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Learner-Controlled Practice Difficulty in the Training of a Complex Task: Cognitive and Motivational Mechanisms

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An inherent aspect of learner-controlled instructional environments is the ability of learners to affect the degree of difficulty faced during training. However, research has yet to examine how learner-controlled practice difficulty affects learning. Based on the notion of *desirable difficulties* (Bjork, 1994), this study examined the cognitive and motivational antecedents and outcomes of learner-controlled practice difficulty in relation to learning a complex task. Using a complex videogame involving both strong cognitive and psychomotor demands, 112 young adult males were given control over their practice difficulty, which was reflected in the complexity of the training task. Results show that general mental ability, prior experience, pre-training self-efficacy, and error encouragement were positively related to learner-controlled practice difficulty. In turn, practice difficulty was directly related to task knowledge and post-training performance, and it was related to adaptive performance through the mediating influences of task knowledge and post-training performance. In general, this study supports the notion that training difficulty operationalized in terms of task complexity is positively related to both knowledge and performance outcomes. Results are discussed with respect to the need for more research examining how task complexity and other forms of difficulty could be leveraged to advance learner-controlled instructional practices.

Keywords: learner control, practice difficulty, task complexity, error framing, individual differences and learning

The use of computers in training and instruction has become a common feature in both educational and organizational settings (Sitzmann, Kraiger, Stewart, & Wisher, 2006). Owing largely to reduced costs as well as advances in software and Internet capabilities, e-learning, multimedia instruction, and other forms of computer-based instruction (CBI) have become increasingly common means of providing instruction not only to individuals located in-house but also to those located in different places across the globe (Artino, 2008; Brown, 2001; DeRouin, Fritzsche, & Salas, 2004; Orvis, Brusso, Wasserman, & Fisher, 2010). In fact, the American Society for Training and Development (ASTD) reported that of all available formal hours of instruction in 2009, 36.5% involved technology, and 27.7% were offered online (ASTD, 2010). In addition, these numbers reflect an increasing trend since 2003 (ASTD, 2010). Similarly, increasing technological capabilities have given rise to the use of synthetic learning environments (SLEs) such as computer-based simulations and games as well as virtual-reality environments (Cannon-Bowers & Bowers, 2009; Wilson et al., 2009). To be sure, virtual training has become a common method of instruction (Behrend & Thompson, 2011). Regardless of the specific form of instruction, learner control is typically an inherent feature of many types of CBI and SLEs. However, while the use of computers in training continues to flourish, research on learner control lags behind.

In any learner-controlled environment, the decisions one makes can have direct effects on the degree of difficulty one experiences while learning. That is, regardless of whether one is able to choose the content, pace, practice opportunities, or any other feature of training, there is an associated degree of difficulty with each choice. For example, some content may be more complex than others and thus more difficult, and a faster pace may be more difficult than a slower pace. Given the fact that technology's already pervasive role in society continues to expand, one can assume that the use of learner-controlled training environments will increase as computers and simulation-based training programs become more prevalent. Moreover, recent meta-analytic evidence supports the effectiveness of computer-based simulation games as a training method for promoting not only self-efficacy but also the acquisition and retention of knowledge (Sitzmann, 2011). Thus, understanding the role of learner-controlled practice difficulty with respect to training outcomes is important, especially given the lack of empirical research examining specific processes associated with

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elements of SLEs and game-based training systems in which learners play active roles (Wilson et al., 2009).

Accordingly, the present study examined the role of learner-controlled difficulty in the training of a complex task within an active learning, gaming environment. Specifically, the purpose of this study was to test a causal model of learner-controlled practice difficulty with respect to both task knowledge and skill-based performance outcomes. This model also examined both cognitive and motivational factors as (a) antecedents to practice difficulty and (b) mediating processes by which practice difficulty relates to training outcomes.

To test this model, participants received training on a first-person shooter videogame followed by a series of practice scenarios for which they were given control over the difficulty level of each game. Difficulty was reflected in the amount of task complexity present in the practice scenarios. Additionally, participants were exposed to an error framing manipulation prior to practice. Participants also completed measures of general mental ability (GMA), videogame experience, self-efficacy, metacognition, and self-evaluation. After practice, participants completed tests of task knowledge, post-training performance, and adaptive performance. Figure 1 shows the Hypothesized Model tested in the present study. Specifically, it was hypothesized that GMA, prior videogame experience, pre-training skill, pre-training self-efficacy, and error framing will be positively related to learner-controlled practice difficulty. In turn, practice difficulty was hypothesized to be positively related to the training outcomes of task knowledge, post-training performance, and adaptive performance via metacognition, self-evaluation, and self-efficacy. In the sections that follow, we review difficulty as it pertains to learner control and learning in general, as well as its potential relationships with self-regulation and self-efficacy. Finally, we discuss the proposed influences of GMA, prior experience, and pre-training self-efficacy on learner-controlled practice difficulty.

Learner Control and Difficulty

Learner control refers to an element of training that allows individuals to make key decisions regarding various features of the instructional program (Orvis, Fisher, & Wasserman, 2009; Reeves, 1993). Although proponents of learner control argue that allowing trainees to focus on content that is most relevant for them and to skip material as they see fit may be beneficial to learning (Corbalan, Kester, & van Merrienboer, 2009; Steinberg, 1989), research has shown that learner control does not always lead to positive training outcomes (DeRouin et al., 2004). As such, active learning models were developed as a means of guiding learner control to facilitate knowledge and skill acquisition (Bell & Kozlowski, 2009).

The active learning approach refers to learner-controlled programs 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” (Bell & Kozlowski, 2008, p. 297). Specifically, active learning interventions target individuals’ self-regulatory behavior thereby indirectly guiding trainees’ decision making and ultimately their learning (Bell & Kozlowski, 2008; Kozlowski, Toney, et al., 2001). Research on active learning has demonstrated positive effects on knowledge and skill-based outcomes, particularly with respect to adaptability (Bell & Kozlowski, 2008; Ford, Smith, Weissbein, Gully, & Salas, 1998; Keith & Frese, 2005; Keith, Richter, & Naumann, 2010). Similarly, in a recent meta-analysis, Sitzmann (2011) found simulation games entailing active rather than passive instruction to be more effective for learning. Nevertheless, research has yet to explore the role of learner-controlled practice difficulty in active learning environments. We propose that giving learners control over the complexity of practice tasks is a way to promote more active learning in simulation games as well as a viable way to examine how practice in active learning environments relates to learning outcomes.

Furthermore, despite previous research that has shown trainees tend to choose fewer practice experiences and spend less time in training when given learner control (Brown, 2001), these findings do not necessarily imply that trainees actively avoid difficult training experiences. For instance, some individuals may choose to complete fewer tasks but also more difficult and complex ones. Also, some trainees may withdraw early from training as a result of frustration with training materials that are too difficult or boredom with materials that are too easy. Additionally, fatigue may cause individuals to withdraw early from learner-controlled training rather than a true aversion to engaging in difficult training tasks. Moreover, some learners might not benefit from learner control simply due to their inability to identify critical content or effectively manage their time (Mayer, 2004; Steinberg, 1989). In

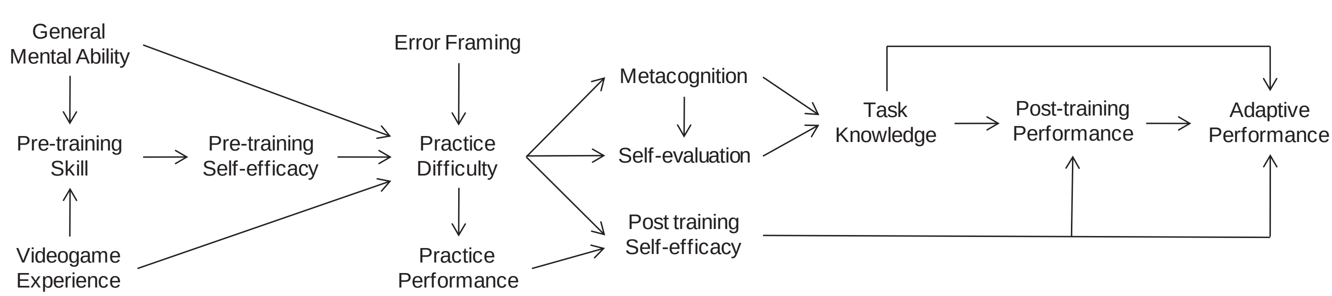

Figure 1. Hypothesized model of learner-controlled practice difficulty, cognitive and motivational antecedents and outcomes, and training outcomes. Although not shown in the figure, paths controlling for the effects of pre-training skill on practice performance and practice performance on post-training performance were proposed as well.

all, it remains unclear whether certain individuals do in fact seek difficult training tasks when given learner control and how one's choices of practice difficulty ultimately affect learning.

Difficulty and Learning

Research suggests that adding difficulties to the instructional process can increase learning (De Corte, 2003; Ghodsian, Bjork, & Benjamin, 1997; Roediger & Karpicke, 2006; R. A. Schmidt & Bjork, 1992). For instance, randomizing task order, delaying or reducing feedback, and varying the nature of practice are a few examples of what Bjork (1994) refers to as *desirable difficulties*. According to Bjork, desirable difficulties are beneficial for learning in as much as they are able to promote retrieval processes. Because recalling knowledge from memory is an inconsistent and somewhat unpredictable process, retrieval of stored information and skill is important in that past retrieval can promote retrieval in the future (Bjork, 1994; R. A. Schmidt & Bjork, 1992). Although adding any amount of difficulty to the learning process can often result in poorer performance during training itself, the focus of training and instruction is on the retention of knowledge and skill evidenced by delayed performance as well as adaptive performance in novel and more difficult contexts (Bjork, 1994; R. A. Schmidt & Bjork, 1992). In fact, many challenging instructional interventions which entail slow and effortful learning facilitate long-term retention and positive transfer in the face of novel performance demands (Roediger & Karpicke, 2006; R. A. Schmidt & Bjork, 1992).

