–0.09 [c]	0.09	–0.10 [c]	0.09	–0.09 [e]	0.09
TA × MAv			0.16 [c]	0.54	0.16 [c]	0.54	0.17 [e]	0.54
RA × MAv			0.18 [c]	0.13	0.20 [c]	0.13	0.18 [e]	0.13
Level 2								
Gender	–14.40** [b]	1.73	–14.43** [b]	1.73	–14.41** [d]	1.72	–14.42** [d]	1.72
General mental ability	0.52** [b]	0.15	0.52** [b]	0.15	0.45** [d]	0.15	0.45** [d]	0.15
Videogame experience	8.08** [b]	0.81	8.09** [b]	0.81	7.76** [d]	0.81	7.80** [d]	0.81
TA × Gender	3.18** [a]	1.23	3.18** [c]	1.23	3.19** [c]	0.46	3.21** [e]	1.23
TA × Videogame experience	–1.40* [a]	0.57	–1.41* [c]	0.57	–1.41* [c]	0.57	–1.47* [e]	0.58
Average MAv					1.36** [d]	0.46	1.38* [d]	0.54
SA × Average MAv							0.00 [e]	0.09
TA × Average MAv							–0.14 [e]	0.56
RA × Average MAv							0.23† [e]	0.13

Note. $N = 253$. $k = 3542$.

[a] $df = 3282$, [b] $df = 249$, [c] $df = 3279$, [d] $df = 248$, [e] $df = 3276$.

† $p < .10$, * $p < .05$, ** $p < .01$.

Table 10

Ancillary Analysis of Multiple Goal Orientations and Performance at the Between-person Level

	Mastery			Performance			All		
	Coef.	*SE*	*t*	Coef.	*SE*	*t*	Coef.	*SE*	*t*
Level 1									
Intercept	33.50	0.96	35.01** a	33.27	0.93	34.26** a	33.33	0.93	34.34** a
Skill acquisition (SA)	5.22	0.35	14.77** a	5.22	0.35	14.77** a	5.22	0.35	14.77** a
Quadratic skill acquisition (SA^2)	–0.53	0.06	–9.60** a	–0.53	0.06	–9.60** a	–0.53	0.06	–9.60** a
Transition adaptation (TA)	–18.98	0.86	–21.96** a	–18.98	0.86	–21.96** a	–18.98	0.86	–21.96** a
Reacquisition adaptation (RA)	–4.64	0.38	–12.34** a	–4.64	0.38	–12.34** a	–4.64	0.38	–12.34** a
Level 2									
Gender	–14.04	1.72	–8.18** b	–13.35	1.69	–7.83** b	–13.56	1.69	–8.03** c
General mental ability	0.45	0.15	3.04** b	0.54	0.14	3.74** b	0.46	0.14	3.18** c
Videogame experience	7.62	0.80	9.46** b	7.33	0.80	9.17** b	7.15	0.80	8.99** c
TA × Gender	3.20	1.22	2.61** a	3.20	1.22	2.61** a	3.20	1.22	2.61** a
TA × Videogame experience	–1.40	0.57	–2.45* a	–1.40	0.57	–2.45* a	–1.40	0.57	–2.45* a
Mastery-approach	1.44	0.54	2.66** b				1.11	0.60	1.85† c
Mastery-avoidance	0.55	0.54	1.01 b				0.79	0.53	1.48 c
Performance-approach				1.42	0.42	3.40** b	0.74	0.48	1.53 c
Performance-avoidance				–1.94	0.52	–3.77** b	–1.94	0.51	–3.81** c

Note. $N = 253$. $k = 3542$.
[a] $df = 3283$, [b] $df = 247$, [c] $df = 245$.
† $p < .10$, * $p < .05$, ** $p < .01$.

