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Interrelationships Among Self-Regulated Learning Processes: Toward a Dynamic Process-Based Model of Self-Regulated Learning

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Self-regulation and learning are fundamentally dynamic phenomena that occur at the within-person level and unfold over time. However, the majority of the extant empirical research on self-regulated learning has been conducted at the between-person level, which can obscure the true nature of interrelationships among self-regulatory mechanisms. In the present study, we seek to advance a more nuanced view of the role of self-regulation in modern training and development by presenting a novel theoretical perspective that integrates cognitive, motivational, and behavioral mechanisms central to the literature on active learning with the more dynamic theoretical principles and mechanisms underlying stage-based cognitive models of skill acquisition. Hypotheses derived from this model were tested in a laboratory study with 305 participants who practiced a dynamic computer game involving strong cognitive and perceptual-motor demands. Bivariate cross-lagged latent growth models generally supported the proposed model, revealing systematic trends over the course of practice consistent with a series of iterative, bidirectional, and self-correcting reciprocal interrelationships among self-efficacy, metacognition, exploratory behavior, and practice performance. Collectively, these findings suggest that strong positive interrelationships among self-regulated learning variables at the between-person level may, in some cases, actually belie the true nature of their functional effects. Implications for theory and practice are discussed.

Keywords: *training and development; motivation; growth/longitudinal modeling; research methods*

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Introduction

One of the keys to effective functioning in modern society is the ability to regulate one's limited pool of effort and attentional resources in pursuit of individual, group, and organizational goals. This is particularly true in modern organizations where a shift toward decentralized organizational structures and an increased emphasis on employee autonomy require that managers place a greater reliance on employees to self-manage their behavior and work activities. To ensure that employees are equipped with the requisite knowledge and skill needed to perform in the more self-directed dynamic performance contexts of the modern workplace, the prevailing paradigm in the field of training and development has shifted over the last 20 years toward one with a greater focus on the potential of technology-based training, informal learning, and active learning for developing depth and adaptability in employee knowledge and skill (Bell & Kozlowski, 2008, 2010; Sitzmann, Bell, Kraiger, & Kanar, 2009). A defining characteristic of this new paradigm is its emphasis on learner control over key instructional decisions. The treatise is that training designed to increase employee participation in the learning process will allow learners to apply knowledge and skill acquired during training to a broader range of anticipated and unanticipated work demands (Kozlowski, Toney, et al., 2001).

Given the more pronounced role of the learner in this new paradigm, it should come as no surprise that *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: 421), is now a fundamental component of nearly all modern theories of adult learning and development. As a result, there are now hundreds of studies that examine the constructs, mechanisms, and principles of self-regulation (Sitzmann & Ely, 2011). Yet, despite a concentrated interest in this topic, our collective understanding of the role of self-regulation in learner-guided training and development remains surprisingly incomplete. For instance, it remains unclear how or why learners make some regulatory decisions and not others; how various cognitive, motivational, and behavioral regulatory processes conspire to promote (and, in some cases, inhibit) learning outcomes; or how learner use of self-regulation changes throughout the learning process. In other words, we know a lot about *what* matters in self-regulated learning but relatively little about *when* or *why* it matters in the learning process.

We believe that one of the primary reasons for slow progress in this area is a fundamental misalignment of theory and research with the dynamic nature of self-regulatory phenomena. Self-regulation and learning are dynamic processes that occur at the within-person level and unfold over time and across multiple levels of analysis (Sitzmann & Ely, 2011; Sitzmann & Weinhardt, 2018, in press). However, the majority of research on self-regulated learning thus far has been conducted at the between-person rather than within-person level. As Dalal and Hulin (2008: 69) warned, "the distinction between within-person and between-person structures of behaviors is ignored at the researcher's peril" because findings derived from between-person methodologies alone present an incomplete and occasionally misleading picture of the dynamic phenomena in question. This issue is particularly relevant to the training and development literature, which has produced several between-person, learner-centric interventions that have been shown to be effective (e.g., error management training, guided exploration, and mastery training; Debowski, Wood, & Bandura, 2001; Keith & Frese, 2005; Kozlowski, Gully, et al., 2001; Wood, Kakebeeke, Debowski, & Frese, 2000) but only a limited understanding of how or why they contribute to learning outcomes (and, perhaps more important, why they sometimes do not). Additional research on the within-person dynamic processes underlying self-regulated learning is needed to better inform managers on the potential benefits (as well as pitfalls) of giving employees more control over their learning opportunities. Although some progress has been made in this area (e.g., Hardy, Day, Hughes, Wang, & Schuelke, 2014; Sitzmann & Ely, 2010; Vancouver & Kendall, 2006), many fundamental questions remain unanswered.

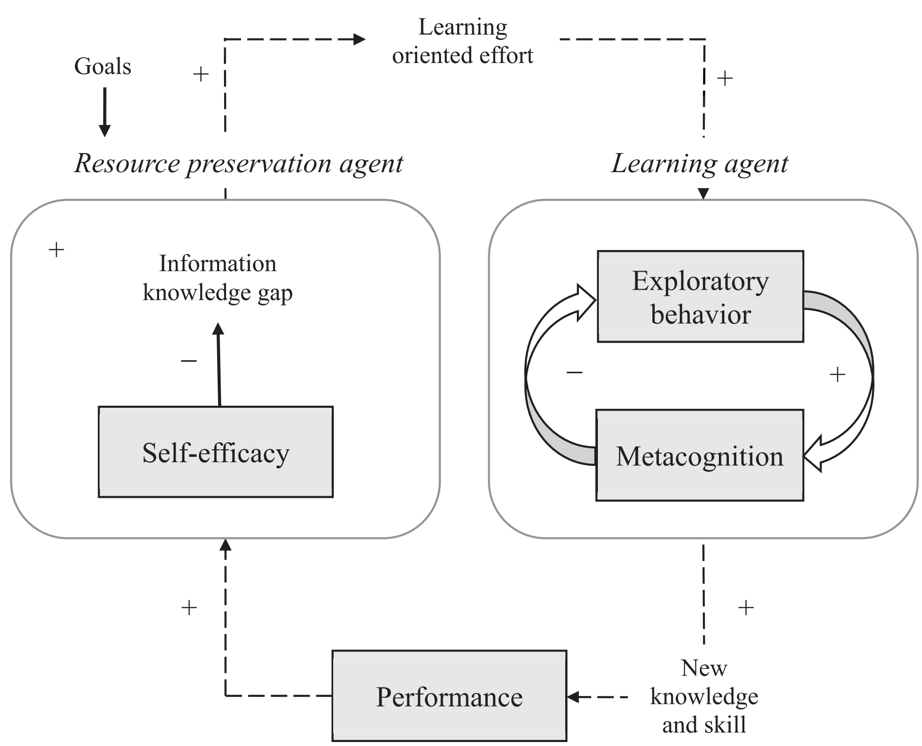
The purpose of the present study is to advance a more nuanced and dynamic view of the role of self-regulation in modern training and development by using a dynamic within-person design to examine the nature and directionality of interrelationships among commonly studied cognitive, motivational, and behavioral self-regulated learning variables in the context of a technology-mediated, learner-controlled training environment. In doing so, we seek to provide data that shed light on the importance of dynamics in the learning process. Toward this end, we present a novel theoretical perspective that integrates mechanisms discussed in the literature on active learning (Bell & Kozlowski, 2008, 2010; Keith & Wolff, 2015) with the theoretical principles and mechanisms of (a) perceptual control theory (Carver & Scheier, 1982; Powers, 1973; Vancouver, 2005), which focuses on the influence of negative feedback loops in the learning process (Vancouver, Weinhardt, & Vigo, 2014), and (b) stage-based cognitive models of skill acquisition (Anderson, 1982, 1996; Kanfer & Ackerman, 1989), which focus on how the needs (and thus behavior) of learners change as they acquire more advanced forms of knowledge and skill capacity. Collectively, we believe that a complete understanding of adult learning processes could benefit from a theoretical integration of these three perspectives.

To demonstrate this point, we show how a model built around such an integration (Figure 1) can be used to predict and explain a complex set of interrelationships among key self-regulated learning processes—namely, self-efficacy, exploratory behavior, and metacognition. Collectively, our findings show that strong interrelationships among regulatory constructs at the between-person level (Sitzmann & Ely, 2011) are not necessarily the product of construct overlap but instead indicate the existence of a more nuanced, richer, and more dynamic set of effects that become apparent only when examined at the within-person level of analysis.

Theoretical Foundation

One of the overarching goals of the modern paradigm of learner-centered training and development is to create interventions that "selectively influence cognitive, motivational, and affective self-regulatory processes to induce an active approach to learning" (Bell & Kozlowski, 2010: 263). To aid in the development of these interventions, Bell and Kozlowski (2010) proposed an integrative conceptual framework of active learning based on the adaptive learning system described by Kozlowski, Toney, et al. (2001) of which self-regulation was a central component. This framework is useful in that it draws on existing research to identify a specific set of individual differences, instructional interventions, self-regulatory processes, and learning outcomes that are most relevant to learner-controlled training and development. However, it reflects a broader limitation of the research upon which it was developed in that it does not offer much in the way of explanation regarding when, why, or

Figure 1
Theoretical Model



Note: Shaded boxes represent variables examined in the present study.

how self-regulation shapes the way effort and attention is allocated in pursuit of one's learning goals. The result is that we are left with a reasonably well-developed understanding of what processes matter in learner-controlled training but a limited understanding of how they actually contribute to the learning process.[1]

To fill this gap, we draw on research in other literatures that have made progress toward understanding the dynamic mechanisms underlying human behavior at work. For instance, research on work motivation is becoming increasingly rich with dynamic self-regulatory frameworks aligned with the within-person nature of the underlying phenomena (Lord, Diefendorff, Schmidt, & Hall, 2010). One notable example of this is the multiple-goal pursuit model (MGPM), which was developed to explain how individuals regulate limited attention and effort while pursuing competing goals (Vancouver, Weinhardt, & Schmidt, 2010). One of the most interesting characteristics of the MGPM is the conceptual parsimony of its central mechanism—the discrepancy-reducing negative feedback loop. Originally derived from perceptual control theory (Carver & Scheier, 1982; Powers, 1973), negative feedback loops portray a simple regulatory system in which system outputs are fed back in a manner that regulates future system behavior. Negative feedback loops are argued to regulate the amount of effort that individuals allocate toward goal pursuit such that expended effort corresponds with the perceived magnitude of the gap (or discrepancy) between the individual's desired state (i.e., goal) and his or her perceptions of one's current state (i.e., current performance). Effort allocated toward a particular goal influences future performance, which shapes future goal selection and effort allocation decisions. Vancouver et al. (2010) demonstrated that simulations generalizing the basic functioning of discrepancy-reducing negative feedback loops within a broader set of interrelated decision-making subprocesses (i.e., agents) of the MGPM successfully reproduced the complex behavior of real-world participants from prior studies of multiple-goal pursuit behavior, including dynamic trends that were otherwise difficult to explain.

