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DISENTANGLING SELF-REGULATION AND PERFORMANCE IN ACTIVE
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SKILL ACQUISITION

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Abstract

Self-regulation is central to many modern theories of training and development, including active-learning theory. However, research in this area often overlooks the role of behavior in self-regulated learning and fails to account for dynamics in the learning process. Using a laboratory study designed to address these limitations, I found that behavioral self-regulation (i.e., exploratory behavior) positively predicted learning and performance outcomes beyond the effects of cognitive and motivational self-regulatory processes (i.e., metacognition and self-efficacy). However, contrary to my predictions, exploration-encouragement instructions did not significantly influence learner exploratory behavior. Regarding self-regulation-performance relationships, I found that the exploration-performance, metacognition-performance, and self-efficacy-performance relationships were all reciprocal in nature. Specifically, lagged exploratory behavior and lagged metacognition were positively related to performance, whereas lagged self-efficacy was negatively related to performance. Performance-to-self-regulation feedback effects were found as well, such that lagged performance was positively related to self-efficacy and metacognition, but was negatively related to exploratory behavior. The interrelationships among behavioral and cognitive/motivational self-regulatory processes were also reciprocal. Specifically, lagged exploratory behavior was positively related to subsequent self-efficacy and metacognition, but lagged self-efficacy and metacognition were negatively related to exploration. Collectively, these findings (a) make a case for including behavioral constructs in models of self-regulated learning and (b) demonstrate that within-person interrelationships among self-regulated learning processes and performance are

dynamic, and are often more complex than was previously thought. Results are discussed regarding implications for theory, research, and practice in active learning.

Introduction

One of the keys to effective functioning in modern society is the ability to maximize long-term interests by controlling impulses and focusing attention and behavior where it is most needed. As such, the ability to engage in effective *self-regulation*, defined as a set of processes that “enable an individual to guide goal directed activities over time and across changing circumstances” through the “modulation of thought, affect, behavior or attention” (Karoly, 1993, p. 25), may be a person’s most essential asset (Porath & Bateman, 2006). Efficient allocation of resources is particularly important for learning difficult and complex tasks (Kozlowski et al., 2001). As a result, *self-regulated learning*, defined as the “modulation of affective, cognitive, and behavioral processes throughout a learning experience to reach a desired level of achievement” (Sitzmann & Ely, 2011, p. 421) is a central component in many modern theories of adult learning and development. Over the last 30 years, self-regulated learning has been one of the most heavily researched topics in the training and development literature (Sitzmann & Ely, 2011), although scholarly interest in the topic goes back much further (Zimmerman, 1986).

Nevertheless, many important gaps in our understanding of how adults regulate their learning remain. For instance, scholars have only recently begun to measure multiple regulatory processes simultaneously when studying self-regulated learning (e.g., Bell & Kozlowski, 2008; Keith & Frese, 2005; Sitzmann & Ely, 2011). Given that meta-analytic findings have established that many self-regulated learning constructs are highly intercorrelated (Sitzmann & Ely, 2011), more work is needed to disentangle the nature of these interrelationships and their implications for the learning process.

Another limitation of this literature is that important behavioral self-regulatory processes are often overlooked in favor of a greater focus on cognitive, motivational, and emotional self-regulation (Hardy, Day, Hughes, Wang, & Schuelke, 2014). Although behavior is recognized as a fundamental self-regulatory process in definitions and models of self-regulated learning (e.g., Kozlowski et al., 2001; Sitzmann & Ely, 2011), researchers often neglect to examine it as such. This tendency limits the theoretical and practical applications of available research for addressing common criticisms of learner-guided training (Hardy et al., 2014). Finally, self-regulation is, by definition, a dynamic, within-person phenomenon (Lord, Diefendorff, Schmidt, & Hall, 2010; Vancouver, Weinhardt, & Vigo, 2014; Yeo & Neal, 2013). However, the majority of research on self-regulation fails to disentangle within- from between-person effects (Lord et al., 2010). Consequentially, little is known about dynamics in the relationships between self-regulatory processes and performance or among cognitive/motivational self-regulatory processes and behavioral self-regulation.

The purpose of the current study is to address these gaps in the self-regulated learning literature in pursuit of four primary research goals. To start, I seek to bolster the case for including behavioral self-regulation in research on active learning. Specifically, I focus on the role of *exploratory behavior*, defined as an active interaction on the part of the trainee with the training environment through attempts at multiple solutions to the problem at hand (Dormann & Frese, 1994). Although a study by Hardy et al. (2014) found that exploratory behavior was positively related to complex skill acquisition, no empirical research has yet examined the extent to which exploratory behavior can predict learning outcomes above established cognitive and motivational

self-regulated learning processes. Identifying key mechanisms in learning contexts carries important implications for the design of active-learning training. Furthermore, demonstrating that exploratory behavior is not simply a byproduct of—or distal antecedent to—established self-regulatory constructs is important for justifying research focusing on exploration’s unique contribution to learning. Accordingly, my first research goal is to examine the incremental validity of exploration relative to cognitive (i.e., metacognition) and motivational (i.e., self-efficacy) self-regulatory processes on proximal and distal learning outcomes. I focus primarily on self-efficacy and metacognition in the present study over possible alternatives (e.g., emotion control, effort, etc.) because (1) they are the two most frequently examined and well established constructs in the self-regulated learning literature and (2) both are strongly related to a wide range of other self-regulatory constructs (Sitzmann & Ely, 2011).

My second research goal is to examine the effect of exploration-encouragement instructions on exploratory behavior in active learning. Many active-learning training interventions assume that instructional design elements boost learner exploration. However, researchers rarely isolate the effect of training design on learner behavioral mechanisms. Examining how training design elements directly influence behavioral self-regulated learning processes provides information that can be used to modify existing training to meet the needs of learners and to adapt existing principles to other areas (Keith & Frese, 2005). Along these lines, I seek to (a) examine if simple, exploration-encouragement instructions influence learner exploratory behavior and (b) test if intervention effects are dependent on learner capability.

My third and fourth goals, respectively, are to address questions of directionality in (a) the relationships between performance and self-regulated learning and (b) the interrelationships among behavioral and cognitive/motivational self-regulation. By combining repeated measurements of self-regulated learning processes over a series of performance sessions with cross-lagged analyses designed to tease apart directional effects, I hope to lay the foundation for a process model of complex skill acquisition. Addressing the dynamic nature of self-regulated learning is important for clarifying the role of self-regulation in active learning and for identifying where guidance may offer the greatest potential benefit.

Toward these ends, I conducted a laboratory study in which participants underwent approximately 3 hours of training on a first-person-shooter computer game that involves both cognitive and psychomotor demands. Trainees received either exploration-encouragement or control instructions prior to and during the practice phase. Exploration was then measured by independent raters who coded behaviors representing different aspects of exploration observed in video playbacks of practice trials. Self-efficacy and metacognition were measured via repeated administrations of self-report scales before and after each practice session. Learning outcomes included practice performance, task knowledge, analogical transfer performance, adaptive transfer performance, and task enjoyment. In the sections that follow, I review my rationale guiding the development of each hypothesis, which are encompassed by the four research goals.

The Incremental Predictive Validity of Exploratory Behavior in Active Learning

Founded in the constructivist vision, active-learning approaches conceptualize training as an inductive, learner-driven process that facilitates a deeper understanding of task rules, principles, and strategies through individual exploration (Bell & Kozlowski, 2010). As such, the success of active-learning training requires that instructional design elements positively influence exploratory behavior and that learner exploration, in turn, positively influences learning and performance outcomes. Although theorists have long acknowledged the value of exploration in the learning process (Berlyne, 1960, 1966; Bruner, 1961; Greif & Keller, 1990), researchers often operationalize it as a core training design element rather than as a behavioral process (for a review, see Bell & Kozlowski, 2008). As a result, exploration is often studied as a distal construct with effects on learning outcomes that are assumed to be mediated by more proximal mechanisms such as metacognition (Ford & Kraiger, 1995; Frese, Albrecht, Altmann, & Lang, 1988), intrinsic motivation (Debowski, Wood, & Bandura, 2001), or willingness to make errors (Keith & Frese, 2005). From this perspective, one might argue that a direct focus on the role of exploratory behavior in active learning is unnecessary, as its positive influence on learning outcomes can be accounted for by cognitive and motivational self-regulation. In fact, apart from its positive influence on learner cognition, some researchers regard learner-initiated exploratory behavior as a nuisance that contributes to inefficiencies in the learning process (Bell & Kozlowski, 2002; Debowski et al., 2001; Mayer, 2004).

Clearly cognitive, motivational, and emotional self-regulatory processes are important in active-learning training and in the learning process in general (Bell &

Kozlowski, 2008, 2010; Sitzmann & Ely, 2011). As such, there is a relatively well-developed empirical literature on these topics (e.g., Brown & Ford, 2002; DeBowski et al., 2001; Keith & Frese, 2005). In contrast, very few studies included in Sitzmann and Ely's (2011) meta-analysis of self-regulated learning directly measured learner behavior. As a result of this lack of research attention, the role of behavior in the learning process remains poorly understood. In a study designed to address these limitations, Hardy et al. (2014) found that exploratory behavior directly benefited learning outcomes in complex task learning. Specifically, learner exploration incrementally predicted proximal performance and post-practice knowledge, performance, and adaptability outcomes beyond the influence of general mental ability (GMA) and pre-training task-related knowledge. These findings support the notion that trainee exploration operates as a systematic self-regulated learning process and suggest that it should be operationalized as such. However, neither cognitive nor motivational self-regulation was measured in Hardy et al.'s study. Accordingly, their findings cannot speak to the value of exploratory behavior relative to the contributions of established cognitive and motivational self-regulation constructs. Accordingly, in the present study, I seek to build upon and extend this research by measuring exploratory behavior directly in relation to other self-regulated learning processes in an effort to (a) better understand its unique role in self-regulated learning and (b) pinpoint how to leverage specific training elements and eliminate those that are redundant or detrimental to learning.

Active learning theory suggests that exploration should affect learning outcomes through relationships with cognitive and self-regulatory processes. Indeed, it is difficult

for one to be truly engaged in active learning without first exploring. Along these lines, Kozlowski et al. (2001) noted that “doing, thinking, and feeling all affect each other” and that “all three are engaged concurrently, such that whenever a trainee has an experience which stimulates her to practice more, she will simultaneously become more cognizant about her practice behaviors” (p. 94). When training is designed to encourage individuals to engage in various cognitive, motivation, and emotion-based self-regulation during practice, it is expected that many benefits of these processes can be attributed to some change in behavior (Kozlowski et al., 2001). However, I argue that exploration also has a direct influence on learning outcomes. Specifically, curiosity theory (Berlyne, 1966; Loewenstein, 1994) suggests that exploration provides learners with the opportunity to engage and resolve novelty (Harrison, 2012), which directly helps increase one’s effectiveness in interacting with the environment (White, 1959). Given this central role in the learning process, I expected that exploratory behavior would provide incremental predictive validity beyond the effects of metacognition and self-efficacy. A focus on exploration can provide insights into the mechanisms of adult learning by drawing attention to the behavioral component of self-regulation often missing in the empirical literature. Such research will help address many of the criticisms of exploratory behavior in active learning.

Because learning is inherently multidimensional (Kraiger, Ford, & Salas, 1993), it is important to consider a variety of criteria when examining relationships between self-regulation constructs and the outcomes of training, such as proximal outcomes (i.e., knowledge and skill), distal outcomes (i.e., adaptation) outcomes, and trainee reactions. This is particularly important given arguments that exploration-based training benefits

adaptability while potentially undermining proximal performance (e.g., Bell & Kozlowski, 2008; McDaniel & Schlager, 1990). In the present study, I examined multiple learning outcomes including task knowledge, practice performance, and analogical and adaptive transfer performance, and training enjoyment. *Task knowledge* is composed of basic task knowledge, defined as the comprehension of basic task features and critical tasks, and strategic task knowledge, defined as the understanding necessary for situational assessment and prioritization (Kozlowski et al., 2001). Skill-based outcomes included *practice performance*, defined as effectiveness during training, and *analogical transfer* (i.e., near transfer), defined as the capability to be effective in familiar performance situations after training. Skill adaptability or *adaptive transfer* (i.e., far transfer) is defined as the capability to use one's existing knowledge and skill in response to novel (e.g., more difficult, complex, and dynamic) performance demands (Ivancic & Hesketh, 2000). *Task-enjoyment* refers to trainee perceptions of the task and how well they liked the training.

Hypothesis 1: Exploratory behavior will incrementally predict learning outcomes (i.e., practice performance, task knowledge, analogical transfer, adaptive transfer, and task enjoyment) above the effects of self-efficacy and metacognition.

The Effect of Exploration Instructions on Exploratory Behavior

According to active learning theory, the role of training design should be to supplement, shape, and support learner self-regulation (Bell & Kozlowski, 2008, 2010). As such, research that clarifies how training design elements directly influence learner self-regulatory processes is necessary to enable practitioners to diagnose and correct inefficiencies in existing training and to adapt instructional principles to new contexts (Keith & Frese, 2005). This information can also be used to test common assumptions

essential to the effectiveness of active-learning training. For example, proponents of error management training (e.g., Gully, Payne, Koles, & Whiteman, 2002; Heimbeck, Frese, Sonnentag, & Keith, 2003; Keith & Frese, 2005) maintain that active-learning instructional design elements should positively influence learner exploration. However, Hardy et al. (2014) did not find a direct effect of error framing instructions on the frequency of learner exploratory behavior. Instead, they found that error instructions moderated the GMA-exploration relationship such that higher-GMA learners explored more in response to positive error framing whereas lower-GMA learners explored less. These findings suggest that the intended effects of training design elements on learner behavior may not always be straightforward—and in some cases may be contingent on characteristics of the learner.

