UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

PROMOTING ADAPTIVE PERFORMANCE THROUGH LEARNER-CONTROLLED PRACTICE DIFFICULTY AND INDIVIDUALIZED CHALLENGE: A LATENT GROWTH MODELING APPROACH

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

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Norman, Oklahoma
2012

PROMOTING ADAPTIVE PERFORMANCE THROUGH LEARNER-CONTROLLED PRACTICE DIFFICULTY AND INDIVIDUALIZED CHALLENGE:
A LATENT GROWTH MODELING APPROACH

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

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Abstract

In any learner-controlled, active learning environment, the choices one makes can influence both the objective training difficulty and individualized levels of trainee challenge faced during learning. Despite research suggesting that certain difficulties experienced while learning can be beneficial for promoting knowledge, skill, and transfer (R. A. Schmidt & Bjork, 1992), the roles of learner-controlled practice difficulty and associated levels of individualized challenge are not well understood. Moreover, research has yet to examine empirically the nature of the cause-and-effect relationships between active learning behaviors and related psychological processes, and single measures of adaptive transfer are typically used despite the multidimensional nature of training transfer (Barnett & Ceci, 2002). Therefore, the present study examined these issues by giving 152 male participants control over their practice difficulty operationalized in terms of objective levels of task complexity while playing a complex videogame. Results revealed that metacognition and self-efficacy each exhibited positive influences on learner-controlled practice difficulty. Furthermore, both the overall average level and growth of practice difficulty had positive relationships with basic knowledge and post-training performance. The overall average level of practice difficulty was also positively related to strategic knowledge. Conversely, growth of individualized challenge had negative relationships with knowledge and post-training performance. In turn, post-training performance mediated the influences of difficulty and challenge on three distinct types of adaptive transfer performance. Findings are discussed with

respect to the beneficial role of practice difficulty during training as well as the need to use multidimensional assessments of transfer outcomes.

Promoting Adaptive Performance through Learner-Controlled Practice Difficulty and Individualized Challenge: A Latent Growth Modeling Approach

Adaptability has become a critical need for the modern organization. A growing global economy (Black, Mendenhall, & Oddou, 1991) and rapid advances in technology (Kozlowski et al., 2001) necessitate adaptability among today's workforce. Similarly, the dynamic nature of work tasks requires that expertise and skills be used in ever-changing ways and contexts (Kozlowski et al., 2001). As such, training has become more than just an instructional process for teaching stable, well-defined procedures and knowledge. Instead, many current perspectives view training as a method for helping learners prepare for uncertain and increasingly complex situations and problems (Kozlowski et al., 2001). Furthermore, as technological innovations continue to flourish, the use of computers in training has also increased (Brown, 2001; DeRouin, Fritzsche, & Salas, 2004). Given these circumstances, it is not surprising that recent research has focused on promoting the adaptive transfer of knowledge and skill through learner-controlled, computer-based instructional environments in which learners play an active role. Nonetheless, unanswered questions remain with respect to adaptive transfer, learner control, and the relationship between the two concepts.

Notably, the roles of training difficulty and trainee challenge in promoting adaptive transfer and other training outcomes have received little empirical attention in the learner control literature despite their conceptual relevance to nearly any instructional environment in which the learner assumes an active role. That is, when learners are given control over elements of a training program, the objective difficulty and personal challenge they experience will be due in no small part to the decisions they make concerning the instructional process. One's pace, review of training content, and engagement in practice opportunities are all examples of potential learner-controlled elements that will likely have direct relationships with the overall degree of difficulty and challenge one faces during learning. Given the increasing popularity of learner-controlled and active learning training environments in both research and practice, the purpose of the present study was to examine the roles of learner-controlled practice difficulty and individualized challenge in the training of a complex task with respect to knowledge, performance, and adaptive transfer outcomes.

This study extends the work of Hughes et al. (2012), who also examined the role of learner-controlled practice difficulty in the training of a complex task. Specifically, Hughes et al. (2012) gave individuals control over the difficulty of their practice games while they learned to play a complex and dynamic first-person shooter videogame that entails strong cognitive and psychomotor components. Through the use of structural equation modeling (SEM), they identified a number of cognitive and motivational antecedents to learner-controlled practice difficulty and demonstrated its positive relationships with post-training knowledge, performance, and transfer outcomes. Using the same complex videogame task, the present study manipulated levels of participants' self-imposed challenge to also examine learner-controlled practice difficulty as well as a number of its potential individual difference antecedents and related processes.

However, there are a number of key differences from Hughes et al. (2012). First, the present study differentiated between objective levels of practice difficulty and individualized levels of participant challenge during the learning process. Second, a latent growth modeling (LGM) approach (Bollen & Curran, 2006; Curran & Bollen, 2001) was used to assess learner-controlled practice difficulty and challenge in terms of both overall average levels and growth over the course of practice. Thus, the effects of the potential antecedents to practice difficulty and challenge (namely general mental ability (GMA), goal orientation, pre-training self-efficacy, pre-training skill, and videogame experience) could be examined at both between and within-persons levels. Third, cross-lagged panel analyses coupled with the latent growth models were used to examine more precisely the causal relationships practice difficulty and challenge share with commonly proposed processes associated with active learning: metacognition, self-evaluation, and self-efficacy. Finally, because research suggests adaptive transfer to be a multifaceted construct, multiple and distinct assessments of adaptive transfer performance were examined.

Learner Control, Difficulty, and Challenge

Learner control refers to elements of training that give learners the ability to make choices regarding various features of an instructional program (Reeves, 1993), and it is typically a key element of computer-based instructional contexts (Brown, 2001; Reeves, 1993). Many advantages of learner control have been proposed in the literature including positive effects on trainee motivation to learn (Schnackenberg & Sullivan, 2000; Scheiter & Gerjets, 2007), attention (Corbalan, Kester, & van

Merrienboer, 2009), depth of cognitive processing (Scheiter & Gerjets, 2007), and overall satisfaction (DeRouin et al., 2004; Orvis, Fisher, & Wasserman, 2009). However, despite the theoretical benefits of learner-controlled instruction, research has shown that learner control does not always lead to positive training outcomes (DeRouin et al. 2004; Kraiger & Jerden, 2007; Reeves, 1993; Steinberg, 1989). Nonetheless, computer-delivered training methods continue to make up a significant proportion of all formal instruction, and the prevalence of such methods has increased in recent years (American Society for Training and Development, 2010). With technological capabilities always advancing, the use of simulations, games, virtual-reality environments, and other related synthetic learning environments are becoming more common as well (Behrend & Thompson, 2011; Cannon-Bowers & Bowers, 2009; Wilson et al., 2009). Therefore, research is needed to identify the conditions and processes that influence the effectiveness of learner-controlled instructional programs (Wilson et al., 2009). One concept central to any learner-controlled training environment that has yet to receive much attention is learner-controlled practice difficulty.

Traditionally, content and features under the control of the learner have included training elements such as instructional pace, study materials, and performance feedback (Orvis et al., 2009; Reeves, 1993). However, regardless of the specific learner-controlled elements present in a particular training program, the decisions one makes will inevitably impact the difficulty of the instructional process and the amount of challenge personally experienced by a given learner. For example, working at a slower rather than faster pace, reviewing the most basic as opposed to most complex materials, or opting to ignore feedback instead of capitalizing on its instructive properties may all serve to increase the difficulty of a learner-controlled training environment thereby making the learning process more challenging. In the present study, participants were given direct control over the difficulty of their practice games. In addition, because research suggests that imposing certain types of difficulties into the instructional process can facilitate learning (De Corte, 2003; Ghodsian, Bjork, & Benjamin, 1997; Hughes et al., 2012; Roediger & Karpicke, 2006; R. A. Schmidt & Bjork, 1992), this study used a self-imposed challenge manipulation that explicitly encouraged participants to select either moderately or extremely challenging practice difficulty levels.

Desirable Difficulties and Learning

For any instructional program, it is critical that learned knowledge and skills be applied not only during training itself but, more importantly, after training and outside of the learning environment. Thus, retrieval of stored information and skill is critical, and engaging in retrieval processes in training can promote successful retrieval in the future (Bjork, 1994; R. A. Schmidt & Bjork, 1992). In fact, Bjork (1994) states that many difficulties faced during the learning process can be characterized as being desirable in as much as they are able to promote retrieval processes, thereby exerting beneficial effects on learning. Furthermore, because difficulty and challenge during the learning process often entail slow and effortful learning, the beneficial effects of difficulty on knowledge and skill should be most apparent given tests of delayed retention and performance as well as adaptive performance in novel, unanticipated contexts (Bjork, 1994; Roediger & Karpicke, 2006; R. A. Schmidt & Bjork, 1992). Nevertheless, few studies have explicitly examined the role of learner-controlled practice difficulty with the exception of Hughes et al. (2012). However, unlike Hughes et al. (2012), which examined practice difficulty only as an objective characteristic of the task, the present study also examined the role of individualized levels of challenge in a learner-controlled training environment.

Learner-controlled Practice Difficulty and Individualized Challenge

In the present study and as with Hughes et al. (2012), practice difficulty was operationalized in terms of objective levels of task complexity. In general, task complexity can be described in terms of objective task characteristics including inputs or paths, products or goals, and the relationships between the elements (Campbell, 1988; Wood, 1986). In particular, Wood (1986) proposed three types of task complexity: component, coordinative, and dynamic. Component complexity entails the number of distinct actions and amount of information needed to perform a task. Coordinative complexity is determined by the intra- and inter-relationships among the task actions, information cues, and products of the task. Lastly, dynamic complexity refers to potential changes that can be made to the nature of the task which can affect the relevance of various task information or actions. In the present research, higher levels of learner-controlled practice difficulty are associated with greater amounts of task complexity with respect to all three types defined by Wood (1986).

Importantly, whereas practice difficulty as conceptualized here refers to the objective complexity of the task, challenge refers to the personal, individualized experience of practice difficulty unique to each participant. Specifically, individualized challenge was conceptualized in terms of reaching beyond what one is confident of achieving. Thus, it was operationalized in a manner that is largely representative of an inverse of one's confidence. Clearly, difficulty and challenge are closely related. That is, the nature of task components and their shared relationships as well as the relative stability and dynamicity of those features will directly impact an individual's cognitive workload, attention, arousal, and general information processing (Campbell, 1988; Robinson, 2001; Wood, 1986). What is important to note, however, is that objective task complexity and the resulting behavioral responses of the task-doer are distinct concepts (Campbell, 1988) and should be described independently (Wood, 1986). That is, given a particular level of practice difficulty (i.e., task complexity), the resulting degree of challenge will be different for different individuals. For instance, in the present study, one participant may find a medium level of practice difficulty to provide little challenge while another participant may find the same objective level of practice difficulty to be overwhelming and too complex. Therefore, it is important to determine the extent to which the apparent benefits of difficult learning experiences are a result of objective task complexity, individualized levels of trainee challenge, or both.

In keeping with the LGM approach, both learner-controlled practice difficulty and individualized challenge were assessed using three repeated observations throughout training. These repeated observations were used to model both the overall average level as well as the growth of each variable over the course of practice. Figure 1 presents a general unconditional latent growth model as used in the present study.

Individual Differences

Given the beneficial role of difficulty during training, it is important to identify the characteristics that influence trainees' choices of both learner-controlled practice difficulty and individualized challenge. However, given the close relationship between practice difficulty (i.e., task complexity) and challenge, specific hypotheses are not proposed differentiating the relationships between learner-controlled practice difficulty and individualized challenge with respect to potential individual difference predictors. Instead, this study seeks to address the following research questions:

> *Research Question 1a:* Do the individual differences predicting learner-controlled practice difficulty differ from those predicting individualized challenge with respect to overall average levels?
>
> *Research Question 1b:* Do the individual differences predicting learner-controlled practice difficulty differ from those predicting individualized challenge with respect to growth over the course of practice?

Below, the individual differences of general mental ability (GMA), goal orientation, pre-training self-efficacy, pre-training skill, and videogame experience are discussed with respect to their likely relationships with learner-controlled practice difficulty and individualized challenge.

General mental ability. The positive influences of GMA can be seen across domains and situations, and it is a crucial factor for dealing effectively with difficult and complex tasks (Gottfredson, 1997; Gordon, 1997). Numerous studies and meta-analytic investigations have shown GMA to be a strong predictor of both job performance and training outcomes (Hunter & Hunter, 1984; Ree & Earles, 1991; Salgado, Anderson, Moscoso, Bertua, & de Fruyt, 2003; F. L. Schmidt & Hunter, 1998), and more recent research suggests that those relationships may be even stronger than previously shown (F. L. Schmidt, Shaffer, & Oh, 2008). In addition, individuals high in GMA are faster learners and able to understand more than less intelligent individuals (Gottfredson, 2002). Similarly, those with more GMA are more likely to challenge themselves by pursuing difficult tasks (Gordon, 1997). In support of these ideas, Hughes et al. (2012) found that GMA was positively related to learner-controlled practice difficulty. Moreover, individuals high in GMA should recognize the need for difficulty and challenge during the learning process to further build knowledge and skill. In all, GMA is expected to be positively related to both learner-controlled practice difficulty and individualized challenge in the present study.

Goal orientation. Goal orientation broadly refers to the motivational patterns one holds towards achievement opportunities (Dweck, 1986). It is a multidimensional construct consisting of three factors: mastery, performance-prove, and performance-avoid goal orientation (Brett & VandeWalle, 1999; VandeWalle, 1997; cf. Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). Mastery (or learning) goal orientation is characterized by a desire to acquire new knowledge and skills in an effort to build one's competence (Dweck, 1986; VandeWalle, 1997). Individuals possessing a mastery goal orientation are motivated to learn (Colquitt & Simmering, 1998) and actively seek challenging opportunities (Elliott & Dweck, 1988). Likewise, possessing a mastery goal orientation has been shown to be positively related to self-efficacy (Ford, Smith, Weissbein, Gully, & Salas, 1998; Payne, Youngcourt, & Beaubien, 2007; Kozlowski et al., 2001) and may help promote persistence when faced with obstacles (Dweck, 1986). Thus, mastery goal orientation is expected to be positively related to learner-controlled difficulty and individualized challenge in the present study.

Performance goal orientations are defined by one's focus on displays of performance. In particular, performance-prove goal orientation is characterized by a willingness to demonstrate one's ability to gain favorable judgments from others (Brett & VandeWalle, 1999; Dweck, 1986). On the other hand, individuals possessing a performance-avoid goal orientation are motivated to avoid appearing incompetent and being judged negatively (Dweck, 1986; VandeWalle, 1997). Unlike mastery goal orientation, performance goal orientations are thought to be maladaptive, associated with anxiety and negative thoughts (Dweck, 1986; Middleton & Midgley, 1997; VandeWalle, 1997), and negatively related to self-efficacy (Ford et al., 1998). Moreover, when individuals possess a performance-avoid goal orientation, they are likely to avoid challenge and become distressed when encountering difficulties (Dweck, 1986; Elliott & Dweck, 1988). Although performance-avoid goal orientation tends to exhibit consistent patterns of relationships, the conclusions regarding the effects of a performance-prove goal orientation are somewhat tenuous (Elliot & Church, 1997; Payne, Youngcourt, & Beaubien, 2007). As such, only performance-avoid goal orientation is expected to be negatively related to learner-controlled practice difficulty and individualized challenge. It should also be noted that the inclusion of goal orientation as a motivational antecedent to learner-controlled practice difficulty and challenge serves as another extension of Hughes et al. (2012), which did not examine its role during training.

Pre-training self-efficacy. Self-efficacy refers to one's beliefs in his or her capabilities to meet the requirements needed to perform a specific task (Bandura & Wood, 1989; Gist & Mitchell, 1992), and it is thought to have its immediate effects on behavior. In particular, effort, task focus and attention, goal setting, and persistence (especially when faced with challenges or failures) are all determined in part by one's level of self-efficacy (Bandura, 1977, 2001; Bandura & Locke, 2003; Bandura & Wood, 1989; Silver, Mitchell, & Gist, 1995; Stevens & Gist, 1997; Wood & Bandura, 1989). When individuals possess a strong sense of self-efficacy, they are likely to view effort as worthwhile (A. M. Schmidt & DeShon, 2010) and seek increasingly difficult tasks to achieve greater success (Bandura, 1997; Tolli & Schmidt, 2008; Wood & Bandura, 1989; cf. Vancouver & Kendall, 2006). In fact, Ford, Quiñones, Sego, and Sorra (1992) found that individuals with higher levels of self-efficacy were more likely to perform difficult and complex tasks following training. Hughes et al. (2012) also found pre-training self-efficacy to be positively related to the overall level of learner-controlled practice difficulty. Thus, pre-training self-efficacy is expected to be positively related to both learner-controlled practice difficulty and individualized challenge in the present study.

Pre-training skill and videogame experience. Pre-training skill and videogame experience are also expected to be positively related to levels of learner-controlled practice difficulty and individualized challenge in the present study. Previous research has found one's prior experience within a domain to be important when learning complex tasks (Kalyuga, Chandler, & Sweller, 2001). Hughes et al. (2012) found prior videogame experience to be positively and directly related to learner-controlled practice difficulty, and pre-training skill was positively related to practice difficulty through the mediating effect of pre-training self-efficacy. More generally, some researchers have suggested that individuals are naturally motivated to seek novel and complex stimuli (Earl, Franken, & May, 1967). Similarly, with more task expertise and experience, the greater the amount of complexity is needed to provide stimulation (Berlyne, 1960; Smith & Dorfman, 1975). Thus, participants in the present study with higher levels of pre-training skill and prior videogame experience may be naturally motivated to select difficult and challenging practice games.