In the years since the MGPM's initial development, Vancouver and colleagues (2014) expanded the model to account for interactions between the individual and her or his environment that contribute to permanent changes in the learner. For example, Vancouver et al. described the functioning of learning mechanisms through which individuals develop beliefs regarding the task context and their capacity for effectively resolving task demands. This work is highly relevant to the literature on self-regulated learning because it suggests that (a) learning and motivation are inextricably linked and (b) the interrelationships among learning and motivational processes elicit an adaptive response that facilitates corresponding changes in the learner and learning environment. This extension of the MGPM is particularly useful for describing the process by which miscalibrated (i.e., biased) performance expectancy perceptions are gradually resolved as individuals gain increased exposure to correcting information. However, the MGPM cannot be used for developing predictions regarding the interrelationships among regulatory processes in learner-controlled training because it was not designed to describe systematic changes in the learner's use of attentional resources over the course of learning.

For this piece of the puzzle, we turn to stage-based cognitive models of skill acquisition. Probably the most well known of these models in the industrial-organizational psychology and management literatures is Kanfer and Ackerman's (1989) cognitive information-processing model of complex skill acquisition. The core argument of Kanfer and Ackerman's model is that cognitive-attentional resources are limited. Thus, the capacity of learners to convert effort into positive performance outcomes depends on a combination of (a) their cognitive ability and (b) how far they have progressed through the various stages of skill acquisition.

The contribution of cognitive ability to this process is largely defined by stable individual differences that collectively determine the overall amount of capacity that individuals have for storing, retrieving, and processing information. Learners with higher levels of general intelligence, perceptual ability, and psychomotor ability are better equipped to manage the elevated attentional demands inherent in complex task performance (Kanfer & Ackerman, 1989). As a result, these individuals acquire knowledge and skill more quickly and are more likely to perform at a higher level in resource intensive tasks than their lower-ability counterparts.

However, knowledge acquisition is not static. For knowledge to be acquired, learners of all ability levels must navigate a series of stages in the learning process. This part of Kanfer and Ackerman's model (1989) draws heavily from the work of cognitive psychologist John Anderson and his adaptive control of thought–rational theory (ACT-R; Anderson, 1982, 1996), which proposed that the complexity of human cognition is a direct reflection of the complexity of the environment in which it operates rather than complexity inherent in the learning process itself. Learning can then be conceptualized as a simple (albeit labor-intensive) process in which individuals systematically acquire knowledge components relevant to performance on a given task (Anderson, 1996). First, learners gather pieces of declarative knowledge (i.e., knowledge about facts and things) into simple encodings of the environment called *chunks*. They then compile those chunks into procedural rules that represent the foundation of procedural knowledge (i.e., knowledge about how to perform various cognitive activities). With continued practice and compilation, performance gradually becomes automated. Consequently, attentional demands decrease as fewer cognitive resources are needed to execute a task.

One implication of ACT-R theory for skill acquisition and complex task performance is that the relevant cognitive demands placed on learners can be expected to differ depending on where learners are within the broader stages of skill acquisition. For instance, resource demands imposed on learners during the declarative phase are greater than during the procedural phase where attentional demands are much lower. Again, self-regulation is expected to play an important role here because without it, "an individual would be expected to continue to devote the same amount of resources originally committed to a task through the initial distal decision process" (Kanfer & Ackerman, 1989: 664). In this regard, stage-based cognitive models of skill acquisition are useful because they allow us to develop predictions regarding how the regulatory processes favored by learners can be expected to change over the course of learning.

An Integrated Dynamic Model of Self-Regulated Learning

Each of the theoretical perspectives described here offers something unique to an understanding of self-regulated learning that we believe can benefit from integration. For its part, active learning theory identifies the regulatory processes most relevant to learner-controlled training and development. Perceptual control theory provides a mechanism (i.e., the negative feedback loop) that can help explain how learners use self-regulation to determine the overall amount of effort that they should devote to the learning process relative to other functions. Stage-based cognitive models of skill acquisition highlight the role of dynamics in the learning process and the relevance of changes in learner cognition to changes in the learning process.

In the following sections, we describe the structure of a model (Figure 1) that integrates these perspectives. We then use this model to develop predictions for the interrelationships among three regulatory variables discussed in the active learning literature: *self-efficacy*, defined as the belief in one's capability to organize and execute the course of action required to succeed (Bandura, 1997); *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 (Hardy et al., 2014); and *metacognition*, which refers to the set of executive control functions that regulate learner self-knowledge and self-control in the learning process (Flavell, 1979).[2] In our model, we argue that dynamic interrelationships among these self-regulated learning processes serve two key functions. First, as noted by control theorists, effective self-regulation involves learners tracking performance levels (either intentionally or automatically) and using this information to allocate an appropriate portion of their limited pool of resources to learning goals. This function is captured in our model by the resource preservation agent (left side of Figure 1). Second, self-regulation helps to ensure that whatever effort is ultimately allocated to learning is then distributed effectively among exploration- and exploitation-oriented behaviors and cognitions as learners progress through knowledge compilation, as described by cognitive stage-based theories of learning. This function is captured in our model by the learning agent (right side of Figure 1). We turn next to describing these agents[3] in greater detail, with an emphasis on the implications for the interrelationships among self-efficacy, metacognition, and exploration.

Resource preservation agent. Learning a complex task is, by definition, a demanding and often overwhelming experience that requires learners to make sense of multiple task components, relationships between those components and the resulting products, and the relative dynamicity of those relationships (Wood, 1986). Self-regulation helps learners manage this complexity by redirecting limited time and attention away from where resources may be wasted (e.g., goals that are not achievable or readily attainable) and diverting them toward areas where they are most needed (i.e., goals where additional resources will help achieve desired outcomes). In the context of self-regulated learning, we refer to this set of functions as the *resource preservation agent*.

As depicted in Figure 1, we argue that self-efficacy is the self-regulatory process most central to the resource preservation agent. Research on self-efficacy in the training literature largely suggests that "self-efficacy leads to learning" and that "training should be designed to promote self-efficacy and then to reinforce it afterward" (Salas, Tannenbaum, Kraiger, & Smith-Jentsch, 2012: 84). However, nearly all this research has been conducted at the between-person level, which risks presenting an oversimplified picture of self-efficacy's role in the learning process. Along these lines, researchers have demonstrated that self-efficacy can have a positive, negative, null, or even spurious relationship with performance, even when the underlying motivational processes remain the same (Vancouver & Purl, 2017). This variability in effects across contexts and level of analysis is a direct by-product of the multiple roles self-efficacy plays in guiding human behavior. Specifically, self-efficacy influences not just the decisions that people make regarding which goals to pursue (i.e., goal choice) but also how much effort they allocate during the goal pursuit process (i.e., goal striving). Positive effects at the between-person level are the result of self-efficacy's positive indirect effect on motivation via goal choice. In contrast, high levels of self-efficacy at the within-person level can lead to overestimates of actual goal progress resulting in a reduction of resources allocated to goal pursuit (Schmidt & DeShon, 2010).

In our model, we propose that the primary function of self-efficacy in self-regulated learning is providing information to learners regarding the potential effectiveness of their future actions. In this regard, self-efficacy is a reflection of prior performance that learners use as a perceptual representation of performance progress. These beliefs arise dynamically via gradual adjustments to existing beliefs made in response to correcting information from the environment (Vancouver et al., 2014). As a result, we expect that the dynamic trajectory of self-efficacy should parallel corresponding trajectories in task performance, which in skill acquisition tends to take the shape of a classic trajectory characterized by a positive slope as learners gain new knowledge and skill that gradually decelerate over time as they reach the ceiling of their capabilities.

However, the true impact of self-efficacy is contingent on how efficacy beliefs are used. To develop predictions in this regard, we return to our earlier discussion of negative feedback loop. As noted, perceptual control theorists posit that people use negative feedback loops to regulate behavior, as they continuously monitor changes in the gap between their desired outcomes (represented by their goals) and beliefs pertaining to their current capabilities (represented by expectancies such as self-efficacy) when making decisions concerning how much of their limited resources, if any, to commit to goal attainment (Powers, 1991; Vancouver, More, & Yoder, 2008). Larger efficacy–goal discrepancies stimulate greater effort, as they are associated with the belief that more resources will be required to reach one's goals.

In dynamic learning contexts, capability–goal discrepancies are not stable (Bandura & Locke, 2003) but instead show a tendency to contract over the course of practice in response to increased feelings of mastery. Learners address gaps in their understanding by expending effort engaging with and exploring sources of unresolved novelty in their environment (Berlyne, 1960). The extent to which people are motivated to allocate resources toward learning-oriented effort is a function of the difference between two key perceptions: what individuals believe they currently know and what they believe they should know. Together, the discrepancy between these two key perceptions form what is known by curiosity theorists as the *information-knowledge gap* (or the *information gap*, for short; Loewenstein, 1994). As shown in Figure 1, we expect that increases in self-efficacy will be negatively related to the magnitude of the information gap, because when learners become more confident, they come to believe that they have less to learn. Consequently, they spend less energy consulting training manuals, asking questions, and, perhaps most important, less time considering the relative merits of their preferred performance strategies to potential alternatives.

If learners' perceptions of their capabilities are accurate, adjusting the pool of resources allocated toward learning-oriented effort in response to changes in information gaps is a perfectly rational response, as fewer resources are required in later stages of the learning process to produce similar outcomes (Kanfer & Ackerman, 1989). However, people show a natural tendency to overestimate their own capabilities (Kruger & Dunning, 1999) and to prematurely settle on suboptimal solutions (Döerner, 1980). Thus, reductions in learning-oriented effort may lead some learners to overlook other sources of information and viable performance strategies that they may not have yet considered. This pattern of effects also implies that self-efficacy will be negatively related to the amount of resources allocated to cognitive and behavioral self-regulated learning processes that emphasize knowledge acquisition and compilation. As such, we hypothesized that self-efficacy will be negatively related to the overall amount of effort devoted to learning goals and will thus be negatively related to both learning-focused behavioral self-regulation (i.e., exploratory behavior) and learning-focused cognitive self-regulation (i.e., metacognition).

Hypothesis 1: Prior self-efficacy will be negatively related to subsequent exploratory behavior.
Hypothesis 2: Prior self-efficacy will be negatively related to subsequent metacognition.

Learning agent. Given the inherent resource constraints prevalent in most learner-guided training and development contexts, it is in the learner's best interest to utilize his or her limited pool of attention and effort as efficiently as possible. To understand how our model proposes that self-regulation helps learners accomplish this goal within the learning process itself, it is important to first consider how the learning process unfolds over time and how these shifting demands correspond with the relative value of resources allocated to exploration-oriented learning behavior versus exploitation-oriented metacognition, respectively. For this, we return to ACT-R theory.