One possible explanation for the lack of a direct effect of error framing on exploratory behavior in Hardy et al.'s study is that positive error framing instructions represent, at best, an indirect approach to boosting learner exploration. As such, one might expect that instructions that more directly encourage learners to engage the task and explore should have a stronger influence on learner behavior. Supporting this notion, Wendel and Frese (1987) found that learners using computer software manuals that explicitly and implicitly supported the use of exploratory strategies tried a greater number of novel software commands than learners using the commercial manual. This led Wendel and Frese to conclude, "it is useful and possible to encourage subjects to explore" (p. 948). In an extension of these findings to experimenter instructions, Frese, Albrecht, Altmann, Lang, et al. (1988) found that exploratory learning styles were positively related to learning outcomes. Furthermore, trainees encouraged by the

instructor to explore learned the task more quickly and performed better on tests of skill transfer than trainees who were simply provided the correct task solutions during practice. Exploration-encouragement instructions reduce anxiety associated with exploration and allow learners to approach the learning process in a manner more consistent with their natural tendencies (Carroll & Mack, 1984; Carroll, Mack, Lewis, Grischkowsky, & Robertson, 1985).

Hypothesis 2: Trainees who receive exploration-encouragement instructions will explore more than trainees who receive no exploration-encouragement instructions.

Nevertheless, many critics of learner-controlled and exploration-based training argue that exploratory behavior imposes an excessive cognitive load on many learners (Kirschner, Sweller, & Clark, 2006) and may distract them from engaging in cognitive self-regulation in a way that ultimately limits the effectiveness of exploration-based training (Mayer, 2004). Contrary to these predictions, Hardy et al. (2014) found that when learners explored, neither GMA nor pre-training task-related knowledge moderated the relationship between exploration and learning outcomes. Instead of a moderating effect, they found that GMA and pre-training task-related knowledge were directly and positively related to overall levels of exploratory behavior during practice. In other words, exploration-based training interventions may not be well suited for lower capability individuals, and not because trainees with low GMA or low pre-training task-related knowledge do not learn from exploration, but rather that such trainees simply explore less when given the opportunity. As a result, for many learners, training design elements must do more than simply make it possible to explore.

Specifically, instruction should actively encourage and, in some cases, require learner exploratory behavior (Wendel & Frese, 1987).

Given the complexity of the task used in the present study, I expected that decisions to engage in exploration in response to exploration-encouragement instructions would be contingent on a trainee's GMA and pre-training task-related knowledge. Higher capability learners are able to recognize and engage a greater amount of novelty in the environment due to their greater availability of cognitive resources (Norman & Bobrow, 1975). Thus, I expected that trainees higher in GMA and pre-training task-related knowledge would explore more in response to exploration-encouragement instructions relative to trainees lower in GMA and pre-training task-related knowledge.

Hypothesis 3: There will be an interaction between exploration instructions and trainee (a) GMA and (b) pre-training task-related knowledge such that the effects of exploration-encouragement instructions on exploratory behavior will be stronger for trainees higher in GMA and pre-training task-related knowledge.

Dynamics of Self-regulation and Performance

Cross-sectional designs are the most commonly used approach for studying the relationship between self-regulation and performance. However, single time point, bivariate methods provide only limited information concerning whether self-regulatory processes precede or follow changes in performance (Shadish, Cook, & Campbell, 2002). Similarly, simple, predictive designs rely on causality assumptions in the relationships among variables that are notoriously difficult to test, but are necessary for practical application of the findings. The result is an oversimplified understanding of what are otherwise dynamic and complex phenomena (Yeo & Neal, 2013). Answering questions regarding directionality in the self-regulation-performance relationship can

help clarify which mechanisms hold the greatest potential for positively influencing the learning process. This information can be used by practitioners who wish to better structure training interventions in a way that supports learner self-regulation and addresses inefficiencies in their natural tendencies. By combining repeated measurements of self-efficacy, metacognition, and exploration over a series of performance sessions with cross-lagged analyses that address issues of directionality, I hope to lay the foundation for a process model of skill acquisition that can speak to how the learning process unfolds. In the following sections, I start by describing four possible self-regulation-performance relationships. I then review the evidence for the bivariate relationship between each of the three self-regulatory processes examined in the present study with performance. Finally, I offer predictions and research questions regarding the directionality of their effects.

There are four general patterns one might expect in a bivariate relationship between a self-regulatory process and performance. In the first relationship, the self-regulatory process precedes performance such that lagged self-regulation predicts performance, but not vice versa. This is the most practically useful relationship because it suggests that an intervention targeting the self-regulatory process will lead to some meaningful and predictable change in learning outcomes. In the second relationship, the opposite pattern exists such that prior performance influences subsequent self-regulation. This relationship implies that self-regulation is a by-product of performance rather than a cause. Although measuring such a process may be useful as a diagnostic tool, an intervention designed to target it directly in order to influence learning outcomes may not be worthwhile. The third type of relationship is a reciprocal

relationship, where the self-regulatory process shows a lagged effect on performance, which subsequently influences future self-regulation. Reciprocal relationships can reflect one of three possible patterns: (1) an upward spiral, (2) a downward spiral, or (3) a self-correcting spiral (Lindsley, Brass, & Thomas, 1995). Variables in upward and downward reciprocal spirals build upon one another such that changes in one reinforce changes in the other (Masuch, 1985; Weick, 1979). For example, proactivity is positively related to increases in job control, which positively predicts subsequent increases in proactivity (Li, Fay, Frese, Harms, & Gao, 2014). Similarly, perceptions of high job demands negatively influence mental health, which increases future perceptions of job demands (De Lange, Taris, Kompier, Houtman, & Bongers, 2004). In contrast, self-correcting spirals allow for adjustments in future behavior that reverse previous changes in each variable. For example, an increase in self-efficacy may lead a learner to reduce the resources allocated to an accepted goal, which may negatively impact future progress toward that goal (Vancouver, More, & Yoder, 2008). Poor goal progress may then negatively influence self-efficacy, signaling to the learner to increase resource allocation in pursuit of their goal (Yeo & Neal, 2013). Finally, it is important to acknowledge the possibility of spurious relationships such that covariation between any two variables is the result of shared variance among the self-regulatory process, performance, and a third, unmeasured confounding variable (Rogosa, 1980). Thus, when considering questions of directionality, it is important to recognize that causal conclusions can be strengthened but not firmly established by examining longitudinal bivariate models relative to cross-sectional designs.

Self-efficacy and performance

Self-efficacy refers to the belief in one's capability to organize and execute the course of action required to succeed and produce positive results (Bandura, 1997). Recent developments in the self-efficacy literature offer a prime example of how considering dynamics by disentangling between- from within-person effects can challenge common causality assumptions in self-regulation-performance relationships. Much of the research on self-efficacy has been based on the predictions of social cognitive theory (Bandura, 1986), of which self-efficacy is a central component (Bandura, 1997). This perspective argues that learners with higher levels of self-efficacy will be more likely to develop, accept, and commit to difficult performance goals, and will perform at a higher level as a result. Supporting this notion, meta-analyses have shown strong, between-person relationships between self-efficacy and performance/training outcomes (G. Chen, Casper, & Cortina, 2001; Colquitt, LePine, & Noe, 2000; Stajkovic & Luthans, 1998).

However, a growing body of research focused on addressing questions regarding directionality in the self-efficacy-performance relationship have demonstrated that self-efficacy may be unrelated, or even negatively related, to performance at the within-person level (Beattie, Lief, Adamoulas, & Oliver, 2011; Beck & Schmidt, 2012; Vancouver et al., 2008; Vancouver, Thompson, Tischner, & Putka, 2002; Yeo & Neal, 2006) and, under the right conditions, at the between-person level as well (Vancouver, Gullekson, Morse, & Warren, 2014). Collectively, these findings suggest that self-efficacy may be a reflection of past performance and actual capacity more than a predictor of future performance (Heggestad & Kanfer, 2005; Sitzmann & Yeo, 2013).

In multiple goal settings and in contexts characterized by time constraints, weak or even negative relationships between self-efficacy and performance may ultimately be adaptive, as they lead learners to reallocate resources where they are most needed (Beck & Schmidt, 2015; Vancouver, Weinhardt, et al., 2014). Nevertheless, this body of research calls into question assumptions regarding directionality of the self-efficacy to performance relationship in that they suggest that self-efficacy may be a result, rather than cause of performance.

The current study contributes to this literature by examining the self-efficacy-performance relationship using cross-lagged panel analyses with non-concurrent assessment (Vancouver, Gullekson, & Bliese, 2007)—an approach that has been shown to be robust to many of the statistical confounds Bandura (2012) argued may explain findings of negative or null within-person self-efficacy-performance relationships. Consistent with the research described above, I expected a unidirectional relationship between self-efficacy and performance such that self-efficacy is an indicator, rather than cause, of changes in performance.

Hypothesis 4: There will be a positive, unidirectional relationship between performance and self-efficacy such that lagged performance is positively related to self-efficacy.

Metacognition and performance

Metacognition refers to an awareness of various aspects of the self, task, and context in a learning environment (Pintrich, Wolters, & Baxter, 2000) and involves exerting control over planning, monitoring, and revising goal-appropriate behavior (Bell & Kozlowski, 2010). Metacognition is thought to be an important mediator of performance effects in self-regulated learning contexts, particularly in response to errors

(Ivancic & Hesketh, 2000; Keith & Frese, 2005). However, meta-analytic findings have shown only a weak, albeit positive relationship between metacognition and learning at the between-person level (Sitzmann & Ely, 2011) and little work has considered dynamics in the metacognition-performance relationship. Nevertheless, planning and monitoring aspects of metacognition remain conceptually important to active learning theory given the relatively unstructured nature of the learning environment (Bell & Kozlowski, 2010; Schmidt & Ford, 2003). Research suggests that metacognition helps learners impose structure on the learning environment by allowing them to recognize changes in task demands and to develop task-appropriate solutions (Ivancic & Hesketh, 2000; Keith & Frese, 2005). Specifically, metacognition enables learners to evaluate factors that contributed to their successes and failures and to adjust and refine their approach accordingly, leading to learning and performance improvements (Ford, Smith, Weissbein, Gully, & Salas, 1998).

Although active monitoring of performance is central to the functioning of metacognition in the learning process, few studies have directly considered the effects of prior performance on metacognition at the within-person level. One notable exception is a recent study by Sitzmann and Ely (2010), who found a positive effect of learning on self-regulatory activity, including metacognition, which was itself positively related to subsequent learning outcomes. This finding is consistent with the conceptualization of metacognition as an exploitative self-regulatory process that allows learners to identify and capitalize on learning improvements. Successes provide learners with opportunities to monitor their performance, to reflect on their experiences, and to identify optimal approaches. Learners can then use this information to refine their

strategic approach going forward. As such, I expected a positive, reciprocal relationship between metacognition and performance such that prior performance generates metacognitive activity, which is positively related to subsequent performance.

Hypothesis 5: There is a positive, reciprocal relationship between performance and metacognition such that lagged performance is positively related to metacognition and lagged metacognition is positively related to performance.

Exploration and performance

The primary function of exploration in active learning is to enable learners to make sense of task novelty (Hardy et al., 2014). Thus, exploration-based training should benefit adult learners who choose to explore. Yet, studies that operationalize exploration as a distal, training design element often show crossover effects with learning outcomes such that trainees in exploration conditions perform worse during training phases but better in post-practice and transfer phases relative to trainees in proceduralized conditions (Bell & Kozlowski, 2008; McDaniel & Schlager, 1990). This may lead one to conclude that exploratory behavior is detrimental to proximal performance. However, these results are relative to proceduralized training programs in which performance may not solely reflect the volition of the learner. Trainees in proceduralized conditions are often provided with step-by-step task solutions during practice—an approach that directly affects proximal performance scores—whereas those in exploration-based conditions are not (e.g., Bell & Kozlowski, 2008; Dormann & Frese, 1994; Frese et al., 1991). Although this approach can be informative in the evaluation of interventions as a whole, such comparisons do not allow for conclusions regarding the effectiveness of exploratory behavior as a self-regulatory process because

trainee decisions and behavior are not the sole determinates of proximal performance outcomes.

When applying a direct measurement approach, Hardy et al. (2014) found that exploratory behavior was positively related to performance at both the between- and within-person levels. In other words, fluctuations in learner exploration during practice were positively related to subsequent performance. Based on these findings and the conceptualization of exploratory behavior as a systematic information-gathering part of the learning process, I expected that exploratory behavior would be positively related to subsequent performance. Indeed, I argue that major improvements in proximal performance are unlikely to come in the absence of exploratory behavior, as trainees who do not explore are less likely to encounter and are thus have fewer opportunities to resolve sources of novelty within the learning environment. As a result, learners who do not explore are less likely to acquire additional knowledge or skill.

Regarding the effect of prior performance on exploratory behavior, curiosity theory (Berlyne, 1954, 1966; Loewenstein, 1994) suggests that as learning occurs, the amount of task novelty one perceives is reduced. Reduced perceptions of novelty and increased feelings of efficacy diminish discrepancies learners perceive between the information available in the environment and one's current level of understanding—a difference known as the information-knowledge gap (Loewenstein, 1994). As performance increases, information-knowledge gaps are reduced, leading to similar reductions in exploratory behavior as learners transition away from strategy discovery and exploration and toward approaches that emphasize exploitation and refinement of known strategies. Along these lines, Hardy et al. (2014) found that exploratory behavior

steadily decreased over the course of practice whereas performance steadily increased. These inversely related trajectories are consistent with the notion that increases in prior performance contribute to decreases in exploratory behavior. As such, I expected a self-correcting, reciprocal relationship between exploration and performance.

Hypothesis 6: There will be a self-correcting, reciprocal relationship between performance and exploration such that lagged performance is negatively related to exploratory behavior whereas lagged exploratory behavior is positively related to performance.

Dynamics among behavioral and cognitive/motivational self-regulatory processes

Self-regulation does not operate as an assembly of isolated mechanisms, but rather functions as a collection of highly interrelated processes that build upon and influence one another over the course of practice (Sitzmann & Ely, 2011). As such, examining the manner in which self-regulatory processes are interrelated is necessary for understanding the role of self-regulation in learning contexts. In particular, it is important to clarify how cognitive and motivational self-regulation influences—and is influenced by—behavioral self-regulation given that cognitive and motivational self-regulated learning processes are thought to show their effects through changes in learner behavior (Kozlowski et al., 2001). Such an approach also allows for a direct test of the proposition that exploration has a distal, causal influence on learning outcomes through more proximal cognitive and motivational processes—a common assumption underlying research on exploratory learning (Bell & Kozlowski, 2008). In the following sections, I review available evidence for the proposed relationships between exploratory behavior, self-efficacy, and metacognition and offer predictions regarding the directionality of these effects.