Active Learning and Self-imposed Challenge

Another focus of the present study was to examine the role of self-imposed challenge as an active learning approach. Active learning approaches encompass a broad range of learner-controlled instructional environments in which learners internally construct their own knowledge via hands-on experience and experimentation (Bell & Kozlowski, 2008; Frese et al., 1991; Smith, Ford, &

Kozlowski, 1997). Common methods of active learning have included the use of error framing (Bell & Kozlowski, 2008; Gully, Payne, Koles, & Whiteman, 2002; Heimbeck, Frese, Sonnentag, & Keith, 2003; Hughes et al., 2012; Keith & Frese, 2005), mastery framing interventions (Bell & Kozlowski, 2008; Kozlowski & Bell, 2006; Kozlowski et al., 2001), and both guided (Bell & Kozlowski, 2002; Debowski, Wood, & Bandura, 2001; Wood, Kakebeeke, Debowski, & Frese, 2000) and exploratory learning (Bell & Kozlowski, 2008; Frese et al., 1988). Regardless of the particular training intervention, active learning approaches are characterized by their use of "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). That is, active learning interventions ultimately seek to promote learning by influencing trainees' self-regulation and guiding their decision making (Bell & Kozlowski, 2008; Kozlowski et al., 2001).

Active Learning Processes

In general, research has indeed demonstrated the mediating roles of various self-regulatory processes between different active learning approaches and important training outcomes (Bell & Kozlowski, 2002; 2008; Debowski et al., 2001; Keith & Frese, 2005, Kozlowski & Bell, 2006). Hughes et al. (2012) also found learner-controlled practice difficulty to be positively related to both self-evaluation and self-efficacy. Although the self-imposed challenge manipulation used in the present study was primarily intended to directly influence participants' practice difficulty choices and associated levels of individualized challenge, its effects on three processes typically associated with active learning were also examined: metacognition, self-evaluation, and self-efficacy. The following research question is proposed to address this issue:

> *Research Question 2:* To what extent does the self-imposed challenge manipulation influence metacognition, self-evaluation, and self-efficacy?

Certainly, understanding the psychological processes related to active learning interventions is important. However, much of the existing empirical literature has treated the associated cognitive, motivational, and other self-regulatory mechanisms largely as proximal outcomes of the active learning process (e.g., Bell & Kozlowski, 2006, 2008; Keith & Frese, 2005), and more studies are needed to examine the potential antecedent roles played by these variables. That is, it is unclear whether the role of certain active learning processes is one of mediation only, linking active learning approaches (e.g., positive error framing, encouraging exploration) to training outcomes. Instead, some processes may also serve to influence individuals' active learning behaviors in addition to following from them. For example, Bell and Kozlowski (2008) found exploratory learning was positively related to subsequent metacognitive activity. However, it is also possible that metacognition has positive effects on subsequent exploratory learning such that metacognitive activity will spur individuals to consider aspects of the task that they had previously not considered thus leading to additional exploration and novelty seeking. In the present study, the LGM approach combined with cross-lagged panel analysis was used to empirically examine the nature of the relationships learner-controlled practice difficulty and individualized challenge have with metacognition, self-evaluation, and self-efficacy. The following research question pertains to this issue:

> *Research Question 3:* Are the cause-and-effect relationships metacognition, self-evaluation, and self-efficacy have with learner-controlled practice difficulty similar to their relationships with individualized challenge?

Below, metacognition, self-evaluation, and self-efficacy are discussed with respect to their potential relationships with both learner-controlled practice difficulty and individualized challenge.

Metacognition. Metacognition, or the knowledge of and control over one's cognitive processing (Flavell, 1979; Ford et al., 1998), has been shown to be positively related to a number of learning and performance outcomes (Berardi-Coletta, Buyer, Dominowski & Rellinger, 1995; Ford et al., 1998; Keith & Frese, 2005; Meloth, 1990; Pintrich & DeGroot, 1990). As previously discussed, difficulty during learning is thought to be beneficial for promoting knowledge and performance as a result of increased cognitive retrieval (Bjork, 1994; R. A. Schmidt & Bjork, 1992). Therefore, metacognition, which entails recalling one's past performance to inform one's decisions about future learning strategies and steps, should be positively related to learner-controlled practice difficulty and individualized challenge.

Recently, Hughes et al. (2012) found that metacognition was unrelated to learner-controlled practice difficulty. However, their study assessed metacognition only once following training. In the present study, metacognition was assessed using repeated measures throughout training. This difference is not insignificant given that self-regulatory processes develop over time, operating throughout the learning process (Sitzmann, Bell, Kraiger, & Kanar, 2009). In addition, unlike Hughes et al. (2012), the present study uses a task-specific measure of metacognition intended to provide a more thorough assessment of participants' metacognitive behavior during practice. In all, metacognition is expected to be positively related to practice difficulty and individualized challenge.

Self-evaluation. Like metacognition, self-evaluation is a form of cognitive self-regulation. Self-evaluation involves comparing one's progress to a goal or other standard (Kanfer, 1990; Kanfer & Ackerman, 1989). Previous research has shown that cognitive effort and self-regulatory behavior increase as perceptions of task difficulty increase (Kanfer & Ackerman, 1989; Yeo & Neal, 2008). Hughes et al. (2012) also found learner-controlled practice difficulty to be directly related to self-evaluation activity. However, they did not examine the potential role self-evaluation may have played with respect to subsequent levels of difficulty. Indeed, the more participants evaluated their progress and performance, the more willing (or unwilling) they may have been to challenge themselves in subsequent games. Regardless of the direction, self-evaluation is expected to be related to learner-controlled practice difficulty and individualized challenge.

Self-efficacy. Hughes et al. found learner-controlled practice difficulty to be positively related to post-training self-efficacy. In fact, this relationship was observed despite the poorer levels of practice performance associated with practice difficulty. This finding is interesting in that success should serve to strengthen one's self-efficacy while failure and poor performance often can be detrimental (Bandura, 1977, 1986). However, because practice difficulty in their study was learner-controlled, trainees who willingly chose more difficult practice tasks likely possessed a greater sense of mastery than those who chose easier and less challenging ones (Hughes et al., 2012). Moreover, success in the face of challenge may be especially beneficial for fostering self-efficacy beliefs (Bandura, 1977). Thus, participants in the present study who choose difficult and challenging games are likely to possess higher levels of self-efficacy as a result. Nonetheless, like pre-training self-efficacy, self-efficacy throughout practice should also influence subsequent levels of learner-controlled practice difficulty and individualized challenge as participants seek higher levels of achievement (Bandura, 1997; Wood & Bandura, 1989).

Training Outcomes

Hughes et al. (2012) found that learner-controlled practice difficulty operationalized as objective levels of task complexity exhibited direct, positive relationships with task knowledge and post-training performance. In addition, these outcomes mediated the relationship between practice difficulty and adaptive transfer performance. Although Hughes et al. (2012) was an important first step investigating the role of learner-controlled practice difficulty in training, there were also a number of limitations that the present study seeks to improve upon.

As previously discussed, the present study not only examined individualized challenge in addition to objective levels of practice difficulty, but it also incorporated both average levels as well as growth over the course of practice of each variable. In this manner, it can be determined whether an increase in the amount of difficulty or challenge of practice games in and of itself is beneficial for learning, regardless of the overall degree. Another addition to the present study is the inclusion of basic and strategic components of task knowledge as separate factors rather than a single composite. In all, it is expected that, in general, both practice difficulty and individualized challenge will be positively related to basic and strategic knowledge as well as post-training and adaptive transfer performance. However, it is unclear how similar (or disparate) those relationships will be across difficulty and challenge. Thus, the following research question is proposed:

> *Research Question 4:* Do learner-controlled practice difficulty and individualized challenge have similar relationships with the training outcomes of basic knowledge, strategic knowledge, post-training performance, and adaptive transfer performance?

Adaptive transfer. Adaptive transfer is the process of applying one's already existing knowledge and skills to perform a different procedure or solve an entirely new problem (Smith et al., 1997). Generally, adaptive performance entails completing more complex and difficult tasks than those previously practiced or performed (Pulakos, Arad, Donovan, & Plamondon, 2000). Accordingly, research that has assessed adaptive transfer (e.g., Bell & Kozlowski, 2008; Ford, Smith, Weissbein, Gully, & Salas, 1998; Joung, Hesketh, & Neal, 2006; Keith & Frese, 2005) typically has used performance tasks designed to be more dynamic and challenging than training tasks or post-training tests of analogical performance (i.e., tests with similar solutions as the training tasks; Keith & Frese, 2008). Although there is consensus in the literature concerning the difficult and complex nature of adaptive transfer tasks, some researchers have suggested that transfer is a multidimensional construct (e.g., Barnett & Ceci, 2002; Pulakos et al., 2000; Pulakos, Schmitt, Dorsey, Arad, Hedge, & Borman, 2002). Importantly, if transfer is indeed multidimensional in nature, single measures or tests of adaptive transfer will provide a vague, if not incomplete, picture.

In the present study, the taxonomy proposed by Barnett and Ceci (2002) served as a guiding framework for conceptualizing and examining adaptive transfer performance. Specifically, they propose adaptive transfer to be composed of two primary factors, content and context. According to this conceptualization, the process of transferring knowledge and skills can be described in terms of *what* gets transferred (i.e., content) in addition to *when* and *where* transfer occurs (i.e., context). In addition, each factor is said to be composed of multiple sub-dimensions. Although both facets are important, the present study focused only on the content dimension of transfer described by Barnet and Ceci (2002).

The first dimension of transfer content examined here concerns the nature of the performance change and "refers to the measure against which improvement is expected" (Barnett & Ceci, 2002, p. 622). For instance, the speed, accuracy, and quality of effective performance may each be used to characterize the transfer that occurs (Barnett & Ceci, 2002). In this case, more marked differences relative to the training tasks with respect to such performance elements may entail a greater level of transfer. In the present study, adaptive transfer as it pertains to a performance change was assessed by testing participants on more difficult games compared to the tests of pre-training and post-training performance, thus requiring greater accuracy and speed for effective performance. It should be noted that the self-imposed challenge approach to active learning used here may have led many participants to practice on games similar if not identical to this particular transfer assessment. Thus, assessing transfer via alternative operationalizations is especially crucial given the present circumstances to determine if difficulty and challenge during practice will facilitate increased understanding and skill necessary for adapting when faced with truly novel performance demands.

The second content dimension of transfer concerns the nature of the skill to be transferred. In particular, Barnett and Ceci (2002) state that a transferred skill may be characterized on a continuum ranging from specific to general. For instance, a transfer task may require only that a specific procedure be transferred, in which case the execution of a given series of steps is required. However, other transfer tasks may entail that one apply general, overarching principles or heuristics when performing in the transfer situation (Barnett & Ceci, 2002). In such instances, individuals may be required to approach a task differently than they had previously and use new strategies based on general principles. In the present study, this dimension was assessed by providing participants with novel resources thereby forcing them to rely on their understanding of broader game principles rather than previously practiced procedures.

Finally, Barnett and Ceci (2002) propose the nature of memory demands associated with a task to be another dimension of transfer content. For instance, some tasks require that one merely recognizes a certain stimulus prompting the execution of a learned activity. Although such circumstances place little demands upon memory, other tasks require trainees to actively recall learned knowledge and skills in order to select appropriate courses of action (Barnett & Ceci, 2002). As such, adaptive transfer performance is likely to be characterized by heightened working memory demands entailing substantially less recognition and more recall relative to analogical transfer performance. To examine the effects of learner-controlled practice difficulty and individualized challenge on this dimension of transfer, participants were tested in a new geographical layout (i.e., map) relative to the pre-training, practice, and post-training games.

It should be noted that Barnett and Ceci (2002) do not intend for their taxonomy to provide a comprehensive description of all possible types of transfer. In addition, they acknowledge the possibility of interactions between transfer types. In fact, the latter two transfer games discussed above (i.e., new resources and a new map) likely overlap with respect to their assessments of transfer types. Nonetheless, current research involving adaptive transfer of complex tasks has yet to examine adaptive transfer as a multidimensional construct. Therefore, it is unknown whether different aspects of adaptive transfer performance can be explained with the same set of predictors. Similarly, it remains unclear whether learner-controlled practice difficulty or individualized challenge will be positively related to adaptive transfer performance requiring a deeper understanding of the task and underlying skills and not just increased levels of difficulty with respect to task complexity as operationalized during practice. As such, the following research question is addressed by the present study:

> *Research Question 5:* Do the relationships learner-controlled practice difficulty and individualized challenge have with adaptive transfer performance differ depending on the type of adaptive transfer being assessed?

Method

Participants were 152 males enrolled at the University of Oklahoma, ranging in age from 18 to 30 years old, $M = 19.36$, $SD = 1.88$. For their participation, all participants received credit to fulfill a psychology course research requirement. Participants were randomly assigned to one of two self-imposed challenge conditions, “matched” or “outmatched”, and they were encouraged to select either moderately or extremely challenging difficulty levels of their practice games, respectively. This manipulation is described later in more detail.

Training Task

Unreal Tournament 2004 (UT2004), a commercially available, first-person shooter computer videogame originally released in 2003, was used as the training task in the present study. While playing the game, participants assume the perspective of an avatar on-screen that they move and manipulate throughout various geographic layouts. The specific game mode played by participants was called Deathmatch, an "every man for himself" style match in which participants compete 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. Whenever a bot or one's avatar is destroyed during a game, that character respawns, reappearing in a new map location to rejoin the match.

Importantly, effective performance of UT2004 features a high degree of both psychomotor and cognitive demands. For instance, players must use both a mouse and keyboard simultaneously to move and control their avatar. Additionally, players must learn how to use a variety of weapons including the nature of each weapon's two distinct fire modes. Similarly, players must learn effective strategies and appropriate circumstances for using the weapons. Also, monitoring of game statistics such as avatar and bot health as well as weapon ammunition levels is critical for effective performance. Furthermore, given the nature of the dynamic and artificially intelligent bots, the most effective players must use planning and problem solving skills to be successful.

Practice Difficulty

In general, practice difficulty of UT2004 is reflected in the skill proficiency (i.e., judgment and decision making, quickness, elusiveness, and accuracy) of the computer-controlled bots. As the bots become increasingly more skilled with increasing levels of difficulty, the game becomes more complex as well. In relation to Wood's (1986) taxonomy, each type of task complexity (i.e., component, coordinative, and dynamic) is affected. For instance, regarding component complexity, bots use more weapons and become more accurate at higher relative to lower difficulty levels. Thus, players have to process more information and perform more actions to be effective at high levels of practice difficulty. Coordinative complexity increases with practice difficulty as well. With bots becoming faster and more elusive, players must simultaneously process multiple pieces of information and perform more coordinated actions when difficulty is high as opposed to low. Similarly, dynamic complexity increases as a function of practice difficulty. Changes in the game occur more frequently as bots use new strategies and become progressively more unpredictable as difficulty increases. As a result, players must change or even altogether abandon previously effective strategies and techniques at high practice difficulty levels.

Practice difficulty choices were presented on a 1–7 scale in numerical form (i.e., 1, 2, 3, etc.) without any other labels using a dropdown menu on participants' computers. Although the game includes eight different difficulty settings (with "1" being the easiest), only the second through the eighth settings were used because previous pilot studies revealed that the first setting (i.e., the easiest setting) appeared to provide little to no challenge for most inexperienced participants.

Procedures

Upon arriving to the study, participants were told that the purpose of the study was meant to examine how different people learn to play a dynamic and complex videogame. Next, participants completed measures of goal orientation and GMA, followed by a 15-minute training PowerPoint presentation explaining the basic game controls and rules of UT2004. Participants were then given a handout summarizing information from the training presentation and had 3 minutes to practice and familiarize themselves with the game without the presence of any computer-controlled bots. Then, participants' played two, 5-minute baseline games of UT2004 against two computer-controlled bots set at a medium level of difficulty (i.e., 4 on a 1-to-7 scale) to assess their pre-training skill. Following these games, participants played two more 5-minute games against two bots. However, these games were set at difficulty levels 2 and 6, respectively, and participants were told that these games were meant to show them what some of the other difficulty settings are like. Also, for all four of the aforementioned games, participants were instructed to "do their best" by trying to maximize their kills while simultaneously minimizing their own avatar's deaths. Following these games, participants completed a measure of pre-training self-efficacy.

Next, participants completed a measure of self-confidence with respect to the seven practice difficulty levels for the purpose of computing individualized challenge scores. Then, the self-imposed challenge manipulation was administered, and participants performed the first of three practice sessions. For each practice session, participants played five, 5-minute games against two bots. Prior to each game, participants selected the level of their upcoming practice difficulty. 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 featured basic information regarding the player's and bots' performance and weapon usage statistics. Participants were also given a game log which they could use to record their performance or make game-related notes throughout practice if they choose to do so.

At the conclusion of the first practice session, participants completed the first of three repeated measures of self-evaluation, self-efficacy, and metacognition, respectively. After a 5-minute break, participants completed the last two practice sessions. Like the first practice session, the remaining two practice sessions were each preceded by the measure of self-confidence in addition to abridged self-imposed challenge instructions. Likewise, assessments of self-evaluation, self-efficacy, and metacognition were administered immediately following each practice session. This format resulted in a total of three assessments of self-confidence and each of the three process variables (i.e., self-evaluation, self-efficacy, and metacognition).