According to ACT-R theory, cognition is the result of an interplay between two related but distinct types of knowledge. *Declarative knowledge*, broadly defined as knowledge about facts and things (Anderson, 2005; Kanfer & Ackerman, 1989), is organized into knowledge units representing factual components of the information to be learned, called *chunks* (Anderson, 1996). *Procedural knowledge*, defined broadly as knowledge of how to perform various activities (Anderson, 2005; Kanfer & Ackerman, 1989), is represented in terms of production rules that define when, where, and how declarative chunks are to be used (Anderson, 1996). In ACT-R theory, declarative knowledge is the foundational unit of cognition. As such, it is typically the first type of knowledge to be assimilated during the learning process and is thus the primary focus of learners during the early stages of knowledge acquisition. Procedural knowledge, which represents a deeper understanding of how declarative knowledge chunks can be used, develops during knowledge compilation. Accordingly, it is generally the focus of learners during the later stages of acquisition, which place a greater emphasis on the integration of declarative chunks into the various production rules needed to perform the task. How efficiently learners are able to compile declarative knowledge into procedural knowledge is a direct function of the complexity of the task and the learner's total resource capacity (Kanfer & Ackerman, 1989).

Demands placed on learners in the declarative knowledge stage differ from the demands in the procedural knowledge stage of the learning process. Consequently, the relative value of exploration versus metacognition gradually shifts in proximity to knowledge compilation. Early in practice, there is a large amount of novelty and complexity in the task environment that remain to be resolved. Furthermore, when a task is new, learners tend to lack the coherent strategic frameworks needed to organize newly gathered knowledge and coordinate the execution of multiple task components. To address these limitations, learners engage in the greatest amount of exploratory behavior during the early stages of the learning process (Hardy et al., 2014). Basic knowledge and strategic knowledge gathered through exploration are important because they provide the foundation for knowledge compilation. However, as practice progresses, learners eventually resolve the most salient sources of novelty in their learning environment. In response, they shift their focus away from acquiring a broad repertoire of relevant declarative knowledge chunks and begin to focus more on consolidating their task understanding into a more streamlined set of production rules and performance strategies. For this reason, exploitation-focused metacognition is likely to become more central to skill acquisition as learning progresses. By focusing resources on a narrower, more limited set of relevant task-appropriate solutions, metacognition enables learners in the later stages of the learning process to evaluate factors that contributed to their prior successes and to adjust and refine their strategies accordingly, leading to performance improvements (Ford, Smith, Weissbein, Gully, & Salas, 1998).

Self-regulation helps learners manage these shifting demands by directing learning-oriented effort toward the specific regulatory strategy that is most likely to benefit each stage of the learning process. In our model, we propose that processes within the learning agent rely on a systematic, self-correcting interrelationship between exploratory behavior and exploitation-focused metacognition to enable learners to balance the amount of resources allocated to the competing (yet often complementary) goals of developing breadth in knowledge (via exploration) and depth in knowledge (via exploitation) as the demands of skill acquisition change. This cycle begins with exploration, which, as noted, helps learners acquire a repertoire of facts and information relevant to the task at hand. This is particularly valuable in the early stages of skill acquisition. New information acts as the “raw material” of knowledge compilation that encourages subsequent metacognition. For this reason, we predict that exploration will stimulate subsequent exploitation-focused metacognition because it compels learners to consider which chunks of knowledge are most pertinent to effective performance.

The corresponding self-correcting component of the exploration-metacognition interrelationship is a necessity of resource constraints placed on learners. Although high-ability learners will be able to maintain elevated levels of exploration and metacognition longer than low-ability learners, all learners will eventually approach the limits of their resource capacity, which means that they eventually must either (a) continue to gather new information or (b) shift toward a focus on processing information that has already been gathered. We predict that elevated levels of metacognition correspond with a natural strategic shift away from a focus on breadth in knowledge and toward a greater emphasis on depth in knowledge. As a result, in resource-constrained learning contexts, elevated levels of metacognition will often accompany a suppression of subsequent effort devoted to exploration due to a systematic reallocation of exploration-allocated resources to exploitation-focused processes. This transition is analogous to the way that organizations and entrepreneurs systematically switch from an emphasis on exploration to exploitation-based strategies as they gain knowledge and experience within a particular domain (Choi & Shepherd, 2004; March, 1991). This shift enables learners to adjust their expenditure of learning-oriented effort to meet the changing demands of late-stage proceduralization. The implication of the resource-dependent nature of exploration and metacognition is that we expect to see a strong positive exploration–metacognition relationship at the between-person level (because both regulatory processes draw from the same overall pool of resources devoted to learning effort, which can fluctuate from learner to learner) but a negative effect of metacognition on subsequent exploration at the within-person level.

Although this argument for a self-correcting reciprocal relationship between exploration and metacognition is intuitive and makes theoretical sense, we are unaware of any research within the industrial-organizational or management literatures that directly examined this relationship at any level of analysis. Fortunately, recent work in the cognitive decision-making literature examined relationships between related phenomena, such as strategy selection, recognition, and judgment (similar to the exploitation-focused conceptualization of metacognition discussed in our model), and information search (a behavior closely related to our conceptualization of exploratory behavior). For instance, Gonzalez and Dutt (2016) found that the primary goal of exploration in decision making appears to be centered on the identification of high-value alternatives. However, once a preferred approach is identified, exploration tends to decrease as decision makers divert available resources to decision implementation, which they perceive as having higher decision-making utility. This pattern is consistent with what we expect in a self-correcting exploration–metacognition relationship in which learners reallocate attentional resources from exploration to metacognition as they shift their focus from breadth of knowledge in the early stages of learning to depth of knowledge in the later stages of learning.

Hypothesis 3: Prior exploratory behavior will be positively related to subsequent metacognition.
Hypothesis 4: Prior metacognition will be negatively related to subsequent exploratory behavior.

The last component of the self-regulatory loop in our model is the feedback effect, in which increases in performance resulting from effective investment of learning-oriented effort are acknowledged by the system, resulting in adjustments to subsequent behavior. As discussed, our model maintains that exploratory behavior and metacognition both contribute to development of new knowledge and skill, which improve learner capabilities for producing high levels of performance. Changes in performance have important implications for how learners should engage the learning process. For instance, learners that have achieved task mastery may not require the same investment of learning-oriented effort as they did before. Conversely, learners who struggle may need to increase their engagement in the learning process to have a chance to meet their learning goals. However, before learners can determine which strategic approach is most appropriate, they must first find a way to convert performance feedback into a psychological representation of their own capability. In this regard, research has shown that the functional role of self-efficacy during goal striving is to serve as a mental reflection of prior performance that provides a perceptual representation of performance progress (Sitzmann & Yeo, 2013; Vancouver & Purl, 2017). This is achieved via gradual adjustments to existing beliefs made in response to correcting information from the environment (Vancouver et al., 2014). Thus, to the extent that exploratory behavior and metacognition lead to discernible improvements in performance, they should also be associated with increases in subsequent levels of self-efficacy at the within-person level. Positive relationships at the between-person level are thus also an expected by-product of this proposed shared positive association with performance.

Hypothesis 5: Prior exploration will be positively related to subsequent self-efficacy.
Hypothesis 6: Prior metacognition will be positively related to subsequent self-efficacy.

Method

Overview

To test our model's predictions, we designed a study in which self-efficacy, metacognition, exploratory behavior, and task performance were measured at repeated intervals within a sample of learners engaged in a semistructured, simulation-based, learner-controlled training environment. Hypotheses regarding the nature of interrelationships among the various processes were then tested with cross-lagged latent growth modeling.

Participants

Three hundred and twelve young adult males attending a large public university in the Southwestern United States participated in the study in exchange for research course credit. Due to computer problems, data from five participants were missing. Two other participants started but did not complete the study. In total, complete data from 305 participants were available for analyses. Participants ranged in age from 18 to 38 years (M = 19.49, SD = 2.23).

Performance Task

The performance task used in the present study was Unreal Tournament 2004 (UT2004; Epic Games, 2004), a commercially available first-person-shooter computer game that was used in prior research on learner decision making and skill acquisition (e.g., Hardy et al., 2014; Hughes et al., 2013). In UT2004, participants compete against computer-controlled opponents from the perspective of their character, which they manipulate in a fast-paced dynamic setting. The objective is to destroy computer-controlled opponents with weapons while minimizing the destruction of one's character. Participants start with only one basic weapon but can collect new weapons or resources (i.e., pickups) to increase their characters' health and capabilities. The game environment (i.e., the map) is arranged such that weapons and pickups appear in consistent locations. Special pickups are available in locations accessible only 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.

UT2004 involves a high degree of perceptual-motor and cognitive demands. In addition to using a mouse and keyboard to move and control their characters, 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 also 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.

Although UT2004 differs from the types of tasks traditionally used in the training and development literature, we determined that it was well suited for the current investigation based on its technology-mediated, shifting, ambiguous, and emergent task qualities (Keith & Wolff, 2015; Kozlowski, Gully, et al., 2001), which highlight its relevance for the types of active learning and simulation-based training contexts that have seen a sharp increase in recent years in the public and private sectors (American Society for Training and Development, 2015). Furthermore, UT2004 is useful as a performance task because it was designed to be relatively easy to learn but surprisingly difficult to master. This allowed us to ensure that changes in task knowledge and skill could be observed within the 3-hour time frame in which the study was conducted while ensuring that few participants could achieve task mastery within this time frame. Finally, UT2004 facilitated effective operationalization and measurement of the underlying regulatory processes in question (i.e., self-efficacy, metacognition, and exploratory behavior), which are mechanisms generalizable to nearly every learning context.

Procedures

Participants were told that the purpose of the study was to examine how people learn to play a dynamic and complex videogame. After providing 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-minute training video explaining the basic controls, rules, and objectives of UT2004, followed by 1 minute of in-game practice without opponents. Participants then performed two trials testing baseline performance on which they were instructed to do their best, followed by an initial self-efficacy questionnaire and a measure of motivation to learn. Next, participants entered a learner-controlled practice phase in which they performed twenty 3-minute practice trials divided into five sessions of four trials each. All participants were instructed to view the practice trials as learning opportunities. Following each of the five practice sessions, participants responded to self-report questionnaires assessing their metacognitive activity during the previous session and their current levels of self-efficacy. Before each session, participants set proximal goals for the following session and distal goals for the end of practice.

Measures

Performance. Scores for task performance were calculated with the following function of multiple in-game statistics originally derived from the formula used by the developers of UT2004 as an index of performance efficiency:

$$\text{performance} = \text{kills} / (\text{kills} + \text{deaths} + \text{rank}).$$

To aid in interpretability, all performance scores were all multiplied by 100. Thus, scores could range from 0 (low) to approximately 100 (high). With this formula, a player with 11 kills and 5 deaths who finished in first relative to the computer opponents in that trial would have a higher performance score (64.7) than a player with 5 kills and 11 deaths who finished in last (i.e., third) place relative to the computer opponents in that trial (26.3).

Self-efficacy. Self-efficacy was measured before each practice session and again following the final practice session with a 12-item task-specific scale adapted from previous studies (e.g., Bell & Kozlowski, 2002; Hughes et al., 2013) for UT2004. Items from this scale include “I feel confident in my ability to perform well in 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 ranged from .92 to .95.

Metacognition. Metacognition was measured following each practice session with 16 task-specific items adapted from Ford et al. (1998). 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 with a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Coefficient alphas ranged from .88 to .94.

Exploratory behavior. Exploratory behavior was coded in each practice trial from video playbacks by the first author and five coders familiar with common videogame environments and strategies. Coders underwent approximately 20 hours of frame-of-reference training in which they were introduced to the UT2004 training environment and the exploration scales.

