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Active Learning: Effects of Core Training Design Elements on Self-Regulatory Processes, Learning, and Adaptability

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This article describes a comprehensive examination of the cognitive, motivational, and emotional processes underlying active learning approaches; their effects on learning and transfer; and the core training design elements (exploration, training frame, emotion control) and individual differences (cognitive ability, trait goal orientation, trait anxiety) that shape these processes. Participants ($N = 350$) were trained to operate a complex, computer-based simulation. Exploratory learning and error-encouragement framing had a positive effect on adaptive transfer performance and interacted with cognitive ability and dispositional goal orientation to influence trainees' metacognition and state goal orientation. Trainees who received the emotion-control strategy had lower levels of state anxiety. Implications for development of an integrated theory of active learning, learner-centered design, and research extensions are discussed.

Keywords: active learning, training, self-regulation, adaptive performance

For many years, training research and practice focused on the learner as a passive recipient, rather than as an active participant, in training interventions (Ford & Kraiger, 1995). Traditional behavioral approaches to learning and instruction emphasized the importance of tightly structuring the learning environment, so as to limit trainees' control, and of providing step-by-step instruction on the complete task and its concepts, rules, and strategies (Ivancic & Hesketh, 1995; Smith, Ford, & Kozlowski, 1997). This approach to training was attractive, because it proved an efficient and effective means of developing routine expertise and of promoting analogical transfer, or the transfer of skills to problems similar to those encountered in training (Frese, 1995).

More recently, a learner-centered approach to training design has evolved that views learners as active participants in their own learning experience (Bruner, 1966; Frese & Altmann, 1989; Salas & Cannon-Bowers, 2001). Although there is a wide variety of educational philosophies that touch a common theme of learner-centered experience (e.g., experiential and action learning), we are particularly interested in active learning approaches. Active learning approaches not only give people control over their own learning but use formal training design elements to shape the cognitive, motivational, and emotional learning processes that support self-regulated learning (Bransford, Brown, & Cocking, 1999; Mayer, 2004). This shift has emerged, in part, from the realization that the routine expertise developed through traditional behavioral approaches to training can be a liability in the flexible and constantly changing work environments that characterize modern organizations (Hesketh, 1997). Research has shown, for example, that individuals who possess routine expertise have difficulty adapting their knowledge and skills when deep structural principles of their problem domain change (Devine & Kozlowski, 1995; Sternberg & Frensch, 1992). Today's computer-based training applications provide individuals with an unprecedented degree of control over their learning (Bell & Kozlowski, 2002; K. G. Brown, 2001). In the words of K. G. Brown and Ford (2002), "Once the computer program is set up, the burden for active learning switches to the learner" (p. 194).

As a result of these changes and challenges, recent years have witnessed growing interest in active learning approaches as an alternative to more traditional training paradigms. Active learning approaches systematically influence self-regulatory processes that have been implicated as critical in the development of more complex skills and promotion of adaptive transfer, which "involves using one's existing knowledge base to change a learned procedure, or to generate a solution to a completely new problem" (Ivancic & Hesketh, 2000, p. 1968). Further, there is a clear need for training tools that help learners manage the flexibility and learner control inherent in computer-based training environments (DeRouin, Fritzsche, & Salas, 2004). Based on theory that addresses the cognitive, motivational, and emotional processes involved in learning and adaptive performance, recent research has focused on interventions designed to support active learning and to affect the nature of self-regulation during practice (Kozlowski,

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Toney, et al., 2001). The emerging body of evidence for these interventions, which include guided exploration, mastery training, and error management training, suggests that they are useful tools for promoting learning and performance and facilitating adaptive transfer (e.g., Debowski, Wood, & Bandura, 2001; Frese et al., 1991; Heimbeck, Frese, Sonnentag, & Keith, 2003; Keith & Frese, 2005; Kozlowski, Gully, et al., 2001; Martocchio, 1994).

Our purpose in this study is to extend research on active learning in three ways. First, although research on active learning techniques has been promising, it has not been well integrated. The literature has developed as a collection of discrete active learning interventions that constitutes an approach to training design, but it has not coalesced into an integrated theoretical framework. There are, however, similarities across different active learning interventions in terms of their core training design elements and theoretical foundation. The current study provides an integrated examination of three core training design elements that cut across a range of distinct active learning interventions. Our goal is to provide a common theoretical foundation that can be used to integrate research on active learning. Second, researchers have called for more attention to identification of the process mechanisms by which active learning approaches have their effects (e.g., Debowski et al., 2001; Gully, Payne, Koles, & Whiteman, 2002; Heimbeck et al., 2003). Although recent research has begun to address this issue (e.g., Keith & Frese, 2005; Kozlowski & Bell, 2006), more work is needed so we can better understand the linkages between active learning interventions and learning processes. Thus, the current study focused on articulating the cognitive, motivational, and emotional process pathways by which the core active learning design elements have their effects. Finally, recent work has begun to examine the effects of individual differences on how learners interact with active learning interventions (Gully et al., 2002; Heimbeck et al., 2003). Our research built on and extended this work by examining several individual differences as both drivers of critical learning processes and moderators of the effects of core design elements that constitute active learning interventions on these processes.

The Active Learning Approach: Overview

The active learning approach has typically been conceptualized by contrasting it to more passive approaches to learning, or what are sometimes called transmission or conduit models of learning (Iran-Nejad, 1990; Schwartz & Bransford, 1998). Such contrasts highlight two key aspects of the active learning approach. First, the active learning approach gives people control over their own learning. That is, the learner assumes primary responsibility for important learning decisions (e.g., choosing learning activities, monitoring and judging progress). In contrast, passive approaches to learning focus on limiting the learner's control and having the instructional system (e.g., instructor, computer program) assume primary responsibility for learning decisions. Thus, the underlying distinction is one of internal versus external regulation of learning (Iran-Nejad, 1990). Second, the active learning approach promotes an inductive learning process, in which individuals must explore and experiment with a task to infer the rules, principles, and strategies for effective performance (Frese et al., 1991; Smith et al., 1997). In contrast, more passive approaches to learning assume that people acquire knowledge by having it transmitted to them by some external source (e.g., teacher, text; Schwartz & Bransford, 1998). Hence, the key distinction is one of active knowledge construction versus the internalization of external knowledge.

At a general level, the idea that the learner should be an active participant in the learning process is not unique to the active learning approach; it cuts across a number of educational philosophies and approaches, such as experiential learning and action learning (Kolb, 1984; Revans, 1982). However, the active learning approach is distinctive, in that it goes beyond simply "learning by doing" and focuses on using formal training design elements to systematically influence and support the cognitive, motivational, and emotional processes that characterize how people focus their attention, direct their effort, and manage their affect during learning. In recent years, researchers have developed a number of discrete active learning interventions, including error management training, mastery training, and guided exploration (Debowski et al., 2001; Keith & Frese, 2005; Kozlowski, Gully, et al., 2001). These interventions represent complex training manipulations composed by combining multiple training design elements intended to selectively influence the nature, quality, and focus of self-regulatory activity (Kozlowski, Toney, et al., 2001). Self-regulation refers to processes that "enable an individual to guide his/her goal-directed activities over time and across changing circumstances" and include the "modulation of thought, affect, behavior, or attention" (Karoly, 1993, p. 25).

Although prior research has convincingly demonstrated that these interventions can enhance important learning outcomes, particularly adaptive transfer, it has not elucidated very well the self-regulatory mechanisms by which these interventions exhibit their effects. In part, this is due to the fact that few studies have attempted to test these mechanisms directly (Keith & Frese, 2005). However, the focus on multifaceted training interventions makes it difficult to map specific pathways between the training design elements that make up these interventions and their hypothesized process targets (Kozlowski & Bell, 2006). Thus, in the current study we focus on disentangling these multifaceted interventions, so as to better identify the core training design elements that distinguish active learning approaches from more passive learning approaches and to examine the self-regulatory processes through which these elements operate.

We examined several key exemplars of the active learning approach and derived three core design elements that cut across these interventions. As shown in Table 1, these three core training design elements are exploration, training frame, and emotion control. In addition, through our conceptual examination, we deducted that these three design elements should be aligned with trainees' cognitive, motivational, and emotional self-regulatory processes, respectively. First, all of these interventions use an exploratory instructional approach, albeit to varying degrees, to engage individuals' metacognitive activities, which researchers have suggested are critical for enabling learners to orchestrate their own learning successfully (Bransford et al., 1999; Keith & Frese, 2005). Some strategies, such as exploratory/discovery learning, error management training, and enactive exploration, provide trainees with minimal guidance and explicitly encourage trainees to engage in active exploration and experimentation with the task (Frese et al., 1991; Heimbeck et al., 2003). In contrast, guided exploration incorporates considerable external direction to engage trainees in systematic and preplanned exploration (Debowski et al., 2001; Wood, Kakebeeke, Debowski, & Frese, 2000). Thus, the

Table 1
Illustrative Examples of Active Learning Interventions: Core Training Design Elements and Self-Regulation Pathways

		Core training design elements		
Intervention	Representative study	Exploration	Training frame	Emotion control
Exploratory/discovery learning	Frese et al. (1988) Kamouri et al. (1986) McDaniel & Schlager (1990)	Exploratory learning: ● No guidance provided ● Exploration and experimentation encouraged ● Inductive learning promoted		
Error management training/enactive exploration	Frese et al. (1991) Gully et al. (2002) Heimbeck et al. (2003) Keith & Frese (2005)	Exploratory learning: ● Minimal or no guidance provided ● Exploration and experimentation encouraged ● Inductive learning promoted	Error framing: ● Errors encouraged ● Errors framed as natural occurrences and as instrumental for learning	Emotion-control statements: ● Anxiety and frustration reduced by positive statements during learning ● Personal control promoted
Guided exploration	Bell & Kozlowski (2002) Debowski et al. (2001) Wood et al. (2000)	Guided exploratory learning: ● Guidance on task sequence provided ● External direction on strategy development provided ● Cognitive modeling emphasized ● Systematic and preplanned exploration encouraged	Practice framing: ● Practice framed as a learning and development opportunity ● Progressive achievement to build self-efficacy emphasized	Guided practice: ● Satisfaction with progress strengthened by enactments of practice
Mastery training	Chillarege et al. (2003) Kozlowski & Bell (2006) Kozlowski et al. (2001) Martocchio (1994) Stevens & Gist (1997) Tabernero & Wood (1999)	Exploratory learning: ● Minimal-to-moderate guidance provided ● Exploration encouraged ● Active practice emphasized	Error/ability framing: ● Errors framed as natural occurrences that are instrumental for learning ● Task ability framed as an acquirable skill ● Mastery goals provided	Self-evaluative guidance: ● Training framed as an opportunity to reduce anxiety and frustration ● Self-management and personal control emphasized
Targeted self-regulation pathway		Cognition: ● Metacognition ● Self-evaluation	Motivation: ● State goal orientation ● Intrinsic motivation ● Self-efficacy	Emotion: ● State anxiety

level of guidance or structure differs, but the focus on using exploratory learning to engage learners' metacognitive activities is a common theme across all the interventions.

Second, several of the interventions incorporate instructions designed to prime specific training frames that shape the orientation that trainees take toward the training task. A prototypical example is error framing, in which training instructions encourage trainees to make errors and frame errors as instrumental for learning (Frese et al., 1991). Error framing is designed to induce a mastery orientation and to positively influence key motivational processes, such as intrinsic motivation and self-efficacy. Finally, because active approaches to learning have the potential to provoke stress and anxiety (Kanfer & Heggestad, 1999; Keith & Frese, 2005), many active learning interventions include a training design element designed to help individuals manage their emotions. Although there are qualitative differences in the specific strategies incorporated into the different interventions, they share the common goal of helping trainees to regulate their emotions during learning.