After the third practice session and final set of repeated measures, training handouts were collected, and participants completed a UT2004 knowledge test. Then, they played two, 5-minute games against two computer-controlled bots at a medium level of difficulty (i.e., 4 on a 1-to-7 scale) assessing their post-training performance. Next, participants completed a measure of videogame experience and took a second 5-minute break. Finally, participants played three pairs of adaptive transfer test games for a total of six games. Because each pair of games entailed unique changes relative to the post-training performance test games, order of the pairs was counterbalanced. Regardless of the type of adaptive transfer being assessed, each adaptive transfer game was five minutes long and played against two computer-controlled bots. In addition, participants completed a measure assessing their perceived differences between the first pair of transfer games they played and the post-training performance test games. The nature of the adaptive transfer test games is described below. Participation in this study lasted approximately 5 hours. Appendix A presents an outline of all study procedures described above.

Adaptive Transfer Test Games

Based on the taxonomy described by Barnett and Ceci (2002), adaptive transfer performance was assessed in three distinct ways, each with two games. For each type of adaptive transfer, games featured the same characteristics as the pre-training skill assessment and post-training performance test games with only one unique difference. Specifically, one pair of transfer games was set to difficulty level 6 (instead of level 4). In this way, adaptive transfer was reflected in one's ability to cope with performance changes associated with the increased difficulty alone. That is, effective adaptive performance in these games required participants to perform with increased speed, accuracy, and maneuverability at the task.

Another pair of adaptive transfer games entailed new weapons previously unused by participants. Specifically, four of the five weapons used throughout training were replaced with new weapons, and each new replacement weapon was chosen based on similarities it shared with its counterpart with respect to some general properties (e.g., fire rate, effective range, stopping power). By capitalizing on these similarities, participants were able to rely on their previous understanding of general game principles and strategies when using the new weapons despite the differences in specific procedures. As such, these games targeted the nature of the transferred skill such that participants' had to apply underlying principles and heuristics learned during training versus specific routinized procedures.

Finally, an additional pair of adaptive transfer games featured a map previously unused in the study. Importantly, this map included vast differences compared to the original training map in terms of its layout, geographic and architectural features, and size. As such, these games were aimed mainly at assessing adaptive transfer performance as it pertains to increased memory demands brought about by the transfer scenario. For instance, because environmental features and landmarks present in the previous map were no longer available, participants were required to recall what they had learned about general environmental features before choosing a strategy. Additionally, being successful on the new map required participants to learn not only different navigational paths and resource locations, but it also entailed learning new skills and techniques that were previously inappropriate or unpracticed given the vastly different game environment. The order of the three types of transfer games was counterbalanced to account for potential order effects on transfer performance. Results of ANOVA analyses revealed that performance in each type of transfer game did not differ by the order in which it was played, all F's(2, 2) < 0.73, p's > .05.

It should be noted, however, that the adaptive transfer games entailing new weapons and those featuring a new map likely overlapped in their assessments of transfer content. For instance, with novel weapons, the transfer assessment was focused primarily on participants' ability to transfer their knowledge of general principles instead of relying on practiced procedures. However, it is likely that heightened memory demands also played a role due to the need for participants to quickly learn the new weapons and their individual characteristics, and then adapt effective strategies for the transfer task. Similarly, although a new transfer map was targeted on transfer with respect to increased memory demands, the new environmental context also required participants to play the game differently than they had previously thereby making their understanding of deeper game principles particularly critical. Thus, a clear distinction with respect to these two dimensions of Barnett and Ceci's (2002) transfer framework is difficult to draw from two types of transfer games used here.

Perceptions of adaptive transfer games. To evaluate the extent to which the three types of adaptive transfer test games matched the intended dimensions proposed by Barnett and Ceci (2002), perceived differences between the adaptive transfer and post-training performance test games were assessed. Participants completed this measure after the first pair of transfer games they played. Because order of the adaptive transfer games was counterbalanced, comparisons between each of the three types of transfer games with the post-training performance games were collected. Responses were made using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Specifically, participants were asked to report the extent to which the transfer games required (1) more accuracy to be successful, (2) changes to their strategies and techniques, (3) playing the game differently, (4) learning new information, and (5) learning new skills and techniques. The first item corresponds to the performance change dimension (i.e., increased difficulty games). The second and third items correspond to the transfer of principles versus procedures (i.e., new weapons games), and were averaged to form a single score for perceptions regarding this dimension. The fourth and fifth items were averaged together as well, and correspond to the dimension associated with increased memory demands (i.e., new map games).

ANOVAs revealed significant differences in participants' perceptions of the three transfer game types with respect to the performance change ($F(2, 149) = 11.53$, $p < .01$, partial $\eta^2 = .14$), principles/procedures ($F(2, 149) = 10.23$, $p < .01$, partial $\eta^2 = .12$), and increased memory demands ($F(2, 149) = 25.67$, $p < .01$, partial $\eta^2 = .26$) dimensions. Subsequent *t*-tests revealed the increased difficulty games ($M = 4.07$, $SD = 0.68$) were perceived to entail a greater performance change than either the new weapons ($M = 3.04$, $SD = 1.19$, $t(94) = 5.11$, $p < .01$, $d = 1.06$) or new map ($M = 3.27$, $SD = 1.27$, $t(96) = 3.80$, $p < .01$, $d = 0.79$) transfer games, which did not differ from each other, $t(100) = 0.94$, $p > .05$, $d = 0.19$. Regarding the principles versus procedures dimension, the new weapons ($M = 4.01$, $SD = 0.60$) and new maps ($M = 4.19$, $SD = 0.87$) games did not differ from each other ($t(101) = 1.22$, $p > .05$, $d = 0.24$), but each differed significantly from the increased difficulty games ($M = 3.49$, $SD = 0.93$, $t(98) = 3.37$, $p < .01$, $d = 0.66$ and $t(99) = 3.95$, $p < .01$, $d = 0.78$, respectively. Finally, regarding the increased memory demands dimension, the new weapons ($M = 4.18$, $SD = 0.50$) and new maps ($M = 4.01$, $SD = 0.97$) games did not differ from each other ($t(101) = 1.11$, $p > .05$, $d = 0.22$), but each differed significantly from the increased difficulty games ($M = 2.99$, $SD = 1.10$, $t(98) = 6.99$, $p < .01$, $d = 1.39$ and $t(99) = 4.92$, $p < .01$, $d = 0.98$, respectively. In all, these results suggest that the increased difficulty games indeed assessed transfer vis-à-vis a performance change. However, the targeted transfer dimensions associated with the games that entailed new weapons and a new map were not distinct as both games equally assessed the transfer of principles opposed to procedures under increased memory demands.

Self-imposed Challenge Manipulation

Participants were randomly assigned to either a "matched" or "outmatched" self-imposed challenge condition. Prior to each practice session, participants received instructions concerning the amount of challenge to seek when choosing the difficulty of their practice games. Participants in the "matched" self-imposed challenge condition were instructed to choose difficulty levels that they would find moderately challenging and matched to their own skill levels. Additionally, they were told to select practice difficulty levels at which they would have a 50-50 chance of beating at least one computer-controlled bot. For the "outmatched" condition, participants were instructed to choose practice difficulty levels that they would find extremely challenging and far above their own skill levels. They were also told to select difficulty levels at which they would have a 0-percent chance of beating either bot. Participants in both conditions were told that following the instructions would lead to improved learning and performance, and were encouraged to think positively about challenge to avoid frustration while practicing. Appendix B presents the full instructions for each experimental condition.

Measures

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). The APM consists of matrix problems arranged in order of increasing difficulty. The administration time for this measure was 15 min. The Spearman–Brown odd-even split-half reliability was .54.

Goal orientation. Mastery, performance-prove, and performance-avoid goal orientation was assessed with a 13-item scale adapted from VandeWalle (1997). Original references to one's job and work were removed for the present study. Example items include "I often look for opportunities to develop new skills and knowledge" (mastery), "I enjoy it when others are aware of how well I am doing" (performance-approach), and "I prefer to avoid situations where I might perform poorly" (performance-avoid). Responses were made using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Coefficient alphas for the mastery, performance-prove, and performance-avoid goal orientation subscales were .77, .80, and .84, respectively.

Videogame experience. Four items were used to measure participants' prior videogame experience. Two items assessed the extent to which participants typically played (1) video/computer games and (2) first-person shooter video/computer games specifically. Participants responded using a 5-point Likert scale ranging from 1 (not at all) to 5 (daily). The other two items were open-ended and asked participants to report the approximate number of hours per week they spend playing (3) video/computer games and (3) first-person shooter video/computer games specifically. All four items were standardized and then averaged to compute a single index of videogame experience. Coefficient alpha for this measure was .84.

Self-efficacy. Twelve task-specific items were used to assess self-efficacy pre-training and at the three repeated times during practice. Items were adapted from previous studies (e.g., Bell & Kozlowski, 2002; Day et al., 2007; Nease, Mudgett, & Quiñones, 1999) and framed with respect to UT2004. Responses were made using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Coefficient alphas for the pre-training and repeated self-efficacy measures were .90, .92, .92, and .94, respectively. Example 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."

Metacognition. Twenty-two task-specific items were used to measure metacognition. In general, items assessed the extent to which participants monitored and reviewed their progress and performance, considered alternative strategies, and thought about the reasons for their performance. In addition, items focused on issues related to the game difficulty (e.g., I monitored how well different strategies and tactics worked at different difficulty levels), weapons (e.g., I considered the reasons why certain weapons and fire modes were not always effective), or map features (e.g., I evaluated how the effectiveness of certain tactics depended on the particular type of area within the map). Responses to each items were made using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Coefficient alphas for the three repeated measures were .88, .90, and .92, respectively.

Self-evaluation. Five open-ended response items were used to assess participants' self-evaluation during training. Specifically, participants were asked to report the (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, they were asked to provide explanations for their answers. Responses were rated by two graduate students on a 4-point

Likert scale ranging from 1 (no self-evaluation activity) to 5 (extensive self-evaluation activity).

It should be noted that the questions themselves did not explicitly ask participants to evaluate their performance or practice behaviors. Instead, participants' self-evaluation was evaluated with respect to (a) self-set goals either stated explicitly in their responses (e.g., destroying a bot at close-range) or referenced implicitly (e.g., mastery of a weapon), and (b) their assessment of their performance with respect to those goals. As such, responses that did not reference any practice objectives received a rating of 1. Inter-rater reliability for this measure at each of the three observations was ICC(3,2) = .85, .85, and .90, respectively. Coefficient alpha for this measure at each time was .82, .80, and .80, respectively.

Learner-controlled practice difficulty. Participants' learner-controlled practice difficulty choices were recorded by the computer for all 15 practice games. To provide an equal number of repeated observations as the cognitive (i.e., metacognition and self-evaluation) and motivational (i.e., self-efficacy) process variables being examined, difficulty choices were averaged within each session to provide three composite learner-controlled practice difficulty scores.

Individualized challenge. Individualized challenge was assessed by adapting a method of measuring self-efficacy previously suggested by Bandura (1986) and Wood and Bandura (1989). Prior to each practice session, participants rated their self-confidence at achieving two distinct levels of performance for each of the seven practice difficulty levels. Participants made their responses using integers on a scale ranging from 0 (*no confidence at all*) to 10 (*total confidence*). Specifically, ratings were made with respect to the following two levels of performance: (a) achieving a higher score than only one of the enemy bots and (b) achieving a higher score than both of the enemy bots. For each level of difficulty, confidence ratings were summed across the two performance levels to obtain a single score for each level of practice difficulty. This procedure resulted in a total of seven self-confidence scores (i.e., one score for each level of practice difficulty from which to choose) for each of the three practice sessions. Appendix C includes this measure as it was presented to participants.

To compute the individualized challenge score, participants' self-confidence scores were first matched to their specific levels of learner-controlled practice difficulty chosen for each practice game. In this way, a particular self-confidence score could be counted as few as zero times and as many as five times when computing individualized challenge for a given practice session (i.e., five practice games per session) depending on the number of times a particular practice difficulty level was chosen. The sum of these self-confidence scores was then averaged and reverse-coded to compute a single individualized challenge score for each practice session. As such, larger values were indicative of greater challenge (i.e., less self-confidence).

For example, if a participant practiced on Difficulty Level 5 for three games and Difficulty Level 4 for two games within a given practice session, his self-confidence ratings at those difficulty levels would be used in computing his individualized challenge score. Additionally, his self-confidence score for Difficulty Level 5 would be weighted by three (i.e., three practice games), and his self-confidence score for Difficulty Level 4 would be weighted by two (i.e., two practice games). Next, the sum of these scores would be divided by five resulting in a single self-confidence score for the given practice session. Finally, to produce the individualized challenge score, this self-confidence score would be reverse-coded by subtracting it from ten (i.e., the highest possible self-confidence score). In the above example, if the participant's self-confidence were 6 and 8 at Difficulty Levels 5 and 4, respectively, his individualized challenge score would be computed as follows:

$$\text{Individualized challenge} = 3.2 = 10 - \left(\frac{6 + 6 + 6 + 8 + 8}{5} \right)$$

Basic and strategic task knowledge. Basic and strategic task knowledge components were assessed with a 34-item multiple-choice test developed for this study. Specifically, 17 items were used to assess each type of knowledge, and the total administration time for the test was 12 min. Appendix D presents example items from the test.

Performance. Pre-training skill, practice, post-training, and all forms of adaptive transfer performance were scored using the same performance index. For each participant, one's kills (i.e., number of times a player destroyed a bot) were divided 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). As such, scores could range from 0 to 1. In this way, performance was measured as an index of efficiency such that a score of 1 represents no deaths or accidental deaths with at least one kill. This index was provided by UT2004 and was chosen for its ability to account for multiple aspects of successful UT2004 performance. In addition, directions for the pre-training, post-training, and adaptive transfer games included explicit instructions to maximize one's kills while also minimizing one's deaths. The formula used in computing performance scores is shown below for clarity.

$$\text{Performance} = \frac{\text{Kills}}{\text{Kills + Deaths + Accidental Deaths}}$$

Results

Means, standard deviations, and intercorrelations for all study variables are presented in Table 1. Table 2 presents means, standard deviations, and intercorrelations for the repeated variables at each observation (i.e., learner-controlled practice difficulty, individualized challenge, metacognition, self-evaluation, and self-efficacy). Learner-controlled practice difficulty (as operationalized as a composite average across all three observations) exhibited positive relationships with all training outcomes including basic and strategic knowledge, post-training performance, and all three types of adaptive transfer performance. However, the composite score for individualized challenge, although positively correlated with practice difficulty, was unrelated to each training outcome. Regarding the repeated variables, practice difficulty at each time demonstrated positive relationships with all three active learning processes across all time points. Individualized challenge was largely unrelated to metacognition, although some positive correlations were observed between it and self-evaluation as measured at the first and second observations. Finally, individualized challenge and self-efficacy were negatively related, particularly with respect to challenge at the second and third observations.

Repeated measures ANOVAs revealed significant linear ($F(1, 2114) = 39.92$, $p < .01$, partial $\eta^2 = .21$) and quadratic ($F(1, 2114) = 19.06$, $p < .01$, partial $\eta^2 = .11$) trends for learner-controlled practice difficulty. Individualized challenge was also characterized by both linear ($F(1, 2114) = 11.87$, $p < .01$, partial $\eta^2 = .07$) and quadratic ($F(1, 2114) = 21.02$, $p < .01$, partial $\eta^2 = .12$) trends. Plots of practice difficulty and challenge by self-imposed challenge condition over the course of practice are provided in Figures 2 and 3, respectively. As can be seen in the graphs, participants in the "matched" condition chose less difficult and challenging games than participants in the "outmatched" condition throughout practice. In addition, differences between conditions in trends for both practice difficulty and individualized challenge are apparent from Games 5 to 6 (i.e., Session 1 to 2), at which point participants in the "outmatched" condition increased their practice difficulty and thus their challenge whereas those in the "matched" condition decreased in terms of difficulty and challenge. Also notable are the sizeable decreases in individualized challenge for all participants from Games 10 to 11 (i.e., Session 2 to 3). Although the magnitudes of those decreases do not seem to match the slight declines in practice difficulty observed at that same time, participants' increasing confidence scores across practice sessions provides a likely explanation. That is, because individualized challenge as operationalized here has a direct negative relationship with self-confidence, participants' could choose the same level of practice difficulty while challenging themselves less over time.

Latent Growth Modeling and Analytic Plan

LGM is a statistical procedure for analyzing longitudinal data within the framework of SEM. As such, latent (i.e., unobserved) factors are used to represent growth (i.e., change) over time of observed, repeated measures variables (Bollen & Curran, 2006; McArdle & Epstein, 1987). In LGM, it is common to represent growth with a single latent factor, or latent slope. The latent slope represents a best-fitting, underlying trajectory (or growth curve) that provides a parsimonious estimation of intraindividual (i.e., within-persons) change across time (Bollen & Curran, 2006). Thus, a mean and variance are estimated for the slope, which capture the average trajectory across all individuals and the individual variability around the mean trajectory, respectively (Curran, Lee, Howard, Lane, & MacCallum, 2012).

In the present study, the SAS CALIS procedure (SAS Institute Inc., 2008) was used to examine all latent growth models of interest. Relying primarily upon the procedures used by Curran and Bollen (2001), a series of latent growth models were examined for each repeated variable. First, means over time for the repeated variables were examined to determine if each variable in fact changed over the course of practice. Following this step, two unconditional univariate models were fitted for each repeated variable. One model contained only a latent intercept, and the other model contained both a latent intercept and latent slope. For all repeated variables, the latent slope was specified to represent linear growth, and higher-order growth trajectories (i.e., quadratic) were not possible given only three available observations per variable. In addition to comparing overall fit of the two models, the mean and variance of the latent slopes were examined as well. In so doing, these unconditional univariate models were used to determine if the inclusion of a latent slope could explain each repeated variable better than the inclusion of a latent intercept alone (Curran & Bollen, 2001). The best-fitting unconditional latent growth model for each repeated variable was retained for subsequent modeling.