Self-efficacy and exploratory behavior

Curiosity theory postulates that exploratory behavior occurs in response to perceptions of novelty (Berlyne, 1966). As noted above, novelty contributes to exploration by exposing gaps between one's knowledge and the information readily available in the environment. Information-knowledge gaps motivate learners to explore in an effort to increase task mastery and to develop a "feeling of efficacy" in dealing with their surroundings (p. 322; White, 1959). In other words, one of the primary purposes of exploratory behavior is to help reduce uncertainty and anxiety—efforts that should also contribute to the development of self-efficacy. Learners who develop a broad repertoire of experiences will feel more knowledgeable and confident that they can respond appropriately across a wide range of demands. Accordingly, I expected that prior exploratory behavior would have a positive effect on subsequent self-efficacy.

Developing predictions for the effect of self-efficacy on subsequent exploratory behavior is a bit more complex, as simultaneous positive and negative influences of self-efficacy on exploratory behavior can plausibly coexist. For instance, research shows that when provided a choice between two novel situations—one that is the same level of complexity at which one currently feels efficacious and another which is slightly more complex—individuals tend to prefer the one that is more complex (Dember & Earl, 1957; Earl, Franken, & May, 1967; May, 1963). Along these lines, one might expect that self-efficacy should have a positive effect on exploration through its influence on factors that shape decisions to explore. Specifically, self-efficacy should contribute to a willingness to branch out and try new things, which raises the upper limits of novelty and complexity learners feel comfortable engaging. However,

arguments can also be made for a negative influence of self-efficacy on exploration through a reduction in perceived information-knowledge gaps. As information-knowledge gaps begin to shrink, trainees will perceive less novelty, feel that they have less to learn, and avoid committing time and energy toward exploratory behavior. In addition, the same aspect of self-efficacy that allows individuals to persevere (Bandura, 1997) may also make it difficult for them to abandon entrenched approaches and explore—even when viable alternatives exist (Whyte, Saks, & Hook, 1997).

Accordingly, the direction of self-efficacy to exploration effects will depend on which forces are stronger in learners in a particular learning environment—the desire to increase novelty and complexity in one’s surroundings and grow, or the associated reduction in the perceived information-knowledge gap and strategy entrenchment. In some cases, these influences may offset, concealing the influence of self-efficacy on exploration in a phenomenon known as inconsistent mediation (MacKinnon, Krull, & Lockwood, 2000). Thus, I expected a reciprocal relationship between self-efficacy and exploration such that self-efficacy influences decisions to engage in exploratory behavior, which in turn contributes to the development of higher levels of self-efficacy. However, predictions regarding self-efficacy-to-exploration effects are less certain.

Thus, the following hypothesis and research question were examined.

Hypothesis 7: There will be a reciprocal relationship between exploratory behavior and self-efficacy such that lagged exploratory behavior is positively related to self-efficacy and lagged self-efficacy influences exploratory behavior.

Research question 1: What is the direction of the effect of lagged self-efficacy on subsequent exploratory behavior?

Metacognition and Exploratory Behavior

Learners that engage in effective monitoring of goal appropriate behavior reflect on prior outcomes in order to gain a better understanding of what they do and do not know (Zimmerman, 2000). This information can then be used to develop plans and revise behavior in pursuit of one's goals. Thus, metacognition operates initially as a reactive self-regulatory process that allows learners to respond to recent changes in their learning and in the performance environment. Indeed, one of the major functions of metacognition in error management training is ensuring that learners "stop and think about the causes of error" (p. 1968; Ivancic & Hesketh, 2000). However, learners must first collect a sufficiently wide sample of behaviors and experiences on which to reflect before metacognitive activity can occur. For this reason, I expect that exploratory behavior will be positively related to metacognition because exploration generates new information about the task and the various potential approaches available to learners. Learners that are not exploring will have little reason to engage in metacognition given the paucity of new information about the task and their goal progress.

In contrast, I expected that prior metacognition would actively suppress subsequent exploratory behavior. Specifically, reflective and refinement functions of metacognition require learners to transition away from expanding their repertoire and toward an emphasis on exploitative learning strategies such as breaking down the task into its essential components and refining one's current strategic repertoire (Zimmerman, 2000). By emphasizing active processing of currently available information, metacognition allows learners to recognize and address mistakes in prior performance. This can lead to mastery over a single approach or set of approaches

(Keith & Frese, 2005), but does not necessarily facilitate the discovery of new ones. As a result, I expected to find a self-correcting, reciprocal relationship between exploration and metacognition such that exploration is positively related to metacognition whereas metacognition is negatively related to exploration. When learning simple tasks, this may be an adaptive tendency as it involves a reallocation of resources away from strategy discovery approaches that quickly become obsolete and toward strategy refinement. However, in complex tasks with many possible solutions, metacognition may inadvertently reduce the upward limits of learner potential by causing learners to settle on a set of suboptimal approaches too early in the learning process.

Hypothesis 8: There will be a self-correcting, reciprocal relationship between exploratory behavior and metacognition such that lagged exploratory behavior is positively related to metacognition whereas lagged metacognition is negatively related to exploratory behavior.

Method

Participants

Participants were 312 young adult males attending the University of Oklahoma receiving research credit for a psychology course research participation requirement. Due to computer problems, data from five participants were missing. Two other participants started, but did not complete the study due to worsening weather conditions. In total, complete data from 305 participants was available for analyses. Participants were randomly assigned to either an exploration encouragement condition ($n = 154$) or control condition ($n = 151$). Participants ranged in age from 18 to 38 years ($M = 19.49$, $SD = 2.23$).

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 with many dynamic decision-making characteristics (Kozlowski et al., 2001)—that is, UT2004 contains technology-mediated, shifting, ambiguous, and emergent task-qualities that are important criterion-task features for studies of active learning. In UT2004, participants compete against computer-controlled opponents from the perspective of their character, which they move and manipulate in a fast-paced dynamic setting. Using weapons, the objective is to destroy the computer-controlled opponents while minimizing the destruction of one's own character. Participants start with a basic weapon and can collect new weapons or resources (i.e., pick-ups) to increase their character's health, basic offensive and defensive capabilities, and advanced capabilities (i.e., power-ups). The game environment (i.e., the map) is arranged such that weapons and pick-ups appear in consistent locations. A few special pick-ups are available in locations only accessible by deliberate choice and precise action. When an opponent or the participant's character is destroyed, that character reappears in a new location on the map with the basic weapon and capabilities. A trial (i.e., game) ends when time runs out. A session is composed of four trials.

UT2004 involves a high degree of both psychomotor and cognitive demands. Participants use a mouse and keyboard simultaneously to move and control their character. Participants must learn how each weapon works, consider weapon strengths and weaknesses, and be able to decide quickly which to use given the circumstances. Participants must learn and remember weapon and resource locations and, in some

cases, use problem solving to access those items. To be effective, participants must employ a dynamic approach to their choice of strategy and tactics. For example, depending on the range and location of their opponents, their surroundings, and their character's health, participants need to decide whether to move to find more health resources or other pick-ups, change their weapon choice and combat tactics, or move to find a more advantageous offensive or defensive position.

Procedures

The study protocol is provided in the Appendix. All participants were told that the purpose of the study was to examine how people learn to play a dynamic and complex videogame. After filling out an informed consent, participants responded to questionnaires assessing videogame experience, demographics including self-reported ACT or SAT score, goal orientation, and a battery of other measures not germane to the study's hypotheses or research questions. Following these initial questionnaires, participants watched a 15-min training video explaining the basic controls, rules, and objectives of UT2004 followed by 1 min of in-game practice without opponents present. Participants then performed two trials testing baseline performance for which they were instructed to do their best, followed by an initial self-efficacy questionnaire and a pre-training motivation to learn measure.

Next, participants entered a practice phase in which they performed twenty, 3-minute practice trials divided into five performance sessions of four trials each. All participants were instructed to view the practice trials as learning opportunities. In addition, exploration instructions were read aloud at the beginning of the first practice session with refresher instructions read aloud before each of the remaining practice

sessions. Following each of the five practice sessions, participants responded to repeated administrations of self-report questionnaires assessing their metacognitive activity during the previous session and their current levels of self-efficacy. Before each session participants also set proximal goals for the following session and distal goals for end of training. Task enjoyment and post-performance self-efficacy questionnaires were administered immediately after practice. Finally, participants performed four test trials; two testing post-practice performance (i.e., near/analogical transfer) and two testing adaptive performance (i.e., far/adaptive transfer) where they were again instructed to do their best. A 12-item short-form of the Raven's APM (Arthur & Day, 1994; Raven, Raven, & Court, 1998) was administered between the post-practice performance and the adaptive performance trials as a short period of non-use.

UT2004 provides objective levels of computer-controlled opponent difficulty ranging from 1 to 8. At higher levels of difficulty, opponents are faster, more elusive, more accurate, and more varied in their tactics. For the baseline trials, practice trials, and the test of post-practice skill-based performance, participants competed against two computer-controlled opponents that were set to perform at a moderate level (5) of in-game difficulty. All of these trials were performed on the same geographical layout. For the test of adaptive performance, participants performed two trials against nine opponents set at a higher difficulty level (6) and on a larger and more varied geographical layout than before. Following the final adaptive transfer test game, participants were debriefed and dismissed.

Exploration Manipulation

Before the first practice session, participants in the exploration-encouragement condition were read aloud exploration-encouragement instructions, which indicated that exploration is beneficial for learning and recommending that they continuously explore and not settle on a single approach. Participants in the control condition were told that practice is beneficial for learning and were encouraged to continually try their best throughout the practice trials. The manipulation instructions for both conditions are provided in the Appendix. Refresher instructions were read aloud at the beginning of each of the remaining practice sessions. All participants were instructed to view the practice sessions as a learning opportunity.

Measures

Learning outcomes

Scores for baseline performance, proximal performance, analogical transfer performance, and adaptive transfer performance were calculated using an identical function of multiple in-game statistics. Specifically, scores for these variables were computed by dividing trainee kills (i.e., number of times a participant destroyed an opponent) by the quantity of kills plus deaths (i.e., number of times a participant's own character was destroyed) plus trainee rank (i.e., if the trainee's score finished them in first, second, or third place relative to the computer opponents in that trial). To aid in interpretability, performance scores were then multiplied by 100. Thus, scores could range from 0 (low) to approximately 100 (high). Task enjoyment was measured using a 6-item self-report scale (1 = *strongly disagree*; 5 = *strongly agree*) developed for this study (e.g., "I had fun learning UT2004" and "If I could, I would play UT2004 at

home”). Task knowledge was measured using a 20-item multiple-choice test reflecting a combination of basic, procedural, and strategic knowledge.

Self-efficacy

Self-efficacy was measured before each practice session and again following the final practice session using a 12-item task-specific scale adapted from previous studies (e.g., Bell & Kozlowski, 2002; Day et al., 2007; Nease, Mudgett, & Quiñones, 1999) for UT2004. Items from this scale include “I feel confident in my ability to perform well in Unreal Tournament,” “I know that I can master Unreal Tournament,” and “I am confident that Unreal Tournament will seem less challenging to me when I have completed this study.” Responses were made on a 5-point Likert scale ranging from 1 (*strongly agree*) to 5 (*strongly disagree*). Coefficient alphas for each of the six administrations of the state-self efficacy scale of .92, .93, .94, .94, .95, and .95 respectively were obtained in the present study.

Metacognition

Metacognition was measured following each practice session using 16 task-specific items adapted from the scale developed by Ford et al. (1998). Specific items were written to measure the extent to which participants (a) monitored and reviewed their progress and performance (e.g., “I paid close attention to when different weapons and fire modes were more effective” and (b) planned to revise their behavior accordingly (e.g., “I thought carefully about what I should do when I did not have certain weapons”). Responses were made using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Coefficient alphas for each of the five

administrations of the metacognition scale of .88, .91, .91, .93, and .94 respectively were obtained in the present study.

Exploratory behavior

Exploratory behavior was coded in each practice trial from video playbacks by me and three to five undergraduate coders experienced with common video-game environments and strategies. Coders underwent approximately 20 hours of frame-of-reference training in which they were familiarized with the UT2004 training environment and the exploration scales. Coders independently viewed game videos for each participant and rated exploratory behavior using four 5-point scales. Video files were stored in a way such that accesses to the videos ensured the coders are blind to the experimental condition as well as information regarding all predictor and criterion variables. Intraclass correlations coefficients (ICCs) were used to examine interrater reliability (Shrout & Fleiss, 1979). As recommended by Cicchetti (1994), ICC's between .60 and .74 are considered good interrater reliability and ICC's above .75 are considered excellent interrater reliability.

The exploration scales were developed via a content analysis of UT2004 in relation to how exploration has been conceptualized in the extant literature on emphasis change exploration (Erev & Gopher, 1999; Gopher, Weil, & Siegel, 1989; Yechiam, Erev, & Gopher, 2001), child exploration (Hutt, 1966; Jennings, Harmon, Morgan, Gaiter, & Yarrow, 1979), animal exploration (Dashiell, 1925; Nissen, 1930), and active learning (Dormann & Frese, 1994). Because exploratory behavior is defined in reference to specific task stimuli, developing scales of exploration in the context of the specific task domain is important for understanding how exploration operates in a

practical learning context (Loewenstein, 1994). Therefore, three of the scales in the current effort measured exploratory behavior in three major game domains: (a) combat strategies, (b) weapons, and (c) map. The fourth scale measured overall exploratory behavior. Exploratory behavior was defined as an active interaction on the part of the trainee with the training environment through the trainee's attempts at multiple solutions to the problem at hand (Dormann & Frese, 1994). The variety of combat strategies scale (ICC = .80) ranges from 1 (*very few strategies tried*) to 5 (*a great deal of strategies tried*). The variety of weapons used scale (ICC = .88) ranges from 1 (*very few weapons tried*) to 5 (*a great deal of weapons tried*). The amount of map visited scale (ICC = .92) ranges from 1 (*very little map visited*) to 5 (*entire map visited*). The overall exploratory behavior scale (ICC = .81) provides a rating of exploration similar to that used in previous research on active learning (i.e., Dormann & Frese, 1994) and accounts for exploratory behavior not captured by the other scales. For this scale, coders are instructed to rate exploratory behavior in the context of participant behavior up until the trial being coded. In this way, the overall exploration scale captures exploration in the context of the other trials. This scale ranges from 1 (*very little exploratory behavior*) to 5 (*a great deal of exploratory behavior*). Correlations among the exploration scale scores ranged from .21 to .76. Together these scales combined to capture both the overall amount (i.e., the total variety of solutions explored during each trial) and uniqueness (i.e., the frequency of brand-new approaches explored during each trial) of participant exploration during practice. A confirmatory factor analysis indicated the four scales loaded on a single factor (CFI = .97, RMSEA = .067). Therefore, the four scale scores were averaged for each trial to create an overall trial-level exploration

index. Hardy et al. (2014) provided support for the content-related validity and construct-related validity (i.e., the sensitivity of scale scores to manipulated changes in exploration) for this operationalization of exploratory behavior.