Notwithstanding the literature on desirable difficulties from the cognitive-experimental psychology literature, the element of multiple levels of difficulty (e.g., in terms of missions and scenarios) is inherent in many SLEs (Hussain et al., 2010). Furthermore, in efforts to enhance self-regulation, immersion, and challenge (i.e., active learning) while balancing the needs of a disparately experienced population of users, developers of SLEs have advocated granting users the ability to select different difficulty levels during training (e.g., Sadagic, 2010). Nonetheless, there is a lack of theoretical understanding regarding the psychological processes associated with learner control of this training element. With a focus on CBI, particularly games and SLEs, we assert that empirical examinations involving task complexity are needed to better understand the notion of desirable difficulties.

In general, task complexity is an important factor to consider in the effectiveness of training complex skills (Paas & Van Gog, 2009). According to Wood (1986), task complexity refers to the number and variety of inputs of a task, the relationships between inputs with respect to products, and the relative dynamicity of those inputs and relationships. Campbell (1988) described complex tasks as entailing multiple paths to meet task goals, multiple goals that may or may not conflict with one another, or uncertain relationships between paths and goals. Campbell's perspective is similar to Wood's in that paths can be viewed as inputs, goals as products, and relationships among the task components as dynamic and thus uncertain. Although previous literature has viewed task complexity also in terms of psychological responses to a task or the interaction between person and task characteristics, objective task characteristics and the subjective experiences of the individuals performing a task are distinct concepts (Campbell, 1988; Wood, 1986). As such, in the present study, task complexity was treated as objective in nature and directly derivable from characteristics of the task itself (Campbell, 1988; Wood, 1986).

In particular, Wood (1986) proposed that task complexity consists of three types: component, coordinative, and dynamic. Component complexity refers to the number of distinct actions entailed by the performance of a task and the amount of information that must be processed (Wood, 1986). Coordinative complexity relates to both the intra- and inter-relationships among the task actions, information cues, and products of the task. For instance, the sequencing, timing, frequency, intensity, and location requirements of actions all affect the amount of coordinative task complexity (Wood, 1986). Finally, dynamic complexity of a task stems from potential changes to the task. For instance, actions required for successful performance may change, or the availability or importance of various task information may change. Importantly, such changes are likely to require adaptability, demanding individuals to acquire and use different knowledge and skills than were previously required to successfully perform the task (Wood, 1986). In the present study, practice difficulty of the performance task was operationalized with respect to this conceptualization of task complexity, and higher levels of practice difficulty were associated with greater amounts of task complexity with respect to the three types defined by Wood.

Although previous research has examined the effect of learner-controlled practice strategies with respect to a complex task, little is known regarding the psychological processes surrounding learners' choices regarding the difficulty of the content to study or tasks to practice. For instance, Ford et al. (1998) gave trainees control over the task complexity of their practice scenarios in learning a complex decision-making task. However, they were particularly interested in understanding the relationship between specific practice strategies and training outcomes, and, aside from post-training self-efficacy, it was unclear from their study what individual differences related to learners' choices. Nonetheless, the cognitive processes of metacognition and self-evaluation as well as the motivational process of self-efficacy are three factors that could explain the potential effects of learner-controlled practice difficulty on training outcomes, particularly adaptive performance.

Metacognition

Metacognition refers to the knowledge of and control over one's cognitive processes and behavior (Flavell, 1979; Ford et al., 1998). Generally, metacognition includes monitoring one's performance and progress as well as deciding how one will go about completing a task (A. M. Schmidt & Ford, 2003). Research has shown metacognition to be related to academic achievement (Pintrich & DeGroot, 1990), problem-solving (Berardi-Coletta, Buyer, Dominowski, & Rellinger, 1995), comprehension (Meloth, 1990), knowledge (Ford et al., 1998), and performance (Ford et al., 1998; Keith & Frese, 2005). Furthermore, not only is metacognition beneficial to learning, but it may be especially important in learner-controlled environments in which individuals are offered little explicit guidance during the learning process (A. M. Schmidt & Ford, 2003).

Regarding the relationship between learner-controlled practice difficulty and metacognition, metacognition involves recalling information in order to make better decisions regarding future steps to be taken during the learning process. Indeed, metacognition entails retrieval on the part of the learner, and difficulty during learning is thought to promote retrieval processes (Bjork, 1994; R. A. Schmidt & Bjork, 1992). Whereas easy tasks may be learned with little effort or concentration, learning difficult tasks may require high levels of cognitive engagement, retrieval, and metacognition. Taken as a whole, it was hypothesized that metacognition would mediate the relationship between learner-controlled practice difficulty and post-training task knowledge, which in turn would be positively related to post-training performance and adaptive performance.

Self-Evaluation

Another way in which learner-controlled practice difficulty may promote learning is via self-evaluation. Self-evaluation involves comparing one's progress to one's desired state or other standard (Kanfer, 1990; Kanfer & Ackerman, 1989), and it is considered an important part of self-regulation (i.e., the set of motivational processes that influence the focus and nature of an individual's effort, affect, thought, and goal-directed behavior; Bell & Kozlowski, 2008; Kanfer, 1990; Karoly, 1993). Research from various domains generally suggests self-regulatory behavior to be favorable to learning (Bell & Kozlowski, 2008; Kanfer & Ackerman, 1989; Sitzmann, Bell, Kraiger, & Kanar, 2009). In fact, many training interventions featuring learner control target self-regulatory behavior to help trainees decide how they should proceed with learning and better recognize what information they have yet to master (Sitzmann et al., 2009). With respect to difficulty, research has shown that as individuals' perceptions of task difficulty increase, so too does their cognitive effort and self-regulatory behavior (Kanfer & Ackerman, 1989; Yeo & Neal, 2008). Given these findings, it was hypothesized that self-evaluation activity, like metacognition, would mediate the relationship between learner-controlled practice difficulty and post-training task knowledge, which in turn would be positively related to post-training and adaptive performance.

Self-Efficacy

Aside from its effects on cognitive processes, learner-controlled practice difficulty should affect individuals' self-efficacy as well. Self-efficacy refers to an individual's belief in his or her ability to perform a given activity (Bandura, 1977), and it has been shown to relate positively to a number of learning, performance, and achievement outcomes (Multon, Brown, & Lent, 1991; Stajkovic & Luthans, 1998; cf. Vancouver & Kendall, 2006). Furthermore, self-efficacy may be particularly relevant to adaptive transfer (Kozlowski, Gully, et al., 2001). By nature, adaptive transfer entails increased challenge for the performer due to novelty and oftentimes increased task difficulty. Self-efficacy may help individuals persevere in such circumstances, influencing individuals' effort and persistence (Gist & Mitchell, 1992). Indeed, Ford, Quiñones, Sego, and Sorra (1992) found that trainees higher in post-training self-efficacy were more likely to perform difficult and complex tasks on the job. In addition, Ford et al. (1998) found that practicing complex training scenarios was positively related to performance on a similarly complex transfer scenario through the mediating process of self-efficacy.

Although self-efficacy beliefs can be influenced by a variety of individual difference variables, performance experiences play a large role in shaping one's self-efficacy (Bandura, 1997). Generally, when individuals succeed, their self-efficacy beliefs are likely to be bolstered as a result of increased mastery expectations, whereas failure can lead to self-doubt and diminished self-efficacy (Bandura, 1977, 1986). Likewise, individuals who succeed on difficult tasks should feel even more competent and self-efficacious than those who succeed on less difficult tasks (Bandura, 1977). Therefore, higher practice difficulty during training should lead to higher self-efficacy following training. In fact, Ford et al. (1998) found that the task complexity of trainees' practice opportunities was positively related to post-training self-efficacy beliefs. However, because practice difficulty should be negatively related to practice performance such that trainees choosing more difficult tasks should have lower practice performance scores overall, practice difficulty should be positively related to post-training self-efficacy only after controlling for practice performance. In all, it was hypothesized that levels of learner-controlled practice difficulty during training would be positively related to post-training self-efficacy, which in turn would be positively related to post-training performance and adaptive performance.

Mechanisms Influencing Learner-Controlled Difficulty

In addition to examining potential cognitive and motivational processes linking learner-controlled practice difficulty to training outcomes, this study sought to examine the factors influencing trainees' practice difficulty choices. Both motivational and cognitive factors were considered. Below, the motivational roles of error framing and pre-training self-efficacy as well as the cognitive roles of GMA and prior experience are discussed.

Error Framing

Typically falling under the domain of error management training (EMT), the positive framing of errors has been recommended for instructional programs involving learner control (e.g., Bell & Kozlowski, 2008; Gully, Payne, Koles, & Whiteman, 2002; Keith & Frese, 2005). EMT is based on the belief that errors ultimately are beneficial in the learning process due to the feedback they provide (Keith & Frese, 2005, 2008). Errors not only serve as an indication that something went wrong but cue an individual into examining the reasons for the mistake (Keith & Frese, 2008). Because EMT is thought to promote effective strategizing and problem solving as well as help mitigate the negative emotions that may arise from one's errors (Frese et al., 1991), error framing also has been viewed as an approach to active learning (Bell & Kozlowski, 2008).

EMT involves not only explaining to trainees the positive role of errors in learning but also explicitly encouraging trainees to make errors (Keith & Frese, 2008). Similarly, active exploration is encouraged in EMT with the expectation that a more thorough understanding of the training content will result, particularly with respect to deep-level structures and foundational elements (Keith & Frese, 2008). With few exceptions, published research has revealed positive effects of EMT on learning (Gully et al., 2002; Heimbeck, Frese, Sonnentag, & Keith, 2003; Keith & Frese, 2005). For example, a meta-analysis by Keith and Frese (2008) found EMT to lead to more positive training outcomes than training manipulations not including positive error framing. Moreover, EMT effects on learning were strongest on tests of adaptive transfer requiring more knowledge extension and application than tests of analogical transfer.