Next, conditional univariate latent growth models were examined for each repeated variable. Specifically, the individual difference predictors (i.e., GMA, pre-training skill, videogame experience, pre-training self-efficacy, and mastery, performance-prove, and performance-avoid goal orientation) were each modeled as manifest variables with direct links to the repeated variables' latent intercepts and slopes (if applicable). The self-imposed challenge manipulation was modeled as a dummy coded variable (0 = matched, 1 = outmatched) also with direct paths leading to each repeated variable's intercept and slope (if applicable). Figure 4 presents the general form of a conditional latent growth model as specified in the present study.

Before proceeding to the bivariate cross-lagged panel analyses, two additional steps were taken to ensure the best-fitting and most parsimonious conditional univariate latent growth models were retained (Curran & Bollen, 2001).

Specifically, autoregressive models were tested by fitting stability coefficients linking the Time 1 to the Time 2 observation, and the Time 2 to the Time 3 observation in each conditional, univariate model. Additionally, the indicator error terms for each repeated variable were constrained to be equal allowing for comparisons with previous models in which error terms were independently estimated. In all, results of these tests were used to determine which model provided the best explanation of each individual repeated variable.

Bivariate, cross-lagged panel models were then examined by combining the best-fitting, conditional univariate models obtained from the previous steps. Specifically, learner-controlled practice difficulty was paired with each active learning process via correlated error terms and cross-lagged parameter estimates between variables. The same procedures were then used to combine individualized challenge with each active learning process. The results of these cross-lagged, latent growth model analyses were used to determine the nature of the cause-and-effect relationships both practice difficulty and individualized challenge shared with the active learning processes.

Finally, the effects of learner-controlled practice difficulty and individualized challenge (with respect to their latent intercepts and slopes) on the training outcomes were examined. In addition, role of the active learning processes were modeled during this step according to the results of the previous cross-lagged panel analyses. The results of these procedures are detailed below.

Equality of Means over Time

For each repeated variable, a model in which indicator means were constrained to be equal at each observation was compared to a model in which means were independently estimated at each time. For all variables, the independently estimated models were just identified (i.e., $df = 0$) and thus each had a chi-square value of 0. Chi-square difference tests indicated that equality constraints on the means resulted in significant decrements in model fit for practice difficulty, individualized challenge, metacognition, and self-evaluation, all $\Delta\chi^2(2) > 6.17$, p's < .05. However, modeling self-efficacy with equal means throughout practice was not significantly worse than independently estimating the means, $\Delta\chi^2(2) = 1.25$, $p > .05$. These results suggest that, with the exception of self-efficacy, the repeated variables exhibited change over the course of practice.

Unconditional Models

Fit statistics and model comparisons for the unconditional LGM analyses are displayed in Table 3. Results of this step revealed univariate latent growth models of learner-controlled practice difficulty, individualized challenge, and metacognition fit better when both latent intercepts and slopes were included compared to intercepts alone, all $\Delta\chi^2(3) > 12.96$, p's < .01. In addition, each of these repeated variables were represented with a significant slope mean and variance, p's < .05. On the other hand, the slope mean and variance were not significant for self-efficacy (p's > .05), and its inclusion did not provide better fit of the data than an intercept-only model, $\Delta\chi^2(3) = 7.64$, $p > .05$. Self-evaluation was also modeled with an intercept only. However, it should be noted that although the inclusion of a latent slope factor improved fit for self-evaluation ($\Delta\chi^2(3) = 82.53$, $p < .01$), the estimated variance of the slope was negative resulting in an inadmissible solution.

Conditional Models

Table 4 provides a summary of the fit statistics for the conditional latent growth models in addition to the parameter estimates for the self-imposed challenge manipulation and individual difference predictors. Specifically, these models addressed Research Questions 1a and 1b, which asked if the individual differences predicting learner-controlled practice difficulty would differ from those predicting individualized challenge with respect to (1a) overall average levels and (1b) growth over the course of practice. Results of these models revealed that pre-training skill ($\gamma = .48$, $p < .01$), videogame experience ($\gamma = .16$, $p < .05$), and pre-training self-efficacy ($\gamma = .26$, $p < .01$) each exhibited positive relationships with the learner-controlled practice difficulty latent intercept. Additionally, GMA ($\gamma = .26$, $p < .05$) demonstrated a positive relationship with the latent slope, while pre-training skill ($\gamma = -.36$, $p < .01$) and performance-avoid goal orientation ($\gamma = -.30$, $p < .05$) demonstrated negative relationships. Concerning individualized challenge, GMA ($\gamma = .20$, $p < .05$) exhibited a positive relationship to the latent intercept, while pre-training self-efficacy exhibited a negative relationship ($\gamma = -.22$, $p < .05$). None of the individual differences were related to the individualized challenge latent slope. In all, the influences of the individual differences on practice difficulty and individualized challenge were dissimilar, with only GMA exhibiting a positive relationship on each variable but in different respects (i.e., intercept versus slope).

The effects of the individual differences on the active learning processes were examined as well. In particular, videogame experience ($\gamma = .30$, $p < .01$), pre-training self-efficacy ($\gamma = .33$, $p < .01$), and mastery goal orientation ($\gamma = .17$, $p < .05$) each exhibited positive relationships with the metacognition intercept, while no variables were related to the metacognition slope. For self-evaluation, GMA ($\gamma = .24$, $p < .01$) and pre-training skill ($\gamma = .24$, $p < .01$) were positively related to the latent intercept (self-evaluation was not modeled with a latent slope). For self-efficacy (which was also not modeled with a latent slope), videogame experience ($\gamma = .14$, $p < .05$) and pre-training self-efficacy ($\gamma = .68$, $p < .01$) had positive relationships with the self-efficacy latent intercept, and performance-avoid goal orientation ($\gamma = -.20$, $p < .01$) had a negative relationship.

Research Question 2 was aimed at examining the potential relationships between the self-imposed challenge manipulation and the active learning processes, and it was also addressed by the conditional latent growth models. Results showed that the self-imposed challenge manipulation was positively related to the self-evaluation intercept, $\gamma = .17$, $p < .05$. However, it was not related to either metacognition or self-efficacy in terms of intercepts or slopes. It should also be noted that the self-imposed challenge manipulation was positively related to the latent intercepts of both learner-controlled practice difficulty ($\gamma = .42$, $p < .01$) and individualized challenge ($\gamma = .54$, $p < .01$), but it exhibited no relationships with either variable's slope. Thus, the self-imposed challenge manipulation does not appear to have had strong direct effects on the active learning processes overall, but it did positively influence practice difficulty and individualized challenge as expected.

Autoregressive and Constrained Error Models

Two separate autoregressive models were compared for each repeated variable. One model included stability coefficients that were constrained to be equal over time, whereas the other model included stability coefficients that were independently estimated. Table 5 presents fit statistics and stability coefficient estimates for all autoregressive models examined in this step. Compared to the previously retained, conditional univariate latent growth models, model fit was improved with the inclusion of constrained stability coefficients for learner-controlled practice difficulty ($\gamma_1 \rightarrow_2 = .10$, $\gamma_2 \rightarrow_3 = .09$, p's $< .01$) and individualized challenge ($\gamma_1 \rightarrow_2 = .24$, $\gamma_2 \rightarrow_3 = .23$, p's $< .01$), both $\Delta\chi^2(1) > 12.68$, p's $< .01$. Independently estimated stability coefficients ($\gamma_1 \rightarrow_2 = -.13$, $\gamma_2 \rightarrow_3 = -.16$, p's $< .01$) improved model fit for self-evaluation, $\Delta\chi^2(2) = 100.70$, $p < .01$. Neither metacognition nor self-efficacy exhibited significant stability coefficients (γ's $< .03$, p's $> .05$) or improved fit given autoregressive models.

Regarding the tests of constrained errors, greater parsimony (as a result of the equality constraints on the indicator errors) without significant decrements to model fit was obtained for the autoregressive individualized challenge model ($\Delta\chi^2(2) = 2.23$, $p > .05$) and metacognition model without stability coefficients ($\Delta\chi^2(2) = 2.22$, $p > .05$). However, for learner-controlled practice difficulty, self-evaluation, and self-efficacy, constraining the indicator errors resulted in significant decreases in model fit compared to independent estimations, all $\Delta\chi^2(2) > 7.20$, p's $< .05$). Table 6 describes the final univariate latent growth models for each repeated variable and provides summary fit statistics for all models.

Cross-lagged Panel Models

Research Question 3 asked whether the cause-and-effect relationships that metacognition, self-evaluation, and self-efficacy shared with learner-controlled practice difficulty would be similar to their relationships with individualized challenge. To examine this issue, six sets of bivariate cross-lagged panel models were tested using the final univariate latent growth models retained from the previous steps. For each pair of repeated variables, cross-lagged parameters were specified in one of four ways: (1) all possible paths were independently estimated, (2) reciprocal paths were constrained to be equal by time, (3) only paths directed *to* the active learning process were estimated, and (4) only paths originating *from* the active learning process were estimated. In addition, correlations were modeled between all possible combinations of latent intercepts and slopes in each bivariate model. Correlations between the indicator error terms at same time points were modeled across variables as well (Curran & Bollen, 2001). In all, the focus of these procedures was to determine the nature of causality between both practice difficulty and individualized challenge and the active learning processes based on an overall pattern of results.

Practice difficulty and active learning processes. Table 7 provides both fit statistics and cross-lagged parameter estimates for the bivariate, cross-lagged latent growth models between learner-controlled practice difficulty and the active learning processes. With respect to learner-controlled practice difficulty and metacognition, independently estimating the cross-lagged parameters returned an inadmissible solution and thus the results of this model were not interpreted. For the constrained and one-way, difficulty to metacognition models, none of the cross-lagged parameters were significant, p's > .05. However, when only the effects of metacognition to practice difficulty were estimated, positive relationships emerged from Time 1 to Time 2 ($\gamma_1 \rightarrow_2 = .16$, $p < .05$) and from Time 2 to Time 3 ($\gamma_2 \rightarrow_3 = .27$, $p < .05$, one-tailed). In addition, this model provided the best fit to the data, $\chi^2(19) = 26.71$, CFI = .99, SRMSR = .02, RMSEA = .05, RMSEA upper 90% CI = .09.

Unlike the previous set of models, the cross-lagged panel models between learner-controlled practice difficulty and self-evaluation revealed no significant cross-lagged parameters between the variables, p's > .05. Additionally, correlations between error terms across the variables were not significant prior to adding any cross-lagged parameters.

Results of the cross-lagged panel models between learner-controlled practice difficulty and self-efficacy revealed significant cross-lagged parameter estimates in two of the four models. In particular, self-efficacy exhibited positive relationships with subsequent practice difficulty when all possible cross-lagged parameters were independently estimated ($\gamma_1 \rightarrow_2 = .27$, $\gamma_2 \rightarrow_3 = .36$, p's < .01), and when only the parameters from self-efficacy to practice difficulty were estimated ($\gamma_1 \rightarrow_2 = .26$, $\gamma_2 \rightarrow_3 = .34$, p's < .01). Moreover, only estimating the paths from self-efficacy to practice difficulty provided the best fit of all four tested models, $\chi^2(32) = 62.81$, CFI = .97, SRMSR = .03, RMSEA = .08, RMSEA upper 90% CI = .11. In no model did learner-controlled practice difficulty exhibit relationships with subsequent measures of self-efficacy, γ's $< .01$, p's $> .05$. Figures 5 and 6 display the best-fitting models between practice difficulty and metacognition, and practice difficulty and self-efficacy, respectively.

Individualized challenge and active learning processes. Table 8 provides fit statistics and cross-lagged parameter estimates for the individualized challenge cross-lagged models. Initially, all four cross-lagged latent growth models between individualized challenge and metacognition returned negative eigenvalues thereby making the solutions inadmissible. Because the variance of the challenge slope was no longer significant at this stage in the analyses, it was removed from the models to resolve the problem. Given this step, results of the cross-lagged analyses failed to support any relationships from individualized challenge to metacognition, $|\gamma\text{'s}| < .05$, p's $> .05$. Similarly, no significant influences were observed for the relationship from metacognition to individualized challenge, $|\gamma\text{'s}| < .06$, p's $> .05$.

Cross-lagged latent growth models between individualized challenge and self-evaluation exhibited no significant cross-lagged parameters between the two variables, $|\gamma\text{'s}| < .04$, p's $> .05$ for paths to self-evaluation, and $|\gamma\text{'s}| < .09$, p's $> .05$ for paths to challenge. Moreover, correlations between the variables' error terms were not significant prior to the inclusion of any cross-lagged parameters.

With respect to individualized challenge and self-efficacy, two of the four cross-lagged panel models resulted in negative variance estimates of the challenge latent slope which could not be resolved. Therefore, the latent slope for challenge was removed, and the cross-lagged models were tested again. Results showed that self-efficacy at Time 2 had a very weak negative relationship with individualized challenge at Time 3 in the associated one-way model, $\gamma = -.08$, $p < .05$. This model also provided the best fit, $\chi^2(46) = 70.94$, CFI = .97, SRMSR = .04, RMSEA = .06, RMSEA upper 90% CI = .09. Self-efficacy at Time 2 also had a very weak negative relationship with individualized challenge at Time 3 when all possible cross-lagged parameters were independently estimated, $\gamma = -.08$, $p < .05$. Individualized challenge did not exhibit relationships with subsequent self-efficacy in any of the tested models, γ's < .03, p's > .05. Figure 7 displays the best-fitting model between individualized challenge and self-efficacy.

Considered as a whole, the results of the cross-lagged panel latent growth models indicate no similarities between the learner-controlled practice difficulty and individualized challenge with respect to their relationships with the active learning processes. Whereas metacognition and self-efficacy each had positive influences on subsequent learner-controlled practice difficulty throughout practice, individualized challenge was mostly unrelated to the active learning processes.

Models Predicting Training Outcomes

Next, the effects of learner-controlled practice difficulty and individualized challenge on the training outcomes were examined to address both Research Questions 4 and 5. Specifically, Research Question 4 asked whether learner-controlled practice difficulty and individualized challenge would have similar relationships with the training outcomes of basic knowledge, strategic knowledge, post-training performance, and adaptive transfer performance. Research Question 5 was concerned expressly with adaptive transfer performance, and asked whether its relationships with practice difficulty and challenge would differ depending on the type of adaptive transfer being assessed.

To answer these questions, separate models were tested for practice difficulty and individualized challenge with the outcomes, and only one type of adaptive transfer was examined in each model. In particular, basic and strategic knowledge, post-training performance, and adaptive transfer performance were modeled as latent variables. Each knowledge factor was modeled with three composite indicators, which were formed by randomly assigning 17 items to one of three parcels. The post-training and three adaptive performance factors were modeled with two indicators each (i.e., two game scores per performance type). Practice performance was modeled with three composite parcels of five games each, grouped according to practice session, and its direct effect on post-training performance was controlled for. Additionally, the self-imposed challenge manipulation, individual difference variables, and stability coefficients (if applicable) were removed from the models to preserve as much variance in the intercepts and slopes of the latent growth models as possible.

To examine these relationships, a series of nested models was tested beginning with a Baseline Model derived from Hughes et al. (2012). Specifically, models with learner-controlled practice difficulty and those with individualized challenge were specified with direct effects from the given variable's latent intercept and slope to basic knowledge, strategic knowledge, and post-training performance. Both basic and strategic knowledge as well as post-training performance more modeled with direct links to adaptive transfer performance. Additionally, the roles of the active learning processes were included in the models based on the nature of the cause-and-effect relationships suggested by the cross-lagged panel analyses. The Baseline Models for learner-controlled practice difficulty and individualized challenge with the training outcomes are shown in Figures 8 and 9, respectively.

Practice difficulty and training outcomes. Fit statistics and model comparisons for all tested models of practice difficulty with the training outcomes are provided in Table 9. In all models, the latent intercepts of self-efficacy and metacognition were modeled with direct paths leading to the practice difficulty intercept. Similarly, the latent slope of metacognition was modeled with a direct link to the practice difficulty slope. This approach to modeling causal relationships between multiple latent growth models was used in previous studies (Peterson, Luthans, Avolio, Walumbwa, & Zhang, 2011; Van Iddekinge et al., 2009).

With respect to the Baseline Models, metacognition (γ's > .23, p's < .05) and self-efficacy (γ's > .38, p's < .01) had positive relationships on learner-controlled practice difficulty with respect to the latent intercepts in the context of all types of adaptive transfer performance. Similarly, the metacognition slope (γ's > .38, p's < .05) was positively related to the practice difficulty slope in all Baseline Models. Regarding the training outcomes, the practice difficulty latent intercept was positively related to basic knowledge (γ's > .58, p's < .01), strategic knowledge (γ's > .71, p's < .01), and post-training performance (γ's > .83, p's < .01) for all forms of adaptive transfer. The practice difficulty latent slope was positively related to basic knowledge (γ's > .30, p's < .05) and post-training performance (γ's > .16, p's < .05, one-tailed) as well. Although post-training performance was positively related to all types of transfer performance (γ's > .73, p's < .01), strategic knowledge demonstrated a positive relationship only when transfer games entailed new weapons, $\gamma = .22$, $p < .05$, one-tailed.