Controls

A composite of self-reported ACT/SAT scores and scores from the 12-item short form of the Raven Advanced Progressive Matrices (Arthur & Day, 1994) was used as an index of GMA. Following recommendations outlined by Wang and Stanley (1970), a composite reliability of .87 was calculated for this index of GMA. A composite index of videogame experience and baseline performance was used for the measure of pre-training task-related knowledge. A 4-item scale was used to measure trainee videogame experience. Videogame experience served as a proxy for pre-training videogame knowledge. For the first two items, participants responded using a 5-point Likert scale ranging from 1 (not at all) to 5 (daily) to the following questions: (a) “Over the last 12 months, how frequently have you typically played video/computer games?” ($M = 3.50$, $SD = 1.18$) and (b) “Over the last 12 months, how frequently have you typically played first-person shooter video/computer games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament)?” ($M = 2.82$, $SD = 1.22$). For the second two items, participants indicated how many hours per week they typically play video/computer games ($M = 6.23$, $SD = 8.87$, $min. = 0.00$, $max. = 60.00$) and how many hours per week they typically play first-person shooter video/computer games ($M = 3.39$, $SD = 6.80$, $min. = 0.00$, $max. = 60.00$). Scores for these four items were standardized and then averaged into a single videogame experience score. Scores for the two baseline performance trials were averaged ($M = 20.75$, $SD = 11.57$) and then standardized.

Finally, the standardized index of videogame experience and the standardized index of baseline performance was averaged to yield a composite index of overall pre-training task-related knowledge. A composite reliability of .82 was calculated for this index of pre-training task-related knowledge. Learning goal orientation (LGO), prove-performance goal orientation (PPGO), and avoid-performance goal orientation (APGO) were measured with a 13-item scale adapted from VandeWalle (1997). Original references to one's job and work were removed for the present study and the scale was adapted to reflect a general trait-based goal-orientation. Responses were made using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Coefficient alphas of .83, .75, and .83 were obtained in the present study for LGO, PPGO, APGO, respectively. Pre-training motivation to learn was measured using a 2-item, five-point Likert scale composed of the following two items: "I will devote my full attention to learning Unreal Tournament during this study" ($M = 4.21$, $SD = .71$) and "I will do my best to learn Unreal Tournament during this study" ($M = 4.29$, $SD = .65$). A coefficient alpha of .88 was obtained in the present study for the motivation to learn scale.

Results

Measurement Invariance

I started by testing two forms of measurement equivalence (i.e., configural and metric invariance) across each measurement occasion for the self-efficacy, metacognition, and exploratory behavior scales respectively. Configural invariance (Horn & McArdle, 1992) refers to the assumption that the overall number of factors in the factor structure is invariant across measurement occasions. Metric invariance refers to the assumption that factor loadings are invariant across measurement occasions.

Changes in the RMSEA for each scale were all less than the suggested cutoff value of $\Delta\text{RMSEA} < .015$ (F. F. Chen, 2007). Thus, constraining same-item factor loadings to be equal across measurement occasions was not found to significantly reduce model fitness for each scale. These findings provide evidence of sufficient configural and metric measurement invariance for each of the repeated measure variables.

Longitudinal Trends and the Influence of Individual Differences

Table 1 shows descriptive statistics and between- and within-person correlations among all study variables. I examined trajectories of performance, self-efficacy, metacognition, and exploratory behavior using a series of univariate latent growth models specified in MPlus version 6 (Muthén & Muthén, 2010). Latent growth modeling is a statistical procedure for modeling longitudinal trends using latent factors (Bollen & Curran, 2006). Specifically, two univariate models were fitted for each repeated variable; one containing only a latent intercept and the other containing both a latent intercept and latent slope centered on the first measurement occasion.¹ Relative fit of these two univariate models were used to determine if the inclusion of a latent slope could explain variance in each repeated variable beyond the inclusion of a latent intercept alone (Curran & Bollen, 2001). The best-fitting latent growth model for each repeated variable was retained for subsequent modeling. Individual differences relevant to learning contexts, specifically GMA, pre-training task-related knowledge, goal orientation, and pre-training motivation to learn were included as controls on the starting values (i.e., the latent intercept) and growth trends (i.e., the latent linear slope) in the final models.

¹ Centering the latent slope in such a manner allows for meaningful interpretations of correlations between intercept and growth terms when similar starting points are available for all subjects (McArdle, 2009).

As depicted in Figure 1, all four repeated variables showed meaningful trends over the course of practice. Thus, the inclusion of a latent slope improved model fit for performance, exploration, self-efficacy, and metacognition respectively relative to the intercept only model (all $\Delta\chi^2(3) > 11.35$, $ps < .01$). Specifically, positive trends were observed for performance ($\gamma_{10} = 28.82$, $SE = 1.41$, $t = 8.88$, $p < .01$), self-efficacy ($\gamma_{10} = .03$, $SE = .01$, $t = 2.92$, $p < .01$), and metacognition ($\gamma_{10} = .06$, $SE = .01$, $t = 5.85$, $p < .01$) whereas exploratory behavior decreased over the course of practice ($\gamma_{10} = -.11$, $SE = .01$, $t = -14.95$, $p < .01$).

Table 2 displays the final results of the univariate latent growth models, including the influence of the individual difference control variables on the starting values and growth trends of performance, self-efficacy, metacognition, and exploration respectively. Although the effects of individual differences on latent intercepts and slopes of the repeated variables were not central to my research questions, several interesting patterns emerged that may inform future research. For instance, pre-training task-related knowledge positively predicted initial levels of all four repeated variables. However, although both pre-training task related knowledge ($\gamma_{02} = .74$, $p < .01$) and GMA ($\gamma_{01} = .10$, $p < .05$) were positively related to initial performance, only GMA predicted growth in performance across practice ($\gamma_{11} = .28$, $p < .01$). Another interesting finding was that learning goal orientation positively predicted initial levels of self-efficacy ($\gamma_{03} = .28$, $p < .05$), but negatively predicted growth in self-efficacy over the course of practice ($\gamma_{13} = -.20$, $p < .05$). For metacognition, the findings showed that higher initial levels of metacognition were typical of learners higher in pre-training task-related knowledge ($\gamma_{02} = .26$, $p < .05$), learning goal orientation ($\gamma_{03} = .16$, $p < .05$),

performance-prove goal orientation ($\gamma_{04} = .16, p < .01$), and pre-training motivation to learn ($\gamma_{06} = .22, p < .01$). In contrast, higher GMA learners engaged in less metacognition early in practice ($\gamma_{01} = -.13, p < .05$), but increased their metacognitive activity at a faster rate over the course of practice relative to lower GMA learners ($\gamma_{11} = .16, p < .05$). Finally, although goal orientations did not influence initial levels of exploratory behavior, individuals higher in learning goal orientation were more likely to continue exploring throughout practice ($\gamma_{13} = .19, p < .05$).

Incremental Predictive Validity of Exploratory Behavior

A series of hierarchical multiple regressions were used to test the incremental predictive validity of behavioral self-regulation on learning outcomes beyond the influence of established cognitive and motivational self-regulatory processes. Specifically, Hypothesis 1 predicted that exploratory behavior would incrementally predict learning outcomes above the influence of self-efficacy and metacognition. As shown in Table 3, Hypothesis 1 was supported. Exploratory behavior predicted variance beyond the influence of self-efficacy and metacognition across all the learning outcomes including practice performance ($\Delta R^2 = .09, p < .01$), task knowledge ($\Delta R^2 = .04, p < .01$), analogical transfer performance ($\Delta R^2 = .04, p < .01$), adaptive transfer performance ($\Delta R^2 = .04, p < .01$), and task enjoyment ($\Delta R^2 = .03, p < .01$).

The Effect of Exploration Instructions on Exploratory Behavior and Learning

Outcomes

Hierarchical multiple regression was also used to examine the influence of exploration-encouragement instructions on trainee exploratory behavior. GMA, pre-training task-related knowledge, goal orientation, and pre-training motivation to learn

were entered in the model in step one. A dummy code representing the main effect of the exploration-encouragement instructions manipulation (control = 0, exploration-encouragement = 1) was entered in step two. Interactions between the dummy-coded exploration-encouragement instructions and both trainee GMA and pre-training task-related knowledge (centered) were entered in step three.

Hypothesis 2 predicted that trainees in the exploration-encouragement instructions condition would explore more relative to trainees in the control condition. Hypothesis 3 predicted that the influence of exploration-encouragement instructions on exploratory behavior would be contingent on learner GMA (H3a) and pre-training task-related knowledge (H3b). As shown in Table 4, neither Hypothesis 2 nor Hypothesis 3 was supported. The exploration-encouragement instructions did not significantly influence learner exploratory behavior ($B = .054$, $SE = .040$, $t = 1.35$, $p > .05$) and the effects of exploration-encouragement instructions was not stronger for trainees higher on either GMA ($B = .060$, $SE = .048$, $t = 1.26$, $p > .05$) or pre-training task-related knowledge ($B = .062$, $SE = .050$, $t = 1.24$, $p > .05$).

Dynamics of Self-regulation and Performance

To test hypotheses regarding directionality in the relationships between self-regulatory processes and performance (H4-H6), I fit a series of bivariate, cross-lagged latent growth models (Curran & Bollen, 2001). As the name suggests, bivariate cross-lagged latent growth modeling allows for analysis of dynamic relationships between two variables by combining the advantages of cross-lagged regression, which focuses on teasing apart issues of directionality, and latent growth modeling, which focuses on covariation between each repeated variable's latent intercepts and growth terms and

addresses potential confounding influences of slope covariation that can lead to misinterpretation of performance-self-regulation relationships (Sitzmann & Yeo, 2013). Similar approaches have recently been used to examine relationships between proactive personality and work attributes (Li et al., 2014), and job burnout and depression (Toker & Biron, 2012). In many ways, the goals of bivariate cross-lagged latent growth modeling are similar to those of hierarchical linear modeling (e.g., Raudenbush & Bryk, 2002) in that both approaches seek to disaggregate relationships at between- and within-person levels (Curran & Bauer, 2011).

After establishing measurement invariance and fitting univariate latent growth models for each repeated variable, cross-lagged effects were examined by combining the best-fitting univariate growth models with lagged parameters representing the lagged effect of each repeated variable upon the other. Four alternative models representing the four possible bivariate cross-lagged relationships between self-regulatory processes and performance (i.e., the independence model, the performance-to-process unidirectional model, the process-to-performance unidirectional model, and the bidirectional reciprocal model) were then compared based on overall model fit and parsimony. In the case of the metacognition-performance relationship, and the exploration-performance relationship, both repeated variables were measured concurrently. Therefore, cross-lagged effects were specified in these models in line with the approach shown in Figure 2a. For the self-efficacy-performance relationship, self-efficacy was measured before, after, and between each practice session, consistent with the model specification approach shown in Figure 2b. This staggered approach allowed me to avoid overlap dependencies between self-efficacy and performance, a design

advantage shown in Monte Carlo simulations to all but eliminate statistical biases in the self-efficacy-performance relationship (Vancouver et al., 2007) that have been offered as an explanation for the findings that have shown negative effects of self-efficacy on performance (Bandura, 2012; Bandura & Locke, 2003).

In all models, paths representing the lagged effect of performance on the self-regulatory process ($P \rightarrow SR$) for each adjacent time point (e.g., P1-SR2, P2-SR3, etc.) were constrained to be equal and paths representing the lagged effect of the self-regulatory process on performance ($SR \rightarrow P$) for each adjacent time point (e.g., SR1-P2, SR2-P3, etc.) were constrained to be equal.² In the independence model, lagged parameters in both directions were constrained to zero. In the performance-to-process unidirectional model, only the lagged effect of performance on the self-regulatory process ($P \rightarrow SR$) was freely estimated. In the process-to-performance unidirectional model, only the lagged effect of the self-regulatory process on performance ($SR \rightarrow P$) was freely estimated. In the bidirectional model, both the lagged effects of performance on the self-regulatory process ($P \rightarrow SR$) and the process on performance ($SR \rightarrow P$) were freely estimated.³ Models were compared based on overall fit and model parsimony using the comparative fit index ($CFI > .90$), the root-mean-square-error of approximation ($RMSEA$ upper 90% $CI < .10$), and the Akaike information criterion (AIC lowest value across models). Coefficients from the best fitting model were used to evaluate the study hypotheses.

² For the sake of completeness, I tested one final model for each relationship removing these constraints, but in none of the analyses did removing these constraints improve model fit.

³ In the case that acceptable model fit was not found for any of the four models, I planned to test one final model in which autoregressive paths and concurrent correlations were added. However, this final step was not ultimately required in any my analyses.

Table 5 reports fit statistics, cross-lagged coefficients, and inter-factor (i.e., between-person) relationships between self-efficacy and performance, metacognition and performance, and exploratory behavior and performance respectively as reported by four models representing the four possible bivariate cross-lagged relationships between self-regulatory processes and performance: the independence model, the performance-to-process unidirectional model, the process-to-performance unidirectional model, and the bidirectional reciprocal model.

Self-efficacy and performance

Hypothesis 4 predicted a unidirectional, positive relationship between self-efficacy and performance such that lagged performance is positively related to subsequent self-efficacy. Providing support for Hypothesis 4, results in Table 5 show that lagged performance was positively related to self-efficacy ($P \rightarrow SE$; $B = .007$, $SE = .001$, $t = 9.03$, $p < .01$, $\beta = .12$). However, contrary to the predictions of Hypothesis 4, the bidirectional model fit the data better than the proposed performance-to-self-efficacy unidirectional model. Specifically, the results showed a negative lagged effect of self-efficacy on performance ($SE \rightarrow P$; $B = -1.65$, $SE = 0.68$, $t = -2.40$, $p < .01$, $\beta = -.10$) in addition to the positive relationship between lagged performance and self-efficacy. Collectively, these results provide evidence for a self-correcting, reciprocal self-efficacy-performance relationship. At the factor level, both the starting values ($B = 1.48$, $SE = 0.40$, $p < .01$, $t = 3.74$, $\beta = .41$) and growth terms ($B = .14$, $SE = .03$, $p < .01$, $t = 4.35$, $\beta = .67$) in the self-efficacy performance relationship were positively related.