Our goal in the current study is to examine the effects of these core training design elements, with a particular emphasis on elucidating the relatively distinct cognitive, motivational, and emotional process pathways they influence. In the sections that follow, we examine these core training design elements and articulate their proposed process pathways in more detail. In addition, we examine several individual differences as potential moderators of linkages between the different training design elements and self-regulatory processes (i.e., aptitude–treatment interactions). The conceptual model that is generated through this effort is shown in Figure 1 and is discussed below.

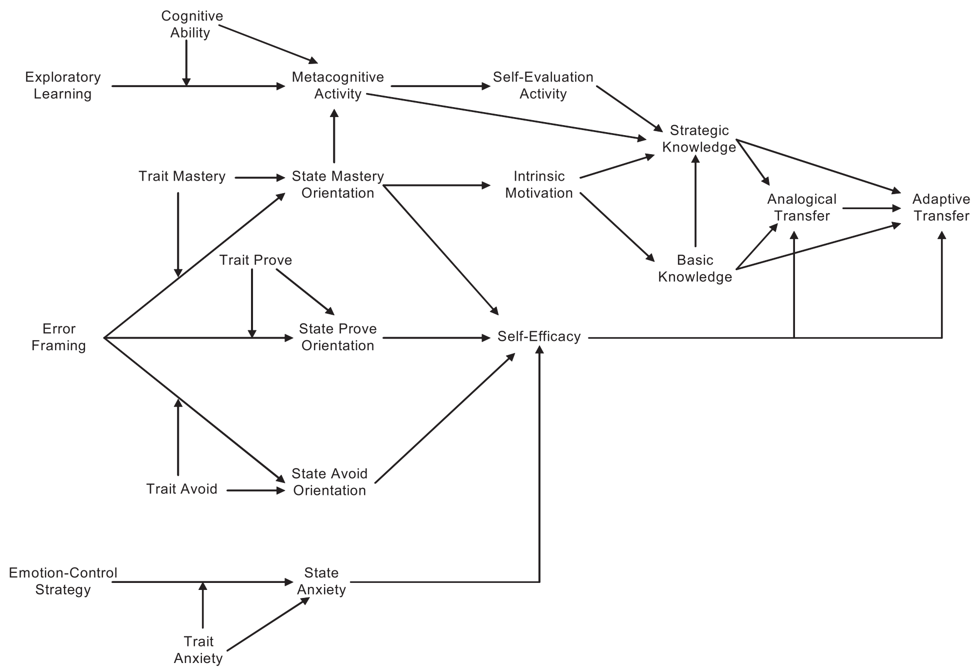

Figure 1. Integrated theoretical model of core training design elements, self-regulatory processes, and learning outcomes.

Exploration

Cognitive pathway. As mentioned above, numerous observers have noted the importance of metacognition for supporting active learning (e.g., Bransford et al., 1999; K. G. Brown & Ford, 2002; Smith et al., 1997). Metacognitive activities include planning, monitoring, and revising goal-appropriate behavior (A. L. Brown, Bransford, Ferrara, & Campione, 1983). As Cannon-Bowers, Rhodenizer, Salas, and Bowers (1998) noted, "Metacognition emphasizes self-monitoring of one's cognitive functions, which assists learners in becoming active in their education instead of being passive recipients of instruction" (p. 296). Metacognition is critical for learning, particularly in environments that provide little external structure, because it is the mechanism through which individuals monitor their progress, determine when they are having problems, and adjust their learning accordingly (Ford, Smith, Weissbein, Gully, & Salas, 1998). In addition, metacognitive skills are critical for adaptive transfer, because they enable learners to recognize changes in task demands, devise new solutions, and evaluate the effectiveness of the implemented solution (Ivancic & Hesketh, 2000). In a study designed to examine the active role of the learner within the learning process, Ford et al. (1998) demonstrated the importance of metacognition for both learning and transfer. They showed that trainees' metacognitive activity positively predicted several learning outcomes, including knowledge and training performance, and that these learning capabilities led to greater adaptive performance on a transfer task.

Exploratory learning. The transfer appropriate processing principle (Morris, Bransford, & Franks, 1977) suggests that if metacognition is required for adaptive transfer, it is critical to engage individuals' metacognition during learning. Critical to promoting metacognition is giving individuals an opportunity to engage in self-directed learning (Holyoak, 1991; Sweller, Mawer, & Ward, 1983). Learning that is directed toward understanding through exploration and experimentation is an inductive process that provides individuals with control over learning, and this control has been identified as a critical condition for stimulating metacognition (Ford & Kraiger, 1995). In contrast, more traditional, deductive approaches to learning (e.g., proceduralized instruction) do not offer the opportunity to engage in metacognitive activities, because individuals are provided with the correct task solution and exploration is restricted (Keith & Frese, 2005).

Frese et al. (1988), for example, compared proceduralized instruction to exploratory learning for training individuals on a word processing system. They hypothesized that the more active, exploratory learning process would stimulate metacognitive activities, such as hypothesis testing, thereby enhancing learning and transfer. The results revealed that exploratory learning was superior to proceduralized instruction not only for training performance but for transfer. Dormann and Frese (1994) further examined the importance of exploration in creating an active approach to learning. Their results revealed that exploratory learning led to higher performance than did proceduralized instruction. Further, the results showed that exploratory behavior partially explained the observed performance differences.

Keith and Frese (2005) examined metacognition as one process that mediates the effectiveness of error management training. They found that more exploratory error management training led to higher levels of metacognitive activity than did the more proceduralized error avoidant training and that metacognitive activity mediated the positive effect of error management training on adaptive transfer performance. Finally, research by McDaniel and

Schlager (1990) provides additional evidence of the benefits of exploratory learning for developing strategic knowledge and solving novel transfer problems. They demonstrated that allowing individuals to devise task strategies during training, as opposed to providing the strategies, did not yield benefits for analogical transfer but did help individuals generate strategies with which to solve novel transfer problems.

Although exploratory learning has been shown to offer many benefits, researchers have noted limitations of unstructured exploration (Debowski et al., 2001; Smith et al., 1997). For example, if learners are given too much freedom, they may fail to come into contact with the to-be-learned material (Mayer, 2004). For this reason, it is important to supplement exploratory learning with guidance that helps focus trainees' cognitive and behavioral activities in productive directions (Bell & Kozlowski, 2002; Mayer, 2004). On the basis of this evidence, we expect that exploratory learning, relative to proceduralized instruction, will lead to greater metacognitive activity, which in turn will lead to increased strategic knowledge and adaptive transfer.

Interactions with cognitive ability. Prior research provides some evidence that the benefits of shifting instructional control to learners may depend on the learners' level of cognitive ability. Snow (1986) suggested that students with lower levels of ability typically benefit from tightly structured lessons, whereas students with higher levels of ability tend to perform better in less structured environments that provide room for independent learning. Consistent with this pattern, Gully et al. (2002) demonstrated that high-ability individuals acquired higher levels of skill when they were encouraged to explore and make errors than when they were instructed to avoid errors. More exploratory or unstructured learning increases cognitive workload (Tuovinen & Sweller, 1999). Thus, asking low-ability trainees to explore a domain may insert an additional layer of complexity that consumes their already limited cognitive resources and detracts from their self-regulatory activities (van Merriënboer, Kirschner, & Kester, 2003). Thus, we expected that exploratory learning would enhance the metacognitive activities of high-ability trainees but would inhibit the metacognitive activities of low-ability trainees.

Training Frame

Motivational pathway. K. G. Brown and Ford (2002) suggested that in situations where learners are expected to be active participants in training, it is important to consider the motivational orientation they take to the learning situation. Recent research in the achievement goal literature has integrated traditional conceptualizations of mastery and performance goals with classic achievement motivation theories, which emphasize that activity in achievement settings can be oriented toward the attainment of success (approach) or the avoidance of failure (e.g., Elliot & Church, 1997; Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002). This research has resulted in a framework in which three achievement orientations are posited: a *mastery* goal, focused on the development of competence and task mastery; a *performance-prove* goal, focused on the attainment of favorable judgments of competence; and a *performance-avoid* goal, focused on avoiding perceptions of failure and incompetence (Elliot & Church, 1997). Research has demonstrated that these orientations have differential effects on how individuals approach, interpret, and respond to achievement activities. For example, a meta-analysis by Rawsthorne and Elliot (1999) revealed that mastery orientation stimulates higher levels of intrinsic motivation than does a performance orientation. Colquitt and Simmering (1998) demonstrated that mastery orientation not only leads to higher levels of motivation to learn than does performance orientation but that it buffers individuals from becoming demotivated in the face of performance difficulties. This finding is consistent with research that has shown that higher levels of mastery orientation lead to higher levels of self-efficacy, which in turn positively impact effort, persistence, and training performance (e.g., Kozlowski, Gully, et al., 2001; Payne, Youngcourt, & Beaubien, 2007; Phillips & Gully, 1997). These findings have led researchers to conclude that individuals who adopt a mastery orientation are more engaged and persistent learners (K. G. Brown & Ford, 2002; Heimbeck et al., 2003).

Error framing. Research has revealed that the adoption of different achievement goals can be influenced by a variety of situational factors or inductions (Archer, 1994; Boyle & Klimoski, 1995; Kozlowski, Toney, et al., 2001; Tabernero & Wood, 1999). In particular, training instructions can be used to create training frames that influence the orientation that trainees take toward the training task (Kozlowski, Toney, et al., 2001). Although active learning interventions have used a variety of methods to shape the framing of training, research by Frese et al. (1991) demonstrated that a particularly potent means of inducing these different motivational orientations involves the framing of errors. Errors serve as salient feedback when individuals are engaged in learning a complex, novel task, and how learners interpret their errors has been identified as a distinguishing feature of the different dimensions of goal orientation (Ames & Archer, 1988; Dweck, 1986). When errors are framed as a natural, instructive part of the learning process and performance evaluation is deemphasized, individuals are more likely to adopt a mastery orientation (Ivancic & Hesketh, 1995). In contrast, when individuals are told to avoid errors during learning, errors are framed as punishment and trainees are more likely to adopt a performance-avoid orientation. Thus, active learning strategies often include task instructions designed to encourage errors and to frame mistakes as instrumental for learning and self-improvement (Frese et al., 1991; Frese & Altmann, 1989; Heimbeck et al., 2003). In contrast, the more traditional, behaviorist approach to training encourages trainees to avoid errors and frames errors as negative occurrences that will detract from learning and performance (Frese et al., 1991; Keith & Frese, 2005). Thus, we expected that the differential framing of errors would induce different levels of mastery and performance-avoid orientations, which, in turn, would influence trainees' self-efficacy and intrinsic motivation. As neither of these approaches emphasizes performance demonstration, we did not expect the inductions would significantly impact trainees' adoption of a performance-prove goal.