In general, EMT studies have shown that by encouraging mistakes and framing errors in a positive manner, trainees will in fact make more errors during the learning process than they otherwise would have made. Although no evidence exists that specifically addresses the relationship between EMT and learner-controlled practice difficulty, it logically follows that positive error framing might also lead trainees to choose more difficult practice opportunities when given the chance to do so. Although more difficult practice experiences will undoubtedly lead to more mistakes (as evidenced by poorer performance during practice), individuals receiving positive error framing are likely to welcome the additional errors as well as the expected learning benefits. Therefore, it was hypothesized that trainees receiving positive error framing during training would be more open to increased practice difficulty and thus choose more difficult practice games than those not receiving positive error framing. Additionally, it should be noted that the empirical literature on EMT has focused primarily on software training and decision-making tasks (Keith & Frese, 2008) and has yet to be applied to tasks entailing strong perceptual-motor components. Therefore, this study also extends error framing research by investigating its effects in the context of a task involving both cognitive and psychomotor demands.

Pre-Training Self-Efficacy

According to Bandura and Locke (2003), people are naturally motivated to achieve future-oriented goals, and they tend to set goals that provide new challenges to be overcome to attain new and greater achievements. However, the particular goals one sets are a function of one's self-efficacy. Indeed, a study by Tolli and Schmidt (2008) showed that self-efficacy positively predicted self-set goal levels over time, and that it was a better predictor of post-feedback goal levels than initial goal levels. Considering findings that demonstrate the role of self-efficacy in predicting individuals' choices of task difficulty on the job (Ford et al., 1992), it was hypothesized that pre-training self-efficacy would be positively related to learner-controlled practice difficulty.

General Mental Ability

Previous research has shown GMA to be strongly related to complex skill acquisition (Ackerman, 1988) and both training and job performance criteria (Ree & Earles, 1991; F. L. Schmidt & Hunter, 1998). In particular, the broad significance of GMA in everyday life (Gordon, 1997) stems from its fundamental role in affording individuals the ability to effectively manage the complexities found across situations and settings (Gottfredson, 1997). Although no research has explicitly examined the potential relationship between GMA and learner-controlled difficulty, it is expected that individuals with higher levels of GMA will choose more difficult tasks during the learning process. In the present study, the amount of practice difficulty chosen by learners was directly related to the amount of task complexity they faced. Because greater cognitive resources are required to deal with increasing task complexity (Norman & Bobrow, 1975; Robinson, 2001; Wood, 1986), higher-ability individuals are likely to possess the resources necessary to effectively manage more complex practice scenarios (Kanfer & Ackerman, 1989). In fact, Gordon (1997) suggested that more difficult and complex tasks are often attempted by individuals with higher levels of intelligence. It is also possible that such individuals will recognize the need to attempt more difficult tasks to build both knowledge and skill. Therefore, it was hypothesized that GMA would be positively related to learner-controlled practice difficulty.

Prior Experience

It has been suggested that trainees with more experience with a given task or subject matter will benefit more from learner control than novices (Scheiter & Gerjets, 2007). Research also has shown prior experience to be critical for learning complex tasks in exploratory environments (Kalyuga, Chandler, & Sweller, 2001). For instance, because experts possess more sophisticated knowledge structures (i.e., mental models) than relative novices (Chi, Glaser, & Rees, 1982), more experienced learners may be better able to identify core elements and concepts as well as formulate more effective strategies for learning that less experienced learners may be unable to do (Corbalan et al., 2009; Steinberg, 1989). Thus, experience is likely to help learners effectively handle task complexity not only at the component level but also at the coordinative and dynamic levels.

In addition, other research suggests that individuals possess a natural preference for novel and complex stimuli (Earl, Franken, & May, 1967; Franken, 2007). Likewise, with more experience, more complex information is needed to provide adequate stimulation (Berlyne, 1960; Smith & Dorfman, 1975). However, because too much complexity can lead to anxiety (Berlyne, 1960), individuals are likely to seek greater levels of complexity only after they have acquired competence at previous levels (Voss & Keller, 1983). Therefore, learners with more prior experience should seek more difficult practice opportunities as they seek to learn and acquire new skills and knowledge entailed by higher levels of task complexity. Accordingly, it was hypothesized that prior videogame experience would be positively related to learner-controlled practice difficulty in the present study.

Alternative Models

Three alternative models also were developed a priori to investigate (a) the potential direct effects of practice difficulty on task knowledge, post-training performance, and adaptive performance, and (b) the potential direct effects of error framing on trainees' metacognition and self-evaluation. In particular, whereas the Hypothesized Model proposed the relationship between practice difficulty and the three training outcomes to be fully-mediated, Alternative Model 1 reflects partial mediation by adding to the Hypothesized Model direct paths between learner-controlled practice difficulty and each of the training outcomes. Specifically, a comparison between Alternative Model 1 and the Hypothesized Model provides a test of whether the processes examined in the present study could fully explain the relationships between practice difficulty and training outcomes. Alternative Model 2 added paths linking error framing to the cognitive processes of metacognition and self-evaluation. This model incorporates the direct effects of error framing on trainees' metacognition and self-evaluation during practice, and it is consistent with previous research by Keith and Frese (2005) that suggests error encouragement can directly influence self-regulatory activity. Finally, Alternative Model 3 combined the additional paths from both of the previous alternative models and was intended as an exploratory model examining the focal issues of the previous two models combined.

Method

Participants

Participants were 118 undergraduate males attending the University of Oklahoma. They ranged in age from 18 to 23 years. For their participation, each individual received credit to fulfill a psychology course research requirement. Participants were randomly assigned to one of three error framing conditions during training: positive error framing, negative error framing, or no error framing. Due to computer problems, data from six participants were missing resulting in complete data for 112 participants.

Performance Task

The performance task was Unreal Tournament 2004 (UT2004), a commercially available, first-person shooter computer videogame originally released in 2003. While playing the game, participants assume the perspective of a given avatar on-screen which they move and manipulate throughout different geographic layouts. The specific game mode used for the present study was an "every man for himself" style match (i.e., "Deathmatch"), such that participants competed against computer-controlled bots in a fast-paced and very dynamic setting. Using weapons, the objective is to destroy the computer bots while preventing the bots from destroying one's own avatar. Also, players can collect resources (i.e., pick-ups) to increase their avatar's health or offensive and defensive capabilities. When a bot or one's avatar is destroyed, that character "respawns," reappearing in a new location.

Performance of UT2004 entails a high degree of both cognitive and psychomotor demands. Players must use both a mouse and keyboard simultaneously to move and control their avatar. Players also can perform a number of advanced techniques (e.g., double-jumping, weapon combinations) by pressing different sequences of key combinations. Although not necessary for playing the game at lower levels of difficulty, mastery of these advanced techniques are essential for success at higher difficulty levels. Additionally, players must learn how each weapon works and be able to quickly decide which to use given the circumstances. In the present study, players had access to eight different weapons, each capable of firing in two distinct ways. Because each method of fire is unique, players need to learn the advantages and disadvantages of each weapon as well as the most appropriate circumstances in which to use the various modes of fire. Similarly, players must learn and remember weapon and resource locations and, in some cases, use problem solving skills to access those items. Also, monitoring of game aspects such as avatar health, bot health, and game strategies are all critical for effective performance. For instance, depending on the health of one's avatar, players might need to decide whether to find health resources, seek additional weapons, or attack a bot.

To make UT2004 more amenable as a research tool, several modifications to the game were made for the present study. First, the maps on which trainees played were altered to ensure in-game weapons and resources were distributed evenly throughout. Also, the size of the map used for basic training, practice, and assessments of pre- and post-training performance was reduced slightly to prevent the computer-controlled bots from becoming isolated from the player's own avatar. Additionally, certain weapons were removed entirely from the game to limit the amount of training time required for the study. Information about the maps used in this study is presented in Appendix A.

Practice Difficulty

Eight different practice difficulty settings ranging from "Novice" (i.e., the easiest setting) to "Godlike" (i.e., the most difficult setting) are available in UT2004. However, only the second through the eighth settings were made available to participants in this study because the first setting (i.e., the easiest setting) appeared to be too easy for even novice players during pilot testing. Difficulty choices were presented on a 1–7 scale in numerical form (i.e., 1, 2, 3, etc.) without any other labels.

As previously stated, the amount of task complexity (i.e., component, coordinative, and dynamic) present in UT2004 is directly related to the game's difficulty settings. Relative to higher practice difficulty levels, task complexity is lower at lower levels of practice difficulty. With respect to component complexity, fewer actions are required and less information cues must be processed when difficulty is low rather than high. For instance, running and shooting are sufficient when practice difficulty is low, but jumping, dodging, and strafing become essential when difficulty is high. Because enemy bots move slower and perform fewer actions at lower levels of practice difficulty but become increasingly fast, elusive, aggressive, and accurate as practice difficulty increases, there are fewer information cues that must be processed when practice difficulty is low. Coordinative complexity increases with increasing practice difficulty as well. Required actions and information cues are relatively discrete at lower practice difficulty levels. However, at higher levels of difficulty, players must frequently perform actions simultaneously (e.g., aiming and shooting while jumping, seeking health while shooting and dodging) and process information sequentially (e.g., finding health before ammunition). Regarding dynamic complexity, increased practice difficulty entails more rapid changes during gameplay thus having instantaneous effects on the relative importance of different actions and information cues. For instance, at lower difficulty levels, changes in an enemy bot's weapon choice make some actions more or less effective (e.g., jumping vs. strafing). At higher difficulty levels, however, enemy bots increasingly utilize special capabilities that further add to the dynamic complexity of the game. For instance, bots suddenly become invisible, acquire super-speed, or regenerate health thus resulting in even greater changes to the nature of the information processing and actions needed for effective performance.