Model 2 added to the Baseline Model direct links from the metacognition intercept and slope to the knowledge outcomes, but it did not improve model fit for any of the adaptive transfer types, all $\Delta\chi^2(4) < 6.80$, p's > .05. Model 3 added to the Baseline Model direct links from the self-efficacy intercept (which was modeled without a slope) to the performance outcomes. For all types of transfer performance, self-efficacy exhibited a positive relationship with post-training (γ's > .19, p's < .01) but not transfer performance. In addition, Model 3 provided a better fit to the data for all transfer game types, all $\Delta\chi^2(4) > 8.14$, p's < .05. Given this increase in fit, Model 3 was retained as the comparison model moving forward.

Relative to Model 3, Model 4 added direct paths from the practice difficulty intercept and slope to adaptive transfer performance. Model 5 added to Model 3 direct paths from the knowledge outcomes to post-training performance. Finally, Models 6 and 7 added to Model 3 direct paths from the metacognition intercept and slope to post-training performance (Model 6) and adaptive transfer performance (Model 7). However, for all types of adaptive transfer, no model improved fit over that of Model 3, all $\Delta\chi^2(2) < 5.16$, p's > .05. Notably, with respect to Model 3, post-training performance exhibited the only direct influence on all types of adaptive transfer performance (γ's > .73, p's < .01) with the exception of transfer that entailed new weapons, which was also positively related to strategic knowledge, $\gamma = .28$, $p < .05$. Figures 10, 11, and 12 display the final models (i.e., Model 3) for learner-controlled practice difficulty with adaptive transfer performance operationalized in terms of increased difficulty, new weapons, and a new map, respectively.

Individualized challenge and training outcomes. Table 10 provides fit statistics and model comparisons for all tested models of individualized challenge with the training outcomes. Based on the results of the cross-lagged latent growth models, the influence of the self-efficacy latent intercept on the individualized challenge intercept was modeled. However, this relationship was not significant in the Baseline Model for any type of adaptive transfer (γ's < .13, p's > .05), and it was thus removed from the Baseline Model and all subsequent analyses. Moreover, adding to the individualized challenge Baseline Models (a) direct links from challenge to adaptive transfer performance and (b) direct links from knowledge to post-training performance did not result in improvements to model fit or otherwise returned inadmissible solutions.

Results of the Baseline Model for all three types of adaptive transfer indicated that the latent slope of individualized challenge was negatively related to both basic and strategic knowledge as well as post-training performance. For basic knowledge, the effects ranged from $\gamma = -.43$ to $\gamma = -.46$, p's < .01. For strategic knowledge, the effects ranged from $\gamma = -.65$ to $\gamma = -.71$, p's < .01. Lastly, the slope's influences on post-training performance were strongest in the context of each adaptive transfer game type, all γ's = -.89, p's < .01. The latent intercept of individualized challenge did not exhibit any relationships with the training outcomes in any of the Baseline Models. However, as in the models of learner-controlled practice difficulty, post-training performance demonstrated a positive relationship with all types transfer performance, γ's > .85, p's < .01 for games that entailed increased difficulty and a new map, and γ =.47, p < .01 for games that entailed new weapons. Additionally, strategic knowledge had a positive influence on adaptive transfer games that included new weapons (γ =.15, p < .05), a relationship that was also observed in the context of learner-controlled practice difficulty. Unlike the learner-controlled practice difficulty models, results of the Baseline Models for individualized challenge revealed a positive relationship between basic knowledge and transfer performance when a new map was used, γ =.20, p < .05, one-tailed. Final models (i.e., the Baseline Model) for individualized challenge with the increased difficulty, new weapons, and new map adaptive transfer games are presented in Figures 13, 14, and 15, respectively.

These results suggest that the effects of learner-controlled practice difficulty and individualized challenge on the training outcomes are markedly different from each other. Whereas learner-controlled practice difficulty demonstrated positive influences on basic and strategic knowledge as well as post-training performance, individualized challenge exhibited strong negative influences on the same three outcomes. Additionally, whereas the effects of practice difficulty were observed primarily with respect to overall average levels, individualized challenge exhibited its negative influences exclusively in terms of growth over the course of practice. Furthermore, although neither practice difficulty nor individualized challenge had a direct influence on any of the types of adaptive transfer performance, both variables were related to adaptive transfer via the mediating role of post-training performance.

Discussion

Active learning approaches to training have become common methods of promoting knowledge, skill, and adaptive transfer. However, the roles of difficulty and challenge in active learning situations have received little empirical attention despite the ability of learners to influence the degree of difficulty in nearly any learner-controlled environment (Hughes et al., 2012). Moreover, given the multidimensional nature of transfer (Barnett & Ceci, 2002), it is important for researchers to begin examining adaptive transfer outcomes using multiple measures with respect to its various subcomponents. Using a LGM approach, the present study examined the roles of learner-controlled practice difficulty and individualized challenge in an active learning environment with respect to key processes as well as knowledge, performance, and adaptive transfer outcomes.

Individual Differences

The influences of the individual differences were disparate with respect to learner-controlled practice difficulty and individualized challenge. This was true whether the dependent variable was operationalized in terms of an overall average level or growth over the course of practice. Specific findings regarding these issues are discussed in more detail below. Results of exploratory analyses of the relationships between the individual differences and the active learning processes are also discussed.

Practice difficulty and individualized challenge. GMA was positively related to the latent slope of practice difficulty and the latent intercept of individualized challenge. With greater levels of GMA, individuals are better able to manage complexity (Gottfredson, 1997; Gordon, 1997) and acquire a deeper understanding of tasks at a faster rate (Gottfredson, 2002). Over the course of practice, participants with more GMA demonstrated greater increases in their practice difficulty relative to those with less GMA suggesting that they were learning the task faster. Moreover, these brighter participants were able to increase their difficulty choices without necessarily challenging themselves at a faster rate than those who had less GMA. Furthermore, because participants with higher levels of GMA challenged themselves more on average, brighter individuals may be more likely to recognize the importance of stretching one's capabilities to promote learning and skill (Hughes et al., 2012).

Additionally, pre-training skill was positively related to the overall level of learner-controlled practice difficulty but was unrelated to individualized challenge. Considered together, this pattern suggests that participants with greater pre-training skill, despite the higher difficulty of their practice games, were not challenged more than less skilled participants who chose easier practice games. Also, pre-training skill was negatively related to the latent slope of learner-controlled practice difficulty. However, given their higher levels of practice difficulty overall, this negative relationship is likely a result of highly skilled participants being limited in their ability to increase their difficulty choices over practice. That is, because participants with more pre-training skill started closer to the upper limit of practice difficulty, they were unable to significantly increase their practice difficulty levels over the course of practice whereas less skilled participants could continue to raise their difficulty levels throughout.

Whereas pre-training skill provided a task-specific indicator of expertise, videogame experience was an assessment of general videogame playing habits. Nonetheless, videogame experience was positively related to the intercept of learner-controlled practice difficulty, providing incremental validity beyond the influence of pre-training skill. Thus, even if one's knowledge is not particular to a given training task, having a broad understanding of a domain in general may promote trainees' overall levels of learner-controlled practice difficulty.

Pre-training self-efficacy was positively related to the overall average level of practice difficulty. Thus, participants with higher self-efficacy prior to training engaged in more difficult games throughout practice. This finding supports the notion that self-efficacy has a positive relationship with individuals' willingness to choose difficult tasks (Bandura, 1997; Tolli & Schmidt, 2008; Wood & Bandura, 1989) and conforms with previous studies that have also shown similar relationships (Ford et al., 1992; Hughes et al., 2012). On the other hand, pre-training self-efficacy demonstrated a negative influence on the overall level of individualized challenge. Although some researchers (e.g., Vancouver & Kendall, 2006; Vancouver, More, & Yoder, 2008) have argued that self-efficacy can lead to decreases in effort and resource allocation (thereby providing a potential explanation for this finding), the way in which individualized challenge was operationalized is more likely the source of this negative relationship. Specifically, individualized challenge was essentially computed by taking the inverse of self-confidence, a variable which by definition should be strongly related to self-efficacy. In fact, the self-confidence measure used in the present study was adapted from a method of assessing self-efficacy proposed in the extant literature (Bandura, 1986; Wood & Bandura, 1989). Therefore, the observed negative influence of pre-training self-efficacy on individualized challenge as a statistical artifact cannot be ruled out.

Finally, with the exception of the performance-avoid dimension, none of the goal orientation variables were related to either learner-controlled practice difficulty or individualized challenge. Particularly unexpected was the lack of a direct positive influence of mastery goal orientation on either repeated variable. That is, individuals with a mastery orientation should seek challenging opportunities from which they can learn (Elliott & Dweck, 1988). Nonetheless, mastery goal orientation was positively related to metacognition, thereby demonstrating an indirect influence on learner-controlled practice difficulty. This finding is discussed later in more detail.

As previously mentioned, the general role of performance-prove goal orientation with respect to a variety of potential outcomes remains unclear in the literature. However, some have suggested that its influence on other variables may be dependent upon task-specific confidence or self-efficacy (Dweck, 1986; Payne et al., 2007). This condition may be especially relevant given the outcome variables of practice difficulty and individualized challenge. That is, participants possessing a tendency to demonstrate their ability would presumably first need to be confident that they could succeed at a given level of difficulty. Additionally, recent meta-analytic evidence suggests that the wording of items used to assess performance-prove goal orientation affects the relationships it has with learning outcomes (Hulleman et al., 2010). Specifically, measures of performance-prove goal orientation containing normative statements (i.e., performance compared to others) tend to exhibit positive relationships whereas measures focused on appearance (i.e., performance displayed to others) demonstrate negative relationships. Both types of items comprised the scale used in the present study.

Regarding performance-avoid goal orientation, a negative influence was observed on the practice difficulty latent slope indicating that participants with a stronger performance-avoid orientation increased the difficulty of their games less over the course of practice. Indeed, performance-avoid goal orientation is characterized by an aversion to negative and unfavorable judgments from others as a result of appearing incompetent (Dweck, 1986; VandeWalle, 1997). Certainly, the degree of difficulty associated with any task is likely to have strong negative relationships with performance. However, because performance-avoid goal orientation was unrelated to the intercept of practice difficulty, the negative influence of performance-avoid goal orientation appears to have developed gradually over the course of practice. For instance, participants may have initially attributed their poor performance to a lack of practice or experience rather than the difficulty of the games. With more practice, the poor performance outcomes associated with high levels of difficulty would have become increasingly salient, and participants possessing a high performance-avoid goal orientation steadily decreased their degree of practice difficulty as a result.

Active learning processes. With respect to metacognition, positive relationships were observed with videogame experience, pre-training self-efficacy, and mastery goal orientation. With more videogame experience, participants likely had a better understanding of the specific game aspects that were important to consider for effective performance. Conversely, participants without sufficient videogame experience may not have known what game aspects to monitor, evaluate, and strategize around. In fact, in any learner-controlled training environment, trainees without some minimal level of task knowledge may fail to learn simply because they are unable to recognize the important elements of the instructional content (Mayer, 2004).

Pre-training self-efficacy also had a positive influence on metacognition during practice. Although studies have often supported the positive effect of metacognitive activity on subsequent self-efficacy (Bell & Kozlowski, 2008; Ford et al., 1998; A. M. Schmidt & Ford, 2003), the direction of the relationship observed in the present study is not typically proposed. Nonetheless, individuals with high self-efficacy are more likely to remain focused on learning the task at hand than those lacking in self-efficacy (Bandura, 1990). Following episodes of poor performance, individuals who lack self-efficacy are especially likely to direct their thought processes inward and attribute their performance to a lack of ability (Bandura, 1990; Silver et al., 1995). Furthermore, possessing a positive sense of self-efficacy helps facilitate one's cognitive engagement in a task and can serve to motivate learners to acquire additional knowledge and skills (Pintrich & De Groot, 1990; Schunk, 1985).

Prior research has also found mastery goal orientation to be positively related to metacognitive activity (Bell & Kozlowski, 2008; Ford et al., 1998). Individuals with a mastery orientation desire to learn (Colquitt & Simmering, 1998). Similarly, they tend to rely on cognitive strategies and processes information at a deep rather than surface level (Dweck, 1986; Elliot, McGregor, & Gable, 1999; Meece, 1994;

VandeWalle, 1997). Moreover, mastery goal orientation did not exhibit a direct relationship to learner-controlled practice difficulty. Instead, the relationship between the two variables was mediated by metacognition. These results support previous research by Ford et al. (1998), who found that mastery goal orientation was related to learning via metacognitive strategies rather than any task-specific practice strategies.

The overall average level of self-evaluation (which was modeled with a latent intercept only) was positively related to GMA and pre-training skill. Some researchers have proposed that engaging in self-regulation requires cognitive and attentional resources (Kanfer & Ackerman, 1989). Although other research suggests such cognitive demands to be minimal (DeShon, Brown, & Greenis, 1996; Sitzmann et al., 2009), many individuals do not maintain self-regulatory processes over the course of instruction (Butler & Winne, 1995; Sitzmann & Ely, 2010). Given the present findings, the greater cognitive resources available to brighter participants may explain the positive influence of GMA on self-evaluation observed here. Furthermore, unlike self-report measures of self-regulation (including the measure of metacognition used here), the present study required participants to freely recall their practice experiences before providing open-ended self-evaluations. Thus, GMA may be more important for engaging in self-evaluation processes when its operationalization necessitates greater cognitive resources.

It is surprising that pre-training skill was positively related to self-evaluation but not metacognition. Nonetheless, those with more pre-training skill were likely better performers during practice. Because reflecting on poor performance can be detrimental to one’s ego and self-efficacy (Bandura, 1977, 1986), participants with lower levels of pre-training skill may have actively avoided evaluating their (poorer) practice performance as opposed to participants with more pre-training skill.

Finally, videogame experience, pre-training self-efficacy, and performance-avoid goal orientation all exhibited influences on self-efficacy during practice (which was also modeled with a latent intercept only). Specifically, videogame experience and pre-training self-efficacy were positively related to the overall level of self-efficacy. With more experience and expertise, participants may have been better able to make sense of the complexities entailed by the game (Haerem & Rau, 2007; Wood, 1986) and therefore possessed more confidence in their playing ability and effectiveness. Likewise, participants who were more self-efficacious prior to training continued to possess higher levels of self-efficacy during practice. Having a strong belief in one’s self-efficacy may be particularly critical when tasks are difficult and perseverance is needed (Gist & Mitchell, 1992).

Performance-avoid goal orientation exhibited a negative influence on self-efficacy during practice. Individuals possessing a performance-avoid goal orientation are anxious about performing, attribute negative performance to a lack of ability, and may become preoccupied with even the possibility of failure (Elliot & Church, 1997; McGregor & Elliot, 2002; VandeWalle, 1997). Similarly, when individuals with low self-efficacy experience failure, they may direct their thoughts inward, focusing on perceived inability rather than the task at hand (Bandura, 1990). Moreover, meta-analytic findings have shown that performance-avoid but not performance-prove orientation is consistently (i.e., reliably) negatively related to self-efficacy (Payne et al., 2007).

Self-imposed Challenge as an Active Learning Intervention

Results of the conditional latent growth models confirmed the positive influence of the self-imposed challenge manipulation on learner-controlled practice difficulty and individualized challenge. Specifically, participants in the “outmatched” condition chose more difficult and challenging games with respect to overall levels than those in the “matched” condition. Self-imposed challenge was unrelated to either variable’s latent slope. However, the instructions were intended to generate differences in overall degree of practice difficulty and challenge, and not to influence differential rates of change.

Concerning the effects of the self-imposed challenge manipulation on the active learning processes, self-imposed challenge was positively related only to the overall level of self-evaluation, and it was unrelated to metacognition and self-efficacy. In general, active learning interventions are meant to direct trainees’ self-regulation to promote learning (Bell & Kozlowski, 2008; Kozlowski et al., 2001). However, metacognition and self-efficacy were linked to practice difficulty, which was the direct target of the self-imposed challenge manipulation. In addition, although these results showed that extreme as compared to moderate levels of self-imposed challenge did not increase one’s metacognitive behavior or self-efficacy, a control condition was not used in the present study. Therefore, it is unclear whether any amount of encouragement to challenge one’s self may lead to increased metacognition and self-efficacy as compared to discouragement from challenge and choosing difficult practice games.

Roles played by the Active Learning Processes

Another important goal of the present study was to empirically examine the nature of the roles played by active learning process variables in relation to learner-controlled practice difficulty, individualized challenge, and ultimately adaptive transfer performance. Self-regulatory variables such as metacognition, self-evaluation, and self-efficacy are commonly proposed as process variables that mediate the influence that active learning behaviors such as exploration have on learning outcomes. However, the results of the present study demonstrate how such self-regulation variables can also influence active learning behaviors. Specifically, metacognition and self-efficacy were positively related to subsequent levels of learner-controlled practice difficulty. In this respect, practice difficulty is akin to exploration in that by choosing to play games at higher levels of difficulty, participants explored higher levels of task complexity.