Interactions with trait goal orientation. Research suggests that the goals individuals adopt during training are determined not only by situational factors but by dispositional influences (Brett & VandeWalle, 1999; Chen, Gully, Whiteman, & Kilcullen, 2000). As Button, Mathieu, and Zajac (1996) stated, "Dispositional goal orientation will predispose individuals to adopt particular response patterns across situations, but situational characteristics may cause them to adopt a different or less acute response pattern for a particular situation" (p. 28). Harackiewicz and Elliot (1993), for example, found that the effects of mastery or performance goals on intrinsic motivation depended on individual differences in achievement motivation (i.e., orientation toward competence). Specifically, mastery goals raised intrinsic motivation for individuals low in achievement motivation but failed to enhance intrinsic motivation among individuals high in achievement motivation. Performance goals, on the other hand, enhanced intrinsic motivation for individuals high in achievement motivation. Harackiewicz and Elliot (1993) interpreted these results as evidence that when an individual is characteristically oriented toward mastery (or performance), the external instantiation of such an orientation is likely to have little effect. Consistent with these results, we expected that error framing would be a more powerful inducement of a particular orientation among individuals with low trait levels of that orientation.

Emotion Control

Emotional pathway. Simons and De Jong (1992) noted that "becoming an active learner is a difficult and stressful process" (p. 342). As a result, a number of researchers have argued that it is important to consider the important role that emotion control plays in reducing anxiety when one adopts an active learning approach (Debowski et al., 2001; Kanfer & Heggestad, 1999; Keith & Frese, 2005). Kanfer, Ackerman, and Heggestad (1996) defined emotion control as "the use of self-regulatory processes to keep performance anxiety and other negative emotional reactions (e.g., worry) at bay during task engagement" (p. 186). Researchers have noted that negative emotions, such as anxiety or frustration, are demotivating and may divert attentional resources away from on-task activities (Wood et al., 2000). Kanfer and Ackerman (1989), for instance, have demonstrated that negative emotions consume valuable attentional resources and hinder learning and performance, especially in the early stages of training, when cognitive demands are high. The demotivating aspect of anxiety manifests in a negative relationship between anxiety and self-efficacy (Bandura, 1997; Chen et al., 2000). For example, a study by Martocchio (1992) found that framing computer training as an opportunity (vs. neutral) lowered participant computer anxiety, which in turn enhanced participant computer-efficacy beliefs.

Emotion-control strategies. Given the negative effects of anxiety on learning and performance, strategies have been developed with the aim of helping individuals to manage their emotions during training. Kanfer and Ackerman, for example, developed an emotion-control strategy that instructed trainees to increase the frequency of positive thoughts and reduce the frequency of negative thoughts. These instructions were reinforced with positive statements during training that emphasized personal control (e.g., "Adopt a positive 'CAN DO' attitude"). Kanfer and Ackerman (1990) found that trainees given this emotion-control strategy reported fewer negative affective reactions and had higher levels of performance. It is important to note that these effects were most pronounced early in training, when attentional demands of the task were highest and trainees were most likely to experience failure. A common element of error management training is a set of heuristics; these error management instructions (e.g., "There is always a way to leave the error situation") are designed to "counter the emotional and frustrating quality of errors" (Frese et al., 1991, p. 83). A recent study by Keith and Frese (2005) examined the utility of error management instructions as an emotion-control strategy. Their study found that the error management instructions enhanced trainees' emotion control (i.e., regulation of negative emotions), which in turn led to greater adaptive transfer. On the basis of this evidence, we expected that trainees provided with emotion-control training would demonstrate lower levels of state anxiety early in training, which in turn would lead to higher levels of self-efficacy and performance.

Interactions with trait anxiety. Whereas state anxiety represents a more localized, temporal condition, trait anxiety is a measure of an individual's natural, or dispositional, level of anxiety. Trait anxiety is often interpreted as a measure of how anxiety prone an individual is. Spielberger (1977), for example, found that among people exposed to an anxiety manipulation, individuals with higher trait anxiety showed a greater increase in state anxiety. The study concluded that the anxiety trait implies a greater susceptibility to influences from situations. Differences in trait anxiety, therefore, may play an important role in determining the impact of an emotion-control intervention. Specifically, it is expected that the negative relationship between emotion-control training and state anxiety may be stronger for individuals high in trait anxiety, because of their enhanced susceptibility to anxiety-provoking events.

Summary and Integration

Figure 1 provides an integration of the three relatively distinct process pathways through which the core training design elements are expected to influence trainees' learning and transfer. It is important to highlight that active learning approaches are designed to improve performance after, as opposed to during, training activity (Keith & Frese, 2005). Thus, all three core elements are expected to have a positive influence on trainees' posttraining performance. In fact, strategies that encourage errors, such as exploratory learning or instructions, may lower performance during training but are expected to enhance transfer (Hesketh, 1997; R. A. Schmidt & Bjork, 1992). Further, as noted earlier, active learning approaches target the development of adaptive expertise. Thus, some research suggests that active learning approaches may produce slight gains in analogical transfer (Ivancic & Hesketh, 2000), but these approaches are expected to have greater utility for facilitating trainees' adaptive performance during transfer (Heimbeck et al., 2003; Keith & Frese, 2005; Kozlowski, Toney, et al., 2001).

Each of the three process pathways was expected to play a role in promoting learning and adaptive transfer. Consistent with our focus on elucidating the core elements of active learning, we designed the model to emphasize the distinctiveness of the process pathways and to enhance parsimony and conceptual clarity. However, as prior research suggested the potential for cross-over effects among some of the processes in these pathways, we explored this issue as we tested alternative models. The first pathway focuses on the quality of trainees' cognitive self-regulatory processes. We expected exploratory learning would facilitate higher levels of metacognitive activity (e.g., planning, monitoring) and self-evaluation activity (e.g., evaluating one's progress), particularly among high-ability trainees. Salomon and Globerson (1987) noted that metacognitive skills are important when tasks are demanding, when they cannot be carried out by reliance on already well-mastered skills, and when alternatives need to be deliberately and effortfully sought. Thus, we predicted that this path would be the primary driver of more complex, strategic knowledge, which would promote adaptive transfer (Kozlowski, Toney, et al., 2001).

The second pathway focuses on the nature of trainees' motivation during learning. In the current study, we examined the joint effects of both situational (i.e., error framing) and dispositional factors on trainees' adoption of achievement goals. When these factors combine to induce a mastery orientation, trainees are expected to exhibit higher levels of intrinsic motivation (e.g., Rawsthorne & Elliot, 1999) and self-efficacy (Phillips & Gully, 1997). We expected this path to be the primary driver of trainees' basic knowledge, because the acquisition of basic task concepts results from repeated exposure (i.e., practice) to material and is, therefore, most heavily influenced by trainee effort (Bell & Kozlowski, 2002). However, we also modeled a path from basic knowledge to strategic knowledge. This path is consistent with contemporary theories of learning that argue for the progressive development of knowledge and skill competencies (J. R. Anderson, 1983). Prior research has also suggested that a positive relationship exists between mastery orientation and metacognition (Ford et al., 1998; A. M. Schmidt & Ford, 2003; Somuncuoglu & Yildirim, 1999). Thus, we expected that a mastery orientation would play a secondary role in shaping trainees' cognitive self-regulatory activity.

The third pathway focuses on trainees' emotions during training. In the current study, we focused on trainees' level of anxiety early in training. We expected that trainees who received an emotion-control strategy and had naturally low levels of trait anxiety would exhibit lower levels of state anxiety. Past research has shown that self-efficacy mediates the relationship between anxiety and performance (Bandura, 1997), so this component of active learning eventually merges with the motivational pathway to influence trainees' learning and transfer performance.

Method

Participants

Participants were 350 undergraduates enrolled in psychology courses at a large midwestern university who received course credit for participating in the study. Of the trainees, 58% were female, 83% were Caucasian, and most (89.4%) were between 18 and 21 years of age.

Task

The task used in this research was a version of TANDEM (Weaver, Bowers, Salas, & Cannon-Bowers, 1995), a PC-based radar-tracking simulation. TANDEM is a dynamic and complex task that requires trainees to learn a number of basic and strategic skills. With respect to the basic skills, participants needed to "hook" contacts on the radar screen, collect information, and make three subdecisions to classify the contact's characteristics. Then they needed to use this information to make an overall decision (take action/clear). Trainees received points for correct decisions and lost points for incorrect decisions. They also needed to learn strategic skills, which involved preventing contacts from crossing two perimeters located on the radar screen. Individuals needed to learn how to identify the perimeters, monitor contacts approaching the perimeters, and determine contact priority. Contacts that crossed perimeters cost points.

Experimental Design and Procedures

Training was conducted in single, 3-hr session. During this session, individuals learned to operate the radar simulation described above. Sessions were conducted with groups of 1–12 participants. The present study employed a 2 (exploratory learning vs. proceduralized instruction) $\times$ 2 (error-encouragement framing vs. error-avoidance framing) $\times$ 2 (emotion-control strategy vs. no emotion-control strategy), fully crossed, between-subjects design. Participants were randomly assigned to one of the eight experimental conditions.

Familiarization. Trainees were first presented with a brief demonstration of the simulation that outlined its features and decision rules. They were also shown how to use an online training manual that contained complete information about the simulation. Participants then had an opportunity to familiarize themselves with the online instruction manual in a 2.5-min study period and were able to practice the task in a 1-min "familiarization" trial. Our purpose in this preliminary trial was to give participants an opportunity to learn how to operate the manual and task and to become familiar with the equipment.

Practice. After the familiarization trial, trainees began the practice section of the training program. The practice section consisted of three blocks, each block consisting of three 8-min trials, for a total of nine training trials. Each training trial consisted of a cycle of study, practice, and feedback. Participants had 2.5 min to study an online manual that contained information on all important aspects of the task. They then had 4 min of hands-on practice. The nine trials all possessed the same general profile (e.g., same difficulty level, rules, number of contacts), but the configuration of contacts (e.g., location of pop-up contacts) was unique for each trial. After each practice trial, participants had 1.5 min to review their feedback. Veridical feedback on all important aspects of the task relevant to both basic and strategic performance was provided immediately following the completion of each practice trial. Participants were given a 5-min break following the third and ninth trials.

Training transfer. Following the second break, trainees participated in two additional trials designed to measure their transfer performance. At this point, the experimental manipulations were removed and participants were instructed to "do their best." This design is similar to that employed by Keith and Frese (2005), who measured transfer in a "test phase" that followed the "training phase." This distinction is important, because, during training, participants' practice is directly influenced by the active learning manipulations and, therefore, does not serve as a true assessment of performance. We designed the first trial to measure analogical transfer. The analogical transfer trial followed the same profile (i.e., equivalent level of difficulty) as that of the training trials. Thus, the analogical transfer trial serves an uncontaminated measure of participants' end-of-training performance. Adaptive transfer was assessed in a second transfer trial that was more difficult, complex, and dynamic than were the practice trials (e.g., Bell & Kozlowski, 2002; Kozlowski, Gully, et al., 2001). Operationalizations of the analogical and adaptive transfer assessments are described in more detail below.