Procedures

All participants were told that the study was designed to examine how different people learn to play a dynamic and complex videogame. Participants first completed an informed consent form followed by a videogame experience measure and a 15-min training slideshow on UT2004. The slideshow explained basic game controls, the on-screen display, game rules, and resources such as avatar health and weapons. Immediately following the training presentation, all participants were given a handout summarizing the information covered by the presentation and had 3 min to practice and familiarize themselves with the basic controls, display, and game environment without any computer-controlled bots present. Then, participants performed two, 5-min games of UT2004 against two computer-controlled bots for which they were instructed to do their best and specifically to get as many kills as possible against the computer bots while also trying to limit their own character's deaths. These two games were used to assess pre-training skill and were set at a medium level of difficulty (i.e., 4 on a 1–7 scale). Participants were informed of this difficulty level and were provided with performance feedback immediately following each game. Following these games, participants completed the measure of pre-training self-efficacy.

Next, the error framing manipulation was administered, and participants were told that they would be performing three training sessions each consisting of five, 5-min games against two bots. Participants were told to think of practice as a learning opportunity in preparation for the end of the study. Participants also were informed that they would be playing four test games following practice and that two of these test games (i.e., the post-training performance assessment games) would be identical to the preceding pre-training skill assessment games. Details regarding the adaptive transfer assessment games were not provided at this time.

Throughout these training sessions, participants were permitted to select the level of difficulty before each of their practice games using a drop-down menu on the computer. Additionally, all participants were instructed to advance at their own pace throughout training and were able to view feedback screens at the conclusion of each game. These screens included basic information regarding the player's and bots' performance (i.e., kills, deaths, accidental deaths) and weapon usage statistics (e.g., how often they used each weapon, their accuracy with each weapon). Likewise, participants were given a game log which they could use to record their performance or make game-related notes throughout practice if they chose to do so. At the conclusion of each practice session, participants completed a questionnaire regarding their game behavior and strategies. These repeated questionnaires were used to assess self-evaluation activity. Participants also received abridged error framing instructions before each of the last two practice sessions.

Immediately following the final practice session, measures of post-training self-efficacy, a manipulation check, and self-reported metacognition were administered. Next, participants played two, 5-min games against two computer-controlled bots at a medium level of difficulty (i.e., 4 on a 1–7 scale) assessing their post-training performance. Once again, trainees were instructed to do their best by getting as many kills as possible against the computer bots while also trying to limit their own character's deaths on each of these two games. Following the post-training test games, participants completed a measure of GMA and a test of task knowledge. Finally, participants played two, 5-min adaptive transfer games at the conclusion of the study. Unlike the previous games played during training and post-training, the adaptive transfer test games included nine computer-controlled bots and were played on a map very different from the one used during practice (see Appendix A for details). Participants were informed of these changes prior to testing and were once again told to do their best by getting as many kills as possible against the computer bots while also trying to limit their own character's deaths. In addition, the difficulty for the adaptive transfer test games was raised one setting above the medium difficulty level (i.e., 5 on a 1–7 scale). In all, these changes were made to ensure the adaptive transfer test games were not just novel but were in fact more difficult and complex than the post-training performance test games (e.g., Bell & Kozlowski, 2008; Ford et al., 1998; Kozlowski, Gully, et al., 2001) and required participants to adapt to changes at a structural level of the task (e.g., Ivancic & Hesketh, 1995–1996). Participation in this study lasted approximately 4 hr.

Error Framing Manipulation

Error framing instructions were administered to trainees at the start of practice. Positive error framing instructions entailed information about the beneficial nature of errors for learning and performance, and explicitly encouraged participants to make errors during practice. Conversely, negative error framing instructions encouraged participants to avoid making errors and stated that errors were bad for learning. Finally, participants receiving no error framing instructions were simply told that practice was beneficial for learning and did not hear any information about errors. For participants in all conditions, abridged error framing refresher instructions were presented before each of the two remaining sets of practice games, and all participants were told to think of the practice games strictly as learning opportunities.

Measures

Self-efficacy. Both pre- and post-training self-efficacy were measured using the same 12 task-specific items adapted from previous studies (e.g., Bell & Kozlowski, 2002; Day et al., 2007; Nease, Mudgett, & Quiñones, 1999) and were framed with respect to UT2004. Two items from this measure are "I can meet the challenges of Unreal Tournament," and "I am confident that I have what it takes to perform Unreal Tournament well." Participants responded using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Coefficient alphas for the pre- and post-training self-efficacy measures were .90 and .92, respectively.

Metacognition. Eleven items adapted from Ford et al. (1998) were used to assess metacognitive behavior. Two example items are "While practicing the game, I monitored how well I was learning its skills and techniques," and "I considered the skills that needed the most practice while playing practice games." Responses were made using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). A coefficient alpha of .89 was obtained for this measure.

Self-evaluation. Five items were used to assess participants' level of self-evaluation. As previously mentioned, this measure was completed three times, once after each practice session. These items were open-ended and asked trainees to report (1) weapons they used, (2) weapons they did not use, (3) resources they focused on using, (4) strategies they found effective, and (5) strategies they found ineffective. In addition, participants were asked to explain the reasons for their answers. These responses were rated for self-evaluation activity by two graduate students on a 4-point Likert scale ranging from 0 (*no self-evaluation activity*) to 3 (*high self-evaluation activity*). That is, although the questions themselves did not explicitly ask participants to evaluate their practice behaviors nor provide an explicit performance standard or goal, participants' degree of self-evaluation was rated with respect to self-set goals either stated explicitly in their responses (e.g., destroying bots at close-range) or referenced implicitly (e.g., mastery of a weapon). The average ratings of each item across all three administrations were used to form a single score of self-evaluation for each participant. Inter-rater reliability for this measure was ICC(3,2) = .75. Coefficient alpha for this measure was .83.

General mental ability. GMA was assessed using the 12-item short form (Arthur & Day, 1994) of the Raven Advanced Progressive Matrices (APM; Raven, Raven, & Court, 1998) with an administration time of 15 min. Like the original 36-item form, the short form of the APM consists of matrix problems arranged in order of increasing difficulty. A Spearman–Brown odd-even split-half reliability of .71 was obtained for this measure.

Videogame experience. Two items were used to measure participants' prior videogame experience. Participants responded using a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*daily*) to the following questions: (1) "Over the last 12 months, how frequently have you typically played video/computer games?" and (2) "Over the last 12 months, how frequently have you typically played first-person shooter video/computer games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament, etc.)?" Coefficient alpha for this measure was .86.

Task knowledge. A 16-item multiple-choice test assessing both basic and strategic task knowledge components was developed specifically for this study. The administration time for the task knowledge test was 8 min. Example items from this test can be found in Appendix B. In addition, it should be noted that results of a confirmatory factor analysis did not support separating the scores into basic and strategic subscales, $\Delta\chi^2(1) = 1.48$, $p > .10$, Bayesian information criterion = 241.90 and 245.24 for the one- and two-factor models, respectively. Thus, a single task knowledge factor was used in all of the tested models.

Pre-training skill, practice performance, post-training performance, and adaptive transfer performance. Pre-training skill, practice performance, post-training performance, and adaptive transfer performance were each calculated using the same function of multiple in-game statistics. Specifically, these variables were computed by dividing a trainee's kills (i.e., number of times a player destroyed a bot) by the quantity of kills plus deaths (i.e., number of times a player's own avatar was destroyed) plus accidental deaths (i.e., number of times a player destroyed his own avatar). In this way, performance scores could range from 0 to 1 with a score of 1 representing a perfect game score (i.e., at least one kill with no deaths or suicides). This formula was the same formula used by UT2004 to create an index of efficiency, and it was chosen for the present study due to its ability to account for multiple aspects of successful UT2004 performance.

Learner-controlled practice difficulty. Participants' chosen level of training task difficulty for each of the 15 practice games was recorded by the computer. Difficulty levels across these games were averaged to form a single index of learner-controlled practice difficulty.

Manipulation check. Following training, all participants responded to two questions about their willingness to make errors during practice. The first item was "While playing Unreal Tournament, I was willing to make errors," and the second item was "While playing Unreal Tournament, I was not willing to make errors." Responses were made on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Analyses of variance (ANOVAs) revealed differences between the conditions for both items, $F(2, 109) = 7.32$, $p < .01$, partial $\eta^2 = .12$, and $F(2, 109) = 8.61$, $p < .01$, partial $\eta^2 = .14$, respectively. Subsequent *t* tests showed that participants in the error encourage condition ($M = 4.23$, $SD = 0.78$) were more willing to make errors than participants in the error avoidance ($M = 3.46$, $SD = 1.12$), $t(74) = 3.50$, $p < .01$, $d = 0.80$, and no error framing conditions ($M = 3.72$, $SD = 0.74$), $t(73) = 2.90$, $p < .01$, $d = 0.67$. Furthermore, participants in the error avoidance condition ($M = 2.65$, $SD = 1.16$) were more unwilling to make errors than participants in the error encouragement condition ($M = 1.74$, $SD = 0.82$), $t(74) = 3.95$, $p < .01$, $d = 0.91$, but not compared to participants in the no error framing condition ($M = 2.33$, $SD = 0.89$), $t(71) = 1.30$, $p > .05$, $d = 0.31$.