One reason for the observed relationship between metacognition and learner-controlled practice difficulty may stem from the ability of self-regulatory processing to enhance one's sense of control. For instance, Sitzmann and Ely (2010) proposed that self-regulation may promote an internal locus of control, thus instilling a belief that one's performance is determined by one's efforts. In support of this theory, they found prompting self-regulation reduced attrition in a learner-controlled environment. That is, learners were willing to continue putting effort into the learning process and thus remained in training. Similarly, Winne (1995) suggested that learners who self-regulate will seek out difficult tasks because they believe greater effort will lead to greater success. Moreover, it is possible that self-regulation and metacognition in particular promote feelings of control as a result of learning. That is, the more participants monitored their progress and performance, considering past failures and planning future strategies, the more task knowledge they presumably acquired. Thus, they viewed their metacognitive efforts as worthwhile given their increased understanding of the game and therefore sought additional difficulty and complexity as a result.

Compared to metacognition, the relationship between self-efficacy and learner-controlled practice difficulty over the course of practice is more straightforward. Indeed, having a strong sense of self-efficacy promotes task effort and goal striving, which ultimately spur one’s desire to seek difficult tasks and persistence in spite of obstacles (Bandura, 1977, 2001; Bandura & Locke, 2003; Bandura & Wood, 1989; Stevens & Gist, 1997; Wood & Bandura, 1989). What is surprising was the lack of an influence of practice difficulty on subsequent levels of self-efficacy. That is, it was expected that learners who chose more difficult games would attain a greater sense of mastery than those who chose easy games, thereby enhancing self-efficacy beliefs (Hughes et al., 2012). However, poor performance can be particularly detrimental to one’s mastery expectations and therefore perceived self-efficacy (Bandura, 1977), and the participants who chose more difficult games in the present study would have experienced more unfavorable performance outcomes as a result.

Surprisingly, self-evaluation was not related to either learner-controlled practice difficulty or individualized challenge. Like metacognition, self-evaluation is a form of cognitive self-regulation, and Hughes et al. (2012) found that learner-controlled practice difficulty had a positive influence on self-evaluation. However, whereas metacognition entails more than just evaluative processes, self-evaluation is concerned only with assessing one's performance. Given that all participants in the present study were instructed to challenge themselves, it is likely that many participants' self-evaluations were unfavorable (i.e., higher difficulty and challenge yield poorer performance). In fact, average levels of learner-controlled practice difficulty were higher in the present study ($M = 4.96$, $SD = 1.08$) compared to Hughes et al. (2012; $M = 3.58$, $SD = 0.93$), which also utilized the same range of practice difficulty settings, $t(272) = 10.85$, $p < .01$, $d = 1.39$. As such, the more participants evaluated their progress and performance, the less likely they would have been to choose difficult or challenging games. If this explanation is correct, the nature of the cause-and-effect relationship between practice difficulty or individualized challenge and self-evaluation may depend upon participants' self-imposed challenge condition.

Indeed, after reexamining the cross-lagged panel analyses between learner-controlled practice difficulty and self-evaluation by experimental condition, results were supportive of this conclusion. Specifically, for participants in the "matched" condition, practice difficulty had a positive influence on self-evaluation from Time 1 to Time 2 ($\gamma_{1 \rightarrow 2} = .08$, $p < .05$). However, this relationship disappeared from Time 2 to Time 3, likely due to their higher levels of practice difficulty at this point in the study. For participants in the "outmatched" condition, practice difficulty exhibited a negative influence on self-evaluation over the course of practice, $\gamma_1 \rightarrow_2 = -.16$, $p < .01$, and $\gamma_2 \rightarrow_3 = -.12$, $p < .05$. These findings are in line with a recent study by Sitzmann and Ely (2010) who found that trainees engaged in less self-regulatory processing following poor performance unless they received explicit prompts to self-regulate throughout practice. Furthermore, the direction of the cause-and effect relationship observed here aligns with the direction found by Hughes et al. (2012). With respect to individualized challenge, inadmissible solutions were obtained for participants in the "matched" condition, and no causal relationships were observed for those in the "outmatched" condition.

Relationships with the Training Outcomes

As described previously, the latent growth models used in this study to examine the roles of learner-controlled practice difficulty and individualized challenge in relation to the training outcomes were based upon the findings from Hughes et al. (2012). Results of the present study support their findings that highlighted the positive role of learner-controlled practice difficulty in directly promoting knowledge and post-training performance. In addition, these results also showed practice difficulty to be positively related to adaptive transfer performance through the mediating effect of post-training performance. Moreover, these relationships were largely analogous across all types of adaptive transfer performance. However, the mediating role of task knowledge between practice difficulty and transfer performance found by Hughes et al. (2012) was mostly unsupported here. It should be noted that unlike Hughes et al. (2012), the present study included both basic and strategic components of task knowledge as separate factors, and strategic knowledge did play a mediating role between practice difficulty and adaptive transfer performance that entailed new weapons. Additionally, Hughes et al. (2012) used a different operationalization of adaptive transfer than any of the three types used here.

Although individualized challenge was not examined by Hughes et al. (2012), the present study also investigated its role with respect to the training outcomes by specifying models in which practice difficulty was substituted with individualized challenge. However, its influences on the knowledge, performance, and adaptive transfer outcomes were vastly different from the influences of practice difficulty. Specific findings regarding both repeated variables with respect to the training outcomes are discussed below.

Practice difficulty. Regardless of the particular type of adaptive transfer game, the best-fitting model for learner-controlled practice difficulty with the training outcomes was obtained by adding to the Baseline Model direct links from self-efficacy to post-training and transfer performance (although only its relationship with post-training performance was significant). Specifically, the overall average level of learner-controlled practice difficulty was positively related to both basic and strategic knowledge. Importantly, practice difficulty was operationalized in terms of objective levels of task complexity as described by Wood (1986). Thus, as difficulty increased, participants would have been exposed to a greater quantity of information cues in terms of the computer-controlled bots' weapon use and gameplay strategies thereby facilitating participants' basic knowledge acquisition. In addition, the inherent coordination between game elements (e.g., players' and bots' maneuvers and strategies) as well as the dynamicity of the task would have been elevated when difficulty was higher. Consequently, participants' also would have learned more strategic knowledge when practice games were more difficult and complex.

The overall average level of learner-controlled practice difficulty also exhibited a positive influence on post-training performance. R. A. Schmidt and Bjork (1992) proposed that difficulties during the learning process have beneficial effects on knowledge and skill due to the retrieval processes that are promoted from managing difficult learning tasks. With respect to the training task used here, effective cognitive retrieval becomes increasingly critical as games become more difficult and thus complex. At high levels of practice difficulty, bots move very fast, attack often, and act without hesitation, all of which enhance the complexity of the game. To be effective at these high levels, participants would have needed to frequently recall appropriate strategies and resource locations to make quick decisions while playing. Conversely, at lower levels of practice difficulty, participants may have been able to rely mostly on trial-and-error and haphazard approaches to be effective.

Growth of learner-controlled practice difficulty over the course of practice also demonstrated positive influences on both basic knowledge and post-training performance in the context of all three types of adaptive transfer. That is, increasing one's practice difficulty levels irrespective of overall average levels had a positive influence on both basic knowledge and post-training performance. This finding is important because it suggests that even participants who practiced on less difficult and complex games overall were still able to build basic task knowledge and skill by increasing their personal levels of learner-controlled practice difficulty over the course of practice.

In addition to its positive relationships with both post-training and adaptive transfer performance via the mediating role of practice difficulty, overall levels of self-efficacy also had a direct positive influence on post-training performance. Although some researchers have suggested that self-efficacy may be particularly important for adaptive transfer performance, motivating individuals to persevere when faced with challenges entailed by many transfer situations (Kozlowski, Gully, et al., 2001), the level of specificity at which self-efficacy was measured may account for its direct influence on post-training rather than transfer performance as observed here. That is, whereas general self-efficacy refers to one's self-confidence to perform across a variety of situations (Judge, Erez, Bono, & Thoresen, 2002), the present study used a task-specific measure of self-efficacy with items framed explicitly with respect to UT2004. This qualification is important because the level of specificity at which self-efficacy is operationalized can influence its relationships with other variables (Chen, Gully, & Eden, 2004). In fact, Yeo and Neal (2006) showed that general self-efficacy was positively related to performance through the mediating effect of task-specific self-efficacy. Regarding the present study, although the task itself did not change from tests of post-training to adaptive transfer, significant features of the task did, thereby changing the nature of the game. As such, self-efficacy as measured here exhibited a stronger relationship with post-training performance than adaptive performance.

Finally, results of the present study showed that strategic knowledge had a positive influence on transfer performance but only when it was assessed with new weapons. Although an assessment of participants' perceptions of the three different transfer game types indicated that adapting to new weapons was not conceptually distinct from adapting to a new map with respect to Barnett and Ceci's (2002) content component of transfer, this finding is indicative of the multidimensional nature of adaptive transfer nonetheless.

Individualized challenge. Unexpectedly, individualized challenge failed to exhibit any positive relationships with the training outcomes examined in this study. Instead, growth of challenge over the course of practice had strong negative influences on both basic and strategic knowledge as well as post-training performance, while overall levels of challenge were unrelated to the training outcomes. That is, increasing one's level of challenge throughout practice was related to marked decrements in knowledge and skill learning.

Scaffolding, a concept from the educational psychology literature, may help provide perspective for interpreting this finding. To be clear, scaffolding is a social process between a learner and instructor (Wood, Bruner, & Ross, 1976), and a detailed discussion of the concept is outside the scope of this paper. Nonetheless, one of the key tenets of scaffolding is that a learner should be presented with tasks at or slightly above his or her capabilities (van de Pol, Volman, & Beishuizen, 2010). Accordingly, learners should be challenged, but challenges should be attainable as insurmountable obstacles will likely lead to frustration and withdrawal from the task (Doering & Veletsianos, 2007).

Adaptive guidance is another instructional approach with relevance to the present findings. Specifically, adaptive guidance is a form of learner-controlled instruction designed to provide personalized feedback, evaluations, and recommendations for progression through a computer-based learning environment (Bell & Kozlowski, 2002). Importantly, trainees' understanding of foundational, prerequisite knowledge and skills provides the basis for adaptive guidance such that learning is sequenced to ensure individuals do not attempt tasks that are too difficult or for which they are unprepared (Bell & Kozlowski, 2002; Hsiao, Sosnovsky, & Brusilovsky, 2010). In fact, some adaptive guidance programs have been developed based on principles of scaffolding (Guzdial & Kehoe, 1998; Kenny & Pahl, 2009). In all, participants who chose increasingly more challenging games over the course of practice may not have developed sufficient knowledge or proficiency of fundamental game principles or skills prior to seeking an even greater degree of challenge. As a result, those participants were unprepared for managing the complexities of the game and were unable to learn from their practice experiences.

Study Limitations and Directions for Research

The use of LGM is becoming an increasingly common approach to investigate phenomena not only at the between-subjects level of analysis but also within-subjects with respect to longitudinal growth. Although the present study was able to use this approach to examine the repeated measures variables in terms of linear growth trends, the availability of only three repeated observations per variable placed limitations on examining higher-order growth curve models. In fact, repeated measures ANOVAs suggested quadratic as well as linear trends for learner-controlled practice difficulty, individualized challenge, and self-evaluation. Thus, future research is needed to determine whether modeling higher-order growth trends result in similar relationships between the repeated variables, individual differences, and training outcomes. Nonetheless, the present study provides the first empirical investigation of learner-controlled practice difficulty and individualized challenge over time in the context of an active learning training environment.

With respect to the operationalization of self-efficacy in particular, the inability to represent its role in this study beyond an overall average level is particularly regrettable. Currently, an accumulating amount of research suggests that the level of analysis at which self-efficacy is conceptualized can have important qualifications regarding its relationships with both knowledge and performance learning outcomes. For instance, research has shown that, despite its generally positive relationships with performance at a between-persons level of analysis, the influence of self-efficacy when examined at the within-persons level is often negative (Vancouver & Kendall, 2006; Vancouver, Thompson, Tischner, & Putka, 2002; Vancouver, Thompson, & Williams, 2001; Yeo & Neal, 2006). Unfortunately, the within-persons effect of self-efficacy on the performance outcomes could not be examined here because individual growth of self-efficacy was not significant in the present study. Consequently, the significant (and nonsignificant) relationships between self-efficacy and learner-controlled practice difficulty as well as the training outcomes reflect only between-persons effects of self-efficacy. Therefore, it is possible that a different pattern of results would have emerged if self-efficacy could have been represented also in terms of growth over the course of practice.

Another limitation of this study concerns the operationalization of individualized challenge. Specifically, participants' self-confidence ratings were assessed prior to each practice session. Those ratings were then used in relation to the actual difficulty levels they chose in that session. In this way, the degree of individualized challenge was also an indication of the degree of challenge participants self-imposed upon themselves. Although this operationalization aligned with the self-imposed challenge manipulation used in the present study, it did not allow any conclusions to be made concerning participants' perceptions. This qualification is important because one's perceptions of challenge can have consequences for the learning process and resulting outcomes.

For a given level of task complexity, different individuals may have different perceptions of task difficulty and thus experience different amounts of challenge while performing a task (Campbell, 1988; Robinson, 2001; Wood, 1986). For instance, individuals with less domain expertise or GMA will experience greater challenge and cognitive load while learning a given task (Beckmann, 2010; Moreno, 2006; Van Gog, Kester, & Paas, 2011). When faced with high amounts of cognitive load, learners may become overwhelmed by a task, which in turn can result in decreased learning (Paas, Van Gog, & Sweller, 2010). However, with more expertise, learners will have greater access to domain-specific schemas (Paas & Sweller, 2012). Schemas, or organized elements of information, make learning and problem solving less challenging because they reduce an individual's working memory load and promote automation (Sweller, 1994). In all, despite the individualized index of challenge used in the present study, the role of subjective perceptions of challenge and associated cognitive demands on the active learning processes and training outcomes cannot be determined.

With respect to the concept of desirable difficulties (Bjork, 1994; R. A. Schmidt & Bjork, 1992), results of the present study replicate findings from Hughes et al. (2012) that demonstrate the positive influence of learner-controlled practice difficulty on knowledge and performance outcomes. In particular, both studies found that post-training performance mediated the effect of practice difficulty on adaptive transfer performance. However, in both studies, tests of performance were administered shortly after practice, and difficulty during the learning process is thought to promote not only performance in novel circumstances but retention and delayed performance as well (Bjork, 1994; R. A. Schmidt & Bjork, 1992). That is, additional research is needed to examine the effects of learner-controlled practice difficulty and individualized challenge on both knowledge and skill learning following extended periods of nonuse.

Additionally, the present findings failed to demonstrate consistent relationships between task knowledge and adaptive transfer performance with the exception of the influence of strategic knowledge on transfer performance entailing new weapons. Instead, the positive relationships between leaner-controlled practice difficulty and the adaptive transfer tests were largely mediated by post-training performance. However, some research suggests that experiential, case-based knowledge is important for learning and promoting transfer (Kolodner, 1997). That is, previous experiences serve as specific lessons which can be retrieved from memory and applied to new situations and problems (Kolodner, 1997), thereby allowing individuals to effectively leverage their knowledge of past successes and failures (Hammond, 1990).

In the present study, post-training performance is reflective of participants' case-based knowledge. Specifically, participants' effective performance in the test of post-training skill may have been heavily dependent upon their ability to recall similar situations experienced during practice and directly apply that knowledge while playing the game. In turn, when faced with the adaptive transfer tests, participants who could most effectively recognize the similarities amongst the differences compared to their previous game experiences may have performed better as a result.

Regarding the assessments of adaptive transfer, participants' perceptions of the three game types indicated that the dimensions proposed by Barnett and Ceci (2002) entailing the transfer of procedures and heightened memory demands were confounded in their measurement. Because the transfer games that included new weapons and those that included a new map assessed both dimensions simultaneously, it is unclear from this study whether learner-controlled practice difficulty and individualized challenge may play different roles in promoting each type of transfer individually. Similarly, the influences of the active learning processes examined here as well as other potential processes need to be examined separately in relation to these dimensions. Furthermore, because interactions between transfer dimensions are possible if not likely (Barnett & Ceci, 2002), future studies should attempt to more precisely determine how the combination of different transfer dimensions affect their prediction.

Nevertheless, it is noteworthy that strategic knowledge had a direct, positive relationship on transfer performance when participants were given new weapons but not when they played in a new map despite participants' perceptions that both games entailed a reliance on principles over procedures as well as heightened memory demands. Although this finding may be due in part to different degrees of each transfer dimension associated with the two game types, it may also be a result of contextual factors not considered by the present study. Barnett and Ceci (2002) describe six contextual dimensions of transfer, one of which relates to the physical environment in which transfer occurs. Although the real-world environment (i.e., the computer lab) did not change across adaptive transfer games, the virtual environment in which participants played was different for the transfer games that used a new map. As such, participants were forced to apply their learned knowledge and skills in a different context given the new game map, which in turn may have influenced the differential relationship strategic knowledge had with the adaptive transfer games.

Furthermore, this finding is important in that it provides empirical evidence for the fact that the way in which adaptive transfer is assessed can alter the relationships that potential influential variables have with performance. Moreover, the present study relied only on the taxonomy proposed by Barnett and Ceci (2002), and additional means of characterizing transfer beyond their taxonomy may exist. Given the importance of promoting adaptive performance in today's organizations and the attention it receives in the training literature, it is surprising that more theoretical work has not been published examining the adaptive transfer construct.

Indeed, attaining a better understanding of adaptive transfer is crucial for advancing the science of training.