Metacognition and performance

Hypothesis 5 predicted a positive, reciprocal relationship between metacognition and performance such that lagged performance is positively related to metacognition (H5a) and lagged metacognition is positively related to performance (H5b). As shown in Table 5, Hypothesis 5 was supported. Lagged performance was positively related to metacognition ($P \rightarrow M$; $B = .003$, $SE = .001$, $t = 4.09$, $p < .01$, $\beta = .07$). Furthermore, lagged metacognition was positively related to performance ($M \rightarrow P$; $B = .374$, $SE = .171$, $t = 2.18$, $p < .05$, $\beta = .02$). Together, these findings provide evidence for a positive, reciprocal relationship between metacognition and performance. At the factor level, both the starting values ($B = 0.87$, $SE = 0.26$, $t = 3.34$, $p < .01$, $\beta = .32$) and growth terms ($B = .09$, $SE = .03$, $t = 2.90$, $p < .01$, $\beta = .42$) in the metacognition-performance relationship were positively related.

Exploratory behavior and performance

Hypothesis 6 predicted a self-correcting, reciprocal relationship between exploration and performance such that lagged performance is negatively related to exploratory behavior (H6a) whereas lagged exploratory behavior is positively related to performance (H6b). As shown in Table 5, Hypothesis 6 was supported. Lagged performance was negatively related to exploratory behavior ($P \rightarrow E$; $B = -.002$, $SE = .001$, $t = -2.70$, $p < .01$, $\beta = -.05$). Lagged exploration, on other the hand, was positively related to performance ($E \rightarrow P$; $B = .489$, $t = 2.55$, $SE = .192$, $p < .01$, $\beta = .02$). Collectively, these findings provide evidence for a self-correcting, reciprocal relationship between exploratory behavior and performance. At the factor level, both the starting values ($B = 0.76$, $SE = 0.17$, $t = 4.58$, $p < .01$, $\beta = .44$) and growth terms (B

= .04, $SE = .02$, $t = 2.06$, $p < .05$, $\beta = .32$) in the exploration-performance relationship were positively related.

Dynamics among Behavioral and Cognitive/Motivational Self-regulatory Processes

Bivariate, cross-lagged latent growth models were also used to test hypotheses regarding directionality in the relationships between behavioral and cognitive/motivational self-regulatory processes (H7, RQ1, and H8). In the case of the metacognition-exploration relationship both repeated variables were measured concurrently. Thus, cross-lagged effects were specified in these models according to the pattern shown in Figure 2a. For the self-efficacy-exploration relationship, self-efficacy was measured before, after, and between each practice session, consistent with the specification pattern shown in Figure 2b. Table 6 reports fit statistics, cross-lagged coefficients, and inter-factor relationships between exploration and self-efficacy/metacognition respectively.

Exploratory behavior and self-efficacy

Hypothesis 7 predicted a reciprocal relationship between exploratory behavior and self-efficacy such that lagged exploratory behavior is positively related to self-efficacy (H7). Although a significant effect of lagged self-efficacy on exploratory behavior was also expected, no specific predictions regarding the nature of that effect were made (RQ1). As shown in Table 6, Hypothesis 7 was supported. The best fitting model was the reciprocal model such that lagged exploratory behavior was positively related to self-efficacy ($E \rightarrow SE$; $B = .046$, $SE = .008$, $t = 5.45$, $p < .01$, $\beta = .03$). Lagged self-efficacy, on the hand, showed a small, negative relationship with exploratory behavior ($SE \rightarrow E$; $B = -.038$, $SE = .022$, $t = -1.65$, $p < .10$, $\beta = -.07$). At the factor level, both the starting

values ($B = 0.04$, $SE = 0.01$, $t = 2.71$, $p < .01$, $\beta = .25$) and growth terms ($B = .002$, $SE = .001$, $t = 1.98$, $p < .05$, $\beta = .18$) in the self-efficacy-performance relationship were positively related. Together, these results provide support for a self-correcting, reciprocal exploration-self-efficacy relationship.

Exploratory behavior and metacognition

Hypothesis 8 predicted a self-correcting, reciprocal relationship between exploratory behavior and metacognition such that lagged exploratory behavior is positively related to subsequent metacognition (H8a) whereas lagged metacognition is negatively related to exploratory behavior (H8b). As shown in Table 6, Hypothesis 8 was supported. Lagged exploratory behavior was positively related to metacognition ($E \rightarrow M$; $B = .033$, $SE = .008$, $t = 3.92$, $p < .01$, $\beta = .02$). Lagged metacognition, on the other hand, was negatively related to exploratory behavior ($M \rightarrow E$; $B = -.012$, $t = -2.25$, $SE = .006$, $p < .05$, $\beta = -.02$). Together, these findings provide support for a self-correcting, reciprocal relationship between exploration and metacognition. There were no statistically significant relationships in the metacognition-exploration relationship at the factor level.

Discussion

Self-regulation frameworks underlie many modern training theories that target learner adaptability, including active learning (Bell & Kozlowski, 2008, 2010)—a learner-centric instructional approach developed to meet the need for training design that can match the dynamism of the modern workplace (Hesketh, 1997). In the coming years, the importance of self-regulation in organizational training and development will continue to grow as the nature of work evolves to become more complex and

knowledge-based (Sitzmann & Ely, 2011). Although researchers have made a great deal of progress in recent years within the self-regulated learning literature, many gaps remain in our understanding of how adults regulate their learning. In particular, I argue that much of the research on self-regulated learning (a) overlooks the central role of behavioral self-regulation in the learning process and (b) fails to fully account for important dynamics in the relationships among self-regulatory processes. The present study was designed to address these limitations with an eye for how developing a better understanding of the role of exploratory behavior in the learning process and of dynamics in self-regulated learning processes can inform active learning theory and the design of training interventions. In the following sections, I start by discussing the results of the present study, organizing my discussion around each of my four original research goals and their implications for theory, research, and practice. I finish by integrating my findings in a dynamic process model of self-regulated learning that speaks to how behavioral, cognitive, and motivational self-regulation can contribute to, and occasionally conspire against, skill-based learning and acquisition.

The Incremental Predictive Validity of Exploratory Behavior in Active Learning

The results of the current study suggest that the benefits of learner behavioral self-regulation go beyond its influence on cognitive and motivational self-regulatory processes. Specifically, exploratory behavior positively predicted all proximal and distal learning outcomes examined in the present study beyond the effects of self-efficacy and metacognition. By helping learners resolve sources of novelty and uncertainty within the task environment, exploration facilitates the development of a deeper understanding of the rules, principles, and strategies underlying effective performance (Smith, Ford, &

Kozlowski, 1997) and contributes to the development of a broader repertoire of experiences upon which learners can draw in response to changing task demands (Dormann & Frese, 1994).

These results support the tenets of constructivist conceptualizations of learning (Bruner, 1961) that underlie active-learning approaches. However, they challenge the common practice in research on active learning of operationalizing exploration solely as a core design element or as a distal predictor of learning outcomes exclusively through its influence on other self-regulatory processes. This is not to say that exploration is unrelated to cognitive and motivational self-regulation. Indeed, my results also indicated that exploration influenced, and was influenced by, both self-efficacy and metacognition. Rather, I argue that future theory and research on active learning should operationalize exploration as a distinct self-regulatory process and directly examine its effects alongside cognitive and motivational self-regulatory processes. Given its central—and notably unique—role in the learning process, a focus on behavioral self-regulation has a great deal of potential for advancing our understanding of the nature of adult learning.

Along these lines, I believe that instructors will be better able to address shortcomings in existing training interventions and will be more effective in positively influencing the learning process simply by paying more attention to learner behavior. In many cases, it may not always be enough to assume that learners are taking advantage of opportunities to explore (Hardy et al., 2014). Thus, when possible, learner behavior should be actively monitored and interventions should be designed with effects on trainee exploratory behavior in mind. This approach is not new in the science education

literature, where researchers implementing interventions that leverage principles of curiosity theory were able to stimulate exploratory behavior and improve learning outcomes for children visiting science museums (D. Anderson & Lucas, 1997; Kubota & Olstad, 1991). There is unique power in the act of exploration as part of the learning process, because exploring exposes learners to information that not only directly benefits learning outcomes, but also fuels learner cognitive and motivational self-regulatory processes. In many ways, behavioral self-regulation is much more readily accessible to researchers and instructors than cognitive or motivational self-regulation, which can only be indirectly inferred. As such, a renewed emphasis on learner behavior offers a great deal of potential for practitioners interested in identifying new ways to support the learning process.

The Effect of Exploration Instructions on Exploratory Behavior

Organizations are increasingly turning to training efforts to help prepare employees to meet the challenges of future jobs (Salas, Tannenbaum, Kraiger, & Smith-Jentsch, 2012). In the last year alone, spending on corporate training grew by 15% to \$70 billion in the U.S. and \$130 billion worldwide (O' Leonard, 2014). Because training generally represents a sizable investment on the part of the organization, it is important to ensure that training interventions are having a positive influence on the learning process. In the current study, I tested two key propositions: (1) that exploration-encouragement instructions positively influence exploratory behavior and (2) that intervention effects on learner exploration may be contingent on learner characteristics. The first proposition is important because a training intervention that influences learning outcomes, but not learner self-regulation, may be affecting the learning process

through unknown mechanisms (Keith & Frese, 2005). Without clarification as to what these hidden influences might be, successful application of the intervention becomes a game of chance wherein the intervention will positively influence learning outcomes when the necessary conditions are present, but show no influence, or even negatively influence learning outcomes when they are not. The second proposition is important for identifying learner characteristics that must be present at the start of training for the intervention to be successful. This proposition speaks to the generalizability of training effects across a wide range of learners and contexts.

Although I expected that exploration-encouragement instructions would positively influence learner exploratory behavior, particularly for trainees higher in GMA and pre-training task-related knowledge, the current results showed that this was not the case. Indeed, my findings suggest that exploration-encouragement instructions had very little influence on the learning process at all. There are a number of possibilities for this finding. First, the exploration instructions used in the present study may have been too weak, or may have lacked a sufficient level of specificity to be of much use to learners. However, highly specific instructions with explicit prescriptions for learner behavior are more characteristic of traditional, proceduralized training and diverge from the instructional philosophy underlying active-learning approaches. Furthermore, prior research in the error management training literature suggests that learners will occasionally ignore instructions and engage in behavior that is most natural to them (Dormann & Frese, 1994). Consequentially, simple exploration-encouragement instructions probably have little to no influence on learner exploration. Supporting this notion, Wendel and Frese (1987) found that the highest levels of exploration were

observed for learners who were not only encouraged, but also required to explore in order to achieve their goals. The primary implication here for training design is that instructors should not expect to take an entirely passive role if they wish to positively influence learner exploration. Instead, instructors must provide reason and incentive to trainees to foster continued exploration. In particular, interventions that directly target the antecedents of exploratory behavior (i.e., learner perceptions of novelty and the information-knowledge gap) rather than the behavior itself may be more effective at shaping and supporting learner exploration. Similarly, aligning the content of training goals with exploration-encouragement instructions may make learners more likely to commit to exploration-based strategies during training (Kozlowski & Bell, 2006).

Dynamics of Self-regulation and Performance

Self-regulation is fundamentally a dynamic phenomenon that operates primarily at the within-person level. As such, research on self-regulation that fails to account for issues pertaining to levels of analysis risks misconstruing the true nature of observed effects (Yeo & Neal, 2013). Indeed, the results of the present study suggest that self-regulation-performance relationships may not be as simple as was previously assumed. Specifically, all three of the self-regulatory processes examined in the present study showed reciprocal relationships with performance such that self-regulation not only influenced, but was also influenced by performance outcomes. Reciprocal self-regulation-performance relationships have major implications for training design—several of which I described when introducing this topic above. In the following sections, I discuss how findings in the present study speak to the nature of the self-efficacy-performance, metacognition-performance, and exploration performance

relationships respectively. I then consider the implications of each finding for training design.

Self-efficacy and performance.

Of all the self-regulated learning processes examined in the present study, the relationship between self-efficacy and performance has received the greatest amount of empirical attention. In recent years, proponents of social cognitive theory and control theory have been engaged in a vigorous debate regarding issues of directionality and causality in the self-efficacy-performance relationship (Bandura, 2012, 2015; Bandura & Locke, 2003; Vancouver, 2012; Vancouver, Thompson, & Williams, 2001; Yeo & Neal, 2013). The findings of the present study provide additional support for arguments that similarities in the trajectories of self-efficacy and performance over time may inflate between-person estimates of the self-efficacy-performance relationship (Sitzmann & Yeo, 2013). As such, I echo the recommendations of Sitzmann and Yeo (2013) who emphasized the importance of controlling for linear trajectories in repeated-measures self-efficacy research. Controlling for these trends in my analyses via the latent growth trajectories revealed that the self-efficacy-performance relationship operated in a self-correcting reciprocal relationship. Specifically, lagged performance positively predicted self-efficacy, whereas lagged self-efficacy negatively predicted performance. These findings challenge claims that negative self-efficacy effects are solely the product of statistical artifacts resulting from overlapping measurement of self-efficacy and performance (Bandura, 2012) and support the notion that a small amount of self-doubt may ultimately benefit learning and performance (Feltz & Wood, 2009).

Nevertheless, it should be noted that an alternative explanation for why I found a negative effect of self-efficacy on performance in the present study rather than the originally proposed unidirectional performance-to-self-efficacy relationship concerns a small degree of achievement ambiguity that may have been present in this particular learning context. Using a computerized anagram task, Schmidt and DeShon (2010) found that ambiguity moderated the effect of self-efficacy on performance such that self-efficacy was negatively related to both effort and performance in high performance ambiguity conditions, but not in conditions characterized by low performance ambiguity. Although participants in present study were provided detailed and accurate performance feedback during and at the end of every trial, they lacked information regarding how well their performance compared to normative standards for success.