Manipulations

Exploratory learning. Trainees in this study were assigned to one of two instructional conditions: exploratory learning or proceduralized instruction. This manipulation was modeled after research on exploratory learning (McDaniel & Schlager, 1990) and on error management training and enactive exploration (Frese et al., 1991; Heimbeck et al., 2003; Wood et al., 2000). Participants in the exploratory condition were not given the task solutions, rules, or strategies and instead were instructed to explore the task and to develop their own understanding of it. They were instructed to use exploration and experimentation to discover the best strategies and methods for handling the task situation. Thus, the emphasis was on providing minimal structure, encouraging active exploration and experimentation, and promoting inductive learning. However, as noted earlier, research suggests that, to be effective, exploratory learning methods must be supplemented with external guidance to help focus trainees' cognitive and behavioral activities in productive directions (Bell & Kozlowski, 2002; Mayer, 2004). In the current study, participants in both conditions received a list of training objectives (i.e., skills, strategies) prior to each of the three training sessions. These objectives were sequenced across training from more basic to more complex elements, thereby providing the type of guidance on task sequence found in guided exploration strategies (Bell & Kozlowski, 2002; Debowski et al., 2001). Participants in the proceduralized instruction condition received detailed written instructions that provided step-by-step instructions for each trial. These instructions specified what actions trainees should take during practice and the commands necessary to complete each task function. Participants were instructed to follow these instructions during each of the practice trials. Consistent with prior research utilizing proceduralized instruction (Dormann & Frese, 1994; Frese et al., 1991), the instructions did not give specific explanations for the steps and commands.

Error framing. The error framing manipulations were administered prior to each training block and were integrated with the instructions for the practice session. The frames were developed on the basis of prior research that has used the framing of errors as a key element of mastery- and performance-oriented inductions (see Chillarege, Nordstrom, & Williams, 2003; Gully et al., 2002; Kozlowski, Gully, et al., 2001; Martocchio, 1994). In the current study, all trainees were given a list of potential errors one could make with respect to the skills or strategies being emphasized in each training block (Frese & Altmann, 1989; Gully et al., 2002). The error framing manipulation determined how these errors were framed. Trainees in the error-encouragement condition were told that "errors are a positive part of the training process" and that "you can learn from your mistakes and develop a better understanding of the simulation." Trainees in this condition were encouraged to make and learn from errors during practice. Trainees in the error-avoidance condition were told that "errors are detrimental to the training process" and that errors would detract from their learning and performance. Trainees in this condition were instructed to avoid errors during practice.

Emotion-control strategy. Following the task demonstration, trainees in the emotion-control strategy condition received training on how to control their emotions during training. This training was modeled after the emotion-control strategy developed by Kanfer and Ackerman (1990) and research on self-dialogue (e.g., T. C. Brown, 2003). The experimenter introduced the emotion-control strategy by discussing the negative effects of anxiety and frustration on learning and performance. The experimenter also described the role of self-dialogue in decreasing the amount of frustration and anxiety that one experiences and in promoting feelings of personal control (Ellis, 1962; Neck & Manz, 1992). Participants were trained to monitor for negative or self-defeating thoughts and were instructed how to replace those thoughts with positive and constructive self-statements. Trainees in the emotion-control strategy condition were provided with emotion-control statements, which were extracted from Kanfer and Ackerman (1990) and were based on the work of Bloom (1985) and Butler (1983). Examples include "Remember, worry won't help anything" and "This task may be challenging, but I know I CAN do it." Participants were encouraged to use these statements, or other positive self-statements of their own design, to modify their self-dialogue and control their emotions. During training, participants were reminded to use the emotion-control strategy, and statements were reinforced by displaying them on a whiteboard in the training room and presenting them periodically on the computer.

Measures

The measures used in this study were administered at four points in time. Demographic information and individual differences were collected through an online questionnaire administered during registration, well before participants were scheduled for the experimental session. State anxiety was assessed early in training, as research suggests that emotion control is most critical during the early stages of learning (Kanfer & Ackerman, 1990). We assessed state goal orientation early in training to create temporal separation in measurement between these measures and trainees' self-reported intrinsic motivation and self-efficacy, which were measured at the end of training (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). All other process variables and trainees' knowledge were measured at the end of training and prior to the two transfer trials, which assessed analogical and adaptive transfer performance.

Cognitive ability. Cognitive ability was measured by having individuals report their highest score on the SAT or ACT. If an individual did not provide his or her score, it was obtained from official university records. Research has shown that the SAT and ACT have a large general cognitive ability component (Frey & Detterman, 2004), and the publishers of these tests claim high internal consistency reliabilities for their measures (e.g., Kuder–Richardson $- 20 = .96$ for the ACT composite score; American College Testing Program, 1989). In addition, previous research has shown that self-reported SAT/ACT scores correlate highly with actual scores. Gully, Payne, Kiechel, and Whiteman (1999) found that self-reported SAT scores correlated .94 with actual scores. We standardized individuals' ACT or SAT scores with norms published by ACT and the College Board and used this standardized score as a measure of cognitive ability. The reliability of cognitive ability scores was set at .90 (i.e., we multiplied the reliability estimate, .96, and the correlation obtained in previous research between self-reported and actual test scores, .94).

Trait goal orientation. Before the experiment, participants completed VandeWalle's (1997) 13-item trait goal orientation measure, which had been modified to be domain general, instead of specific to the work domain. The VandeWalle (1997) measure contains 13 items, with responses made on a 6-point scale that ranges from 1 (*strongly disagree*) to 6 (*strongly agree*). The Mastery Orientation scale consisted of 5 items ($\alpha = .85$). A sample item is "I enjoy challenging and difficult tasks where I'll learn new skills." The performance-avoid orientation measure consisted of 4 items ($\alpha = .83$). A sample item is "I prefer to avoid situations where I might perform poorly." Performance-prove orientation was assessed with 4 items ($\alpha = .84$). A sample item is "I try to figure out what it takes to prove my ability to others."

Trait anxiety. We assessed participants' trait anxiety using the 20-item Trait-Anxiety subscale of the State–Trait Anxiety Inventory (STAI; Spielberger, 1983). These 20 items are rated on a 4-point scale that ranges from 1 (*not at all*) to 4 (*very much so*). The STAI is a widely used and extensively validated measure of trait anxiety. Individuals who score high on trait anxiety are considered to be more anxiety prone. Reliability of this scale was .91.

Metacognitive activity. Following the ninth trial, participants completed a 12-item measure of metacognitive activity adapted from Ford et al. (1998). This measure is designed specifically to examine metacognitive activity (e.g., self-monitoring of learning, planning of learning activities) within the context of the TANDEM simulation. A few items were modified, due to changes in task design and the focus of training. All items were measured on a 5-point scale that ranged from 1 (*never*) to 5 (*constantly*). Coefficient alpha for the metacognitive activity measure was .93.

Self-evaluation activity. We calculated the extent to which trainees exhibited self-evaluation activity by assessing the amount of time they spent reviewing feedback. In this study, descriptive feedback was presented via a computerized feedback program, which automatically assessed trainees' practice activities and presented this information on the computer screen. The amount of time that trainees spent reviewing this information was recorded by the software, and we used the time spent reviewing feedback following the last three trials to measure trainees' self-evaluation activity.

State goal orientation. Participants completed three scales designed to measure their state goal orientation. The scales, which were adapted from Horvath, Scheu, and DeShon (2001), treat state mastery, performance-prove, and performance-avoid orientations as separate constructs, to ensure distinction from the VandeWalle (1997) trait measures of goal orientation. All items were rated on a 5-point Likert-type scale, with responses ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Mastery orientation was measured with 4 items ($\alpha = .88$). A sample item is "The opportunity to learn new things about this task is important to me." The performance-avoid measure contained 4 items ($\alpha = .83$). A sample item is "On this task, I would like to avoid situations where I might demonstrate poor performance to myself." Performance-prove orientation was also measured with 4 items ($\alpha = .79$). A sample item is "I want to show myself how good I am on this task."

Intrinsic motivation. Participants' intrinsic motivation was assessed with the Interest/Enjoyment subscale from Deci and Ryan's Intrinsic Motivation Inventory (IMI). The IMI has been used in numerous experiments related to intrinsic motivation, and this subscale is considered to be the self-report measure of intrinsic motivation (Deci, Eghrari, Patrick, & Leone, 1994; Ryan, 1982; Ryan, Koestner, & Deci, 1991). We rated 7 items using a 5-point Likert type scale that ranged from 1 (*not at all true*) to 7 (*very true*). A sample item is "I enjoyed doing this activity very much." Reliability for this scale was .93.

Self-efficacy. We assessed self-efficacy with an 8-item self-report measure developed for use in this research paradigm (Ford et al., 1998; Kozlowski, Gully, et al., 2001). This measure assessed self-efficacy with a Likert-type scale rather than with ratings of confidence about particular aspects of the task (Hysong & Quinones, 1997; Lee & Bobko, 1994). Response options for this scale ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). A sample item is "I am certain I can manage the requirements of this task." Internal consistency for this scale was .92.

State anxiety. State anxiety was assessed with a 5-item measure drawn from Deci and Ryan's Intrinsic Motivation Inventory. This scale measures the extent to which individuals feel pressure and tension in relation to a target activity. The 5 items were rated on a 7-point Likert-type scale that ranged from 1 (*not at all true*) to 7 (*very true*). A sample item is "I felt very tense while doing this activity." Internal consistency reliability was .87.

Declarative knowledge. At the end of training, trainees completed a test of basic knowledge. This test consisted of 11 multiple-choice items focusing on the extent to which declarative knowledge (e.g., cue values; basic operating features of the task) about the task had been acquired. Strategic task knowledge was also assessed at the end of training; we used an 11-item multiple-choice test that focused on the extent to which strategic knowledge (e.g., locating the perimeters, prioritizing targets) about the task had been acquired. A confirmatory factor analysis showed that the two-factor model of basic and strategic knowledge provided acceptable fit to the data, $\chi^2(69, N = 350) = 109.20$, $p < .01$, normed chi-square (χ^2/df) = 1.58, comparative fit index (CFI) = .87, root-mean-square error of approximation (RMSEA) = .041. A chi-square difference test also showed that the two-factor model fit the data significantly better than did a one-factor model, $\Delta\chi^2\,(1) = 18.59$, $p < .01$. Using the equation specified in Fornell and Larcker (1981, p. 45), we calculated the composite reliability, which is analogous to coefficient alpha, of each of the knowledge measures. The composite reliabilities for the basic and strategic knowledge scales were .80 and .81, respectively.

Skill-based performance. Trainees' performance was measured during training as well as in two transfer trials. The training performance measure was based on performance during the ninth training trial and was computed by adding 100 points to the trainee's performance score every time a target was identified and prosecuted correctly and by subtracting 100 points from the trainee's score each time a target was misidentified or prosecuted incorrectly. In addition, 10 points were deducted from the trainee's score for each target that crossed the inner or outer defensive perimeter.

Following training, individuals participated in two transfer trials. All trainees received similar instructions to do their best and to use the transfer trials as an opportunity to demonstrate what they had learned during the training phase (cf. Keith & Frese, 2005; Wood et al., 2000). In addition, we removed the manipulations prior to the transfer phase to ensure that participant performance represented skill acquisition and was not constrained by the training manipulations. That is, because exploration or making errors hinders performance during training, it was necessary to get uncontaminated assessments posttraining. We designed the first transfer trial to assess analogical transfer, so the format (e.g., duration, rules) and difficulty level (e.g., number of targets) were consistent with the prior training trials. Thus, in this design analogical transfer represents an assessment of end-of-training performance. The second transfer trial was designed to measure adaptive transfer. Using a design consistent with prior research (Bell & Kozlowski, 2002; Kozlowski, Gully, et al., 2001), we guided its operationalization by Wood's (1986) typology of task complexity to ensure a substantial increment in difficulty and complexity. To increase difficulty, we increased the number of targets from 22 to 60, a 172% increase. In addition, the length of the adaptive transfer trial was increased from 4 to 10 min. Task complexity was heightened by (a) including more pop-up targets, which appeared suddenly on the screen; (b) changing the "rules of engagement," so a greater number of points was deducted when targets crossed the visible inner perimeter (175 points) and the invisible outer defensive perimeter (125 points); (c) creating more defensive perimeter intrusions; (d) creating pop-up targets that appeared very close to defensive perimeters; and (e) differentially distributing boundary intrusions to create a situation in which many targets threatened the outer perimeter and fewer targets threatened the inner perimeter, which required strategic trade-offs on the part of trainees.