An additional research need stemming from this study concerns the generalizability of these findings. Specifically, participants in in the present study were all males. This limitation arose as a result of pilot testing with the game in which the majority of female participants displayed a general lack of interest and motivation to learn. Also related to the issue of generalizability, the videogame training task used here entails both cognitive and psychomotor components making it quite distinct from other instructional settings focused primarily on facilitating cognitive learning outcomes and decision making processes. However, synthetic learning environments including the use of computer-based simulations and even videogames are becoming more common in today's technology-driven society (Cannon-Bowers & Bowers, 2009; Committee on Modeling, Simulation, and Games; Standing Committee on Technology Insight–Gauge, Evaluate, and Review; National Research Council, 2010; Hays & Vincenzi, 2000; Hussain et al., 2009; U.S. Air Force, Air Education and Training Command, 2008). Nonetheless, future research should examine the roles of learner-controlled practice difficulty, individualized challenge, and various active learning processes in the context of other training environments.

Conclusion

Given the importance of an adaptable workforce to modern organizations in a wide variety of settings, this study examined the roles of learner-controlled practice difficulty and associated levels of individualized challenge in promoting adaptive transfer of a complex task. Specifically, the present research used LGM to examine learners' choices of practice difficulty and individualized challenge longitudinally in an active learning environment. In addition to identifying a number of individual differences influencing learners' difficulty and challenge choices with respect to both overall average levels and growth over the course of practice, the influence of metacognition and self-efficacy during training on learner-controlled practice difficulty were demonstrated. Although current literature emphasizes the effect of active learning interventions on self-regulatory processes, the present findings highlight the need to examine the potential role that such processes can have on influencing active learning behaviors over time. The present study also extends the work of Hughes et al. (2012) by demonstrating that increases in learner-controlled practice difficulty as well as overall levels can be beneficial for building both knowledge and skill. Moreover, practice difficulty was shown to have a positive influence on adaptive transfer performance via the mediating effect of post-training performance. Conversely, increasing one's personal level of individualized challenge over the course of practice was negatively related to both knowledge and post-training performance, and ultimately adaptive transfer performance. Furthermore, the findings from this study emphasize the need for a better understanding of the adaptive transfer construct and the use of multidimensional frameworks when assessing transfer outcomes.

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Table 1

Means, Standard Deviations, and Correlations for all Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Challenge manipulation	0.50	0.50																			
2. GMA	8.41	2.23	-.07																		
3. Mastery GO	4.01	0.48	.03	.01																	
4. Performance-prove GO	3.96	0.60	-.13	-.14	.14																
5. Performance-avoid GO	2.67	0.81	-.03	-.23**	-.30**	.24**															
6. Pre-training self-efficacy	3.44	0.66	-.03	.08	.16	-.07	-.21**														
7. Pre-training skill	0.33	0.11	-.12	.01	.08	-.07	-.00	.37**													
8. Videogame experience	0.00	0.82	.05	.07	-.01	-.06	.10	.13	.36**												
9. Metacognition	3.71	0.46	.11	.14	.27**	-.06	-.24**	.38**	.26**	.28**											
10. Self-evaluation	2.67	0.57	.13	.26**	.06	-.18*	-.17*	.22**	.26**	.12	.36**										
11. Self-efficacy	3.57	0.62	-.05	.11	.22**	-.09	-.32**	.86**	.40**	.21**	.46**	.24**									
12. Practice difficulty	4.96	1.08	.42**	.17*	.17*	-.06	-.16	.38**	.43**	.35**	.34**	.37**	.42**								
13. Individualized challenge	5.00	2.08	.51**	.16*	-.01	-.08	-.04	-.20*	-.12	.07	.03	.22**	-.19*	.48**							
14. Basic knowledge	14.86	1.87	-.11	.30**	-.07	.03	-.10	.18*	.31**	.33**	.18*	.15	.28**	.32**	.03						
15. Strategic knowledge	11.94	2.28	-.17*	.13	-.01	.06	-.02	.17*	.34**	.26**	.09	.07	.25**	.29**	-.09	.55**					
16. Practice performance	0.36	0.09	-.62**	-.03	-.08	.07	.20*	-.12	.24**	.13	-.09	-.17*	-.07	-.53**	-.52**	.13	.16*				
17. Post-training performance	0.47	0.14	-.03	.07	.24**	-.06	-.11	.26**	.57**	.40**	.26**	.23**	.40**	.51**	-.06	.31**	.33**	.21*			
18. Transfer performance – Increased difficulty	0.28	0.12	-.06	.13	.08	-.06	-.01	.27**	.56**	.39**	.35**	.27**	.35**	.47**	-.06	.35**	.31**	.27**	.66**		
19. Transfer performance – New weapons	0.35	0.10	-.01	.23**	.03	-.11	-.08	.24**	.40**	.33**	.21**	.18*	.30**	.46**	.05	.34**	.36**	.17*	.50**	.63**	
20. Transfer performance – New map	0.34	0.13	.05	.11	.04	-.08	-.03	.28**	.56**	.45**	.27**	.21**	.36**	.53**	.07	.37**	.25**	.14	.60**	.61**	.55**

Note. $N = 152$. For Challenge manipulation, matched = 0 and outmatched = 1. GMA = general mental ability; GO = goal orientation. Scores for practice difficulty, individualized challenge, metacognition, self-evaluation, and self-efficacy are averaged across all three observations for each variable.
* $p < .05$, ** $p < .01$ (two-tailed).

Table 2

Means, Standard Deviations, and Correlations for Repeated Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Metacognition 1	3.66	0.49														
2. Metacognition 2	3.72	0.51	.75**													
3. Metacognition 3	3.74	0.55	.60**	.73**												
4. Self-evaluation 1	2.92	0.67	.33**	.28**	.29**											
5. Self-evaluation 2	2.60	0.57	.27**	.31**	.31**	.76**										
6. Self-evaluation 3	2.50	0.61	.26**	.28**	.36**	.77**	.78**									
7. Self-efficacy 1	3.59	0.66	.52**	.38**	.25**	.25**	.25**	.19*								
8. Self-efficacy 2	3.62	0.67	.46**	.39**	.26**	.15	.22**	.14	.81**							
9. Self-efficacy 3	3.62	0.76	.41**	.39**	.35**	.19*	.25**	.20*	.77**	.84**						
10. Practice difficulty 1	4.60	1.17	.31**	.29**	.21**	.20*	.23**	.23**	.38**	.35**	.31**					
11. Practice difficulty 2	5.10	1.23	.39**	.25**	.19*	.32**	.31**	.30**	.45**	.35**	.29**	.74**				
12. Practice difficulty 3	5.17	1.33	.26**	.23**	.26**	.36**	.34**	.34**	.32**	.30**	.30**	.51**	.66**			
13. Individualized challenge 1	4.56	2.28	.17*	.11	.04	.18*	.18*	.13	.02	-.03	-.10	.43**	.50**	.34**		
14. Individualized challenge 2	5.34	2.56	.03	-.05	-.03	.15	.18*	.14	-.22**	-.17*	-.23**	.18*	.47**	.32**	.57**	
15. Individualized challenge 3	5.10	2.71	-.04	-.06	.07	.19*	.20*	.14	-.16*	-.17*	-.14	.07	.21**	.57**	.42**	.58**

Note. $N = 152$. Self-evaluation, self-efficacy, and metacognition were assessed in that order immediately after the corresponding practice session at each observation.

* $p < .05$, ** $p < .01$ (two-tailed).

Table 3

Fit Statistics for Unconditional Latent Growth Models

Variable	Model	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]
Practice difficulty	Intercept-only	60.07	4	.72	.17	.30 [.38]
	Intercept & slope	11.61	1	.95	.05	.27 [.41]
Individualized challenge	Intercept-only	26.43	4	.82	.11	.19 [.27]
	Intercept & slope	10.59	1	.92	.06	.25 [.40]
Metacognition	Intercept-only	14.34	4	.96	.08	.13 [.21]
	Intercept & slope	1.38	1	1.00	.02	.05 [.23]
Self-evaluation	Intercept-only	102.03	4	.67	.18	.40 [.47]
	Intercept & slope			*Inadmissible solution*		
Self-efficacy	Intercept-only	8.28	4	.99	.07	.08 [.17]
	Intercept & slope	0.65	1	1.00	.01	0.00 [.20]

Note. The self-evaluation, intercept & slope model returned an inadmissible solution, thus fit statistics are not reported. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval.

Table 4

Fit Statistics and Predictor Coefficients for Conditional Latent Growth Models

							γ							
Variable	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	DV[a]	Chal.	GMA	M GO	PP GO	PA GO	Pre-SE	Pre-Skill	VG Exp.
Practice difficulty	25.51	9	.96	.03	.11 [.16]	Intercept	.42**	.06	.02	.08	.03	.26**	.48**	.16*
						Slope	.14	.26*	.10	.03	-.30*	-.15	-.36**	.07
Individualized challenge	23.93	9	.94	.03	.10 [.16]	Intercept	.54**	.20*	.11	.04	.08	-.22*	.08	.16
						Slope	.19	.11	-.31	-.06	-.34	-.08	-.22	-.23
Metacognition	11.34	9	.99	.01	.04 [.11]	Intercept	.08	.10	.17*	.06	-.09	.33**	.03	.30**
						Slope	.10	-.06	.01	-.12	-.15	-.16	.13	-.19[†]
Self-evaluation	119.46	20	.75	.06	.18 [.21]	Intercept[b]	.17*	.24**	-.03	-.11	-.07	.11	.24**	-.02
Self-efficacy	38.78	20	.97	.03	.08 [.12]	Intercept[b]	-.04	-.01	.07	.00	-.20**	.68**	.09	.14*

Note. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; γ = standardized coefficient; Chal. = self-imposed challenge manipulation (0 = matched, 1 = outmatched); GMA = general mental ability; M GO = mastery goal orientation; PP GO = performance-prove goal orientation; PA GO = performance-avoid goal orientation; Pre-SE = pre-training self-efficacy; Pre-Skill = pre-training skill; VG Exp. = videogame experience.

[a]For each repeated variable, either its latent intercept or latent slope (if applicable) was the dependent variable associated with the predictor coefficients presented in the columns to its right. [b]Self-evaluation and self-efficacy were each modeled with an intercept only.

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

Table 5

Fit Statistics and Stability Coefficients for Autoregressive Latent Growth Models

Variable	Stability Coefficients	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	$\gamma_1\rightarrow_2$	$\gamma_2\rightarrow_3$
Practice difficulty	Constrained	12.82	8	.99	.02	.06 [.12]	.10**	.09**
	Independent	11.02	7	.99	.02	.06 [.13]	-.22	-.42
Individualized challenge	Constrained	10.88	8	.99	.02	.05 [.11]	.24**	.23**
	Independent	8.86	7	.99	.02	.04 [.11]	-.15	-.44
Metacognition	Constrained	9.91	8	.99	.01	.04 [.11]	.02	.01
	Independent				*Inadmissible solution*			
Self-evaluation	Constrained	38.21	19	.95	.03	.08 [.12]	-.14**	-.11**
	Independent	18.76	18	.1.00	.02	.02 [.08]	-.13**	-.16**
Self-efficacy	Constrained	36.61	19	.97	.03	.08 [.12]	.01	.01
	Independent	36.57	18	.97	.03	.08 [.12]	.01	.01

Note. The metacognition, independent stability coefficients model returned an inadmissible solution, thus fit statistics and stability coefficients are not reported. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; $\gamma_1\rightarrow_2$ = Time 1–Time 2 standardized stability coefficient; $\gamma_2\rightarrow_3$ = Time 2–Time 3 standardized stability coefficient.
* p < .05, ** p < .01 (two-tailed).

Table 6

Specification and Fit Statistics for Final Univariate Latent Growth Models

Variable	Slope	Stability Coefficients	Error Terms	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]
Practice difficulty	Yes	Constrained	Independent	12.82	8	.99	.02	.06 [.12]
Individualized challenge	Yes	Constrained	Constrained	13.11	10	.99	.02	.05 [.11]
Metacognition	Yes	None	Constrained	13.56	11	.99	.02	.04 [.10]
Self-evaluation	No	Independent	Independent	18.76	18	1.00	.02	.02 [.08]
Self-efficacy	No	None	Independent	38.78	20	.97	.03	.08 [.12]

Note. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval.

Table 7

Fit Statistics and Coefficients for Cross-lagged Latent Growth Models with Practice Difficulty

Process Variable	Cross-lagged Parameters	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	BIC	Difficulty to Process $\gamma_{1\to2}$	Difficulty to Process $\gamma_{2\to3}$	Process to Difficulty $\gamma_{1\to2}$	Process to Difficulty $\gamma_{2\to3}$
Metacognition	Independent					*Inadmissible solution*					
	Constrained	28.32	19	.99	.02	.06 [.10]	530.71	-.10	-.19	-.02	-.03
	Difficulty to Process	27.87	19	.99	.02	.06 [.10]	530.26	-.04	-.09		
	Process to Difficulty[a]	26.71	19	.99	.02	.05 [.09]	529.09			.16*	.27[†]
Self-evaluation	Independent	33.40	28	.99	.02	.04 [.08]	490.57	-.02	-.07	-.07	-.15
	Constrained[a]	34.16	30	.99	.02	.03 [.07]	481.29	-.01	-.06	.00	-.01
	Difficulty to Process	34.30	30	.99	.02	.03 [.07]	481.42	.00	-.05		
	Process to Difficulty	34.96	30	.99	.02	.03 [.07]	482.08			-.04	-.09
Self-efficacy	Independent	61.95	30	.97	.03	.08 [.11]	509.08	.01	.01	.27**	.36*
	Constrained	67.44	32	.96	.03	.09 [.11]	504.51	.01	.00	.00	.00
	Difficulty to Process	67.61	32	.96	.03	.09 [.11]	504.69	.01	.00		
	Process to Difficulty[a]	62.81	32	.97	.03	.08 [.11]	499.89			.26*	.34*

Note. Cross-lagged parameters were specified in four ways: (1) Independent = all possible paths were independently estimated, (2) Constrained = reciprocal paths were constrained to be equal by time, (3) Difficulty to Process = only paths directed *to* the active learning process were estimated, and (4) Process to Difficulty = only paths originating *from* the active learning process were estimated. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; BIC = Schwarz Bayesian Criterion; $\gamma_{1\to2}$ = Time 1–Time 2 cross-lagged parameter; $\gamma_{2\to3}$ = Time 2–Time 3 cross-lagged parameter.
[a]Indicates best-fitting model for each process variable.
[†] $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 8

Fit Statistics and Coefficients for Cross-lagged Latent Growth Models with Individualized Challenge

								Challenge to Process		Process to Challenge	
Process Variable	Cross-lagged Parameters	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	BIC	$\gamma_1 \rightarrow_2$	$\gamma_2 \rightarrow_3$	$\gamma_1 \rightarrow_2$	$\gamma_2 \rightarrow_3$
Metacognition[b]	Independent	40.52	32	.98	.03	.04 [.08]	477.60	.03	.01	-.03	-.05†
	Constrained	46.25	34	.98	.04	.05 [.08]	473.28	.02	-.03	.00	.00
	Challenge to Process	46.62	34	.98	.04	.05 [.08]	473.65	.04	.02		
	Process to Challenge[a]	42.36	34	.99	.03	.04 [.08]	469.39			-.03	-.05†
Self-evaluation	Independent	34.57	30	.99	.02	.03 [.07]	481.70	.01	-.04	-.05	-.09
	Constrained	34.83	32	1.00	.02	.02 [.07]	471.91	.02	-.03	.01	-.01
	Challenge to Process[a]	34.83	32	1.00	.02	.02 [.07]	471.91	.02	-.03		
	Process to Challenge	35.35	32	.99	.02	.03 [.07]	472.43			-.03	-.06
Self-efficacy[b]	Independent	69.12	44	.97	.04	.06 [.09]	445.91	.03	.01	-.05	-.08*
	Constrained	77.12	46	.96	.04	.07 [.09]	443.87	.02	.01	.00	.00
	Challenge to Process	77.13	46	.96	.04	.07 [.09]	443.88	.03	.02		
	Process to Challenge[a]	70.94	46	.97	.04	.06 [.09]	437.68			-.05†	-.08*

Note. Cross-lagged parameters were specified in four ways: (1) Independent = all possible paths were independently estimated, (2) Constrained = reciprocal paths were constrained to be equal by time, (3) Challenge to Process = only paths directed *to* the active learning process were estimated, and (4) Process to Challenge = only paths originating *from* the active learning process were estimated. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval; BIC = Schwarz Bayesian Criterion; $\gamma_1 \rightarrow_2$ = Time 1–Time 2 cross-lagged parameter; $\gamma_2 \rightarrow_3$ = Time 2–Time 3 cross-lagged parameter.
[a]Indicates best-fitting model for each process variable. [b]Challenge was modeled with an intercept only due to negative variance estimates of the slope or otherwise inadmissible solutions given its inclusion.
† $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Table 9

Fit Statistics and Model Comparisons for Latent Growth Models with Practice Difficulty and Training Outcomes

Transfer Game	Model	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	Models Compared	$\Delta\chi^2$	Δdf
Increased difficulty	Baseline	328.13	185	.93	.09	.07 [.08]			
	2	321.33	181	.93	.09	.07 [.08]	Baseline vs. 2	6.80	4
	3[a]	319.61	183	.93	.09	.07 [.08]	Baseline vs. 3	8.52*	2
	4	318.75	181	.93	.09	.07 [.08]	3 vs. 4	0.85	2
	5	317.99	181	.93	.09	.07 [.08]	3 vs. 5	1.61	2
	6	316.66	181	.93	.09	.07 [.08]	3 vs. 6	2.94	2
	7	314.45	181	.93	.09	.07 [.08]	3 vs. 7	5.16	2
New weapons	Baseline	307.21	185	.93	.09	.07 [.08]			
	2	300.55	181	.94	.08	.07 [.08]	Baseline vs. 2	6.66	4
	3[a]	297.81	183	.94	.09	.06 [.08]	Baseline vs. 3	9.40**	2
	4	297.74	181	.94	.09	.07 [.08]	3 vs. 4	0.07	2
	5	295.67	181	.94	.09	.06 [.08]	3 vs. 5	2.14	2
	6	295.75	181	.94	.09	.06 [.08]	3 vs. 6	2.06	2
	7	297.05	181	.94	.09	.07 [.08]	3 vs. 7	0.76	2
New map	Baseline	301.63	185	.94	.09	.06 [.08]			
	2	295.23	181	.94	.09	.06 [.08]	Baseline vs. 2	6.40	4
	3[a]	293.49	183	.94	.09	.06 [.08]	Baseline vs. 3	8.14*	2
	4	289.22	181	.94	.09	.06 [.08]	3 vs. 4	4.27	2
	5	290.44	181	.94	.09	.06 [.08]	3 vs. 5	3.05	2
	6					*Inadmissible solution*			
	7					*Inadmissible solution*			

Note. Model 2 added to Baseline paths from metacognition to knowledge outcomes. Model 3 added to Baseline paths from self-efficacy to performance outcomes. Model 4 added to Model 3 paths from difficulty to transfer performance. Model 5 added to Model 3 paths from knowledge outcomes to post-training performance. Model 6 added to Model 3 paths from metacognition to post-training performance. Model 7 added to Model 3 paths from metacognition to transfer performance. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval.