Results

Means, standard deviations, and intercorrelations for all study variables are presented in Table 1. As expected, learner-controlled practice difficulty was positively related to positive error framing and pre-training self-efficacy as well as GMA and prior experience. However, negative error framing was unrelated to practice difficulty. In addition, similar to other research, positive error framing was positively related to self-evaluation (e.g., Keith & Frese, 2005) and was negatively related to practice performance (e.g., Gully et al., 2002). Regarding the hypothesized mediating processes of metacognition, self-evaluation, and post-training self-efficacy, only self-evaluation exhibited a positive relationship with difficulty. Finally, difficulty was negatively related to practice performance but positively related to the three training outcomes of task knowledge, post-training performance, and adaptive performance. In sum, these findings suggest that despite its negative relationship with practice performance, practice difficulty is positively related to task knowledge and performance.

Before examining the proposed causal models, the level of learner-controlled practice difficulty was examined across all 15 practice games. The results of a repeated measures ANOVA showed that both linear, $F(14, 98) = 8.95$, $p < .01$, and quadratic, $F(14, 98) = 20.86$, $p < .01$, trends were observed for difficulty over time. As shown in Figure 2, learner-controlled practice difficulty primarily increased over the first four practice games but remained relatively stable thereafter.

Structural equation modeling using the SAS Calis procedure (SAS Institute, 2004) was applied to compare the proposed models. Each model tested was evaluated with multiple goodness-of-fit indices. Specifically, the overall chi-square (χ^2), χ^2/df statistic, Bentler's comparative fit index (CFI; Hu & Bentler, 1999), the root-mean-square error of approximation (RMSEA), and the standardized root-mean-squared residual (SRMR) were examined. Table 2 shows the fit statistics for each of the models tested in this study.

Table 1
Means, Standard Deviations, and Intercorrelations of Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Positive error framing	0.35	0.48	—													
2. Negative error framing	0.33	0.47	−.51**	—												
3. GMA	7.71	2.40	.16	−.17	(.71)											
4. Videogame experience	3.19	1.14	.13	.07	.05	(.86)										
5. Pre-training skill	0.28	0.12	−.08	.00	.21*	.35**	—									
6. Pre-training self-efficacy	3.46	0.65	.09	.06	.01	.45**	.36**	(.90)								
7. Practice difficulty	3.58	0.93	.23*	−.06	.24*	.32**	.39**	.42**	—							
8. Self-evaluation	23.57	4.96	.25**	−.07	.36**	.12	.26**	.34**	.37**	(.83)						
9. Metacognition	3.76	0.50	.10	.02	−.09	.10	.11	.43**	.03	.15	(.89)					
10. Post-training self-efficacy	3.70	0.66	.08	.00	.01	.16	.16	.62**	.12	.15	.55**	(.92)				
11. Task knowledge	9.77	2.63	−.05	.00	.40**	.27**	.44**	.34**	.36**	.27*	.03	.10	—			
12. Practice performance	0.45	0.11	−.29*	.18	.05	.02	.21*	.00	−.60**	−.14	.15	.19*	.09	—		
13. Post-training performance	0.38	0.13	−.05	.10	.28**	.36**	.57**	.40**	.35**	.20*	.23*	.29**	.31**	.30**	—	
14. Adaptive performance	0.27	0.10	.00	.04	.35**	.36**	.53**	.36**	.46**	.32**	.02	.19*	.46**	.18	.57**	—

Note. $N = 112$. For positive error framing, error encourage = 1, error avoid and no error framing = 0. For negative error framing, error avoid = 1, error encourage and no error framing = 0. For self-evaluation, scores could range from 0 to 45. Internal consistencies are presented along the diagonal. GMA = general mental ability.
* $p < .05$. ** $p < .01$ (two-tailed).

With respect to the measurement model, the fit indices indicated that the model fit the data well, $\chi^2 = 544.31$, $\chi^2/df = 1.20$, CFI = .96, SRMR = .06, RMSEA = .04. Specifically, three composite parcels were used in modeling the latent factors representing GMA, pre-training self-efficacy, post-training self-efficacy, metacognition, and task knowledge. These composites were formed by randomly assigning all indicators for each variable to one of the three composites. The latent factors of practice difficulty and practice performance were created using the same methods. Parceling was used to preserve degrees of freedom and to reduce problems of multicollinearity. Aggregate scores used in parceling are more reliable than individual item scores (Little, Cunningham, Shahar, & Widaman, 2002) and may be preferred when sample sizes are relatively small (Bagozzi & Edwards, 1998; Bagozzi & Heatherton, 1994). For the variables of pre-training skill, post-training performance, and adaptive performance, however, individual items were used in modeling the latent factors given only two items available for each. The latent factor of self-evaluation was modeled using each of its five items as well.

Given the fit of the measurement model, the hypothesized structural equation model was tested next. Results indicated that the Hypothesized Model fit the data, $\chi^2 = 822.27$, $\chi^2/df = 1.46$, CFI = .88, SRMR = .14, RMSEA = .06. Many of the hypothesized paths were statistically significant. For instance, both GMA ($\beta = .31$, $p < .01$) and pre-training self-efficacy ($\beta = .39$, $p < .001$) were positively related to learner-controlled practice difficulty. Also, learner-controlled practice difficulty was related to self-evaluation ($\beta = .40$, $p < .001$), which in turn related to task knowledge ($\beta = .57$, $p < .001$). Subsequently, task knowledge was related to both post-training performance ($\beta = .46$, $p < .01$) and adaptive performance ($\beta = .70$, $p < .001$). Contrary to expectations, however, neither videogame experience ($\beta = .09$, $p > .05$) nor error framing (positive framing: $\beta = .12$; negative framing: $\beta = .11$, $ps > .05$) was significantly related to practice difficulty. In addition, practice difficulty did not relate to metacognition ($\beta = .05$, $p > .05$) or post-training self-efficacy ($\beta = .06$, $p > .05$), although post-training self-efficacy was related to post-training performance ($\beta = .30$, $p < .01$). Before drawing any conclusions regarding the observed relationships from the Hypothesized Model, the proposed alternative models were examined to determine if they fit the data better.

Alternative Model 1 examined if learner-controlled practice difficulty had any direct effects on the outcomes of task knowledge, post-training performance, and adaptive performance. As such, paths linking difficulty to each of these variables were added to the Hypothesized Model. Overall, this model exhibited better fit ($\chi^2 = 739.65$, $\chi^2/df = 1.32$, CFI = .91, SRMR = .12, RMSEA = .05), and it improved significantly in fit compared to the Hypothesized Model, $\Delta\chi^2(4) = 82.62$, $p < .001$. Furthermore, the direct paths linking practice difficulty to task knowledge ($\beta = .44$, $p < .01$) and post-training performance ($\beta = 1.13$, $p < .001$) were both statistically significant, with the relationship between difficulty and adaptive performance being mediated by task knowledge ($\beta = .50$, $p < .01$) and post-training performance ($\beta = .85$, $p < .001$). Additionally, once the direct effects of practice difficulty to the training outcomes were added, videogame experience ($\beta = .18$, $p < .05$) as well as positive error framing ($\beta = .19$, $p < .05$) both demonstrated positive relationships with learner-controlled practice difficulty. Also, the positive effect of practice difficulty on post-training self-efficacy emerged

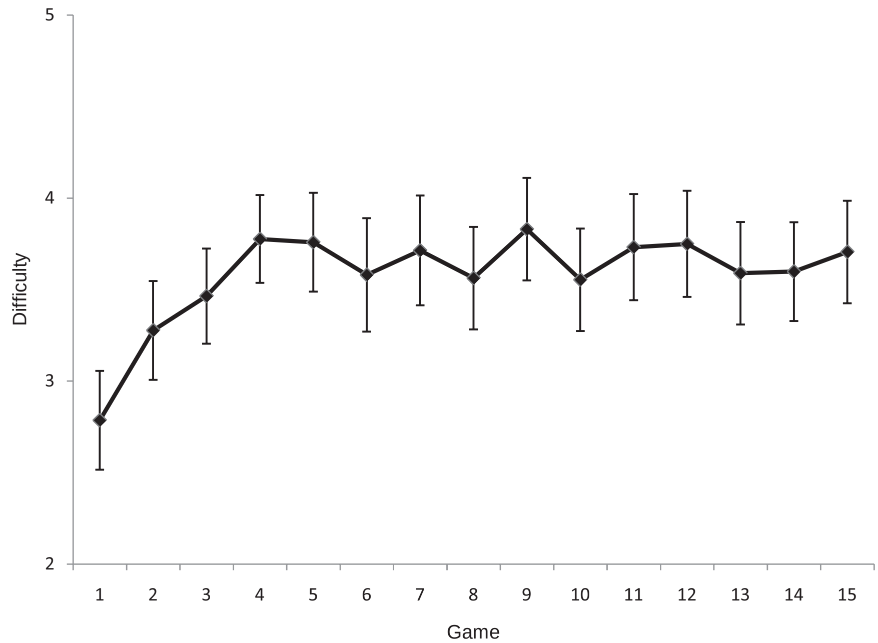

Figure 2. Graph of learner-controlled practice difficulty means over time. Error bars represent twice the standard errors.

(β = .28, p < .05). However, unlike the paths observed in the Hypothesized Model, the relationship between self-evaluation and task knowledge (β = .19, p > .05) and the relationship between task knowledge and post-training performance (β = –.20, p > .05) were not significant in Alternative Model 1.

Next, Alternative Model 2 was tested in which the direct effects of the error framing manipulation were modeled on the variables of metacognition and self-evaluation in addition to learner-controlled practice difficulty. Specifically, using the Hypothesized Model as a baseline model, links between error framing and both metacognition and self-evaluation were added. Unlike Alternative Model 1, fit of this model overall (χ^2 = 817.49, χ^2/df = 1.46, CFI = .88, SRMR = .14, RMSEA = .06) was no better than that of the Hypothesized Model, $\Delta\chi^2(4)$ = 4.88, p > .05. Moreover, error framing did not exhibit significant effects on either metacognition (β = .16 for positive error framing, and β = .10 for negative error framing, *p*s > .05) or self-evaluation (β = .18 for positive error framing, and β = .02 for negative error framing, *p*s > .05).