Coders independently viewed game videos for each participant and rated exploratory behavior with four 5-point scales. Video files were stored in a way such that access to the videos ensured that the coders were blind to all information regarding predictor and criterion variables. Intraclass correlation coefficients (ICCs) were used to examine interrater reliability (Shrout & Fleiss, 1979). As recommended by Cicchetti (1994), ICCs between .60 and .74 are considered good interrater reliability, and ICCs >.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 other research based on this task (e.g., Hardy et al., 2014). Three scales in the current effort measured exploratory behavior in three major game domains: combat strategies (1 = *very few strategies tried*, 5 = *a great deal of strategies tried*; ICC_2 = .80), weapons (1 = *very few weapons tried*, 5 = *a great deal of weapons tried*; ICC_2 = .88), and map (1 = *very little map visited*, 5 = *entire map visited*; ICC_2 = .92). The fourth scale measured overall exploratory behavior and thus accounted for behavior not captured by the other scales (1 = *very little exploratory behavior*, 5 = *a great deal of exploratory behavior*; ICC_2 = .81). Support for the content- and construct-related validity (i.e., the sensitivity of scale scores to manipulated changes in exploration) for this operationalization of exploratory behavior was provided by Hardy et al. (2014). Together these scales combined to capture 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. Correlations among the exploration scale scores ranged from .21 to .76. A confirmatory factor analysis indicated that the four scales loaded onto a single factor (comparative fit index = .97, root mean square error of approximation = .06). Therefore, scale scores were averaged for each trial to create trial-level exploration indices, which were then averaged within each session to create session scores.

Control variables. Because we wished to isolate the natural interrelationships among self-regulatory processes as the primary explanation for the observed effects, we controlled for established predictors of learning and skill acquisition in all of our analyses. These variables included general mental ability (GMA), pretraining task-related knowledge, goal orientation, and pretraining motivation to learn. 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; completed after practice) was used as an index of GMA (composite reliability = .87).

Similar to Hardy et al. (2014), we used a composite index of videogame experience and baseline performance as a measure of pretraining task-related knowledge. Four items assessed trainee videogame experience. For the first two items, participants responded with a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*daily*) to the following questions: "Over the last 12 months, how frequently have you typically played video/computer games?" (M = 3.50, SD = 1.18) and "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, minimum = 0.00, maximum = 60.00) and how many hours per week they typically play first-person shooter video/computer games (M = 3.39, SD = 6.80, minimum = 0.00, maximum = 60.00). Scores for these four items were standardized and then averaged into a videogame experience score. Scores for the two baseline performance trials were also averaged (M = 20.75, SD = 11.57) and standardized. Finally, the standardized index of videogame experience and the standardized index of baseline performance were averaged to yield a composite index of pretraining task-related knowledge (composite reliability = .82).

Learning goal orientation, prove-performance goal orientation, and avoid-performance goal orientation were measured with a 13-item scale adapted from VandeWalle (1997). Responses were made with a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Coefficient alphas of .83, .75, and .83 were for learning goal orientation, prove-performance goal orientation, and avoid-performance goal orientation, respectively. Pretraining motivation to learn was measured with a 5-point Likert scale composed of the following two items: “I will devote my full attention to learning Unreal Tournament during this study” ($M = 4.21$, $SD = 0.71$) and “I will do my best to learn Unreal Tournament during this study” ($M = 4.29$, $SD = 0.65$; $\alpha = .88$).

Analytic Approach

To test our proposed hypotheses, we 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 in relationships, and latent growth modeling, which focuses on modeling covariation between each repeated variable’s latent intercept and growth terms, thus addressing the potential confounding influences of slope covariation (i.e., spurious positive relationships that may emerge due to similarities in the trajectories of two variables). In many ways, the goals of bivariate cross-lagged latent growth modeling are similar to those of hierarchical linear modeling in that both approaches seek to disaggregate relationships at the between- and within-person levels.

After univariate latent growth models were fit for each repeated variable, cross-lagged effects were examined by combining the best-fitting univariate growth models with parameters representing the lagged effect of each repeated variable upon the other (e.g., variable A on variable B at the subsequent time point and vice versa). Four alternative models with constraints specified to represent the four possible patterns of bivariate cross-lagged interrelationships among the self-regulatory variables (i.e., the independence model, the variable $A \rightarrow B$ unidirectional model, the variable $B \rightarrow A$ unidirectional model, and the bidirectional reciprocal model) were then compared according to overall model fit and parsimony. In the independence model, lagged parameters in both directions ($A \rightarrow B$ or $B \rightarrow A$) were constrained to be zero, implying no relationship between variables. In the unidirectional models, only the lagged effect of one regulatory process on the other ($A \rightarrow B$ or $B \rightarrow A$) was freely estimated with the other effect constrained to be zero, representing a one-way relationship with no feedback effects. In the bidirectional reciprocal model, the lagged effects of both regulatory processes on the other (e.g., $A \rightarrow B$ and $B \rightarrow A$) were freely estimated, implying the presence of two-way feedback effects.

Results

Dynamic Trends of Study Variables

Table 1 shows descriptive statistics and between- and within-person correlations among all study variables (including controls). We started by examining the dynamic trends of

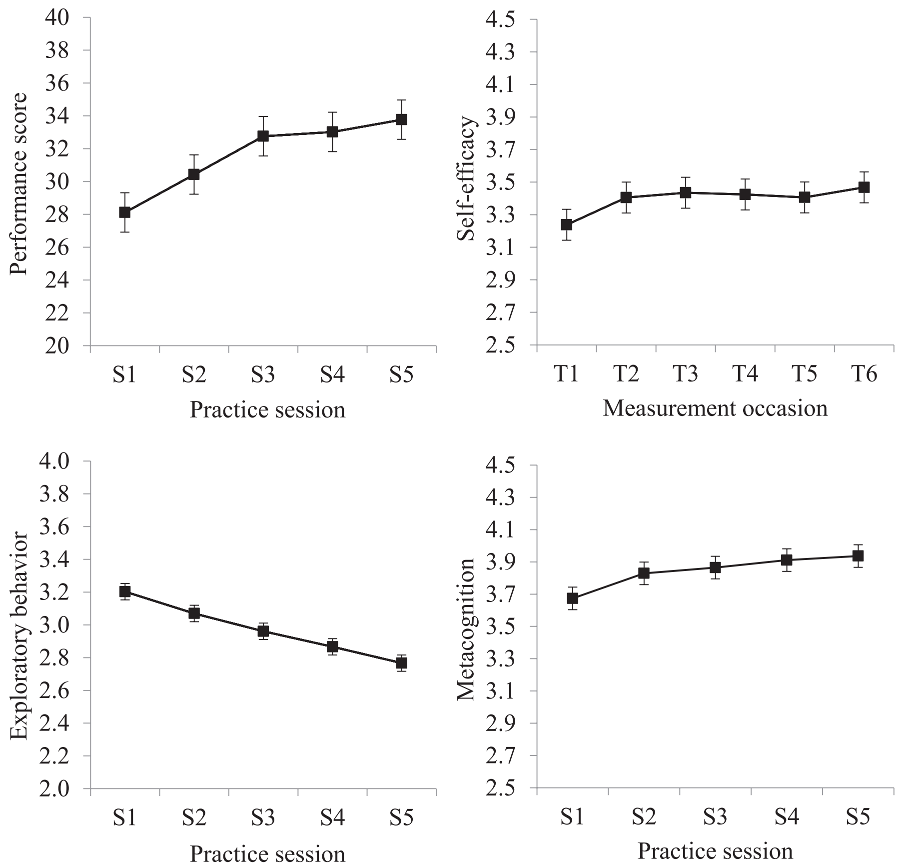
Table 1

Means, Standard Deviations, and Intercorrelations of Study Variables (Including Controls) at the Between- and Within-Person Levels

Between-person level	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. General mental ability	0.00	0.85									
2. Pretraining task-related knowledge	0.00	0.81	.15**								
3. Learning goal orientation	3.99	0.55	.05	.01							
4. Performance-prove goal orientation	3.79	0.59	−.06	.02	.18**						
5. Performance-avoid goal orientation	2.61	0.80	−.07	.06	−.42**	.15**					
6. Pretraining motivation to learn	4.25	0.64	.08	.24**	.23**	.09	−.10†				
7. Exploratory behavior	2.97	0.38	.16**	.38**	.07	−.08	−.01	.27**			
8. Self-efficacy	3.40	0.76	.08	.49**	.22**	.10†	−.08	.30**	.38**		
9. Metacognition	3.84	0.51	.02	.23**	.29**	.21**	−.13*	.40**	.23**	.57**	
10. Practice performance	31.62	11.59	.27**	.70**	.02	−.01	.03	.23**	.51**	.63**	.40**
Within-person level			ICC_2	1	2	3	4				
1. Practice session	—	—									
2. Exploratory behavior	2.97	0.49	.50	−.49**							
3. Self-efficacy	3.40	0.83	.68	.13**	−.06**						
4. Metacognition	3.84	0.63	.40	.23**	−.08**	.16**					
5. Practice performance	31.62	13.59	.63	.14**	−.04	−.04	.14**				

Note: Between-person $n = 305$. Within-person $n = 1{,}525$. All p-values are two-tailed. ICC = intraclass correlation coefficient.
†$p < .10$.
*$p < .05$.
**$p < .01$.

Figure 2
Observed Mean Scores for Performance and Self-Regulated Learning Processes Over the Course of Practice

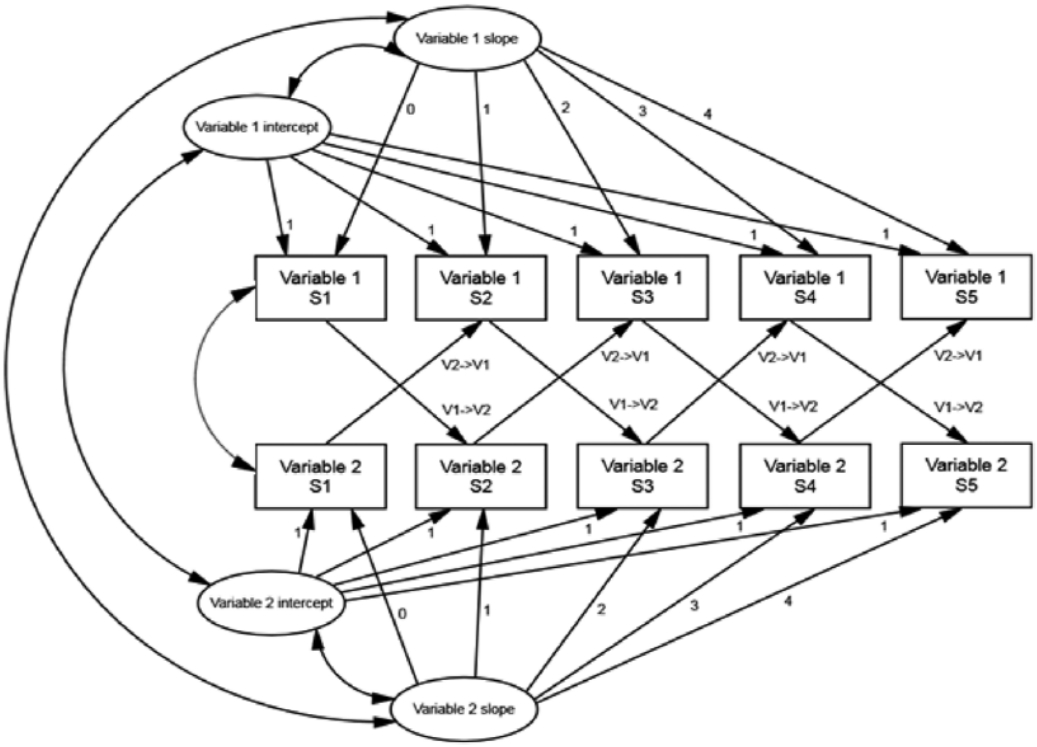


Note: Measurement occasion T1 preceded practice session S1; T2 preceded S2; and so on. The *y*-axis is scaled to represent approximately 1 *SD* around the grand mean. Error bars reflect ± 1.96 *SE*.

self-efficacy, metacognition, exploratory behavior, and performance scores with a series of univariate latent growth models specified in MPlus version 6 (Muthén & Muthén, 2010). The best-fitting growth model for each repeated variable was then retained for subsequent modeling. The effects of GMA, pretraining task-related knowledge, goal orientation, and pretraining motivation to learn on the latent intercepts and slopes were included as controls in all models.