Manipulation Checks

At the end of training, participants in the proceduralized instruction condition responded to the item "I followed the step-by-step instructions given to me for each trial" on a 5-point Likert scale that ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). The results showed that 81.4% of the participants in the proceduralized instruction condition responded "agree" or "strongly agree" to this item. In addition, analyses revealed that the nature of instruction had a significant effect on the number of errors the trainees made during training, $F(1, 345) = 101.51$, $p < .01$. As would be expected, exploratory learning led to more errors than did proceduralized instruction.

At the end of training, all participants responded to two items designed to check the error framing manipulation: "I tried to make errors as I practiced the simulation" and "I tried to avoid errors as I practiced the simulation." Both items were rated on a 5-point Likert scale that ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). The results revealed that participants who received the error-encouragement manipulation, as compared with the error-avoidance manipulation, were more likely to indicate that they had tried to make errors, $t(348) = 12.24$, $p < .01$ and were less likely to indicate that they tried to avoid errors, $t(348) = -9.52$, $p < .01$. Additionally, participants in the error-encouragement condition made more errors during training than did participants in the error-avoidance condition, $F(1, 345) = 3.96$, $p < .05$.

Finally, all participants responded to the item "I made a conscious effort to control my emotions during training" on a 5-point Likert scale that ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). The results revealed that participants who received the emotion-control strategy were more likely to indicate that they had consciously monitored their emotions during training, $t(348) = 2.65$, $p < .01$. As noted above, we reinforced the emotion-control manipulation periodically by presenting strategy statements on the final screen of the computerized feedback. Analysis of the average time that individuals had spent viewing these screens revealed that individuals in the emotion-control condition spent significantly more time on this screen than did control participants, $t(348) = 2.34$, $p < .05$, which indicated that they had processed the emotion-control strategy statements.

Analytic Strategy

Our first set of analyses was designed to assess the overall effect of the three training design elements on trainees' performance. We used analysis of variance to examine the effects of the three elements on trainees' performance at three points in time: the final trial during the training phase, analogical transfer (end-of-training performance for the test phase), and adaptive transfer (performance adaptation for the test phase).

We then focused on evaluating our hypotheses by testing a moderated structural equation model (MSEM). Specifically, we used LISREL 8.52 and employed the MSEM procedure outlined by Mathieu, Tannenbaum, and Salas (1992). Cortina, Chen, and Dunlap (2001) found that the Mathieu et al. (1992) procedure produced values similar to those generated by other available procedures for MSEM and suggested that the method should recover parameters equally as well as other available procedures. Cortina et al. (2001) asserted that the Mathieu et al. procedure "may be especially useful when testing more complicated theoretical models that include both mediated and moderated relationships" (p. 358).

The first part of the Mathieu et al. (1992) procedure involves creation of composites for each of the latent variables that are to constitute the latent products by summing the indicators of each of these component variables and standardizing, which includes centering, each of these composites. This method was applied to each of the individual differences involved in forming the latent products. Second, these standardized scale scores were multiplied by the single indicators representing each of the manipulations to create the latent products. We mean centered the indicators representing the manipulations before we created the latent products; the paths from the latent manipulation variables to their single indicators were set to unity, and the error variances of these paths were set to 0. Third, the measurement properties for the composite variables were fixed using the square roots of the scale reliabilities. Specifically, the path from the latent individual difference variables to their standardized composite indicators was set equal to the square root of the reliability, and their respective error variances were set to 1 minus their reliability multiplied by the variance of their observed scores (Jöreskog & Sörbom, 1993). Similarly, we used the composite reliabilities and variances of basic and strategic knowledge to fix their error variances and the paths from their latent variables to the single indicators.

To preserve valuable degrees of freedom, we created composite measures for each of the following latent variables in the model: metacognition, state mastery orientation, state prove orientation, state avoid orientation, intrinsic motivation, self-efficacy, and state anxiety. Specifically, we employed the random composite formation method described by Landis, Beal, and Tesluk (2000), which involves randomly assigning all items of a scale to one of two composites. Landis et al. (2000) found that the random method optimally balanced concerns over both efficiency (i.e., sample size to estimated paths ratio) and effectiveness (i.e., superior model fit).

Single indicators were used for the objective measures of self-evaluation activity, analogical transfer performance, and adaptive transfer performance; their paths were fixed to unity, and error variances were set to 0.

With these values fixed, the next step in the Mathieu et al. (1992) procedure is to test an additive model (i.e., a model not containing latent products) to determine the correlation between the latent variables representing the components of the product terms. Fourth, the values from the analysis of the additive model are used to compute the reliability for the product terms using the formula advanced by Bohrnstedt and Marwell (1978). Their formula takes into account the reliabilities of both variables that constitute the product term and the correlation between the latent variables. The resulting values are then used to fix the path from the latent products to their indicators and to fix the error variance of the indicators of the latent products in the analysis of the structural model. The final step is to test the model with and without the paths from the latent products to the criterion variables, thus allowing a chi-square test of the difference in fit between the models (Cortina et al., 2001).

Using the two-step procedure advanced by J. C. Anderson and Gerbing (1988), we tested the fit of the measurement model. We then tested the fit of the hypothesized structural model by comparing the fit of the model with and without the paths from the latent products and the criterion variables, as recommended by Mathieu et al. (1992). Because all hypotheses were directional, one-tailed tests of significance were used.

Results

The means, standard deviations, and intercorrelations for all variables examined in this study are presented in Table 2. The first set of analyses examined the impact of the three manipulations on trainees' performance in the final trial of the training phase and in the analogical (end-of-training test phase) and adaptive transfer (performance adaptation test phase) sessions. The analyses revealed that the nature of instruction had a significant effect on trainees' performance at all three measurement periods. As expected, trainees who received exploratory learning displayed significantly lower levels of performance in the final trial of the training phase than did trainees in the proceduralized condition, $F(1, 342) = 8.88$, $p < .01$. However, trainees in the exploratory condition displayed significantly higher levels of analogical transfer, $F(1, 342) = 4.03$, $p < .05$, and of adaptive transfer performance, $F(1, 342) = 8.41$, $p < .01$.

Figure 2 shows that although trainees who received exploratory learning exhibited lower levels of performance during training, they performed better on the transfer trials. Essentially, this figure demonstrates the transfer crossover effect—that is, training strategies that yield lower performance during training may have benefits that emerge during transfer—discussed by several researchers (e.g., R. A. Schmidt & Bjork, 1992). Moreover, the benefits associated with exploratory learning were greatest for adaptive transfer, a finding consistent with the argument that active learning approaches are best suited for developing adaptive skills and helping individuals to recognize and respond to changes in task conditions (Heimbeck et al., 2003; Keith & Frese, 2005; Kozlowski, Toney, et al., 2001).

The analyses revealed that the error framing manipulation did not have a significant effect on trainees' performance in the final trial of the training phase, $F(1, 342) = 0.08$, *ns*, or on analogical transfer performance, $F(1, 342) = 0.92$, *ns*. However, trainees who received the error encouragement frame evidenced marginally significant higher levels of adaptive transfer, $F(1, 342) = 3.19$, $p < .10$. This finding provides more evidence for the utility of active learning approaches for promotion of adaptive performance. Contrary to expectations, the emotion-control strategy did not directly impact training performance, $F(1, 342) = 0.81$, *ns*; analogical transfer, $F(1, 342) = 0.18$, *ns*; or adaptive transfer, $F(1, 342) = 1.32$, *ns*. The analyses did not reveal any significant two- or three-way interactions among the training manipulations on the outcomes. This finding is consistent with our conceptualization of three relatively distinct training design elements that target different sets of self-regulatory processes. We examine these process pathways in more detail below.

Moderated Structural Equation Modeling Results

Fit statistics for the various moderated structural equation models are presented in Table 3. Following accepted practice in structural equation modeling, we used several different fit indices in evaluating each model to provide convergent validity in model fit assessment (Bollen, 1990). First, we present the chi-square value and the normed chi-square, for which a ratio of 2.0 or less indicates good fit (Arbuckle, 1997). Next, we present the CFI, incremental fit index (IFI), and nonnormed fit index (NNFI), with values above .90 generally indicating acceptable fit and values above .95 indicating good fit (Hoyle, 1995; Hu & Bentler, 1999). Finally, we present the RMSEA and its 90% confidence interval. RMSEA values between .05 and .08 indicate reasonable fit, and values below .05 indicate close approximate fit (Kline, 2004).

Analysis of the measurement model indicated that the data fit the model well, $\chi^2(182, N = 350) = 232.07$, $p < .01$, $\chi^2/df = 1.28$, CFI = .99, IFI = .99, NNFI = .97, RMSEA = .024. Following the Mathieu et al. (1992) procedure, we then tested the fit of the hypothesized model with and without interactions and conducted a chi-square test of the difference in fit between the models (Cortina et al., 2001). The fit statistics reported in Table 3 indicate that both models provided a good fit to the data. A chi-square difference test revealed that the hypothesized model with interactions provided a significantly better fit to the data than did the model without interactions ($\Delta\chi^2 = 18.55$, $df = 5$, $p < .01$). Thus, the hypothesized model with interactions was retained, $\chi^2(366, N = 350) = 628.05$, $p < .01$, $\chi^2/df = 1.72$, CFI = .95, IFI = .95, NNFI = .93, RMSEA = .044.