Although the fit of the previous model did not improve over that of Alternative Model 1, a third alternative model was tested in keeping with the proposed plan of analysis. Specifically, Alternative Model 3 included direct effects of difficulty on the training outcomes tested in Alternative Model 1 as well as the effects of error framing on the cognitive variables examined in Alternative Model 2. Although the fit of this model (χ^2 = 736.57, χ^2/df = 1.33, CFI = .91, SRMR = .11, RMSEA = .05) improved over that of the Hypothesized Model, $\Delta\chi^2(8)$ = 85.69, p < .001, it did not improve compared to that of Alternative Model 1, $\Delta\chi^2(4)$ = 3.08, p > .05. In summary, Alternative Model 1 exhibited the best fit of all the tested models. Therefore, findings from this study will be discussed primarily with respect to Alternative Model 1, which is presented in Figure 3.

Discussion

This study examined the role of learner-controlled practice difficulty in the training of a complex task. Previous research

Table 2
Goodness-of-Fit Statistics for Tested Models

Model	*df*	χ^2	χ^2/df	CFI	SRMR	RMSEA	RMSEA 90% CI
Measurement	452	544.31	1.20	.96	.06	.04	[.03, .06]
Hypothesized	563	822.27	1.46	.88	.14	.06	[.05, .07]
Alternative 1	559	739.65	1.32	.91	.12	.05	[.04, .06]
Alternative 2	559	817.49	1.46	.88	.14	.06	[.05, .07]
Alternative 3	555	736.57	1.33	.91	.11	.05	[.04, .06]

Note. Alternative Model 1 added to the Hypothesized Model direct links from difficulty to the three training outcomes (i.e., task knowledge, post-training performance, and adaptive performance). Alternative Model 2 added to the Hypothesized Model direct links from error framing to both metacognition and self-evaluation. Alternative Model 3 included all of the paths from both Alternative Models 1 and 2. CFI = comparative fit index; SRMR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval.

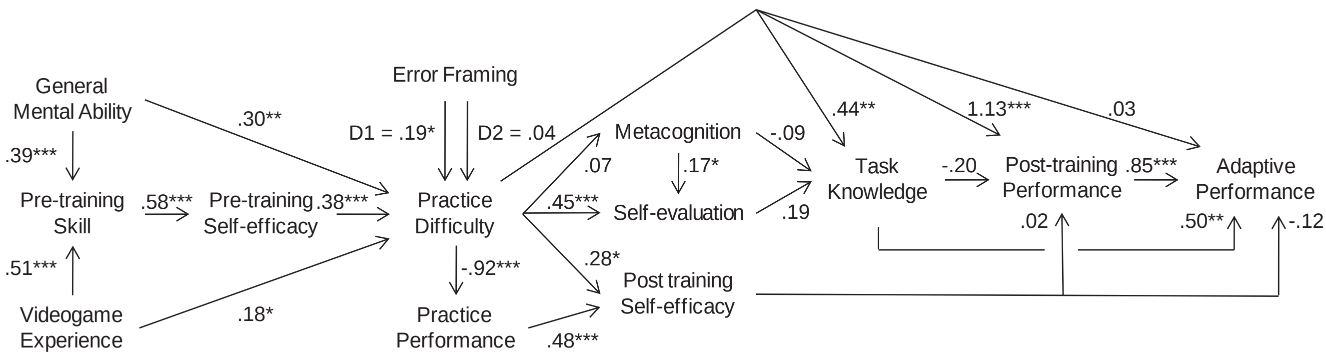

Figure 3. Alternative model of learner-controlled practice difficulty, cognitive and motivational antecedents and outcomes, and training outcomes. Values shown are standardized path estimates. Although not shown in the model, paths controlling for the effects of pre-training skill on practice performance ($\beta = .79$) and practice performance on post-training performance ($\beta = 1.07$) are significant ($ps < .001$). For error framing, D1 was dummy coded as 1 = positive error framing, and 0 = no positive error framing. D2 was dummy coded as 1 = negative error framing, and 0 = no negative error framing. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$ (one-tailed).

involving relatively simple cognitive tasks showed how difficulties during training can be beneficial for learning, especially with respect to tests of retention and adaptability, leading to the notion of desirable difficulties (R. A. Schmidt & Bjork, 1992). However, the precise role played by difficulty with respect to training outcomes as well as the surrounding psychological processes involved have yet to be thoroughly examined in the context of learner-controlled environments. Using a dynamic and complex task entailing both cognitive and psychomotor components, findings from this study suggest that learner-controlled practice difficulty as reflected in the complexity of the task is positively related to training outcomes. In particular, learner-controlled practice difficulty appears to be related to adaptive performance via task knowledge and improved skill (i.e., post-training performance). In the sections that follow, we review the findings regarding the cognitive and motivational mechanisms and the direct effects of practice difficulty with respect to Alternative Model 1. Finally, we discuss the limitations of the present study and provide directions for future research and practice.

Cognitive and Motivational Mechanisms

With respect to the mechanisms influencing learner-controlled practice difficulty, hypotheses were largely supported regarding both the cognitive and motivational variables examined in this study. However, rather than showing indirect links to the training outcomes via the cognitive and motivational mediators examined in this study, the results showed strong direct effects of learner-controlled practice difficulty on both task knowledge and post-training performance. Moreover, practice difficulty was positively related to adaptive performance via its relationships with both task knowledge and post-training performance, which is consistent with previous research showing how gains in knowledge and skill for open tasks are built upon previously acquired knowledge and skill (Ackerman, 2007). Findings concerning the cognitive and motivational antecedents and proximal outcomes of learner-controlled practice difficulty are discussed below.

Antecedents to practice difficulty. GMA was directly related to learner-controlled practice difficulty even after controlling for its effects on pre-training skill. This finding suggests that individuals with higher levels of GMA, regardless of their pre-training skill, possessed the cognitive resources necessary to handle the increased complexity of the task entailed by higher levels of practice difficulty (Gordon, 1997; Kanfer & Ackerman, 1989). Similarly, individuals with greater prior videogame experience were more willing to choose more difficult practice opportunities during training. This finding supports the notion that individuals will seek new and more complex interactions with a task relative to their personal levels of expertise (Berlyne, 1960; Smith & Dorfman, 1975; Voss & Keller, 1983). In addition, individuals possessing high levels of GMA and prior experience may have also recognized the need to engage difficult and complex practice tasks to build task knowledge and skill.

The motivational mechanisms of pre-training self-efficacy and positive error framing also exhibited significant positive relationships with learner-controlled practice difficulty. In particular, the positive relationship between pre-training self-efficacy and learner-controlled practice difficulty is not surprising because trainees with high levels of self-efficacy will seek increasingly difficult tasks as well as devote the necessary effort in the pursuit of those endeavors (Bandura & Locke, 2003; Wood & Bandura, 1989). In addition, because difficult tasks can lead individuals with low self-efficacy to engage in internally-focused thinking, possessing a strong sense of self-efficacy likely helped trainees who encountered high levels of task complexity during practice by facilitating their use of task-directed problem solving (Bandura, 1990).

Regarding the role of error framing, positive but not negative error framing during training was directly related to learner-controlled practice difficulty. Results from the manipulation check revealed that participants in the error avoidance and no error framing conditions did not differ in their willingness to make errors, whereas participants in the positive error framing condition were significantly more willing to make errors. These results suggest that trainees may have possessed a tendency to avoid errors regardless of whether they were explicitly discouraged to do so. That is, those who did not receive any error framing as well as those who were discouraged to make errors did not differ in their perspectives on errors and therefore did not differ in their practice difficulty choices. Instead, only the participants in the positive error framing condition were significantly more willing to make errors and therefore chose higher levels of practice difficulty. These findings are consistent with previous literature that suggests positive rather than negative error framing generally leads to favorable training outcomes (Keith & Frese, 2008).

In addition, this study has demonstrated that error framing interventions can be used in the context of complex tasks. Indeed, much of the research on EMT has involved traditional CBI and decision-making tasks. Keith and Frese (2008) acknowledged that 21 out of the 24 primary studies investigated in their meta-analysis on error framing used computer software training. Although Joung, Hesketh, and Neal (2006) used errors to train firefighters, a job with strong physical requirements, they focused on the decision making aspects of the job rather than psychomotor ones.

Proximal outcomes of practice difficulty. Regarding the cognitive and motivational mediating mechanisms investigated in the present study, the hypothesized pathways linking learner-controlled practice difficulty to task knowledge via self-evaluation and metacognition were not supported. The data also failed to support the hypotheses that post-training self-efficacy would mediate the relationships between learner-controlled practice difficulty and both post-training and adaptive performance. However, the positive relationship between learner-controlled practice difficulty and self-evaluation was significant. This finding is in line with previous literature that suggests one's cognitive effort and self-regulatory behavior increase as a function of task difficulty (Kanfer & Ackerman, 1989; Yeo & Neal, 2008). Furthermore, the inherent difficulties generally associated with active learning approaches (e.g., EMT, exploratory learning) may in part account for the observed positive relationships between such interventions and self-regulatory processes (e.g., Bell & Kozlowski, 2008; Keith & Frese, 2005).

After controlling for practice performance, learner-controlled practice difficulty also exhibited a positive relationship with post-training self-efficacy. In fact, the positive relationship between practice difficulty and post-training self-efficacy emerged despite the negative relationship between practice difficulty and practice performance. Thus, rather than undermining post-training self-efficacy, practice difficulty appears to have promoted trainees' self-efficacy perceptions despite its relationship with poorer levels of practice performance. In other words, this finding suggests that trainees who chose more difficult practice games had enhanced feelings of mastery than trainees who chose less difficult practice levels (Bandura, 1977).