As depicted in Figure 2, all four repeated variables showed dynamic trends over the course of practice. As a result, the inclusion of a latent slope improved model fit for each variable relative to the intercept-only model, all $\Delta\chi^2(3) > 11.35$ (p's $< .01$). Positive trends were observed for performance ($\gamma_{10} = 1.41$, $SE = .16$, $t = 8.88$, $p < .01$), self-efficacy ($\gamma_{10} = 0.03$, $SE = .01$, $t = 2.92$, $p < .01$), and metacognition ($\gamma_{10} = 0.06$, $SE = .01$, $t = 5.85$, $p < .01$), whereas the trend was negative for exploratory behavior ($\gamma_{10} = -0.11$, $SE = .01$, $t = -14.95$, $p < .01$).

Figure 3
Specification of the Bivariate Cross-Lagged Latent Growth Model of the Relationship Among Repeated Variables Measured Concurrently

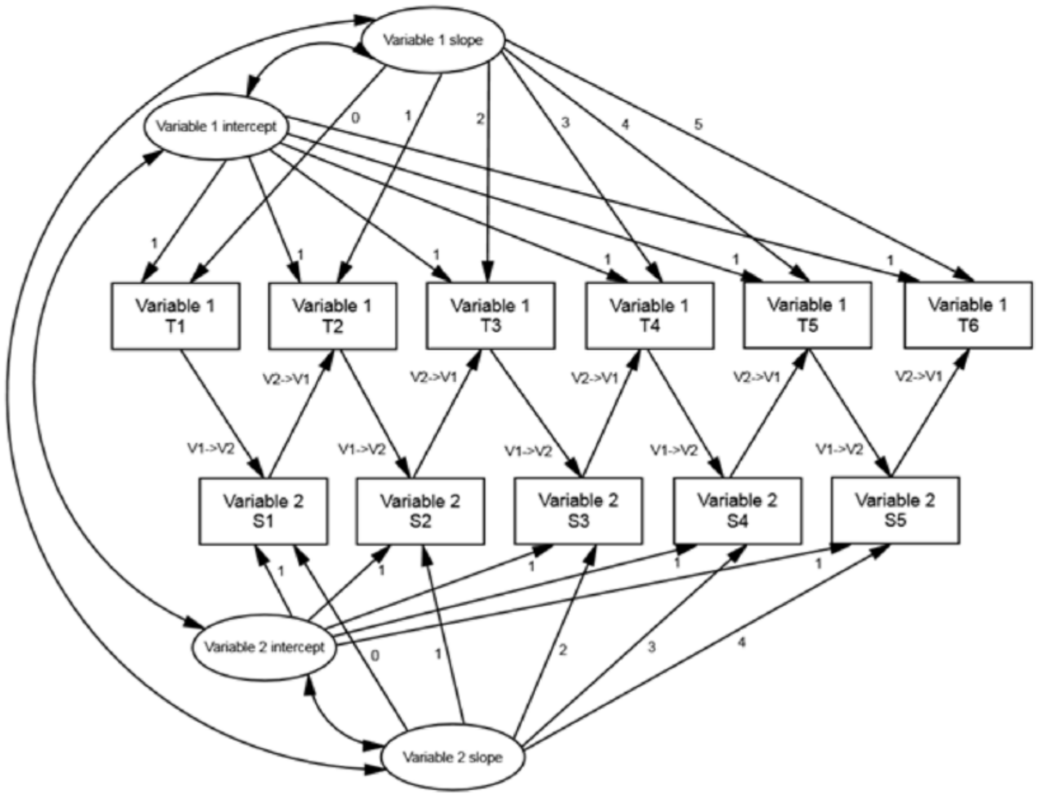


Note: Specifications for when the variables were measured concurrently (e.g., exploratory behavior and metacognition). For figure simplicity, error terms and influence of the control variables on the latent intercepts and slopes are not shown.

Tests of Hypotheses

As described earlier, bivariate cross-lagged latent growth models were used to test hypotheses regarding the nature of interrelationships among self-efficacy, metacognition, and exploratory behavior. In the case of the metacognition–exploration relationship, both repeated variables were measured concurrently. As such, cross-lagged effects were specified in these models according to the pattern shown in Figure 3. For the self-efficacy–exploration and self-efficacy–metacognition relationships, self-efficacy was measured between practice sessions, consistent with the specification pattern shown in Figure 4. Tables 2 and 3 summarize the results of the model comparisons. As shown in Table 2, acceptable model fit was not achieved in the models representing the self-efficacy–metacognition relationship under a stricter set of assumptions. Thus, consistent with the plan described earlier, we tested an additional model in which invariance assumptions regarding the effect of metacognition on self-efficacy were relaxed, thus allowing for the possibility that this effect is dynamic (i.e., the effect changes in strength over the course of practice). This model provided improved fit relative to the invariant cross-lagged model and was thus retained for use in subsequent hypothesis testing.

Figure 4
Specification of the Bivariate Cross-Lagged Latent Growth Model of the Relationship Among Repeated Variables Measured Sequentially



Note: Specifications for when the variables were measured sequentially (e.g., self-efficacy and exploratory behavior). Measurement occasion T1 preceded practice session S1, T2 preceded S2, and so on. For figure simplicity, error terms and influence of the control variables on the latent intercepts and slopes are not shown.

In Hypotheses 1 and 2, we predicted a negative effect of prior self-efficacy on subsequent exploratory behavior and metacognition, respectively. As shown in Table 2, the best-fitting model for the self-efficacy–exploration relationship was a reciprocal model in which lagged self-efficacy showed a small negative effect on exploratory behavior. This seems to suggest that higher levels of within-person self-efficacy suppress subsequent exploratory behavior. However, the effect of self-efficacy on exploratory behavior did not achieve traditional levels of statistical significance (self-efficacy → exploration; $B = -.038$, $SE = .022$, $t = -1.65$, $p = .07$, $\beta = -.07$). Therefore, Hypothesis 1 was not supported. Regarding the self-efficacy–metacognition relationship, the dynamic unidirectional "metacognition to self-efficacy" model proved to be the one with the best overall fit. In this model, self-efficacy did not have an effect on subsequent metacognition. Therefore, Hypothesis 2 was also not supported.

In Hypotheses 3 and 4, we predicted that exploratory behavior would be positively related to subsequent metacognition, whereas prior metacognition would be negatively related to subsequent exploratory behavior, respectively. As shown in Table 2, the best-fitting model for the exploration–metacognition relationship was indeed a reciprocal model in which

Table 2

Fit Statistics and Coefficients for Cross-Lagged Latent Growth Models Among Self-Regulation Variables

Cross-lagged model	χ^2 (*df*)	CFI	SRMR	RMSEA (Upper 90% CI)	AIC	$A \rightarrow B$	$B \rightarrow A$
Self-efficacy and exploratory behavior							
1. Independence	300.82 (94)	.94	.05	.085 (.096)	3,560.45		
3. Self-efficacy (*A*) → exploration (*B*)	269.49 (93)	.94	.05	.085 (.096)	3,558.12	$-.09^{**}$	
2. Exploration (*B*) → self-efficacy (*A*)	270.53 (93)	.94	.05	.079 (.090)	3,532.16		$.05^{**}$
4. Bidirectional reciprocal[a]	267.84 (92)	.95	.05	.079 (.090)	3,531.47	$-.07^{\dagger}$	$.03^{**}$
Self-efficacy and metacognition							
1. Independence	407.45 (94)	.91	.04	.105 (.115)	4,309.34		
2. Self-efficacy (*A*) → metacognition (*B*)	407.30 (93)	.91	.04	.105 (.116)	4,311.18	−.02	
3. Metacognition (*B*) → self-efficacy (*A*)	348.75 (93)	.93	.04	.095 (.106)	4,252.63		
Without cross-lagged parameter invariance[a,b]	300.18 (89)	.94	.04	.088 (.099)	4,212.06		$.08^{**}$–$.25^{**}$
4. Bidirectional reciprocal	348.59 (92)	.93	.04	.096 (.106)	4,254.49	−.02	$.04^{**}$
Exploratory behavior and metacognition							
1. Independence	196.65 (76)	.94	.06	.072 (.085)	2,978.50		
2. Exploration (*A*) → metacognition (*B*)	182.02 (75)	.95	.06	.068 (.081)	2,965.87	$.02^{**}$	
3. Metacognition (*B*) → exploration (*A*)	191.95 (75)	.94	.06	.072 (.084)	2,975.80		$-.02^{*}$
4. Bidirectional reciprocal[a]	176.97 (74)	.95	.06	.068 (.080)	2,962.83	$.02^{**}$	$-.02^{*}$

Note: All *p*-values are two-tailed. CFI = comparative fit index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval; AIC = Akaike information criterion.

[a]Best-fitting model.

[b]Invariance assumptions for cross-lagged parameters were removed to address issues of poor model fit in the invariant model. The effect of metacognition on self-efficacy increased over practice from .08 in the first lagged path to .25 in the final lagged path.

$^{\dagger}p < .10$.

$^{*}p < .05$.

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

Table 3
Interfactor Relationships From the Best Fitting Cross-Lagged Latent Growth Models Among Self-Regulation Variables

	Exploratory behavior		Metacognition	
Intercept and slope relationships	Intercept	Slope	Intercept	Slope
Self-efficacy				
Intercept	.25**	.03	.52**	−.26**
Slope	.03	.18*	.01	.50**
Exploratory behavior				
Intercept			.12	−.09
Slope			.05	.10

Note: All *p*-values are two-tailed.
$^{**}p < .01$.

lagged exploration was positively related to subsequent metacognition (exploration → metacognition; $B = .033$, $SE = .008$, $t = 3.92$, $p < .01$, $\beta = .02$), whereas lagged metacognition was negatively related to subsequent exploration (metacognition → exploration; $B = -.012$, $t = -2.25$, $SE = .006$, $p < .05$, $\beta = -.02$). Thus, Hypothesis 3 and Hypothesis 4 were both supported. These findings support a self-correcting reciprocal relationship between exploration and metacognition.