Having found that the hypothesized model provided a good fit to the data, we explored potential alternative models (J. C. Anderson & Gerbing, 1988). Because the original model emphasized parsimony and the distinctiveness of the process pathways, the exploratory analyses served as a means for us to expand our focus and to consider additional paths that might further elucidate active learning processes. We used the modification indices from the hypothesized model with interactions to identify potential model respecifications. However, researchers have cautioned that model modifications often take advantage of sampling error and are rarely cross validated (Williams, 1995). To mitigate these problems, we considered only modifications that were theoretically

Table 2
Means, Standard Deviations, and Intercorrelations Between Observed Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Exploratory learning	0.49	0.50	—																				
2. Error framing	0.51	0.50	−.01	—																			
3. Emotion-control strategy	0.50	0.50	.03	−.01	—																		
4. Cognitive ability	0.00	1.00	.06	.05	−.10*	—																	
5. Trait mastery orientation	0.00	1.00	.06	−.02	.11*	.14**	—																
6. Trait prove orientation	0.00	1.00	.16**	−.04	.00	.08	.18**	—															
7. Trait avoid orientation	0.00	1.00	.02	.04	−.01	−.13**	−.29**	.39**	—														
8. Trait anxiety	0.00	1.00	.13**	.05	−.01	−.07	−.19**	.21**	.35**	—													
9. Metacognitive activity	3.65	0.73	.16**	.03	.04	−.06	.24**	.06	−.09	−.06	—												
10. Self-evaluation activity	130.82	45.40	.04	−.03	−.09*	.07	.03	.00	−.03	−.03	.21**	—											
11. State mastery orientation	3.67	0.82	−.05	.02	.10*	−.04	.33**	−.09*	−.24**	−.09*	.37**	.05	—										
12. State prove orientation	3.12	0.84	.08	.03	.09*	.04	.10*	.43**	.23**	.12*	.24**	.05	.25**	—									
13. State avoid orientation	2.20	0.89	.04	.06	−.10*	.04	−.18**	.33**	.43**	.34**	−.03	.05	−.16**	.31**	—								
14. Intrinsic motivation	4.28	1.34	.06	.03	−.01	.03	.15**	−.02	−.10*	−.11*	.48**	.23**	.39	.09*	−.11*	—							
15. Self-efficacy	3.87	0.63	.07	.03	.10*	.09*	.30**	.08	−.19**	−.25**	.38**	.11*	.28**	.15**	−.26**	.26**	—						
16. State anxiety	3.12	1.41	.06	−.01	−.14**	−.03	−.07	.09*	.10*	.28**	.08	.13**	−.11*	.01	.34*	.01	−.25**	—					
17. Basic knowledge	9.81	1.43	.09*	.03	−.05	.33**	.16**	.07	−.02	−.01	.07	.07	.10*	.19**	−.03*	.17**	.15**	−.07	—				
18. Strategic knowledge	8.44	1.87	.05	.01	−.11*	.39**	.14**	−.01	−.10*	−.09*	−.02	.16**	.04	.00	.01	.11**	.04	.06	.33**	—			
19. Training performance	0.00	1.00	−.16**	.02	−.05	.31**	.06	−.03	−.10*	−.12*	.03	.09*	.05	−.02	−.11*	.19**	.21**	−.08	.39**	.23**	—		
20. Analogical transfer	0.00	1.00	.11*	.02	−.02	.30**	.15**	.04	−.11*	−.04	.04	.04	.14**	.08	−.04	.11*	.26**	−.06	.47**	.20**	.51**	—	
21. Adaptive transfer	0.00	1.00	.15**	.09*	−.06	.49**	.14**	.09*	−.13**	−.09	.09	.13**	.09*	.12*	−.04	.18**	.29**	−.10*	.50**	.38**	.55**	.60**	—

Note. For exploratory learning, exploratory instruction = 1 and proceduralized instruction = 0. For error framing, error encouragement = 1 and error avoidance = 0. For emotion-control strategy, emotion-control strategy = 1 and no emotion-control strategy = 0. Training performance was measured in Trial 9.
* $p < .05$ (one-tailed). ** $p < .01$ (one-tailed).

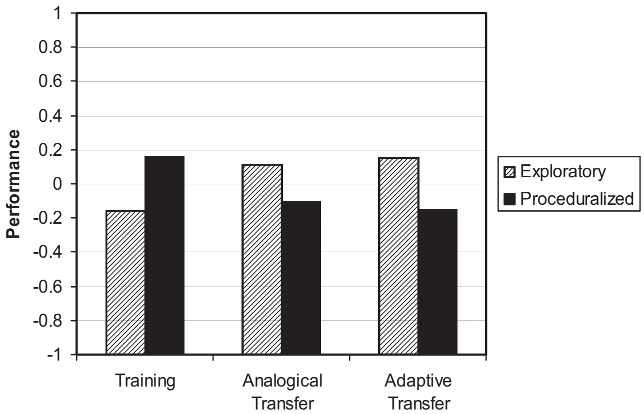

Figure 2. Effects of exploratory learning on trainees' performance.

supported (MacCallum, 1986). As J. C. Anderson and Gerbing (1988) noted, "Consideration of theory and content both greatly reduces the number of alternate models to investigate and reduces the possibility of taking advantage of sampling error to attain goodness of fit" (p. 416).

First, a path was modeled from state avoid orientation to state anxiety. This path is consistent with work by Elliot and McGregor (2001) and McGregor and Elliot (2002), which has demonstrated a positive relationship between performance-avoid goals and state anxiety. Also, two paths were added from metacognitive activity to intrinsic motivation and self-efficacy. These paths are supported by Pintrich and De Groot (1990), who found that self-regulated learning (a broader construct that included metacognitive activity) was positively related to both the expectancy (e.g., self-efficacy) and value (e.g., intrinsic motivation) components of motivation. In addition, A. M. Schmidt and Ford (2003) demonstrated that prompting learners to engage in self-monitoring increases self-efficacy, and Carver and Scheier (1990) suggested that self-monitoring activity can increase intrinsic motivation. Although each of these paths is supported by existing theory, these additions to the model are post hoc in nature, need to be interpreted with appropriate caution, and should be examined by future research.

An alternative moderated structural equation model containing these three paths was tested. All of the paths that were significant in the original model remained significant, with the exception of the path from mastery orientation to self-efficacy, which became nonsignificant in the revised model. The three exploratory paths added to the model were all significant. This model provided a good fit to the data, $\chi^2(363, N = 350) = 511.75$, $p < .01$, $\chi^2/df = 1.41$, CFI = .97, IFI = .97, NNFI = .96, and RMSEA = .031. In addition, a chi-square difference test revealed that this model provided significantly better fit to the data than did the hypothesized model with interactions, $\Delta\chi^2(3, N = 350) = 116.30$, $p < .01$. We also tested several alternative direct effects models, in which different mediating paths were constrained and direct paths were added.[1] None of these models significantly improved fit; thus, the more parsimonious fully mediated model was retained. Overall, as expected, these results provide support for a moderated and fully mediated model. The results for the exploratory alternative model, however, suggest greater crossover among the cognitive, motivational, and emotional process pathways than was hypothesized by the more parsimonious model. The standardized solution for this model is presented in Figure 3 and is discussed in more detail below.

The model explained 22.1% of the variance in trainees' metacognitive activity. Trainees with higher levels of state mastery orientation had higher levels of metacognitive activity. Also, as predicted, trainees who received exploratory learning had, on average, higher levels of metacognitive activity. This effect, however, was qualified by a significant interaction between the instructional manipulation and trainees' cognitive ability. This aptitude–treatment interaction is depicted in Figure 4. We created this figure by adapting the procedure described in Aiken and West (1991) using the standardized path coefficients (Cortina et al., 2001).

Using Ping's (2002) procedure for interpreting latent variable interactions, we also performed tests to determine whether the predicted values of metacognitive activity for the different types of instruction differed significantly at the high (i.e., one standard deviation above the mean) and low (i.e., one standard deviation below the mean) values of cognitive ability. These tests revealed that individuals low in ability displayed similar levels of metacognitive activity when given exploratory learning or proceduralized instruction, $t(348) = 0.88$, *ns,* but that individuals high in ability displayed significantly higher levels of metacognitive activity when given exploratory learning, $t(348) = 4.36$, $p < .01$. This finding partially supports our hypothesis that only high-ability trainees would demonstrate enhanced metacognitive activity under exploratory learning conditions. Metacognitive activity did not exhibit a significant direct relationship with strategic knowledge. However, trainees who reported higher levels of metacognitive activity engaged in greater self-evaluation activity, which was significantly and positively related to strategic knowledge. Further, metacognitive activity exhibited a significant relationship with several of the motivational processes. Specifically, trainees with higher levels of metacognitive activity were more intrinsically motivated and had higher levels of self-efficacy.

The model explained a total of 16.8% of the variance in trainees' state mastery orientation. Trait mastery orientation exhibited a significant, positive relationship with trainees' state mastery orientation, as expected. Contrary to expectations, error framing did not have a significant direct effect on trainees' state mastery orientation. However, there was a significant interactive effect of error framing and trainees' trait mastery orientation on state mastery orientation. The nature of this aptitude–treatment interaction is shown in Figure 5. Using Ping's (2002) procedure, we performed tests to decompose this interaction. These analyses revealed that error framing did not significantly influence the state mastery orientation of individuals high in trait mastery orientation, $t(348) = -1.51$, *ns*. However, error framing did significantly impact the state mastery orientation of individuals low in trait mastery orientation, such that they displayed greater levels of state mastery orientation under error-encouragement conditions than in error-avoidance conditions, $t(348) = 2.12$, $p < .05$. This result provides support for our hypothesis that the error-encouragement framing would lead to higher levels of state mastery orientation among those individuals with low levels of dispositional mastery

[1] The results of these analyses can be obtained from Bradford S. Bell upon request.

Table 3
Goodness-of-Fit Summary for Moderated Structural Equation Models

Model	*df*	χ^2	χ^2/df	CFI	IFI	NNFI	RMSEA	RMSEA 90% CI
Measurement	182	232.07	1.28	0.99	0.99	0.97	0.024	0.008, 0.035
Hypothesized without interactions	371	646.60	1.74	0.95	0.95	0.93	0.045	0.039, 0.051
Hypothesized with interactions	366	628.05	1.72	0.95	0.95	0.93	0.044	0.038, 0.050
Alternative	363	511.75	1.41	0.97	0.97	0.96	0.031	0.024, 0.038

Note. CFI = comparative fit index; IFI = incremental fit index; NNFI = nonnormed fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval.

orientation. State mastery orientation did not significantly predict self-efficacy, but state mastery did exhibit a significant, positive relationship with intrinsic motivation.

The model explained 28.3% of the variance in trainees' state performance-prove orientation. The MSEM analyses revealed that trait performance-prove orientation had a significant effect on trainees' state performance-prove orientation, as expected. However, error framing did not significantly affect state prove orientation, nor did trait prove orientation interact with the manipulation to affect trainees' state prove orientation. This finding is consistent with our expectation that error-avoidance framing would not influence trainees' state prove orientation, because it emphasized avoiding errors, not proving one's ability. State prove orientation significantly and positively predicted trainees' self-efficacy.

The model accounted for a total of 31.3% of the variance in trainees' state performance-avoid orientation. As would be expected, trait avoid orientation exhibited the strongest relationship with trainees' state avoid orientation. Although, contrary to expectations, error framing did not have a significant direct effect on trainees' state performance-avoid orientation, error framing and trainees' trait avoid orientation interacted to significantly influence state performance-avoid orientation. This aptitude–treatment interaction is shown in Figure 6. Using Ping's (2002) procedure, we found that error framing did not significantly influence the state