Furthermore, a growing body of research indicates that there are several key moderators of self-efficacy-performance relationships such as prior performance (Schmidt & DeShon, 2009), failure experiences (Hardy, 2014), and even one's overall level of self-efficacy (Beck & Schmidt, 2012). As such, I do not wish to make the claim that self-efficacy is universally detrimental to the learning process. In fact, in multiple goal contexts characterized by time and resource constraints, negative self-efficacy effects may suggest that learners are attempting to balance allocation of limited resources across competing demands (Beck & Schmidt, 2015). As such, negative effects of self-efficacy may be indicative of shortcomings in training design rather than low learner motivation. Accordingly, I recommend that instructors spend less time trying to influence learner self-efficacy and more time developing learning environments that minimize biases, both positive and negative, in learner perceptions of their own

capability. Establishing clear expectations, improving the quality of learner goals, and providing detailed, informative feedback with updated goals (Kluger & DeNisi, 1996, 1998) can be instrumental in helping learners avoid pitfalls associated with overconfidence.

Metacognition and performance.

Relative to the amount of attention given to the self-efficacy-performance relationship, considerably less research has empirically examined dynamics in the relationship between metacognition and performance. In fact, based on my review of the literature, only a single study by Sitzmann and Ely (2010) examined the possibility that the relationship may be bidirectional. Even then, metacognition was studied as a part of a broader self-regulation index that also included motivation and concentration. This lack of research on the dynamics of the metacognition-performance relationship is surprising, particularly since metacognition is argued to be a key learning mechanism in many active learning interventions (Bell & Kozlowski, 2008, 2010; Keith & Frese, 2005; Schmidt & Ford, 2003). As such, the current study provides a unique contribution to research on metacognition in self-regulated learning because it (a) directly tests the assumption that metacognition is positively related to subsequent performance and (b) considers the possibility of feedback effects wherein changes in performance influence subsequent metacognition.

In general, the findings of the present study support claims that metacognition is positively related to performance in active-learning training (Brown & Ford, 2002; Smith et al., 1997). However, my results also revealed a positive feedback effect of prior performance on metacognition. The positive, reciprocal relationship between

metacognition and performance found in the present study is consistent with the notion that metacognition is an exploitation-oriented self-regulatory process that emphasizes reflecting on what worked in prior performance trials and identifying ways to capitalize upon short-term successes (Soderstrom & Bjork, 2015). It should be noted that an approach that emphasizes leveraging prior successes likely has mixed effects in the learning process. For instance, an exploitation focus can help learners identify and resolve the sources of error, which can lead to immediate performance improvements (Ivancic & Hesketh, 2000; Keith & Frese, 2005). However, the current results also suggest that a less desirable side effect of metacognition is that it inhibits exploratory behavior by focusing learner attention primarily on identifying and replicating strategies that had proved effective in the past. As a result, although metacognition is beneficial to immediate performance outcomes, excessive amounts of metacognition may ultimately limit the upward bounds of learner potential—particularly when learning tasks with that require proficiency in a number of varied strategies. Future research should further examine the nuances of this complex relationship, with an emphasis on identifying ways to balance these competing, but not necessarily opposing learning strategies. In the meantime, active learning interventions should seek to balance the need for learners to (a) reflect upon the success and effective performance strategies they identify via metacognition and (b) continue to expand their repertoire and experiment with other potential task solutions.

Exploratory behavior and performance.

The four key findings of the present study regarding dynamics in the exploration-performance relationship—namely, the positive trajectory of performance,

the negative trajectory of exploratory behavior, the positive effect of exploration on subsequent performance, and the negative effect of performance on subsequent exploration—all support the conceptualization of exploration as a systematic, information-gathering, behavioral self-regulatory process (Hardy et al., 2014). As such, the exploration-performance relationship can be best understood by considering how the antecedents of exploration (i.e. perceptions of novelty and information-knowledge gaps) evolve over the course of practice. Early in training, learners perceive high amounts of novelty, leading them to explore in an effort to reduce perceived information-knowledge gaps. As they explore, they learn, elevating subsequent levels of performance. However, performance increases also lead to trainee confidence in their own understanding and mastery over the task environment (Sitzmann & Ely, 2011). As a result, perceived information-knowledge gaps decline as skill acquisition progresses, leading to a similar decline in exploratory behavior. The result is the self-correcting, reciprocal relationship observed in the present study.

Given that exploratory behavior showed a positive, direct effect on performance and learning, the findings of the present study suggest that active learning interventions be designed with a clear understanding of how core training design elements influence learner exploration. In particular, I recommend that instructors carefully consider what novel information is available to trainees in the learning environment and how trainees perceive it. Moderate amounts of novelty invoke the greatest amount of exploratory behavior (Berlyne, 1966). As such, deviations from this middle ground may explain why many active-learning interventions fail. Trainees who feel they have little to learn (i.e., trainees with small information-knowledge gaps) will be unlikely to take

advantage of opportunities to explore in active-learning training. Conversely, trainees who lack the experience or ability to perform basic task functions will be overwhelmed by the amount of novelty available in active-learning environments, reducing their engagement in the learning process.

As such, trainers should take care to align the needs of learners with opportunities to engage novelty via exploratory behavior. Part of this alignment process is a recognition of the dynamics of exploration during training. In particular, my findings showed that overall levels of exploratory behavior were lowest late in practice. Continuously introducing small amounts of novelty into the learning environment as training progresses may help prevent learners from prematurely settling on a suboptimal approach and may help prevent them from failing to learn strategies that may be needed in future transfer situations. Adaptive training systems that provide real-time adjustments in the learning environment to meet the changing needs of learners (Shute & Zapata-Rivera, 2008) may be well suited for this purpose. However, adaptive training techniques are relatively new and many key empirical questions and technological limitations critical to their implementation remain (Landsberg et al., 2012). Nevertheless, the potential offered by systematically aligning the presentation of training content with changing learner needs is great. Future research should consider ways that adaptive training or other similar techniques can support exploratory behavior and other learner self-regulatory processes.

Dynamics among Behavioral and Cognitive/Motivational Self-regulatory Processes

Although the findings of the present study support the notion that self-regulated learning processes are inextricably interrelated (Sitzmann & Ely, 2011), they challenge

claims that these relationships necessarily imply construct redundancy. This is not to say that some degree of construct consolidation is not warranted in the self-regulated learning literature. Rather, I argue that an overemphasis on identifying which regulatory processes have the strongest bivariate relationships with learning outcomes may cause researchers to overlook the complexity underlying the interrelationships among these mechanisms. By adopting a process conceptualization of self-regulation and examining directionality of effects at the within-person level of analysis, the present study revealed that both self-efficacy and metacognition showed self-correcting reciprocal relationships with exploration. These dynamics carry important implications for the learning process and for the design of training interventions. In the following sections, I review the findings regarding both the exploration-metacognition and exploration-self-efficacy relationships and their implications for research and practice in active learning.

Self-efficacy and exploratory behavior.

Examining effects primarily at the between-person level might lead one to conclude that self-efficacy and exploration are strongly and positively related. However, this approach risks misrepresenting the true nature of what is, in actuality, a fundamentally within-person relationship (Yeo & Neal, 2013). Specifically, the findings of the present study revealed a self-correcting, reciprocal relationship such that exploration positively influenced subsequent self-efficacy whereas self-efficacy negatively influenced subsequent exploration. This feedback effect bears a remarkable similarity to both the exploration-performance and self-efficacy-performance relationships, suggesting that the mechanisms underlying these relationships might be similar. For example, the positive effect of exploration on self-efficacy is likely a reflection of the positive

influence of exploration on performance. Trainees who explore become more competent in their dealings with the environment, which helps build feelings of efficacy (White, 1959). Feelings of efficacy resulting from performance gains reduce the information-knowledge gap, causing learners to feel that further exploration is no longer necessary. These findings suggest that changes in self-efficacy likely underlie the negative performance-to-exploration relationship.

As such, I again reiterate my earlier claim that interventions that emphasize targeting learner self-efficacy may be misguided. Rather than devoting time, energy, and resources toward elevating learner self-efficacy, instructors should seek to prevent learners from underestimating the true nature of their information-knowledge gaps and to help them identify and feel comfortable engaging novelty in the task environment. Nevertheless, similar to the self-efficacy-performance relationship, I expect that there are several boundary conditions and moderators of self-efficacy-to-exploration effects. For example, when developing predictions for the self-efficacy-to-exploration effects, I argued that trainees higher in self-efficacy would feel more comfortable embracing and exploring sources of complexity in the learning environment. This would be particularly important in high stakes situations where the costs of failure are high, and may counteract, or even reverse, the negative efficacy-to-exploration relationships found in the present study. Furthermore, research and theory supports the notion that self-efficacy is positively related to goal acceptance (Bandura, 1997; Vancouver et al., 2008). Thus, another situation where self-efficacy might positively predict subsequent exploratory behavior is in contexts where learners are generally hesitant to accept goals. Because exploration is a type of goal-directed behavior, I expect that a minimum

threshold of self-efficacy must be met before learners will commit energy and resources toward exploring. However, future research is needed to test these propositions and to identify other possible moderators of exploration-self-efficacy relationships.

Metacognition and exploratory behavior

Similar to the self-efficacy-exploration relationship, the findings of the present study suggested a self-correcting, reciprocal relationship between metacognition and exploration. However, contrary to the findings for self-efficacy, both metacognition and exploration were positively related to subsequent performance. Together, these findings support the notion that exploration and metacognition are two important pieces of the learning process. Exploration allows learners to engage novelty and complexity in the environment, gain a deeper understanding of the task, and develop a broader strategic repertoire whereas metacognition helps learners reflect on, refine, and improve upon available approaches to task performance. Moreover, exploration supports metacognitive functioning by exposing learners to a broader range of task information upon which they can reflect and plan for future performance. However, a unique finding in this study was the negative feedback effect of metacognition on exploration. This pattern is consistent with the conceptualization of metacognition as an exploitative, performance-oriented rather than exploratory, learning-oriented approach. As such, although metacognition contributes to learning by improving immediate task performance, it may limit learner potential by narrowing their focus on a suboptimal range of strategies too early in practice.

These findings carry several important implications for research and practice on self-regulated learning. At a conceptual level, they suggest that the relationship between

self-regulated learning processes and performance may be more complex than originally thought. Although metacognition can benefit the learning process, it may ultimately limit learner potential by suppressing learner exploratory behavior. These findings also highlight the importance of studying self-regulated learning where it occurs—at the within person level. A “horse race” approach where incremental predictive validities are the primary goal may not be appropriate when studying the learning process. Research designed to unravel the nuances of complex relationships like these at the appropriate level of analysis is lacking and is much needed. In particular, tracking changes in learner self-regulation along with potential mechanisms underlying their interrelationships throughout training can aid in the design of more effective and reliable active-learning interventions. For example, the self-correcting reciprocal relationships found in the present study among self-regulated learning processes suggest that there is potential in developing instructional environments that help learners better balance their conflicting tendencies. Such a training paradigm would work to make instructors and learners alike more cognizant of their learning process and to be more sensitive to the positive and negative consequences of learner thoughts and behaviors.

Toward a Dynamic Process Model of Self-regulated Learning

Collectively, the findings of the present study suggest that self-regulation in learning contexts is best understood as a collection of closely interrelated processes that increase and decrease over the course of practice in response to changes in performance. To help make sense of what the findings of the present study suggest regarding how self-regulation unfolds over the course of practice, I organize them here into a dynamic process model of self-regulated learning shown in Figure 3. I do not intend for this

model to serve as a formal theory of self-regulated learning. Rather, I intend to use it as an organizing heuristic for understanding and applying the findings of the present study. Nevertheless, the model shown in Figure 3 bears several notable similarities to existing theories of self-regulation. First, I conceptualize self-regulation as a phase-based phenomenon that unfolds throughout the learning process, an approach similar to that taken by Pintrich (2000). Moreover, consistent with Zimmerman's (2000) social-cognitive model of self-regulation, this framework allows for iterative feedback loops in recognition of learning as a dynamic phenomenon that is constantly changing.

One aspect of my model that differs from many other theories of self-regulated learning is that behavior is conceptualized as an early rather than late step in the learning cycle. This is not to say that exploration always precedes cognitive or motivational self-regulation. Indeed, the iterative nature of the learning cycle makes it difficult to clearly distinguish what is the "first step." Nevertheless, I begin with exploration in my model to emphasize the importance of exploration as a facilitator of cognitive and motivational self-regulation. This characteristic of the model reflects my findings, which showed that exploration alone was positively related to metacognition, self-efficacy, and performance outcomes. Exploratory behavior directly benefits performance and learning outcomes by allowing learners to develop a broader repertoire of strategies and approaches that they can use in response to a wide range of task demands. Moreover, learners who explore develop experiences and are exposed to information that enables them to engage in effective performance and learning-oriented cognition. However, an interesting aspect of both the present findings and of the model shown in Figure 3 is that although exploration and metacognition both positively

influenced performance outcomes, metacognition also had a negative influence on subsequent exploration. This pattern of findings implies that the learning process is comprised of parallel, and occasionally competing, internal processes focused around (a) performance/exploitation cycles—that is, a pattern of behavior centered around exploiting one’s knowledge and experiences and acquiring immediate performance gains—and (b) learning/exploration cycles—that is, a pattern of behavior focused on distal performance gains resulting from exploring unresolved sources of novelty and complexity in the task. Future research should explicitly examine the interplay between the performance/exploitation cycle and the learning/exploration cycle and the implications of these relationships for learning, retention, and transfer outcomes.

Another notable aspect of the model is the inclusion of self-efficacy as a consequence of performance outcomes rather than as a predictor. This represents a marked departure from the traditional conventional wisdom based on a long history of between-person research (e.g., Colquitt et al., 2000) that suggested that self-efficacy was a primary antecedent of motivation in learning contexts. Although a hearty debate on the functional properties of self-efficacy in the learning cycle remains active (Bandura, 2015), this study contributes to a growing body of evidence that suggests that interventions targeting learner self-efficacy may not show benefits in performance where they matter most—the within-person level. Moreover, my model reflects the findings of the present study that suggest that self-efficacy may even be limiting learner potential by diverting resources away from constructive learning processes such as exploratory behavior.