Finally, in Hypotheses 5 and 6, we predicted a positive effect of prior exploratory behavior and metacognition, respectively, on subsequent self-efficacy. As shown in Table 2, Hypothesis 5 was supported. Lagged exploratory behavior was positively related to subsequent self-efficacy (exploration → self-efficacy; $B = .046$, $SE = .008$, $t = 5.45$, $p < .01$, $\beta = .03$). The effect of metacognition on self-efficacy was dynamic such that it increased in strength from the first practice session ($B = .106$, $SE = .011$, $t = 9.68$, $p < .01$, $\beta = .08$) to the final practice session ($B = .332$, $SE = .042$, $t = 7.93$, $p < .01$, $\beta = .25$). Nevertheless, the effect remained positive at all stages of practice. Thus, Hypothesis 6 was supported.

Relationships With Performance

To put these findings into context, we ran a second set of cross-lagged latent growth models to examine questions pertaining to the relationships between the self-regulatory variables and performance in the current data. 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 3. For the self-efficacy–performance relationship, self-efficacy was measured between practice sessions. Thus, for these models, we utilized the model specification approach shown in Figure 4. A unique advantage of this staggered approach is that it allowed us to avoid overlap dependencies between self-efficacy and performance—a design advantage shown by Vancouver, Gullekson, and Bliese (2007) in Monte Carlo simulations to reduce statistical biases that were offered as an explanation for findings demonstrating negative effects of self-efficacy on performance (cf. Bandura & Locke, 2003).

Table 4
Fit Statistics and Coefficients for Cross-Lagged Latent Growth Models With Performance

SRV: Cross-lagged model	χ^2 (*df*)	CFI	SRMR	RMSEA (Upper 90% CI)	AIC	Performance → SRV	SRV → performance
Self-efficacy							
Independence	378.76 (94)	.92	.03	.100 (.110)	13,443.96		
Performance → SRV	285.64 (93)	.95	.03	.082 (.093)	13,352.84	.12**	
SRV → performance	357.78 (93)	.93	.03	.086 (.107)	13,424.98		−.19**
Bidirectional reciprocal[a]	279.92 (92)	.95	.03	.082 (.093)	13,349.12	.12**	−.10*
Metacognition							
Independence	187.65 (76)	.95	.04	.069 (.082)	12,897.52		
Performance → SRV	172.20 (75)	.96	.04	.065 (.078)	12,884.07	.07**	
SRV → performance	184.06 (75)	.95	.04	.069 (.082)	12,895.93		.01†
Bidirectional reciprocal[a]	167.48 (74)	.96	.04	.064 (.077)	12,881.35	.07**	.02*
Exploratory behavior							
Independence	142.55 (76)	.97	.05	.054 (.067)	12,061.55		
Performance → SRV	134.46 (75)	.97	.05	.051 (.065)	12,055.46	−.05**	
SRV → performance	135.28 (75)	.97	.05	.051 (.065)	12,056.28		.02**
Bidirectional reciprocal[a]	127.99 (74)	.98	.05	.049 (.063)	12,050.99	−.05**	.02**

Note: All *p*-values are two-tailed. SRV = self-regulated variable; CFI = comparative fit index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval; AIC = Akaike information criterion.
[a]Best-fitting model.
†$p < .10$.
*$p < .05$.
**$p < .01$.

Table 5
Interfactor Relationships From the Best Fitting Cross-Lagged Latent Growth Models With Performance

	Self-efficacy		Metacognition		Exploratory behavior	
Performance	Intercept	Slope	Intercept	Slope	Intercept	Slope
Intercept	.41**	.16†	.32**	−.10	.44**	.15
Slope	.05	.67**	.07	.42**	−.16	.32*

Note: All *p*-values are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.

Tables 4 and 5 summarize the results of the model comparisons for performance. The results shown in Table 4 support a self-correcting reciprocal relationship in which lagged performance was positively related to self-efficacy ($B = .007$, $SE = .001$, $t = 9.03$, $p < .01$, $\beta = .12$), whereas lagged self-efficacy was negatively related to performance ($B = -1.65$, $SE = .68$, $t = -2.40$, $p < .01$, $\beta = -.10$). Lagged exploratory behavior and metacognition, however, were both positively related to subsequent performance scores (exploration → performance; $B = .489$, $t = 2.55$, $SE = .192$, $p < .01$, $\beta = .02$; metacognition → performance; $B = .374$, $SE = .171$, $t = 2.18$, $p < .05$, $\beta = .02$). Put into context, these findings indicate that a 1-*SD* fluctuation in either exploratory behavior or metacognition corresponded with an average 17.0% and 16.9% increase in the rate of learning, respectively, relative to the baseline trajectory of participant performance scores. Furthermore, Table 4 shows that performance scores were positively related to subsequent metacognition ($B = .003$, $SE = .001$, $t = 4.09$, $p < .01$, $\beta = .07$) but negatively related to subsequent exploration ($B = -.002$, $SE = .001$, $t = -2.70$, $p < .01$, $\beta = -.05$). In addition to providing evidence supporting the positive effects of metacognition and exploratory behavior on skill acquisition, these findings are consistent with the notion that increases in capability partially explain the positive "exploration to self-efficacy" and "metacognition to self-efficacy" effects as well as the systematic switch from exploratory behavior to metacognition in response to increases in practice performance capability.

Influence of Individual Differences

Finally, given the prominent role of individual difference variables, such as GMA and pretraining task-related experience, to learning research, we ran one final set of ancillary analyses in which we examined the influence of each control variable on the starting values (i.e., the intercept) and growth trends (i.e., the slope) of performance, self-efficacy, metacognition, and exploration. Although these effects were not central to our research questions, the results shown in Table 6 revealed several interesting patterns that may inform future research. For instance, although both pretraining task-related knowledge ($\gamma_{02} = 0.74$, $p < .01$) and GMA ($\gamma_{01} = 0.10$, $p < .05$) were positively related to initial performance, only GMA predicted growth in performance across the practice trials ($\gamma_{11} = 0.28$, $p < .01$). Another interesting finding was that learning goal orientation positively predicted initial levels of self-efficacy ($\gamma_{03} = 0.28$, $p < .05$) but negatively predicted growth in self-efficacy over the course of practice ($\gamma_{13} = -0.20$, $p < .05$). For metacognition, the findings showed that higher initial levels of metacognition were typical of learners higher in pretraining task-related knowledge ($\gamma_{02} = 0.26$, $p < .05$), learning goal orientation ($\gamma_{03} = 0.16$, $p < .05$), prove-performance goal orientation ($\gamma_{04} = 0.16$, $p < .01$), and pretraining motivation to learn ($\gamma_{06} = 0.22$, $p < .01$). In contrast, higher GMA learners engaged in less metacognition early in practice ($\gamma_{01} = -0.13$, $p < .05$) but increased their metacognitive activity at a faster rate over the course of practice relative to lower GMA learners ($\gamma_{11} = 0.16$, $p < .05$). The results also showed that pretraining task-related knowledge ($\gamma_{02} = 0.36$, $p < .01$) and motivation to learn ($\gamma_{06} = 0.18$, $p < .01$) were positively related to initial levels of exploratory behavior. Initial levels of exploratory behavior were also positively related to GMA, but the effect did not reach conventional levels of statistical significance ($\gamma_{11} = 0.10$, $p < .10$). 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 ($\gamma_{13} = 0.19$, $p < .05$).

Discussion

The results of the present study reveal a number of interesting findings pertaining to the inner workings of self-regulated learning in active learning and learner-controlled training and development contexts. For instance, our findings demonstrate that the trajectories of self-regulated learning processes tend to show systematic and predictable changes over the course

Table 6
Predictor Coefficients for Control Variables in the Conditional Univariate Latent Growth Models

		γ					
Variable: DV[a]	Slope	GMA	Pre-TK	LGO	PPGO	APGO	MTL
Performance							
Intercept	.20	.10*	.74**	.06	−.03	.09†	.04
Slope		.28**	.08	−.16	−.03	−.22†	.13
Self-efficacy							
Intercept	−.10	−.05	.50**	.28**	.08	.05	.13*
Slope		.08	−.01	−.20**	−.04	−.16*	.06
Metacognition							
Intercept	−.40**	−.13*	.26*	.16*	.16**	−.03	.22**
Slope		.16*	−.15*	.03	.00	−.06	.15*
Exploratory behavior							
Intercept	−.06	.10†	.36**	−.06	−.06	−.03	.18**
Slope		.02	.08	.19*	−.12†	.11	.06

Note: All *p*-values are two-tailed. DV = dependent variable; GMA = general mental ability; pre-TK = Pretraining task-related knowledge; LGO = learning goal orientation; PPGO = performance-prove goal orientation; APGO = performance-avoid goal orientation; MTL = pretraining motivation to learn.
[a]For 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. Latent intercepts and slopes were centered on the first measurement occasion.
†$p < .10$.
*$p < .05$.
**$p < .01$.

of practice such that learner self-efficacy, metacognition, and performance tend to increase whereas learner exploration tend to decrease. Furthermore, the present findings suggest that interrelationships among self-regulated learning mechanisms tend to be iterative, bidirectional, and self-correcting in nature. Specifically, we found support for the proposed self-correcting relationship between exploration and metacognition as well as the presence of feedback effects wherein learning-oriented self-regulatory processes (i.e., exploration and metacognition) positively influenced subsequent learner self-efficacy. Ancillary analyses provided preliminary support for the notion that changes in performance capability resulting from the expenditure of learning-oriented effort are responsible for this feedback effect. In contrast, we found only limited support for the notion that self-efficacy significantly influences subsequent self-regulated learning processes. In the following sections, we explore the implications of these findings for theory and practice in the domain of learner-controlled self-regulated training and development.

Implications for Theory and Practice

Dynamics in the learning process. Collectively, the findings of the present study suggest that self-regulation is best understood as a collection of closely interrelated processes that increase and decrease in response to changes in performance capability. From a methodological standpoint, the existence of these dynamic effects indicate that it is critical for researchers to control for these trajectories when conducting repeated measures research on self-regulated learning processes (Sitzmann & Yeo, 2013). However, characteristics of self-regulatory trajectories are theoretically and practically interesting as well. 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 thus 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, Toney, et al., 2001), additional research devoted to identifying factors that influence and alter shifts in regulatory processes is warranted.

Role of self-regulation in learning. Furthermore, we believe that the findings of the present study contribute to the literature on self-regulated learning by challenging two common misconceptions pertaining to the role of self-regulation in adult learning. First is the notion that strong positive intercorrelations among self-regulated learning constructs at the between-person level suggest that many of these variables provide overlapping (and thus theoretically redundant) contributions to the learning process (Sitzmann & Ely, 2011). We argue that such conclusions are premature given the paucity of research on within-person interrelationships in this domain. To be clear, we are not denying that some degree of conceptual redundancy exists within this literature. Rather, we argue that between-person correlations among self-regulated learning constructs tell very little about the true nature of their respective interrelationships because they fail to capture fundamental characteristics of the regulatory process that unfold over time.