Despite the lack of support for the mediating mechanisms examined here, it is possible that other factors may have played a role in the relationships between learner-controlled practice difficulty and the knowledge and skill-based performance outcomes. In the section that follows, we discuss some potential alternative explanations for the direct effects of learner-controlled practice difficulty observed in the present study.

Direct Effects of Practice Difficulty

Although learner-controlled practice difficulty showed direct effects on task knowledge and post-training performance in the present study, mental models are a potential mechanism that, if examined, may have mediated these relationships. Mental models represent the organization of one's knowledge based on patterns and relationships between concepts (Johnson-Laird, 1983). Research on mental models has shown that trainees' mental models predict learning, retention, and adaptive performance of complex skills (Day, Arthur, & Gettman, 2001) and provide incremental validity in the prediction of skill-based outcomes beyond that explained by traditional measures of task knowledge (Schuelke et al., 2009). Moreover, the experience of errors may facilitate the development of mental models due to the additional information and feedback that errors provide (Frese, 1995; Kozlowski, Gully, et al., 2001). In the present study, increased practice difficulty likely caused participants to make more mistakes. In turn, mistakes prompted learners to explore the reasons for their errors (Dormann & Frese, 1994), consequently fostering more coherent and comprehensive mental models (Bell & Kozlowski, 2009; Heimbeck et al., 2003). Likewise, coping with errors during the learning process can increase one's cognitive processing which also may have a positive effect on mental model formation (Heimbeck et al., 2003).

The notion of implicit learning provides another plausible explanation for the direct effects of learner-controlled practice difficulty observed in the present study. Implicit learning refers to the acquisition of implicit knowledge (i.e., knowledge related to stimuli covariation which occurs through exposure with the stimuli and without intent or explicit awareness; Holyoak & Spellman, 1993). Importantly, implicit knowledge cannot be fully verbalized or recalled, although it is demonstrable through performance (Holyoak & Spellman, 1993; Lewicki, Hill, & Czyzewska, 1992). In relation to the present study, metacognition and self-evaluation may not have mediated the relationships between learner-controlled practice difficulty and the training outcomes because learning predominantly occurred implicitly. Thus, much of the participants' cognitive activity may not have been accessible or describable vis-à-vis self-report measures. Indeed, because motor skills provide particularly salient evidence for the existence of implicit knowledge and learning (Pew, 1974), the strong psychomotor components of our criterion task may in part account for trainees' post-training and adaptive performance gains despite the nonsignificant mediating processes.

With respect to the lack of relationships between post-training self-efficacy and both post-training and adaptive performance, the degree of performance ambiguity associated with the present task may have been influential. Previous research has found self-efficacy to be unrelated to task performance at a between-person level of analysis (and even negatively related at a within-person level) given ambiguous performance contexts (A. M. Schmidt & DeShon, 2010). Likewise, Chen, Casper, and Cortina (2001) found task complexity to moderate the relationship between self-efficacy and performance such that the relationship was strong given low complexity tasks but near zero given high complexity tasks. In general, complex tasks are ambiguous by nature (Campbell, 1988). In particular, performance is ambiguous when one's true level of task performance cannot be definitively determined and instead must be inferred from the information one has available (A. M. Schmidt & DeShon, 2010). In the present study, although trainees were provided with objective performance feedback after each practice game, no true standards for success were provided or salient. That is, despite being able to track their personal levels of practice performance over time, performance was ambiguous in that trainees did not know when mastery of the present task had been achieved.

Regardless of the specific mediating mechanisms involved, findings from this study support the notion of desirable difficulties. Not only was learner-controlled practice difficulty as reflected in the complexity of the task directly related to knowledge and post-training performance, but ultimately it was positively related to adaptive performance as well. Despite the positive influences of practice difficulty on the training outcomes, difficulty was also negatively related with practice performance lending weight to the notion that measures of skill acquisition and learning should be administered at a period that is both subsequent to and separate from training (R. A. Schmidt & Bjork, 1992). Indeed, previous research has shown that better post-training and adaptive performance outcomes are often observed in protocols associated with lower practice performance and slower rates of acquisition (Bell & Kozlowski, 2008; Keith & Frese, 2005; R. A. Schmidt & Bjork, 1992).

Limitations

Several limitations of the present study are worth noting. Only young adult males participated in this study. Thus, future research should examine the extent to which the effects of learner-controlled practice difficulty as well as the surrounding psychological processes generalize across gender and age. In addition, unlike many other learner-controlled instructional environments that focus primarily on the development of declarative and procedural knowledge, the first-person shooter task used here features high levels of both cognitive as well as psychomotor demands. In fact, previous empirical literature on learner control has focused primarily on settings entailing the presentation of traditional classroom-based instructional materials through computer-delivered means. As such, the findings from the present study may not generalize to other settings entailing CBI or learner control. Nonetheless, in any learner-controlled environment, the choices a learner makes are likely to have direct effects on the difficulty of the learning process. Therefore, it is likely that GMA, prior task experience, and pre-training self-efficacy play influential roles with respect to learner choices regardless of the specific training context.

Moreover, the present study serves as an important step in expanding the learner-controlled training literature to include complex tasks involving both cognitive and psychomotor components. Currently, computer simulations and games are becoming more common among virtual training environments and SLEs generally. Game-based training systems and SLEs provide unique learning environments for training complex skills that may be too dangerous or impractical to practice in real life (Cannon-Bowers & Bowers, 2009). For instance, virtual reality training simulations have become a common and oftentimes preferred method of instruction in multiple domains including general medicine (Dunne & McDonald, 2010), surgery (van der Meijden & Schijven, 2009; Wohaibi, Bush, Earle, & Seymour, 2010), dentistry (Luciano, Banerjee, & DeFanti, 2009), and disaster response efforts (Andreatta et al., 2010). In addition, computer simulations and even videogames continue to play a role in a variety of military efforts (Hays & Vincenzi, 2000; Hussain et al., 2009; U.S. Air Force, Air Education and Training Command, 2008) with the use of such programs likely to increase (Committee on Modeling, Simulation, and Games; Standing Committee on Technology Insight–Gauge, Evaluate, and Review; National Research Council, 2010). Given technological advances and the cost-savings typically associated with such instructional environments (Cannon-Bowers & Bowers, 2009), the widespread use of SLEs in the training of complex skills is likely to increase. In sum, this study has demonstrated that learner-controlled practice difficulty of a complex gaming task can lead to increased post-training knowledge, performance, and adaptability.

It is important to note, however, that some caution is needed regarding conclusions about the benefits of practice difficulty on task knowledge and performance. As one reviewer pointed out, it is unclear from the present study whether practice difficulty would have positive effects on training outcomes given varying levels of trainee individual differences such as cognitive ability, prior experience, pre-training skill, or pre-training self-efficacy. In the present study, trainees initially higher in these characteristics chose more difficult and complex practice games, which led to more positive training outcomes. However, it is unknown whether trainees lower in these characteristics would similarly benefit from more difficult and complex games especially early in the learning process. Indeed, one might expect individuals with low levels of GMA, prior experience, or pre-training self-efficacy to learn poorly when exposed to extremely difficult and complex training tasks or concepts (Bandura, 1990; Berlyne, 1960; Gottfredson, 1997; Norman & Bobrow, 1975; Robinson, 2001; Wood, 1986). As such, increased control over task complexity may be advantageous but only when trainees have first acquired some minimally sufficient level of experience and skill within a domain (Berlyne, 1960; Voss & Keller, 1983). Thus, despite the positive relationship between learner-controlled practice difficulty and training outcomes observed in the present study, future research is needed to identify the potential moderating role of individual differences that affect when and how difficulty during the learning of complex tasks may in fact be beneficial or detrimental, and why.

Another limitation of the present study is the absence of a measure of subjective perceptions of practice difficulty and task complexity. As discussed in the introduction, practice difficulty in the present study was operationalized in terms of objective levels of task complexity (i.e., objective characteristics of the task itself; Campbell, 1988; Wood, 1986). Although perceptions of difficulty stemming from objective levels of task complexity are likely to be related (Robinson, 2001), different levels of complexity may be perceived as more or less challenging by different trainees (Campbell, 1988). For instance, compared to lower GMA individuals, higher GMA individuals may be more likely to perceive the complexities of a given task as less challenging given their greater availability of cognitive resources (Norman & Bobrow, 1975; Robinson, 2001). Similarly, even the most objectively complex practice scenarios may be perceived as fairly simple to the most knowledgeable and skilled experts. In fact, research has shown that the structural level at which task complexity is embedded (i.e., deep, underlying principles vs. surface, superficial characteristics) can affect both the perceptions of complexity and the performance of experts and novices (Haerem & Rau, 2007). Future research should examine the role of subjective perceptions of task complexity in the learning process as well as the individual differences that may influence those perceptions. The relative roles played by objective task complexity and subjective perceptions of challenge in the learning process should also be examined.

The use of a single assessment of metacognition is another limitation. Although metacognition, like self-evaluation, is a form of cognitive self-regulation, it was unrelated to learner-controlled practice difficulty in this study. However, unlike self-evaluation which was assessed multiple times throughout practice, metacognition was measured only once at the conclusion of training. Because previous research has found that the relationship between self-regulation and learning develops over time (Sitzmann et al., 2009), measuring metacognition only once following practice may not have accurately and comprehensively captured the dynamic nature of trainees' self-regulatory behavior throughout the entire learning process. As a result, our metacognition scores were found to be unrelated to learner-controlled practice difficulty and subsequent training outcomes.