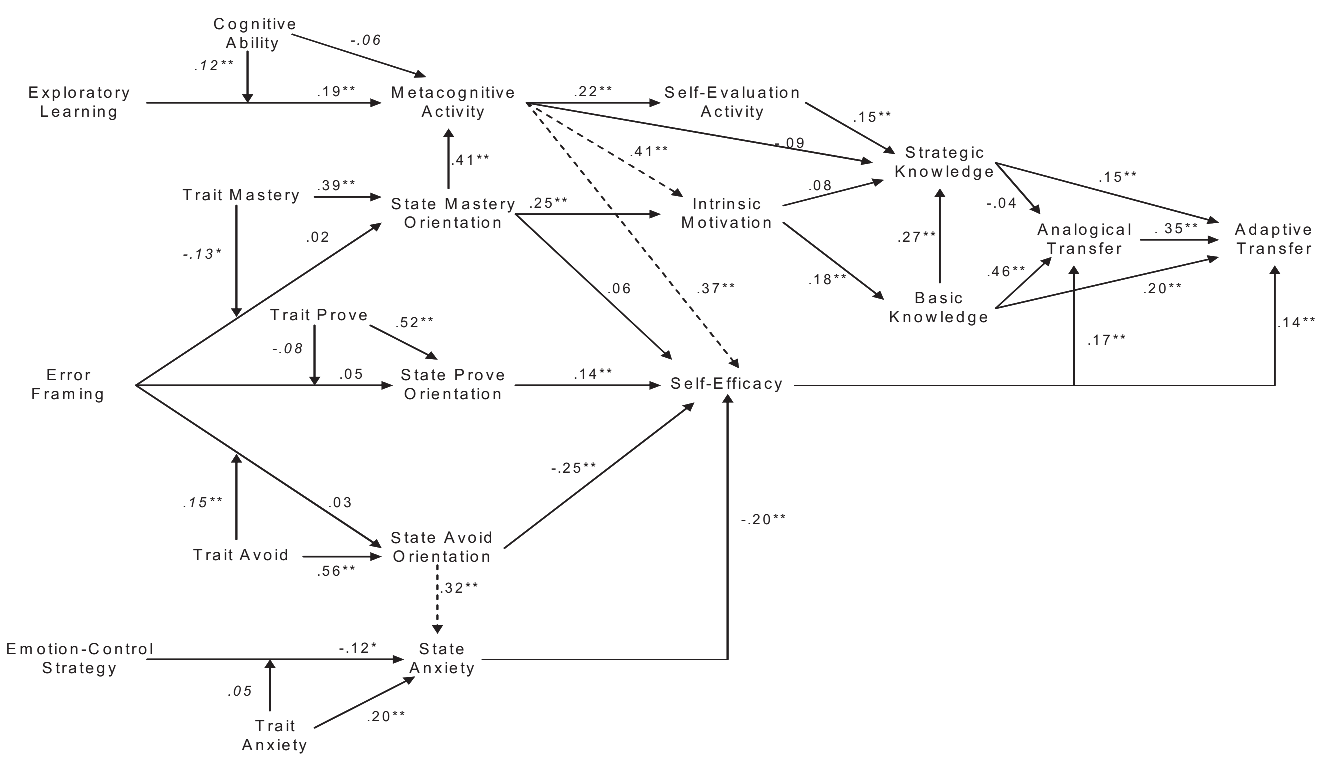

Figure 3. Moderated structural equation model results. Standardized path coefficients are reported. Although the model does not depict this, we controlled for the effects of cognitive ability on knowledge and performance. Interactive effects are reported in italics and are represented by the individual difference path that bisects the path from the respective training design element. When a significant interaction term is present, the main effects are conditional, although the direct relationship can be interpreted as the average effect (Aiken & West, 1991). Dashed lines represent exploratory paths. $^{*}p < .05$. $^{**}p < .01$.

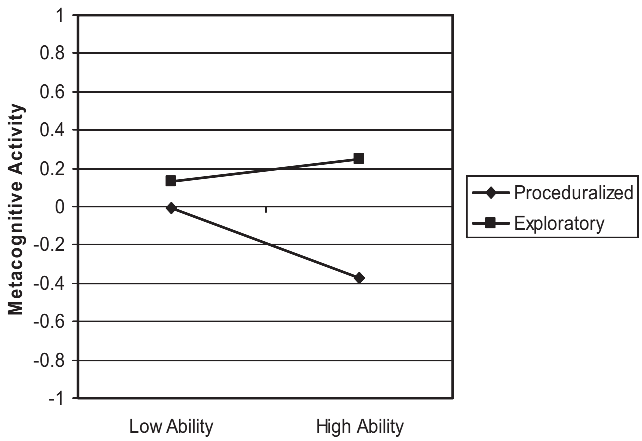

Figure 4. Interaction between exploratory learning and cognitive ability on trainees' metacognitive activity.

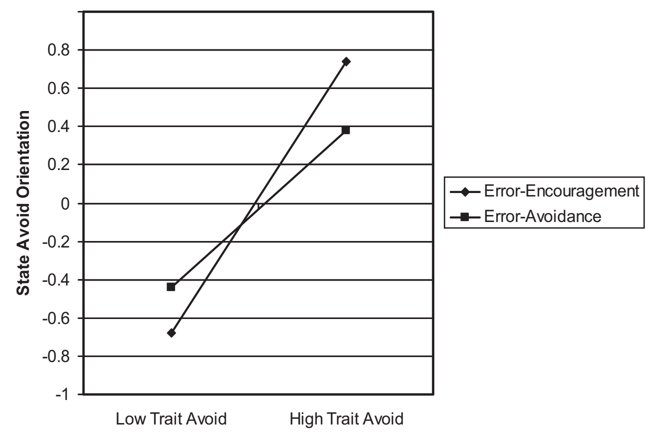

Figure 6. Interaction between error framing and trait avoid orientation on state avoid orientation.

avoid orientation of individuals low in trait avoid orientation, $t(348) = -1.65$, *ns,* but that individuals high in trait avoid orientation displayed significantly lower levels of state avoid orientation when given the error-avoidance (vs. the error-encouragement) frame, $t(348) = 2.51$, $p < .05$.

Although it is contrary to our hypothesis, this pattern of results may be explained by the recent findings of Heimbeck et al. (2003), who found that people with high avoidance orientation showed better performance effects in an error avoidant training situation than did people with low avoidance orientation. Heimbeck et al. suggested that this result may occur because error avoidant training is more adaptive for highly avoidant individuals; it is nonthreatening and should lead to less anxiety about making errors and failing. Our results show that when high-avoidance-oriented individuals were encouraged to avoid errors, an adaptive condition, they exhibited less fear of failure (i.e., lower state avoid orientation). This lower level of state avoid orientation may ultimately lead to positive performance effects. Indeed, our results show that state avoid orientation exhibited a significant, positive relationship with state anxiety and a significant, negative relationship with self-efficacy; self-efficacy was significantly related to both analogical and adaptive transfer performance.

Figure 5. Interaction between error framing and trait mastery orientation on state mastery orientation.

The model explained 19.5% of the variance in trainees' state anxiety. Trainees' trait anxiety level exerted a significant, positive relationship with state anxiety, as did state performance-avoid orientation. Yet, the emotion-control strategy resulted in a significant reduction in trainees' state anxiety levels, over and above these effects. Contrary to our expectations, we did not find a significant interaction between the emotion-control strategy and trainees' trait anxiety on state anxiety. Trainees' state anxiety also had motivational implications, in that it exhibited a negative relationship with trainees' self-efficacy.

The model explained 18.2% of the variance in trainees' basic knowledge and 29.0% of the variance in trainees' strategic knowledge. Intrinsic motivation significantly predicted trainees' basic knowledge but not trainees' strategic knowledge. Basic knowledge was significantly and positively related to trainees' strategic knowledge. The model predicted 30.3% of the variance in analogical transfer performance (end-of-training performance during the test phase) using basic and strategic knowledge and self-efficacy. One noteworthy finding is that strategic knowledge did not significantly predict analogical transfer. This finding supports the notion that strategic knowledge is more critical when individuals are required to adapt their knowledge and skills (Bell & Kozlowski, 2002; Salomon & Globerson, 1987). Finally, the model predicted 54.1% of the variance in adaptive transfer performance using basic and strategic knowledge, analogical transfer performance, and self-efficacy, each of which provided a unique contribution to the prediction of adaptive transfer performance.

Discussion

Over the past decade, we have witnessed substantial changes in the nature of work and organizations, including technological advances that have made jobs more cognitively complex and dynamic, a growing focus on quality and reengineering, and the globalization of business (Ford & Fisher, 1997; Salas & Cannon-Bowers, 2001). As a result of these changes, organizations must, now more than ever, rely on workplace learning to gain competitive advantage. Over this same time period, there have been dramatic changes in how training is delivered to employees. In particular, there has been steady growth in the use of e-learning and a trend toward self-managed learning (K. G. Brown & Ford, 2002; Warr & Bunce, 1995), both of which shift greater responsibility for learning to employees. These trends have resulted in growing interest in the concept of active learning, not only because of the potential utility of active learning approaches for development of complex skills and promotion of adaptive transfer but because such approaches may be valuable for support of self-directed learning initiatives.

In recent years, a number of studies have examined different active learning approaches and have advanced our understanding of trainee self-regulation, learning, and adaptive performance. Yet, this field of research is fragmented—characterized by a diversity of theoretical approaches—and important questions remain. Our goal in the current study was to integrate and extend this research through a comprehensive examination of self-regulatory process pathways, through which the core training design elements of active learning approaches and individual differences influence learning, performance, and adaptability. Below, we discuss the key results of this effort and highlight the implications of these findings for future research and practice.

Key Findings and Implications for Theory

Core training design elements of active learning interventions. One of our goals in the current study was to provide an examination of the effects of three core training design elements that cut across a range of active learning interventions. Our review of the extant literature revealed that active learning interventions have often utilized a combination of exploratory learning, error framing, and emotion-control strategies to influence trainees' self-regulation processes. Past research has typically combined these elements into a single intervention, which has made it difficult to determine which element or elements of active learning interventions account for the pattern of findings. Thus, in the current study, these elements were disentangled and their independent effects were modeled.

The results revealed that trainees who received exploratory learning, as opposed to proceduralized instruction, performed more poorly during training but demonstrated significantly higher levels of both analogical transfer and adaptive transfer. This finding provides further support that active learning approaches, although not necessarily associated with better outcomes during training, produce superior transfer relative to more traditional, proceduralized instruction (Heimbeck et al., 2003; Keith & Frese, 2005; R. A. Schmidt & Bjork, 1992). The error framing manipulation also influenced trainees' performance, as trainees who received the error-encouragement frame demonstrated higher levels of adaptive transfer than did trainees exposed to the error-avoidance frame. This finding suggests that encouraging trainees to make and learn from their errors can aid in the development of adaptive expertise. Contrary to expectations, the emotion-control strategy did not exhibit a direct impact on trainees' performance. Yet, as we discuss below, the emotion-control strategy successfully lowered trainees' anxiety. This finding suggests that, under certain conditions, it may be important for supporting trainees' learning and performance.

Self-regulatory processes. Our second goal in the current study was to provide an examination of the process pathways by which the core training design elements influence learning and performance. Frese et al. (1991) stated, "We do not know whether strategy, memory, motivational, or emotional effects are important or whether all of them have an influence" (p. 91). With a few exceptions (e.g., Debowski et al., 2001; Keith & Frese, 2005; Kozlowski & Bell, 2006; Kozlowski, Gully, et al., 2001), research in this area conducted over the past decade has had limited focus on potential process variables; this question has, therefore, remained largely unanswered. In the current study, we not only examined the role of cognitive, motivational, and emotional processes in shaping trainees' learning and performance but examined how these processes were shaped through the interplay of training design and individual differences.

Kozlowski, Gully, et al. (2001) argued that self-regulatory processes play a key role in active learning and identified the need to "expand our assessment to include factors that reference self-monitoring, self-evaluation, and attributions" (p. 25). Our study demonstrated that self-evaluation activity positively influenced strategic knowledge and that strategic knowledge, although unrelated to analogical transfer, exhibited a positive relationship with adaptive transfer. When the goal of training is to develop more complex and adaptive skills, our findings point to the quality of trainees' cognitive self-regulatory activities as a determinant of training effectiveness (Kozlowski & Bell, 2006). The current study also demonstrates that one way to shape these cognitive activities is through instructional design, as exploratory learning was shown to prompt trainees' metacognitive activity.