For instance, positive relationships between exploratory behavior and metacognition at the between-person level seem to imply that a good way to encourage exploration is to prompt metacognitive activity early and often throughout the learning process. However, our findings indicate this between-person effect is driven primarily by the within-person positive effect of exploration on metacognition—not the other way around. In fact, the support that we found for a self-correcting, reciprocal relationship at the within-person level indicates that metacognition may actually *suppress* subsequent exploratory behavior, particularly in the later stages of the learning process. As a result, the effectiveness of training interventions designed to enhance metacognitive activity will be contingent not only on whether learners are willing and able to engage in additional metacognition but also how far along they are within the learning process itself. Prompting metacognitive activity too early may backfire downstream by exacerbating the natural tendency of learners to seek out preferred optimal solutions before they are equipped with the requisite knowledge and skill to do so (Döerner, 1980).

Similarly, at first glance, moderate to strong positive correlations among self-efficacy, exploratory behavior, and metacognition at the between-person level seem to support arguments that self-efficacy plays an important role in facilitating learner self-regulatory functioning (Bandura, 1997). However, our findings at the within-person level support the notion that self-efficacy is merely epiphenomenal and thus does not play a functional role in self-regulation (Sitzmann & Yeo, 2013). Specifically, our findings suggest that in stable learning contexts in which learners are at least somewhat familiar with the task, self-efficacy is merely a by-product of gains in performance capability associated with prior investments of learning-oriented effort in the learning process. In this regard, the data did not support our model's predictions pertaining to the role of self-efficacy in guiding effort allocation decisions within the resource preservation agent. Nevertheless, our results provide a process account for the way that learning effort translates into corresponding changes in self-efficacy by way of performance improvements. Specifically, our model indicates that learner decisions regarding resource allocation in feedback-rich learning contexts (e.g., the transition of learners from exploratory behavior early in practice to metacognition later on) are defined more by changes in actual performance capability than *perceptions* of performance capability. As such, we believe that learners would be better served by interventions that improve the quality of the performance feedback provided or enhance foundational performance potential than by interventions that target self-efficacy beliefs.

Taken together, these findings suggest that interrelationships among self-regulated learning constructs are not as straightforward as their between-person correlations might suggest. Instead, they tend to be iterative, bidirectional, and self-correcting in nature. This brings up a second common misconception pertaining to the role of self-regulation in adult learning to which our study can speak: the assumption that effective self-regulation is a natural by-product of learner engagement and can thus be treated in much the same way when it comes to intervention design. From this perspective, the natural tendency is to believe that more self-regulatory activity is better than less and that we should thus recommend interventions designed to "prompt self-regulatory activity by trainees" more often (Salas et al., 2012: 87). Although research has clearly shown that encouraging trainees to engage in self-regulatory activity can benefit learning outcomes for those who would not have otherwise done so (Sitzmann & Ely, 2010; Sitzmann et al., 2009), moving too far in the direction of an overly simplistic "more is better" approach to intervention design can be problematic because it risks overlooking important nuances in the process by which self-regulation and learning unfold over time.

In this regard, the present study highlights the value of integrating key concepts from the active learning literature with more dynamic conceptualizations of self-regulation and learning. In particular, the more dynamic perspective offered by cognitive models of learning proved to be useful in developing predictions pertaining to how and when learners decide to allocate learning-oriented effort within the learning process. For instance, the present findings suggest that the type of self-regulatory activity favored by learners differs depending on how far along they were in the learning process. In early stages, learners favored exploration, whereas in later stages they favored metacognition. These preferences corresponded with stage-based cognitive models of skill acquisition (Anderson, 1982, 1996; Kanfer & Ackerman, 1989), which posit a strong emphasis on declarative knowledge acquisition early in the learning process that gradually gives way to a greater emphasis on proceduralization. In this way, the present findings provide a better understanding of the dynamics in self-regulated learning that is useful for more accurately identifying when and where interventions designed to correct flaws in learner behavior will be most effective. Furthermore, understanding the order in which regulatory mechanisms influence one another (e.g., knowing that exploration comes before metacognition) can aid in the design of interventions that can interface more seamlessly with a learner's natural regulatory tendencies.

Individual differences. Finally, our results suggest that individual differences influence the way that learners engage the self-regulated learning process. For instance, our results suggest that high-GMA, experienced, and motivated learners not only performed better and improved more quickly than low-ability, inexperienced, and unmotivated learners but also showed a tendency to explore more often in the early and later stages of practice. These findings are consistent with Kanfer and Ackerman's (1989) assertions that learners with greater capacity for learning are better equipped to engage in higher amounts of resource demanding self-regulated learning. However, our findings also suggest that high-GMA learners are more intentional and strategic in the way that they approach the learning process. Specifically, we found that high-GMA learners engaged in *less* metacognition early in practice when they were less likely to possess the requisite knowledge structures but *more* in the later stages after a foundational understanding of the task had been acquired. Prior task experience had the opposite effect in that experienced learners engaged in more metacognition early on but showed less of a transition to metacognition in later stages. This pattern of effects is consistent with prior research showing that experts tend to identify key characteristics of the task and settle on a preferred solution more quickly than novices (Stanislaw, Hesketh, Kanavaros, Hesketh, & Robinson, 1994), a tendency that can paradoxically cause them to struggle when characteristics of the problem domain change (Devine & Kozlowski, 1995; Sternberg & Frensch, 1992). Collectively, these results emphasize a recent point made by Sitzmann and Weinhardt (2018) that a multilevel perspective is essential for understanding the factors that influence training behavior and effectiveness.

Limitations and Future Directions

Several limitations of the present study should be noted in the interpretation and application of these results. First, generalizability is a concern. Only young adult men participated in the present study, and the videogame task used differs from those typically found in more traditional training programs. Although UT2004 involves a combination of cognitive and perceptual-motor demands and a computer-based interface typical of technology-based training environments often found in more dynamic and adaptive industries (e.g., technology, medicine, and aviation), it remains to be seen whether the findings of the present study extend to a broader range of more static or structured learning environments. For instance, the self-correcting exploration–metacognition interrelationship found in the present study will likely be less salient for regulating behavior for learners with limited decisional control over how they engage the learning process. Similarly, the positive effect of self-regulated learning processes on subsequent self-efficacy might be less pronounced in learning environments where learners have limited access to performance-based feedback. Given the large impact that environmental constraints can have across all levels of the learning process (Sitzmann & Weinhardt, 2018), it is important to consider the extent to which the nature of interrelationships among regulatory processes transfer to any given organizational or research context. For example, our findings are more likely to generalize to open-ended, complex task domains characteristic of active learning environments than to simple, closed task domains in which traditional proceduralized training is more relevant (Bell & Kozlowski, 2008). With more open-ended and complex domains in mind, we speculate that our findings generalize to other work-related phenomena that involve self-regulated learning and a salient tension between exploration and exploitation, such as job search and turnover behavior (Direnzo &

Greenhaus, 2011) and entrepreneurial learning (Politis, 2005; Trevelyan, 2011). Nevertheless, the generalizability of our findings likely depends on a variety of contextual factors, including environmental turbulence and the extent to which exploration is rewarded.

Second, although self-efficacy, metacognition, and exploratory behavior collectively encompass a broad range of established self-regulated learning mechanisms and have been argued to be the processes that are most central to the functioning of self-regulated learning (Hardy et al., 2014; Sitzmann & Ely, 2011), the current research was necessarily limited in its coverage of other regulatory processes such as emotion control and time management. Furthermore, because we did not directly measure theoretical mediators underlying these relationships (e.g., perceptions of novelty and information-knowledge gaps), we can only speculate about the exact functioning of these submechanisms. On this point, it should be noted that this is not a precise characterization of learning (in the cognitive sense) but was instead designed as an integrated explanatory model for describing interrelationships among processes. Nevertheless, the pattern of findings that emerged in the present study led us to suspect that these and other self-regulatory processes are likely to show similar self-correcting reciprocal interrelationships in response to changes in learner capability over the course of practice that are not always consistent with their effects at the between-person level. We hope that future research continues to expand on the present effort by examining the dynamics and subprocesses underlying in these and other less commonly examined regulatory processes.

Finally, in an effort to align the methodology of our study as closely as possible with extant research in this area, we utilized an adapted version of the popular Ford et al. (1998) scale as our measure of metacognition. Although this measure is well established in the literature as a measure of metacognition, it has a tendency to place a greater emphasis on the self-knowledge aspect of metacognition than on the self-control function that was most relevant to our model. As such, there may be some degree of noise in our results resulting from the conceptual overlap between metacognition and other components of the self-regulated learning process. In general, additional work is needed to clean up the conceptual messiness in the metacognition literature, including the development of more targeted measures of metacognitive self-control that can be administered before, during, and after important learning events.

One benefit of developing a better understanding of the learning process is that these principles can be leveraged to improve training design and benefit learning outcomes. In particular, a dynamic approach to the study of self-regulated learning can provide interesting insights relevant to training design, such as when, where, and how self-regulation interventions can support natural learning processes (Sitzmann & Ely, 2010; Sitzmann et al., 2009). As such, in tandem with expanding, testing, and refining dynamic theories of self-regulated learning, researchers should seek to develop training interventions that identify and resolve common shortcomings in natural regulatory processes. For example, technologies that actively encourage learners to track their self-regulated learning processes over the course of practice in real time may help them more effectively control 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 and foregoing exploration prematurely (Hardy et al., 2014; Yechiam, Erev, & Gopher, 2001). Similarly, interventions that expose learners to potential miscalibrations in their perceptions of their information-knowledge gaps may hold promise for helping learners overcome natural biases and enhance the functioning of their natural learning processes.

Along these lines, future research should examine how interrelationships between 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 (e.g., variable practice) 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, Toney, et al., 2001) and that continued exploratory behavior has been argued to be an important contributor to adaptability (Hardy et al., 2014), additional research is warranted targeting the role that self-regulation plays in the development of adaptability outcomes.

Notes

1. Note that this is not a limitation unique to the active learning literature. Indeed, an examination of the studies included in Sitzmann and Ely's (2011) recent meta-analysis reveals that the majority of empirical research on self-regulated learning either failed to examine effects at the within-person level of analysis at which it occurs (a limitation noted by the authors) or overlooked the possibility that multiple self-regulatory mechanisms work in tandem to shape learning and performance. This state of affairs is not entirely surprising given (a) the complexity inherent in properly collecting and analyzing data on self-regulatory processes and (b) recent evidence suggesting that even well-educated individuals have a difficult time understanding simple dynamic phenomena (Cronin, Gonzalez, & Sterman, 2009). As evidence of this, it took the advent of recent advances in multilevel research before the limitations of traditional between-person methodologies used in self-efficacy research were first acknowledged (Sitzmann & Yeo, 2013; Vancouver, Thompson, & Williams, 2001).