Appendix B: Figures

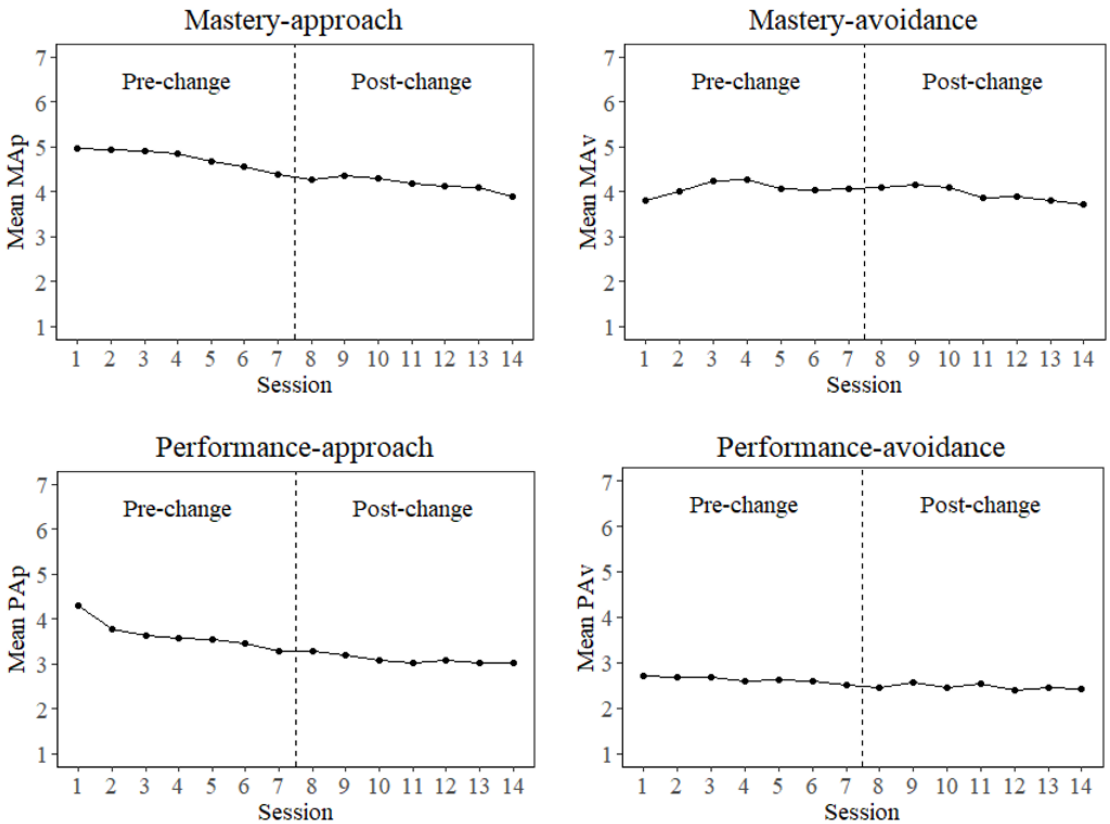

Figure 1. Trends in average levels of goal orientation
(1-7 = pre-change; 8-14 = post-change). MAp = mastery-approach; MAv = mastery avoidance; PAp = performance-approach; PAv = performance-avoidance.

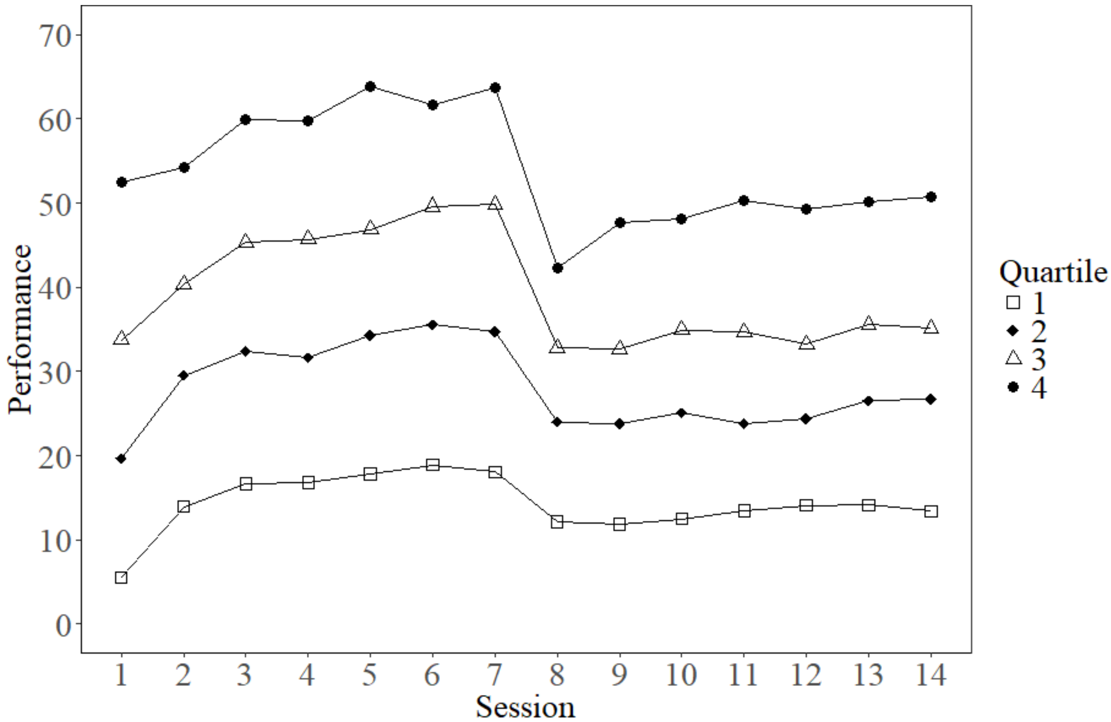

Figure 2. Performance means across sessions for each quartile of session 1 performance