The second pathway we examined focused on trainees' motivational orientation. Our results revealed that trainees who adopted a mastery orientation demonstrated increased intrinsic motivation, self-efficacy, and metacognitive activity, all of which related to learning and transfer performance. The motivational processes (intrinsic motivation, self-efficacy) emerged as the key predictors of trainees' basic knowledge and analogical transfer. This finding was expected, as these outcomes are heavily influenced by individuals' effort and persistence during training. Contrary to our expectations, error framing did not have a significant, direct effect on trainees' state goal orientations. However, as we discuss below, error framing and trait goal orientation interacted to significantly influence trainees' state mastery and performance-avoid orientation. These findings are consistent with those of Gully et al. (2002), who failed to find a direct effect of error framing on trainees' self-regulation (i.e., self-efficacy). They argued that the absence of main effects can be explained by the presence of aptitude–treatment interactions; these interactions suggest that error framing initiates different regulatory processes among trainees with different personality characteristics. In sum, these results provide further evidence that motivational orientation is important when learners assume an active role in the learning process (K. G. Brown & Ford, 2002; Heimbeck et al., 2003).

The final pathway we examined emphasizes the role of trainees' emotions in supporting an active approach to learning. We found, as expected, that trainees who reported higher levels of state anxiety early in training had lower levels of self-efficacy at the end of training and that the emotion-control strategy served as an effective tool for lowering trainees' state anxiety. Ultimately, the effect of emotion control on performance is likely to depend on the level of physiological arousal that individuals experience during training. In the current study, state anxiety levels reported by trainees were, on average, moderate ($M = 3.12$), and these levels may have attenuated the emotion control–performance relationship. Yet, our results suggest that, in situations where trainees are likely to experience more extreme levels of stress or worry, emotion-control training may be a useful tool for reducing anxiety levels and sustaining trainees' motivation and performance. Future research is needed to further clarify the conditions under which emotion-control training is a necessary and critical element of active learning approaches.

Although our hypothesized model emphasized the relative distinctiveness of the process pathways to enhance parsimony and conceptual clarity, we tested an alternative model that included three exploratory paths that were designed to explore potential effects across the different process domains. The results obtained for the alternative model suggest that there may be significant interconnectivity among the process pathways.[2] In particular, metacognitive activity exhibited significant relationships with trainees' intrinsic motivation and self-efficacy, a finding that suggests efforts to enhance trainees' cognitive self-regulatory activity may indirectly enhance motivation. Also, state avoid orientation was positively related to trainees' state anxiety, which in turn significantly influenced trainees' self-efficacy. Thus, it appears that the motivational and emotional process pathways are intertwined. Although these results are exploratory and need to be cross-validated by future research, they are consistent with the argument of K. G. Brown and Ford (2002) that active learning processes, such as mastery orientation and metacognition, are "reciprocal states that reinforce each other over time" (p. 202). By using the self-regulation framework, future research can further elaborate the interrelations among these process pathways. For example, particular self-regulatory processes, such as mastery orientation and emotion control, may serve as prerequisites, such that they create supporting conditions for other cognitive, motivational, or emotion-control processes (Keith & Frese, 2005).

Role of individual differences in active learning. Although considerable research has examined the implications of individual differences in instructional programs (for a review, see Snow, 1986), previous research on active learning approaches has not focused much attention on trainee characteristics. As a result, researchers such as Gully et al. (2002) have argued that "the relationship between individual differences and other approaches similar to error training like discovery learning and mastery-oriented training should be investigated" (p. 153). In the current study, we examined the role of several individual differences as drivers of trainees' self-regulation. Our findings revealed that several individual differences, including trait mastery orientation, trait performance-avoid orientation, and trait anxiety, demonstrated significant relationships with self-regulatory processes. These findings are important, due to the interest in identifying the characteristics of self-directed learners (Anderman & Young, 1994; Salas & Cannon-Bowers, 2001).

In addition to testing the direct effects of individual differences, we examined the individual differences as potential moderators of the effects of the core training design elements on trainees' self-regulation processes. This focus on aptitude–treatment interactions responds to Keith and Frese's (2005) recent call for studies that "look at differential processes induced by such interactions of training condition and person characteristics" (p. 688) and to suggestions that knowledge of such interactions can enable active learning to be tailored to the person (Kozlowski, Toney, et al., 2001). The MSEM analyses provided strong evidence that the aptitude–treatment interactions are an important component of our model that help advance our understanding of how the core training design elements shape trainees' self-regulation, an important area for theoretical extension. Whereas low-ability trainees had similar levels of metacognitive activity regardless of whether they had received exploratory or proceduralized instruction, high-ability trainees demonstrated significantly higher levels of metacognitive activity when they had been given exploratory instruction. This finding is consistent with previous research that suggests high-ability trainees excel under learner control (as opposed to program control) conditions (DeRouin et al., 2004; Gully et al., 2002; Snow, 1986) and that highlights the importance of considering trainees' ability levels before adopting an exploratory learning approach.

We found several aptitude–treatment interactions between the error framing manipulation and trainees' trait goal orientation. For instance, among individuals with low levels of trait mastery orientation, error-encouragement framing had a compensatory effect; it led to higher levels of state mastery orientation among these trainees but not among those trainees with already high levels of trait mastery orientation. These findings indicate that active learning approaches are not a universal strategy; thus, attention needs to be devoted to understanding how to tailor specific treatments to align with the characteristics different individuals possess. Given the high potential for flexibility inherent in the design of technology based training systems (Kozlowski & Bell, 2007), theoretical and research-based elaboration and extension of our model are warranted.

Limitations and Research Extensions

This research has some limitations that should be acknowledged. First, training is always grounded in a specific instructional context, content, and sample. This research was conducted with a synthetic task and college student trainees; therefore, appropriate caution must be exercised when generalizing these findings to other settings, tasks, and trainee populations. College students have specific characteristics, such as higher than average cognitive ability relative to the general population, that may influence the utility of the active learning approach examined in the current study. Thus, as noted earlier, it is important to continue to explore the role of individual differences in this context. Similarly, it is important to recognize that the use of a complex, computer-based simulation limits the extent to which the results of the present study can be generalized to other (e.g., web-based) computer-based training applications or to more traditional (e.g., instructor led) modes of training delivery. Yet, we should note that the task used in this study is based on a cognitive task analysis, has psychological fidelity with the real-world task it emulates (Kozlowski & DeShon, 2004), and uses a trainee population that is comparative with that of the real-world task. Thus, within the specific boundary conditions we have identified, the core psycho-

[2] We thank an anonymous reviewer for highlighting this issue.

logical constructs and self-regulatory processes examined in this research can be expected to generalize to similar tasks, training, and trainees. Going forward, research is needed to examine the application of these findings to a broader array of training delivery contexts, content, and trainee populations.

Future research is also needed to map the potential boundary conditions under which emotion-control strategies may have more or less of an influence on trainees' performance and adaptability. Our results revealed that the emotion-control strategy did not have a unique, direct effect on trainees' performance. Yet, trainees who received the strategy demonstrated lower anxiety, which merged with the motivational pathway to influence self-efficacy. These results suggest that emotion control is an element worthy of further exploration. Indeed, Keith and Frese (2005) found that emotion control mediated the effects of error management training on adaptive performance. One specific avenue of future inquiry involves testing different methods of structuring emotion-control training interventions. For example, Kanfer and Ackerman (1990) suggested that there may be utility in gradually phasing out emotion-control interventions over the course of training, whereas Heimbeck et al. (2003) argued that it may be most appropriate to implement these types of interventions after trainees have acquired a foundation of knowledge and skills. Future research should examine the implications of these implementation strategies and of other design issues, such as the effectiveness of different emotion-control techniques (e.g., self-dialogue vs. imagery). Further, future research should consider the implications of different strategies for measuring emotion control processes. In the current study, we measured trainees' state anxiety as an indicator of emotion control, whereas Keith and Frese (2005) focused on more directly assessing trainee use of strategies for regulation of negative emotions. An optimal measurement strategy may be to capture both emotion control strategies and the negative emotions these strategies are designed to regulate.

We believe that the current study provides one of the most comprehensive examinations of the active learning approach to date. Yet, future research is needed to expand the scope of this research to include other training design elements, self-regulatory processes, and individual differences that we were unable to examine. For example, research should further examine emerging active learning approaches that tailor instructional prompts to the learner to support more learner-centered exploratory instruction, such as adaptive guidance that adapts feedback and instruction to learner progress (Bell & Kozlowski, 2002). Research should be conducted to examine the role of additional psychological mechanisms in active learning. For example, several researchers have discussed mental models as a key construct in active learning (Frese, 1995; Kozlowski, Gully, et al., 2001). Cognitive mapping techniques may provide useful insight into the impact of active learning approaches on trainees' knowledge structures and the role of these structures in promoting adaptability. Finally, the current study indicates that cognitive ability and the dispositional traits of learners play a crucial role in active learning contexts and can interact with and influence the way in which trainees react to specific training design elements. The traits examined in the current study are nevertheless focused, and future research should explore the potential role of other personality traits (e.g., core self-evaluation traits) and cognitive skills (e.g., metacognitive skills) that may influence the pathways by which active learning approaches influence learning and adaptability. Continued research along these lines should enhance our ability to tap the potential inherent in the active learning approach.

Implications for Practice

It has been argued that active learning interventions, such as guided exploration, mastery training, and error management training, may be well suited for today's emerging training challenges. The results of the present study provide further support for this contention by showing that specific training design elements that constitute these interventions, such as exploratory learning and error-encouragement framing, enhance trainees' self-regulatory processes, learning, and adaptive transfer. At the same time, however, our results suggest that organizations need to consider various factors, including the goals of the training program and characteristics of the trainees, when deciding whether to deploy an active learning approach to tackle a particular employee training need. For example, our results demonstrated that exploratory learning and error-encouragement framing were more effective for promoting adaptive as opposed to analogical transfer. Similarly, we found that error-encouragement framing enhanced the state mastery orientation only of individuals who had low levels of dispositional mastery orientation. As Gully et al. (2002) noted, it is important to avoid a "one-size-fits-all" attitude toward active learning approaches. As research and theory continue to develop around active learning, we should gain a better understanding of the training conditions and trainees for which these design elements are best suited.

At a broader level, the present study adds to a growing line of research that implicates a number of individual differences as important in training. These individual differences include not only cognitive ability but dispositions that capture different learning styles, such as goal orientation. Our results revealed that several of these individual differences related directly to the self-regulatory processes. These results suggest that organizations may benefit, therefore, by including these individual differences in the needs assessment process. In addition, the increased use of computer technologies in training provides unprecedented capability to design training that adapts to individual differences in learners by ameliorating negative influences, strengthening positive ones, and tailoring active learning interventions to learner preferences and progress (Bell & Kozlowski, 2002; Kozlowski & Bell, 2007). Thus, it will be important to continue to explore aptitude–treatment interactions in future active learning research.

Conclusion

More than a decade of theoretical development and research progress has suggested the potential of active learning as a key means to develop principles of training design that are learner centered (Smith et al., 1997). Although promising, this work has been somewhat fragmented because of its tendency to combine different training design elements in an effort to create effective interventions. The interventions have often been effective, but what elements are essential and why? This article advances recent research (e.g., Keith & Frese, 2005; Wood et al., 2000) designed to synthesize and integrate this body of work by evolving the focus of theory and research from intervention design (e.g., Kozlowski, Toney, et al., 2001) to a focus on identifying core training design elements, mapping their interaction with individual differences, and modeling the distinctive self-regulatory process pathways by which the core design elements and learner characteristics exert effects on learning, performance, and adaptability. We believe that continued work in this stream will foster theory development and research progress in the science of learner-centered design.

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