Although the model provided here is by no means comprehensive, future research on self-regulated and active learning can benefit greatly from adopting a dynamic, within-person, process-based conceptualization of learning. It is my hope that the findings of the present study and the process model provided here inspire future researchers to adopt similar approaches to the study of self-regulation in the learning process. This area is in desperate need of more research and theory that accounts for dynamics in the learning process. Only by studying the phenomena at the level at which it occurs can we hope to make future advances in this area.

Limitations and Directions for Future Research

Several limitations of the present study should be noted when interpreting and applying these results. First, the videogame task used in the present study differed from tasks typically found in more traditional training programs and the training environment lacked real-world consequences for trainees based on training outcomes. Thus, appropriate caution should be exercised when generalizing the current findings across training contexts. That being said, characteristics of the task and the sample used in this study reflect aspects typical of active-learning training approaches. For example, UT2004 possesses a combination of cognitive and psychomotor demands and a computer-based interface typical of technology-based training such as synthetic learning environments (SLE; Cannon-Bowers & Bowers, 2010), which is seeing increased usage in organizational training and development (American Society for Training and Development, 2010). Thus, the processes examined in this study can be expected to generalize to other active-learning training contexts. Another strength of this task is that many of my participants had prior experience with videogames—a

condition that is common in many real-world training contexts, but is rare in lab-based training and development research. Because of this, I was able to examine variability in pre-training task-related knowledge as a predictor of learning processes and outcomes. Nevertheless, additional research is needed to examine if the current findings generalize to other types of tasks and across a broader array of training delivery approaches and populations.

Second, although self-efficacy, metacognition, and exploratory behavior collectively encompass a broad range of established self-regulated learning mechanisms, the current research was necessarily limited in its coverage of other regulatory processes such as emotion control and time management. As such, the model shown in Figure 3 may ultimately be incomplete, as it does not take into account how affect, emotion, and time pressure play a role in the learning process. Accordingly, future research should expand the present effort to examine dynamics in less commonly examined regulatory processes.

Finally, the present study is unique in the extent to which dynamic interrelationships among multiple self-regulated learning constructs over the course of practice were examined. However, because I did not directly measure the theoretical mediators underlying these relationships (e.g., perceptions of novelty, information-knowledge gaps, resource allocation, and effort), I could only speculate as to the exact functioning of these theoretical sub-mechanisms. Although such a fine grained approach was beyond the scope of the present study, future research that empirically examines these and other sub-processes as mediators of the dynamic interrelationships among self-regulatory processes and learning outcomes can provide important insights

into how the learning process unfolds. To provide structure to such investigations, it may be helpful to point out that many of the explanations offered in the present study are consistent with control theory frameworks (Carver & Scheier, 1982, 2001; Powers, 1973). Specifically, the majority of my predictions as well as my findings imply discrepancy-reducing feedback loops that operate through cybernetic structures containing input, comparator, and output functions (Vancouver, 2005). As such, computational modeling approaches (e.g., Vancouver, Weinhardt, & Schmidt, 2010) may be particularly useful for representing the complex interrelationships among self-regulatory processes and their sub-mechanisms. Computational theories can be used to develop specific and falsifiable predictions for how self-regulated learning changes over time (Vancouver, Weinhardt, et al., 2014). Indeed, a paradigm shift toward computational theories that account for dynamics in relationships across levels of analysis may be critical for making further progress toward our understanding of human learning (J. R. Anderson et al., 2004).

One benefit of developing a better understanding of the learning process is that these principles can be leveraged to improve training design and to positively influence learning outcomes for trainees in active-learning contexts. As such, in tandem with expanding, testing, and refining dynamic theories of self-regulated learning, researchers should also seek to develop training interventions that identify and resolve shortcomings in the learning process. For example, allowing learners to track their own self-regulated learning processes over the course of practice in real time may help them more effectively regulate their cognitions and behaviors and allow them to avoid

common pitfalls identified in the literature, such as overconfidence (Soderstrom & Bjork, 2015) or settling too early on a suboptimal approach (Yeucham et al., 2001).

Moreover, future research should examine how interrelationships among self-regulated learning processes and performance change as a function of the learning environment. For example, a sudden influx of novelty resulting from a fundamental shift in the task rules, principles, or structure, may alter the trajectory of learner exploration, self-efficacy, and metacognition and reshape the nature of the self-regulation-performance relationship. Given that the development of learner adaptability is argued to be a key advantage of active learning frameworks over more traditional training designs (Bell & Kozlowski, 2010; Kozlowski et al., 2001), additional research targeting the role self-regulation plays in the development of adaptability outcomes is warranted.

Conclusion

Dynamic, within-person, process-based research on self-regulated learning has a lot to offer researchers and practitioners interested in implementing and improving active-learning training. By considering the dynamics of self-regulatory processes, this study (a) makes a case for including behavioral self-regulation in models of self-regulated learning, (b) calls into question the capability of exploration instructions to meaningfully influence learner behavior, (c) reveals feedback loops in the relationships between self-regulatory processes and performance, and (d) contributes to the development of a process-based model of self-regulated learning that describes how self-regulatory processes can show both positive and negative effects on skill acquisition at the within-person level. It is my hope that this study provides a

foundation for future research that can build upon and expand the present findings and inspires future research on active learning to recognize the centrality of considering the dynamics of self-regulation in the learning process.

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Appendix A: Tables

Table 1

Means, Standard Deviations, and Intercorrelations of Study Variables at the Between- and Within-person Levels

<i>Between-person level</i>	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Exp. condition	0.50	--														
2. GMA	0.00	0.85	.09													
3. Pre-TK	0.00	0.81	-.02	.15**												
4. LGO	3.99	0.55	.03	.05	.01											
5. PPGO	3.79	0.59	-.07	-.06	.02	.18**										
6. APGO	2.61	0.80	.06	-.07	.06	-.42**	.15**									
7. MTL	4.25	0.64	.00	.08	.24**	.23**	.09	-.10†								
8. Exploratory beh.	2.97	0.38	.08	.16**	.38**	.07	-.08	-.01	.27**							
9. Self-efficacy	3.40	0.76	-.10†	.08	.49**	.22**	.10†	-.08	.30**	.38**						
10. Metacognition	3.84	0.51	-.06	.02	.23**	.29**	.21**	-.13*	.40**	.23**	.57**					
11. Practice perf.	31.62	11.59	-.02	.27**	.70**	.02	-.01	.03	.23**	.51**	.63**	.40**				
12. Task knowledge	0.61	0.13	.08	.36**	.39**	.05	-.06	-.06	.18**	.26**	.21**	.07	.40**			
13. Test perf.	38.13	16.78	.03	.24**	.54**	.03	-.02	.04	.21**	.37**	.47**	.21**	.69**	.34**		
14. Transfer perf.	22.43	11.42	.01	.15*	.56**	.01	.00	.10†	.14*	.36**	.50**	.28**	.69**	.34**	.53**	
15. Task enjoyment	3.52	0.86	-.03	.10†	.35**	.03	.01	.00	.24**	.38**	.60**	.45**	.52**	.18**	.31**	.37**

<i>Within-person level</i>	M	SD	1	2	3	4	5
1. Practice session	0.00	1.41					
2. Exploratory beh.	2.97	0.49	-.49**				
3. Self-efficacy	3.38	0.83	.13**	-.06**			
4. Metacognition	3.84	0.63	.23**	-.08**	.16**		
5. Practice score	31.62	13.59	.14**	-.04	-.04	.14**	
6. Practice score lag	28.36	13.66	.27**	-.13**	.19**	.11**	.67**

Note. Exp. Condition = Exploration manipulation (coded: 0 = control, 1 = exploration instructions); GMA = general mental ability;

Pre-TK = Pre-training task-related knowledge; LGO = learning goal orientation; PPGO = performance-prove goal orientation; APGO = performance-avoid goal orientation; MTL = pre-training motivation to learn.

N between-person = 305. *N* within-person = 1525. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 2

Fit Statistics and Predictor Coefficients for Conditional Latent Growth Models

Variable	$\chi^2(df)$	CFI	SRMR	RMSEA [upper 90% CI]	DV ^a	γ						
						GMA	Pre-TK	LGO	PPGO	APGO	MTL	
Performance	35.47 (28)	.99	.03	.030 [.056]	Intercept	.10*	.74**	.06	-.03	.09†	.04	
					Slope	.28**	.08	-.16	-.03	-.22†	.13	
Self-efficacy	180.10 (40)	.94	.03	.107 [.123]	Intercept	-.05	.50**	.28**	.08	.05	.13*	
					Slope	.08	-.01	-.20**	-.04	-.16*	.06	
Metacognition	86.88 (28)	.95	.05	.083 [.103]	Intercept	-.13*	.26*	.16*	.16**	-.03	.22**	
					Slope	.16*	-.15*	.03	.00	-.06	.15*	
Exploratory behavior	76.10 (28)	.95	.06	.075 [.096]	Intercept	.10†	.36**	-.06	-.06	-.03	.18**	
					Slope	.02	.08	.19*	-.12†	.11	.06	

Note. CFI = comparative fit index; SRMR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; γ = standardized coefficient; GMA = general mental ability; Pre-TK = Pre-training task-related knowledge; LGO = learning goal orientation; PPGO = performance-prove goal orientation; APGO = performance-avoid goal orientation; MTL = pre-training motivation to learn. Not shown are the relationships between the performance intercept and slope ($\gamma = .20, p > .05$), the self-efficacy intercept and slope ($\gamma = -.10, p > .05$), the metacognition intercept and slope ($\gamma = -.40, p < .01$), and the exploration intercept and performance slope ($\gamma = -.06, p > .05$).

^aFor each repeated variable, either its latent intercept or latent slope was the dependent variable associated with the predictor coefficients presented in the columns to its right.

[†] $N = 305$. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 3

Hierarchical Multiple Regression Results for the Prediction of Learning Outcomes by Self-regulatory Processes

Model/Variable	<i>B</i>	<i>SE</i>	β	R^2	ΔR^2
Practice performance					
1. Self-efficacy	7.32**	0.81	.48	.40**	
Metacognition	1.24	1.13	.06		
2. Exploratory behavior	9.71**	1.36	.32	.49**	.09**
Task knowledge					
1. Self-efficacy	.028*	.012	.17	.05**	
Metacognition	-.019	.016	-.08		
2. Exploratory behavior	.069**	.020	.21	.09**	.04**
Analogical transfer					
1. Self-efficacy	9.60**	1.40	.43	.23**	
Metacognition	-2.76	1.96	-.08		
2. Exploratory behavior	9.91**	2.35	.23	.27**	.04**
Adaptive transfer					
1. Self-efficacy	6.37**	0.95	.42	.24**	
Metacognition	-0.17	1.32	-.01		
2. Exploratory behavior	6.16**	1.59	.21	.28**	.04**
Task enjoyment					
1. Self-efficacy	0.51**	0.07	.45	.37**	
Metacognition	0.26**	0.09	.15		
2. Exploratory behavior	0.38**	0.11	.17	.40**	.03**

Note. The regression weights shown are from the final model.
N = 305. †*p* < .10, **p* < .05, ***p* < .01 (two-tailed).

Table 4

Hierarchical Multiple Regression Results for the Exploration Instructions on Exploratory Behavior and Learning Outcomes

Model/Variable	<i>B</i>	<i>SE</i>	β	R^2	ΔR^2
Exploratory behavior					
1. GMA	.003	.036	.01	.20**	
PTK	.124**	.035	.26		
LGO	.035	.042	.05		
PPGO	-.074*	.036	-.11		
APGO	.013	.028	.03		
MTL	.116**	.033	.20		
2. Exp. condition	.054	.040	.07	.20**	.00
3. Exp. condition \times GMA	.060	.048	.10	.21**	.01
Exp. condition \times PTK	.062	.050	.09		

Note. Exp. Condition = Exploration manipulation (coded: 0 = control, 1 = exploration instructions); GMA = general mental ability; PTK = pre-training task-related knowledge; LGO = learning goal orientation; PPGO = performance-prove goal orientation; APGO = performance-avoid goal orientation; MTL = pre-training motivation to learn. The regression weights shown are from the final model. $N = 305$. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 5
Fit Statistics, Coefficients, and Inter-factor Relationships for Cross-lagged Latent Growth Models with Practice Performance

Process variable	Cross-lagged model	$\chi^2(df)$	CFI	SRMR	RMSEA [upper 90% CI]	AIC	Performance to process	Process to performance
Self-efficacy	Independent	378.76 (94)	.92	.03	.100 [.110]	13443.96		
	Performance to process	285.64 (93)	.95	.03	.082 [.093]	13352.84	.12**	
	Process to performance	357.78 (93)	.93	.03	.086 [.107]	13424.98		-.19**
	Bidirectional	279.92 (92)	.95	.03	.082 [.093]	13349.12	.12**	-.10*
Meta-cognition	Independent	187.65 (76)	.95	.04	.069 [.082]	12897.52		
	Performance to process	172.20 (75)	.96	.04	.065 [.078]	12884.07	.07**	
	Process to performance	184.06 (75)	.95	.04	.069 [.082]	12895.93		.01†
	Bidirectional	167.48 (74)	.96	.04	.064 [.077]	12881.35	.07**	.02*
Exploratory behavior	Independent	142.55 (76)	.97	.05	.054 [.067]	12061.55		
	Performance to process	134.46 (75)	.97	.05	.051 [.065]	12055.46	-.05**	
	Process to performance	135.28 (75)	.97	.05	.051 [.065]	12056.28		.02**
	Bidirectional	127.99 (74)	.98	.05	.049 [.063]	12050.99	-.05**	.02**
Inter-factor relationships	Self-efficacy intercept						Exploration intercept	Exploration slope
	Performance intercept	.41**	.16†	.32**	-.10	.44**		.15
	Performance slope	.05	.67**	.07	.42**	-.16		.32*

Note. Cross-lagged parameters were specified in four ways: (1) Independent = cross-lagged paths constrained to 0, (2) Performance to process = only paths directed to the active-learning process were estimated, (3) Process to performance = only paths originating from the active-learning process were estimated, and (4) Bidirectional = both paths to and from the active-learning process were estimated. CFI = comparative fit index; SRMR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; AIC = Akaike information criterion.
 $N = 305$. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 6
Fit Statistics, Coefficients, and Inter-factor Relationships for Cross-lagged Latent Growth Models with Exploratory Behavior