With respect to the nonsignificant relationships between post-training self-efficacy and both post-training and adaptive performance, it is possible that effects were not observed in the present study due to the close temporal proximity of both performance assessments. Because many mediating mechanisms do not have instantaneous effects, allowing more time to pass between the measurements of post-training self-efficacy and the performance outcomes may have been necessary for these relationships to emerge (Stone-Romero & Rosopa, 2008). For example, after extended periods of nonuse, the effects of self-efficacy on performance should be stronger as needed knowledge and skills are more difficult to retrieve (R. A. Schmidt & Bjork, 1992). In turn, self-efficacy facilitates persistence and on-task focus in the face of performance difficulties (Bandura, 1990; Wood & Bandura, 1989) thereby enabling individuals to retrieve stored information and take appropriate actions. These delayed effects of self-efficacy might be even stronger given novel performance demands as persistence and on-task focus would be especially critical when individuals are forced to not only retrieve and apply relevant information but actually adapt their knowledge and skills to new circumstances.

Directions for Future Research

A number of potential directions for future research are derivable from this study. Importantly, we believe future research is needed that takes a longitudinal approach and examines causal relationships taking into account both inter- and intra-individual variability (Curran & Bauer, 2011; Curran & Bollen, 2001). In fact, relationships between variables concerning learner choices of difficulty in practice and training could be obscured, if not confounded, if changes within persons as well as between persons are not jointly examined. That is, the relationships between subjective perceptions of challenge, objective task complexity, actual performance, and other variables of interest including metacognition, self-evaluation, and self-efficacy are likely to change over the course of skill acquisition.

For example, by taking into account within- and between-person levels, Yeo and Neal (2004) showed that the relationship between effort and performance increased over the course of practice on an air traffic control task, and that rate of this increase was stronger for higher-GMA individuals. Using a multilevel approach, A. M. Schmidt and DeShon (2009) showed that self-efficacy following poor performance on an analytical game was positively related to future performance, whereas self-efficacy following successful performance was negatively related to future performance. With this past research in mind, one might hypothesize that the relationships between learner-controlled practice difficulty and metacognition, self-evaluation, and perhaps self-efficacy would change (i.e., increase) over the course of practice, especially for higher-GMA individuals (cf. Vancouver, More, & Yoder, 2008). Similarly, perhaps within-person changes in metacognition, self-evaluation, and self-efficacy during practice stemming from within-person changes in practice difficulty choices would yield stronger and statistically significant relationships with cognitive and skill-based learning outcomes as opposed to the lack of relationships found in the present study using a simple, between-persons examination.

Another important direction for training research concerns the concept of desirable difficulties. R. M. Schmidt and Bjork (1992) provided three examples of how desirable difficulties can be induced: randomizing task order, delaying or reducing feedback, and varying the nature of practice. These examples illustrate the fact that inducing difficulty into the learning process can be achieved through interventions both external (e.g., randomizing task order, delaying or reducing feedback) and internal (e.g., varying the nature of practice) to the criterion task itself. In the present study, task complexity was conceived as a desirable difficulty internal to the task. We believe implementing task complexity as a desirable difficulty is especially amenable to learner-controlled contexts involving simulation games, other SLEs, and the training of complex tasks in general. Nonetheless, difficulty can be operationalized in a variety of ways, and both external and internal interventions can be used simultaneously in any instructional setting. Given the relative simplicity of the types of tasks used in previous research on desirable difficulties, it remains largely unclear what types of difficulty as reflected in different training elements may be more or less beneficial to learning and performance in the context of more complex tasks (cf. Kraiger, 2003). Therefore, future research should investigate alternative desirable difficulties in learner-controlled and active learning environments.

With respect to task complexity in particular, more empirical research is needed to better understand its role as a desirable difficulty in the learning process. In the present study, we relied on Wood's (1986) framework of task complexity for guidance. However, all three types (i.e., component, coordinative, dynamic) covaried with differing levels of practice difficulty. As a result, the relative amounts of each type with respect to each level of practice difficulty are unknown. Thus, it is unclear whether different types of task complexity played larger roles in the learning process. Similarly, it is possible that the presence of different combinations of the types had stronger relationships with training outcomes. As such, future studies are needed to better isolate the relative influence of different complexity types and combinations in relation to learning outcomes.

Furthermore, various descriptions of task complexity have been proposed in the literature. Given the theoretical overlap between some conceptualizations (e.g., Campbell, 1988; Wood, 1986), researchers should work toward developing a more integrated and parsimonious theory of task complexity in the interest of advancing future research and providing more targeted recommendations for practitioners. However, regardless of the particular frameworks used, we believe it is important that task complexity be treated as an objective task variable independent of subjective psychological experiences. Certainly, examining the processes that relate to task complexity is critical for both science and practice. However, "if we wish to separate individual and task effects, then we should logically expect to describe tasks independently of individuals who perform the task" (Wood, 1986, p. 62).

Finally, the relationship between error framing and learner-controlled practice difficulty was examined in the present study. Based on these results, it is possible that positive error framing interventions used in other active learning environments may be associated with learning due in part to direct effects on the difficulty and complexity associated with learners' choices. However, it is also possible that errors during training may serve to increase the amount of complexity present in the instructional content particularly with respect to dynamic complexity. Dynamic complexity refers to the changing nature of a task with respect to actions and information cues (Wood, 1986). When errors occur, the outcomes of those errors are likely to entail unexpected and abrupt changes to the learning environment from the perspective of the learner. Thus, learners are forced to dynamically change their actions, strategies, or understanding of instructional content based on the feedback provided by the errors (Keith & Frese, 2008). Given the need to identify more mediating factors between error framing and learning outcomes (Keith & Frese, 2005), future research should examine the potential role played by task complexity in EMT interventions.

Practical Implications

Undoubtedly, adaptability is a crucial need across a variety of work settings today. Given the popularity of simulation games and other forms of CBI, we suggest that learner-controlled practice difficulty is an important feature to consider in training for adaptive performance. Specifically, individuals should be encouraged to attempt difficult and complex training tasks to facilitate increased knowledge, performance, and adaptability. However, because individual differences including GMA, prior task experience, pre-training skill, and pre-training self-efficacy were related to levels of learner-controlled practice difficulty in the present study, training practitioners should carefully consider the characteristics of learners prior to training and perhaps tailor the complexity of the instructional content accordingly. Moreover, because learner characteristics may also moderate the effectiveness of instructional difficulties on training outcomes, it may be beneficial to provide easier and less complex training content early on because inexperienced trainees may become overwhelmed if their choices lead to overly complex processing demands (Berlyne, 1960; Kalyuga & Renkl, 2010).

It is also important that practitioners working with learner-controlled instructional environments consider not only the areas in which trainees play an active role but also the aspects of training not under the control of the trainees. For instance, using simulation games in conjunction with more traditional instructional methods appears to be more effective than training in which hands-on experience with a simulation game is the sole means of instruction (Sitzmann, 2011). In the present study, participants viewed a 15-min training presentation prior to practice and were provided with a training handout to reference throughout training. In addition, DeRouin et al. (2004) suggested that providing learners with upfront instructions regarding the nature of the training program and the control they will be given may be one way to promote task efficacy. Because trainees with low self-efficacy may be willing to select only the most basic instructional content, providing individuals with such additional guidance early on may be particularly important. By exposing all trainees to some of the more basic instructional content prior to giving them control, instructors may be able to ensure learners have sufficient prior experience and knowledge of the material to make effective decisions (Kalyuga & Renkl, 2010) and be better able to deal with the more difficult and complex training content (Berlyne, 1960; Voss & Keller, 1983). Ultimately, by initially promoting trainees' pre-training self-efficacy and task knowledge, positive learner-controlled training outcomes may be obtained as a result of learners being better prepared for handling complex training content and being more likely to attempt difficult practice opportunities when given the choice (Voss & Keller, 1983).

Conclusion

In summary, this study bridges the concept of desirable difficulties with the learner control literature by examining a causal model of learner-controlled practice difficulty in the training of a complex task. Using a computer-based gaming task, this study demonstrates the importance of learner decisions regarding the difficulty of their practice games in an active learning context. Specifically, practice difficulty, as reflected in the complexity of the task, played a lynchpin role linking error framing and individual differences known to be important for learning with post-training task knowledge, performance, and adaptability. Given the increase in active learning environments, particularly those featuring simulation games and other SLEs, we believe more research on the role of learner-controlled practice difficulty is needed. We hope the present study spurs future research that better examines task complexity as a desirable difficulty, as well as other forms of difficulty, in relation to psychological processes associated with active learning to better understand how to promote adaptive learning outcomes through learner-controlled instructional practices.

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(*Appendices follow*)

Appendix A

Descriptions of UT2004 Maps Used in the Present Study

Map	Role in study	No. of enemy bots	Description
Albatross	Pre-training practice, pre-training skill assessment (2×), training practice (15×), post-training skill assessment (2×)	2	Moderately-sized, outdoor grassy area featuring rock walls, pits, and elevated pathways surrounded by cliffs. Includes multiple enclosed areas connected by narrow pathways and tunnels. Variety of environmental conditions requires different strategies, tactics, and weapons to be used depending on the specific location of one's avatar.
Sulphur	Adaptive skill assessment (2×)	9	Large, outdoor metal structure featuring a series of intertwining, multi-level catwalks elevated high in the sky. Unlike *Albatross*, walkways are not enclosed so that falling off walkways results in respawning. Very expansive so that long-range attack strategies are required in addition to face-to-face, close-range attack strategies. Additionally, given increased number of bots, players are constantly engaged with enemy bots and thus must decide immediately which tactics they wish to use.

Note. UT2004 = Unreal Tournament 2004.

Appendix B

Example Items From the Task Knowledge Test

1. How many armor points is a shield pick-up worth?
   a. 20
   b. 25
   c. 50*
   d. 75

2. What will your character do if you quickly press the D key (or the → key) two times in a row?
   a. Double-jump
   b. Dodge forward
   c. Dodge right*
   d. Crouch right

3. If you were trying to do the most damage to a slow-moving and far-away bot, which one of these weapons would be best?
   a. Shock Rifle
   b. Lightning Gun*
   c. Flak Cannon
   d. Link Gun

Note. An asterisk indicates the correct answer.

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