2. Note here that metacognition has been defined in many ways over the years, sometimes as broadly as to encompass the entirety of self-regulation itself (Kanfer & Ackerman, 1989). In the training and development literature, the term *metacognition* is often used more narrowly as a way to describe a set of constructs related to the planning, monitoring, and evaluative aspects of self-regulation (Bell & Kozlowski, 2010; Ford et al., 1998). However, research on this topic does not always do a good job of specifying differences between metacognition as a regulatory construct and the collective process of self-regulation as a whole. As such, it is important to define what specific components of self-regulation are of primary interest when the construct is utilized for research purposes. In our model, we are interested in the exploitation-oriented self-control aspect of metacognition through which learners identify and evaluate factors contributing to prior successes before refining their strategies accordingly.

3. To be clear, our model is intended to serve as an explanatory model rather than as a precise neurological/cognitive characterization of learning. As such, use of the term "agent" here and in the following sections is used to indicate that the proposed structures parsimoniously represent the collective set of conscious, unconscious, deliberate, and unintentional decision-making processes that form the corresponding subfunctions of self-regulated learning.

References

American Society for Training and Development. 2015. *2015 State of the industry report*. Alexandria, VA: Author.

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

Anderson, J. R. 1996. ACT: A simple theory of complex cognition. *American Psychologist*, 51: 355-365.

Anderson, J. R. 2005. *Cognitive psychology and its implications*. New York: Macmillan.

Arthur, W., & Day, D. V. 1994. Development of a short form for the Raven Advanced Progressive Matrices Test. *Educational and Psychological Measurement*, 54: 394-403.

Bandura, A. 1997. *Self-efficacy: The exercise of control*. New York: Freeman.

Bandura, A., & Locke, E. A. 2003. Negative self-efficacy and goal effects revisited. *Journal of Applied Psychology*, 88: 87-99.

Bell, B. S., & Kozlowski, S. W. J. 2002. Adaptive guidance: Enhancing self-regulation, knowledge, and performance in technology-based training. *Personnel Psychology*, 55: 267-306.

Bell, B. S., & Kozlowski, S. W. J. 2008. Active learning: Effects of core training design elements on self-regulatory processes, learning, and adaptability. *Journal of Applied Psychology*, 93: 296-316.

Bell, B. S., & Kozlowski, S. W. J. 2010. Toward a theory of learner-centered training design: An integrative framework of active learning. In S. W. J. Kozlowski & E. Salas (Eds.), *Learning, training, and development in organizations*: 263-300. New York: Routledge.

Berlyne, D. E. 1960. *Conflict, arousal, and curiosity*. New York: McGraw-Hill.

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

Choi, Y. R., & Shepherd, D. A. 2004. Entrepreneurs' decisions to exploit opportunities. *Journal of Management*, 30: 377-395.

Cicchetti, D. V. 1994. Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. *Psychological Assessment*, 6: 284-290.

Cronin, M. A., Gonzalez, C., & Sterman, J. D. 2009. Why don't well-educated adults understand accumulation? A challenge to researchers, educators, and citizens. *Organizational Behavior and Human Decision Processes*, 108: 116-130.

Curran, P. J., & Bollen, K. A. 2001. The best of both worlds: Combining autoregressive and latent curve models. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change*: 107-135. Washington, DC: American Psychological Association.

Dalal, R. S., & Hulin, C. L. 2008. Motivation for what? A multivariate dynamic perspective of the criterion. In R. Kanfer, G. Chen, & R. Pritchard (Eds.), *Work motivation: Past, present, and future*: 63-100. New York: Taylor & Francis.

Debowski, S., Wood, R. E., & Bandura, A. 2001. Impact of guided exploration and enactive exploration on self-regulatory mechanisms and information acquisition through electronic search. *Journal of Applied Psychology*, 86: 1129-1141.

Devine, D. J., & Kozlowski, S. W. 1995. Domain-specific knowledge and task characteristics in decision making. *Organizational Behavior and Human Decision Processes*, 64: 294-306.

Direnzo, M. S., & Greenhaus, J. H. 2011. Job search and voluntary turnover in a boundarlyless world: A control theory perspective. *Academy of Management Review*, 36: 567-589.

Döerner, D. 1980. On the difficulties people have in dealing with complexity. *Simulation and Games*, 11: 87-106.

Flavell, J. H. 1979. Metacognition and cognitive monitoring: A new area of cognitive-developmental inquiry. *American Psychologist*, 34: 906-911.

Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. 1998. Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology*, 83: 218-233.

Gonzalez, C., & Dutt, V. 2016. Exploration and exploitation during information search and consequential choice. *Journal of Dynamic Decision Making*, 2(6): 1-8.

Hardy, J. H., Day, E. A., Hughes, M. G., Wang, X., & Schuelke, M. J. 2014. Exploratory behavior in active learning: A between- and within-person examination. *Organizational Behavior and Human Decision Processes*, 125: 98-112.

Hughes, M. G., Day, E. A., Wang, X., Schuelke, M. J., Arsenault, M. L., Harkrider, L. N., & Cooper, O. D. 2013. Learner-controlled practice difficulty in the training of a complex task: Cognitive and motivational mechanisms. *Journal of Applied Psychology*, 98: 80-98.

Kanfer, R., & Ackerman, P. L. 1989. Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of Applied Psychology*, 74: 657-690.

Keith, N., & Frese, M. 2005. Self-regulation in error management training: Emotion control and metacognition as mediators of performance effects. *Journal of Applied Psychology*, 90: 677-691.

Keith, N., & Wolff, C. 2015. Encouraging active learning. In K. Kraiger, J. Passmore, N. R. dos Santos, & Malvezzi (Eds.), *The Wiley-Blackwell handbook of training, development, and performance improvement*: 92-116. London: Wiley-Blackwell.

Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. 2001. Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes*, 85: 1-31.

Kozlowski, S. W. J., Toney, R. J., Mullins, M. E., Weissbein, D. A., Brown, K. G., & Bell, B. S. 2001. Developing adaptability: A theory for the design of integrated-embedded training systems. In E. Salas (Ed.), *Advances in human performance and cognitive engineering research*: 59-123. Amsterdam: JAI/Elsevier Science.

Kruger, J., & Dunning, D. 1999. Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, 77: 121-134.

Loewenstein, G. 1994. The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, 116: 75-98.

Lord, R. G., Diefendorff, J. M., Schmidt, A. M., & Hall, R. J. 2010. Self-regulation at work. *Annual Review of Psychology*, 61: 543-568.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organization Science*, 2: 71-87.

Muthén, L. K., & Muthén, B. O. 2010. *Mplus user's guide* (6th ed.). Los Angeles: Muthén & Muthén.

Politis, D. 2005. The process of entrepreneurial learning: A conceptual framework. *Entrepreneurship Theory and Practice*, 29: 399-424.

Powers, W. T. 1973. *Behavior: The control of perception*. Oxford, England: Aldine.

Powers, W. T. 1991. Commentary on Bandura's "Human agency." *American Psychologist*, 46: 151-153.

Salas, E., Tannenbaum, S. I., Kraiger, K., & Smith-Jentsch, K. A. 2012. The science of training and development in organizations: What matters in practice. *Psychological Science in the Public Interest*, 13: 74-101.

Schmidt, A. M., & DeShon, R. P. 2010. The moderating effects of performance ambiguity on the relationship between self-efficacy and performance. *Journal of Applied Psychology*, 95: 572-581.

Shrout, P. E., & Fleiss, J. L. 1979. Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, 86: 420-428.

Sitzmann, T., Bell, B. S., Kraiger, K., & Kanar, A. M. 2009. A multilevel analysis of the effect of prompting self-regulation in technology-delivered instruction. *Personnel Psychology*, 62: 697-734.

Sitzmann, T., & Ely, K. 2010. Sometimes you need a reminder: The effects of prompting self-regulation on regulatory processes, learning, and attrition. *Journal of Applied Psychology*, 95: 132-144.

Sitzmann, T., & Ely, K. 2011. A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin*, 137: 421-442.

Sitzmann, T., & Weinhardt, J. M. 2018. Training engagement theory a multilevel perspective on the effectiveness of work-related training. *Journal of Management*, 44: 732-756.

Sitzmann, T., & Weinhardt, J. M. in press. Approaching evaluation from a multilevel perspective: A comprehensive analysis of the indicators of training effectiveness. *Human Resource Management Review*. Advance online publication. doi:10.1016/j.hrmr.2017.04.001

Sitzmann, T., & Yeo, G. 2013. A meta-analytic investigation of the within-person self-efficacy domain: Is self-efficacy a product of past performance or a driver of future performance? *Personnel Psychology*, 66: 531-568.

Soderstrom, N. C., & Bjork, R. A. 2015. Learning versus performance an integrative review. *Perspectives on Psychological Science*, 10: 176-199.

Stanislaw, H., Hesketh, B., Kanavaros, S., Hesketh, T., & Robinson, K. 1994. A note on the quantification of computer programming skill. *International Journal of Human-Computer Studies*, 41: 351-362.

Sternberg, R. J., & Frensch, P. A. 1992. On being an expert: A cost-benefit analysis. In R. R. Hoffman (Ed.), *The psychology of expertise*: 191-203. New York: Springer.

Trevelyan, R. 2011. Self-regulation and effort in entrepreneurial tasks. *International Journal of Entrepreneurial Behaviour & Research*, 17: 39-63.

Vancouver, J. B. 2005. The depth of history and explanation as benefit and bane for psychological control theories. *Journal of Applied Psychology*, 90: 38-52.

Vancouver, J. B., Gullekson, N., & Bliese, P. 2007. *Lagged regression as a method for causal analysis: Monte Carlo analyses of possible artifacts*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, New York.

Vancouver, J. B., & Kendall, L. N. 2006. When self-efficacy negatively relates to motivation and performance in a learning context. *Journal of Applied Psychology*, 91: 1146-1153.

Vancouver, J. B., More, K. M., & Yoder, R. J. 2008. Self-efficacy and resource allocation: Support for a nonmonotonic, discontinuous model. *Journal of Applied Psychology*, 93: 35-47.

Vancouver, J. B., & Purl, J. D. 2017. A computational model of self-efficacy's various effects on performance: Moving the debate forward. *Journal of Applied Psychology*, 102: 599-616.

Vancouver, J. B., Thompson, C. M., & Williams, A. A. 2001. The changing signs in the relationships among self-efficacy, personal goals, and performance. *Journal of Applied Psychology*, 86: 605-620.

Vancouver, J. B., Weinhardt, J. M., & Schmidt, A. M. 2010. A formal, computational theory of multiple-goal pursuit: Integrating goal-choice and goal-striving processes. *Journal of Applied Psychology*, 95: 985-1008.

Vancouver, J. B., Weinhardt, J. M., & Vigo, R. 2014. Change one can believe in: Adding learning to computational models of self-regulation. *Organizational Behavior and Human Decision Processes*, 124: 56-74.

VandeWalle, D. 1997. Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement*, 57: 995-1015.

Wood, R. E. 1986. Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes*, 37: 60-82.

Wood, R. E., Kakebeeke, B. M., Debowski, S., & Frese, M. 2000. The impact of enactive exploration on intrinsic motivation, strategy, and performance in electronic search. *Applied Psychology: An International Review*, 49: 263-283.

Yechiam, E., Erev, I., & Gopher, D. 2001. On the potential value and limitations of emphasis change and other exploration-enhancing training methods. *Journal of Experimental Psychology: Applied*, 7: 277-285.