Process variable	Cross-lagged model	χ^2 (df)	CFI	SRMR	RMSEA [upper 90% CI]	AIC	Exploration to process	Process to exploration
Self-efficacy	Independent	300.82 (94)	.94	.05	.085 [.096]	3560.45		
	Exploration to process	270.53 (93)	.94	.05	.079 [.090]	3532.16	.05**	
	Process to exploration	269.49 (93)	.94	.05	.085 [.096]	3558.12		-.09**
	Bidirectional	267.84 (92)	.95	.05	.079 [.090]	3531.47	.03**	-.07†
Metacognition	Independent	196.65 (76)	.94	.06	.072 [.085]	2978.50		
	Exploration to process	182.02 (75)	.95	.06	.068 [.081]	2965.87	.02**	
	Process to exploration	191.95 (75)	.94	.06	.072 [.084]	2975.80		-.02*
	Bidirectional	176.97 (74)	.95	.06	.068 [.080]	2962.83	.02**	-.02*
Inter-factor relationships				Self-efficacy intercept		Metacognition intercept		Metacognition slope
	Exploration intercept	.25**		slope		slope		
	Exploration slope	.03		.03		.12		-.09
				.18*		.05		.10

Note. Cross-lagged parameters were specified in four ways: (1) Independent = cross-lagged paths constrained to 0, (2) Exploration to process = only paths directed to the active-learning process were estimated, (3) Process to exploration = only paths originating from the active-learning process were estimated, and (4) Bidirectional = both paths to and from the active-learning process were estimated. CFI = comparative fit index; SRMR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; AIC = Akaike information criterion. $N = 305$. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Appendix B: Figures

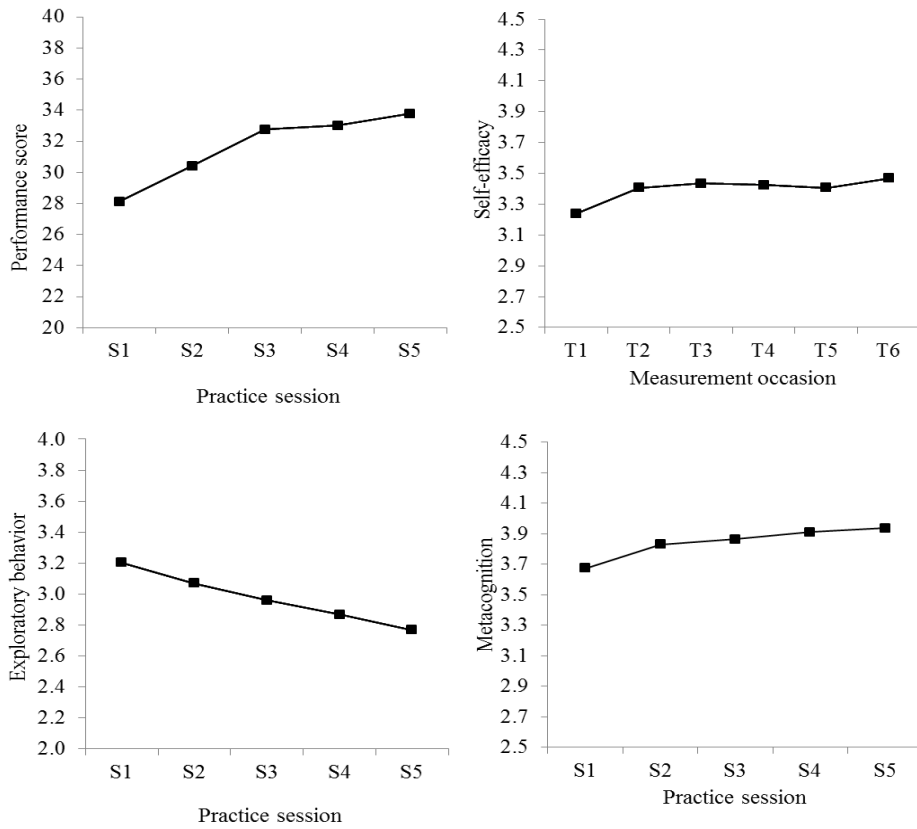


Figure 1. Dynamic trends in study variables over the course of practice. Measurement occasion T1 preceded practice session S1, T2 preceded S2 etc. The y-axis is scaled to represent approximately +/- one standard deviation around the mean.

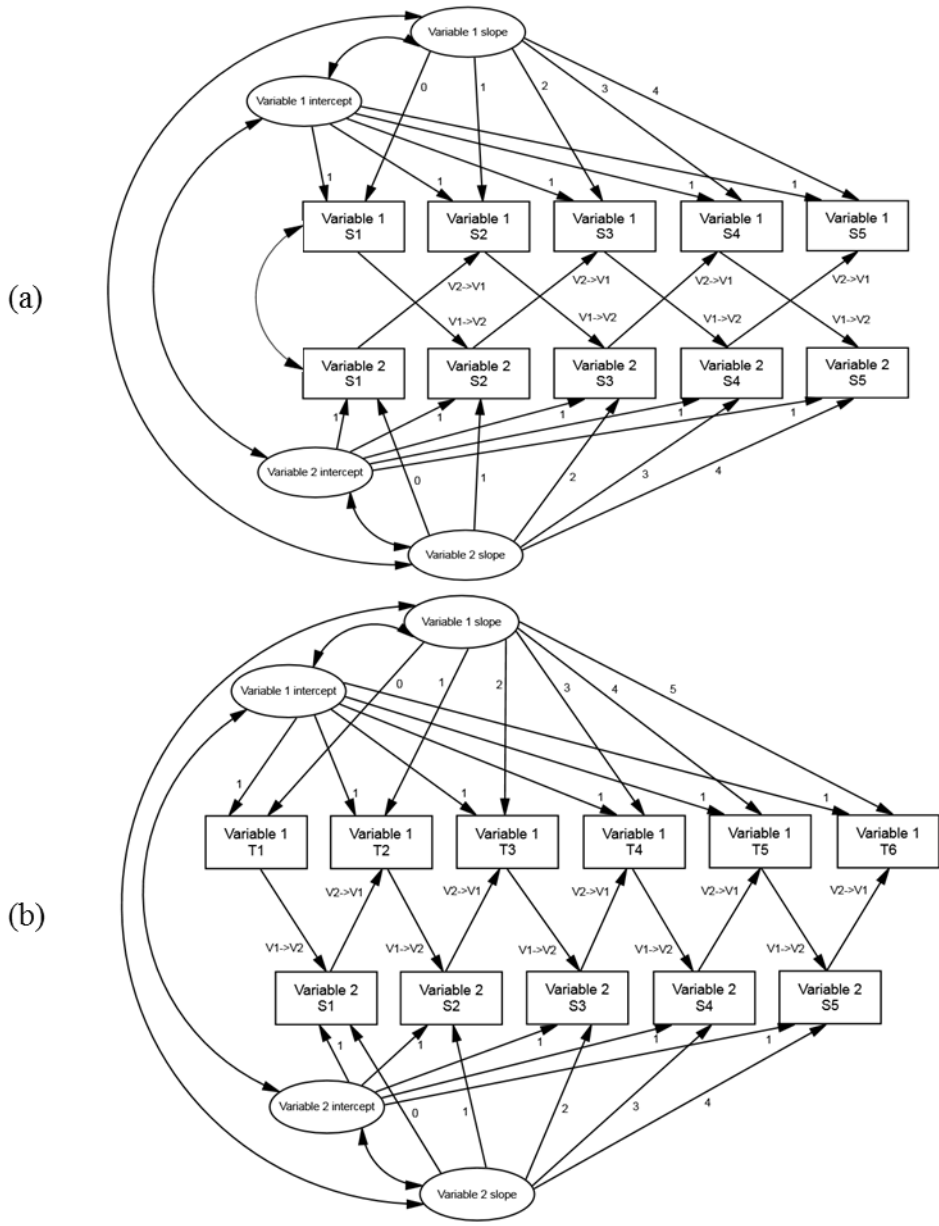


Figure 2. Models representing the specification of the bivariate cross-lagged latent growth model of the dynamic relationship between repeated variables. For figure simplicity, error terms and influence of the control variables on the latent intercepts and slopes are not shown.

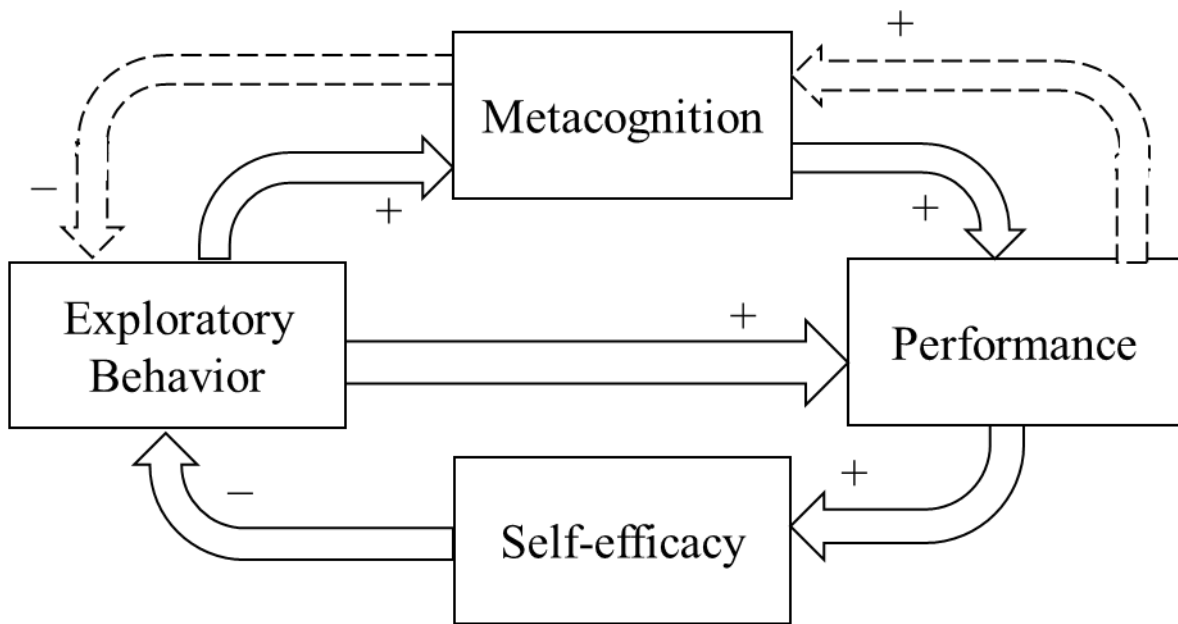


Figure 3. Dynamic process model of self-regulated learning.

Appendix C

Study Protocol

Task

Introduction

Informed consent

Demographic questionnaire and control measures

Training PowerPoint presentation

Practice trial (1 min)

Baseline skill assessment, trials 1 and 2 (3 min each)

Pre-training self-efficacy measure

Session 1

Exploration instructions manipulation

Session 1, practice trials 1-4 (3 min each)

Metacognition measure, time 1

Self-efficacy measure, time 1

Session 2

Exploration instructions manipulation refresher

Session 2, practice trials 5-8 (3 min each)

Metacognition measure, time 2

Self-efficacy measure, time 2

5 min break

Session 3

Exploration instructions manipulation refresher

Session 3, practice trials 9-12 (3 min each)

Metacognition measure, time 3

Self-efficacy measure, time 3

Session 4

Exploration instructions manipulation refresher

Session 4, practice trials 13-16 (3 min each)

Metacognition measure, time 4

Self-efficacy measure, time 4

Session 5

Exploration instructions manipulation refresher

Session 5, practice trials 17-20 (3 min each)

Metacognition measure, time 5

Self-efficacy measure, time 5

Enjoyment measure

Test phase

Post-training performance test, trials 1 and 2 (3 min each)

Advanced progressive matrices

Task knowledge test

Adaptive transfer performance test, trials 1 and 2 (3 min each)

Appendix D

Exploration instructions

Recent research in our lab has shown that when learning a skill such as Unreal Tournament, **learners will often settle on a single strategy they discover early on in practice and will not try anything else.** However, this learning approach was found to be inefficient and will often lead learners to get stuck in a rut and not get any better. **By only trying one approach, you will miss out on alternative strategies that allow you to get better at the game.**

As you practice Unreal Tournament in this study, pay attention to this tendency in yourself and work to overcome it *by practicing as many different things as possible* and carefully considering your successes and failures in reference to each approach you try.

For example, during practice, make sure you try *all of the weapons as well as their secondary capabilities* to find which one works best for you. Consider the different situations in which each weapon might be useful. Sometimes combinations of primary and secondary firing modes or even various weapons can be combined for increased effectiveness.

Also, *try to visit and fight in as many places on the map as you can* so you can get a good feeling for how the environment affects your performance and style of play. By exposing yourself to many different locations, you will improve your ability to succeed in a variety of environments.

Finally, *make sure to try many different strategic approaches as you practice.* You may experience success with one approach; however, there may be an even better strategy that you simply have not tried yet. By trying multiple strategies, you will become a more flexible player better able to adapt to the environment.

So remember, for the next 4 practice games; *continue exploring the Unreal Tournament game.* In the long run, the more willing you are to try multiple approaches during practice, the better you will be at Unreal Tournament when you are asked to perform your best.

For the rest of the practice session, you may use the cutie window to proceed at your own pace. And remember, **THE MORE YOU EXPLORE DURING PRACTICE, THE BETTER YOU WILL BE AT UNREAL TOURNAMENT IN THE END.**

Control instructions

Recent research in our lab has shown that when learning a skill such as Unreal Tournament, **practice is important.** However, not trying hard enough was found to be an inefficient approach and will lead learners to not achieve their full potential. **By not doing your best, you will miss out on learning that will allow you to get better at the game.**

As you practice Unreal Tournament in this study, pay attention to whether or not you are trying your best and carefully consider your successes and failures.

For the next 4 practice games; *continue to try your best in the Unreal Tournament game.* In the long run, the harder you try, the better you will be at Unreal Tournament when you are asked to perform your best.

For the rest of the practice session, you may use the cutie window to proceed at your own pace. And remember, **THE HARDER YOU TRY TO DO YOUR BEST DURING PRACTICE, THE BETTER YOU WILL BE AT UNREAL TOURNAMENT IN THE END.**