[a]Indicates best-fitting model for each type of transfer game.

* $p < .05$, ** $p < .01$ (two-tailed).

Table 10

Fit Statistics and Model Comparisons for Latent Growth Models with Individualized Challenge and Training Outcomes

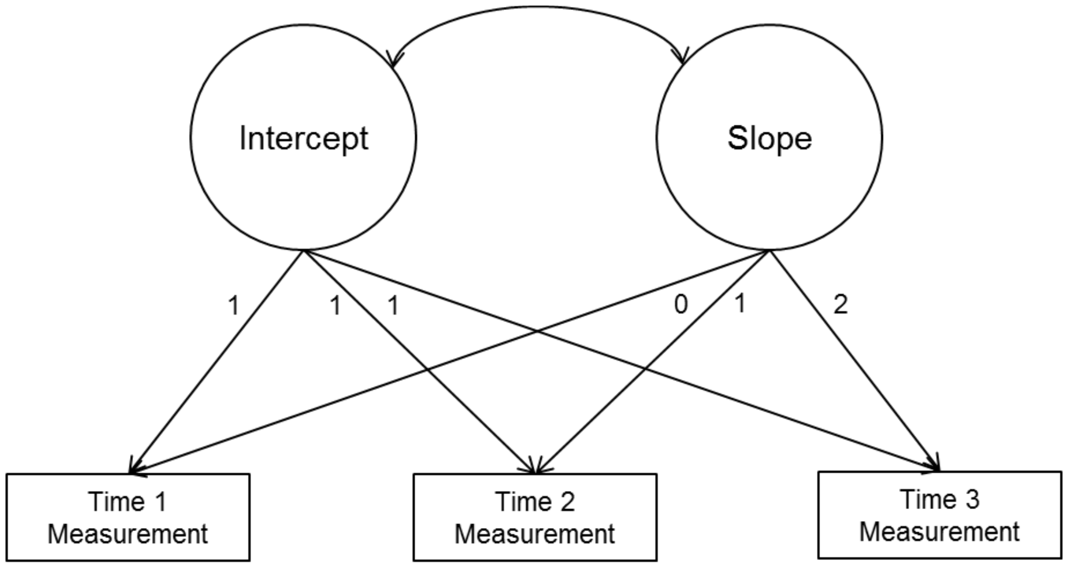
Transfer Game	Model	χ^2	*df*	CFI	SRMSR	RMSEA [upper 90% CI]	Models Compared	$\Delta\chi^2$	Δdf
Increased difficulty	Baseline	160.05	83	.89	.10	.08 [.10]			
	2					*Inadmissible solution*			
	3					*Inadmissible solution*			
New weapons	Baseline[a]	148.05	83	.89	.10	.07 [.09]			
	2	142.40	81	.90	.09	.07 [.09]	Baseline vs. 2	5.65	2
	3					*Inadmissible solution*			
New map	Baseline[a]	143.23	83	.91	.09	.07 [.09]			
	2	140.76	81	.91	.09	.07 [.09]	Baseline vs. 2	2.47	2
	3					*Inadmissible solution*			

Note. Model 2 added to Baseline paths from challenge to transfer performance. Model 3 added to Baseline paths from knowledge outcomes to post-training performance. CFI = comparative fit index; SRMSR = standardized root-mean-squared residual; RMSEA = root-mean-square error of approximation; CI = confidence interval.

[a]Indicates best-fitting model for each type of transfer game.

Figure 1

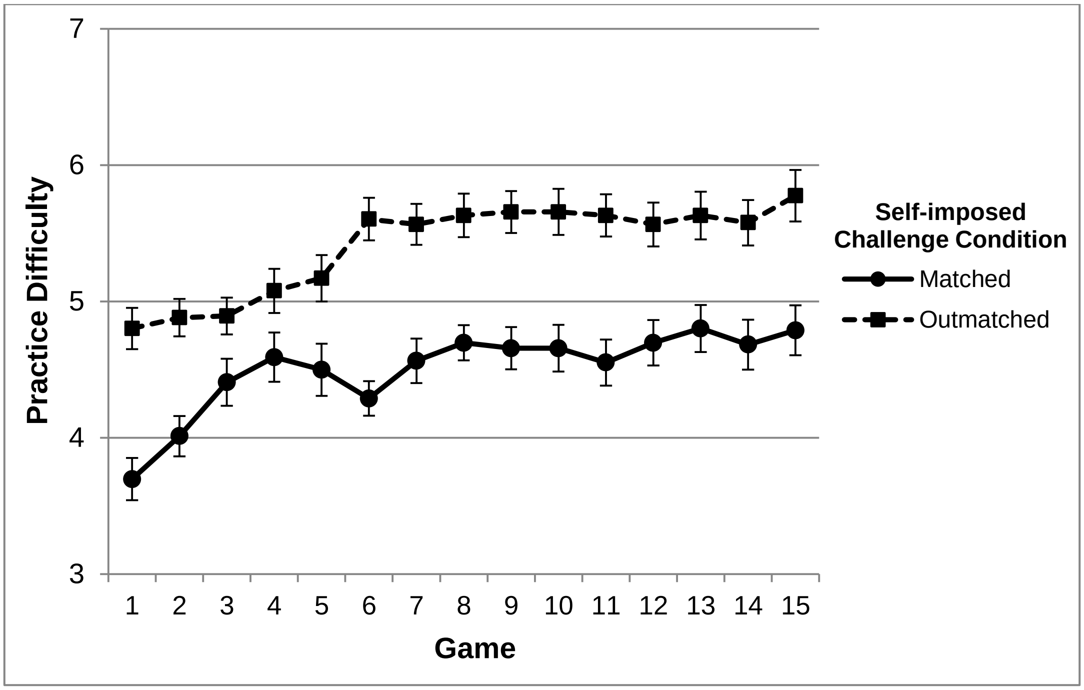
Unconditional Latent Growth Model



Note. Indicator coefficients for the latent intercept are fixed to 1. Indicator coefficients for the latent slope are fixed to 1, 2, and 3 for the first, second, and third observations, respectively.

Figure 2

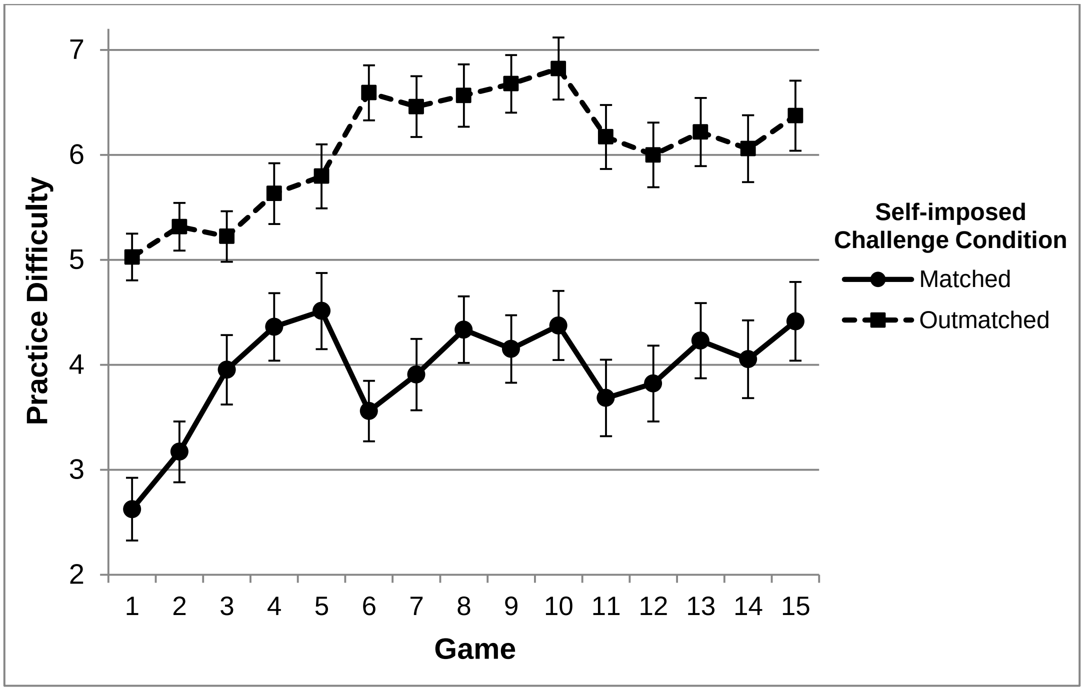
Practice Difficulty Means over Time by Self-imposed Challenge Condition



Note. Standard errors are represented by the bars at each observation.

Figure 3

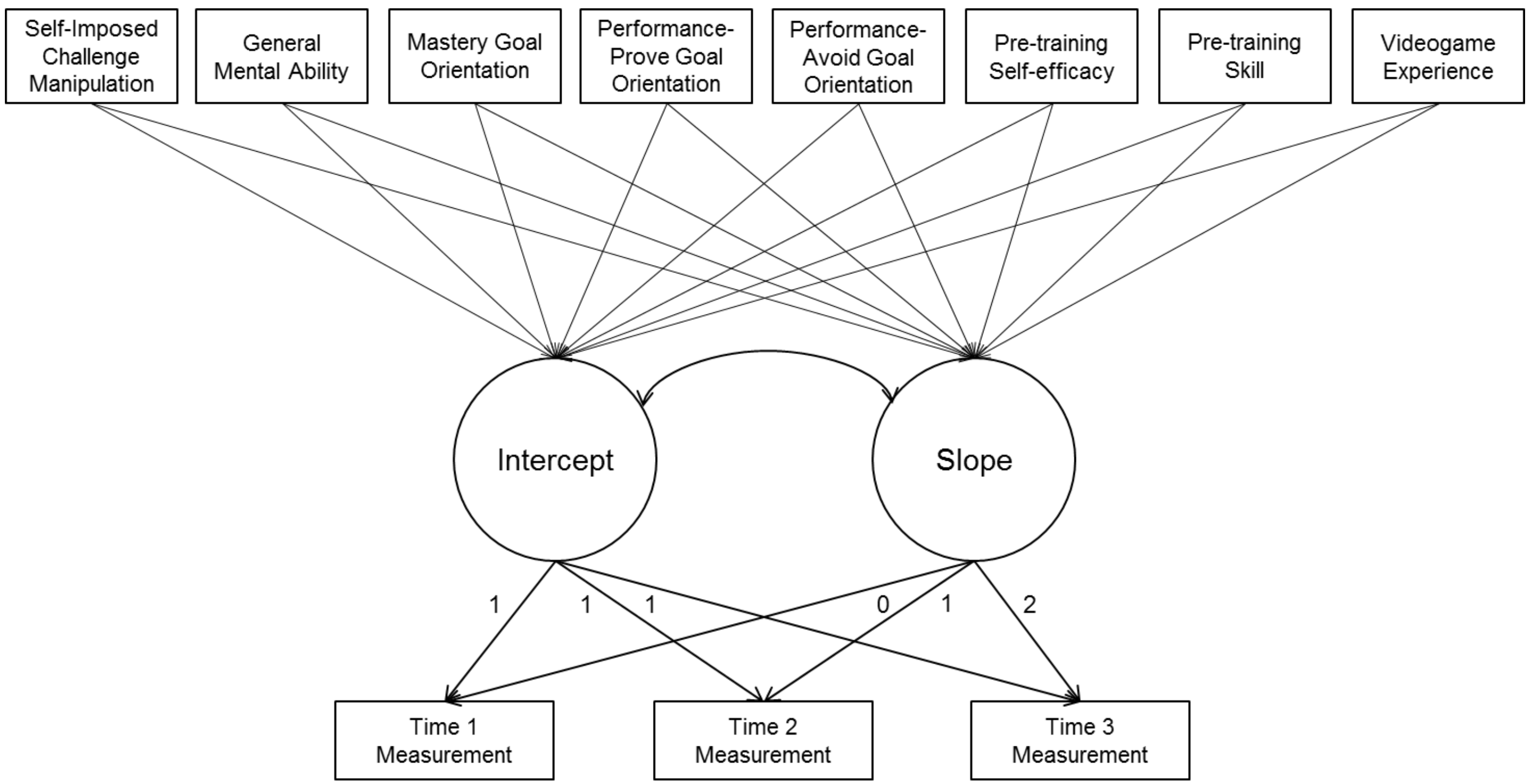
Individualized Challenge Means over Time by Self-imposed Challenge Condition



Note. Standard errors are represented by the bars at each observation.

Figure 4

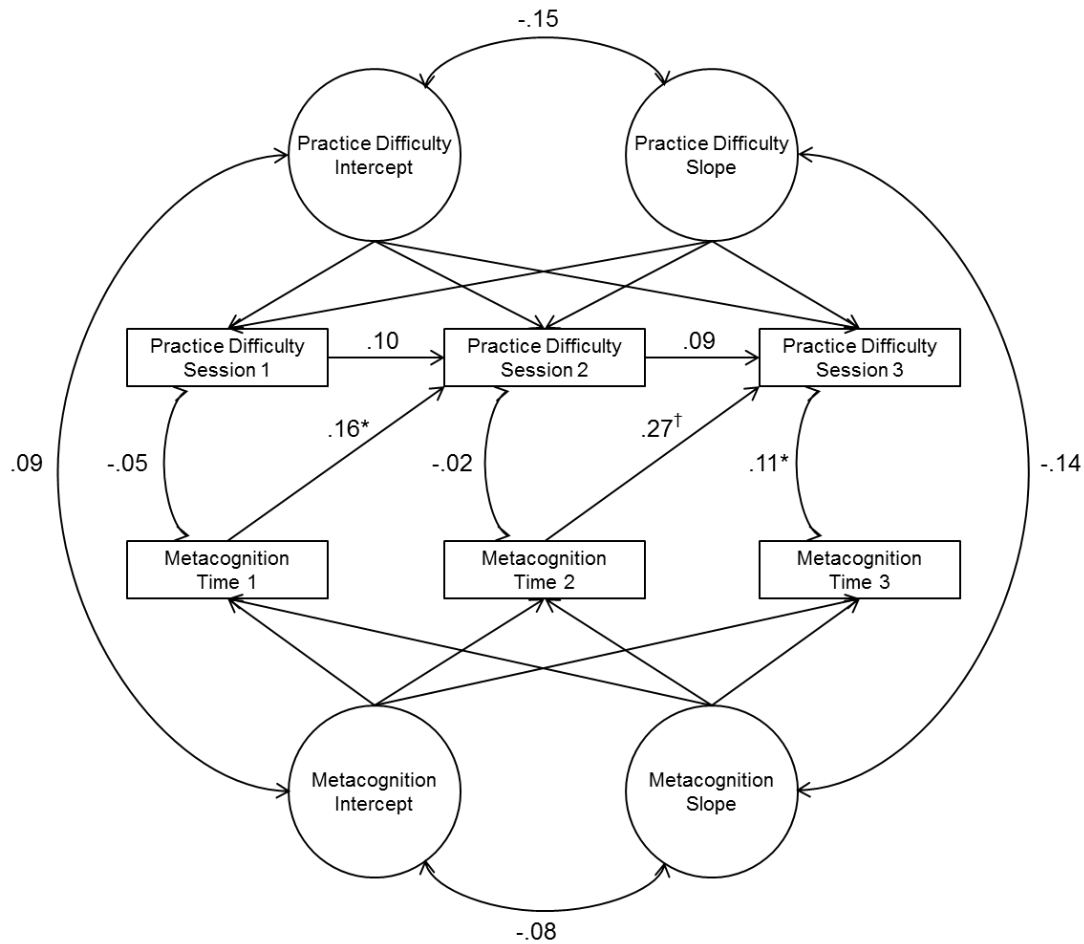
Conditional Latent Growth model



Note. Indicator coefficients for the latent intercept are fixed to 1. Indicator coefficients for the latent slope are fixed to 1, 2, and 3 for the first, second, and third observations, respectively. For the repeated variables of self-evaluation and self-efficacy, a latent slope factor was not modeled.

Figure 5

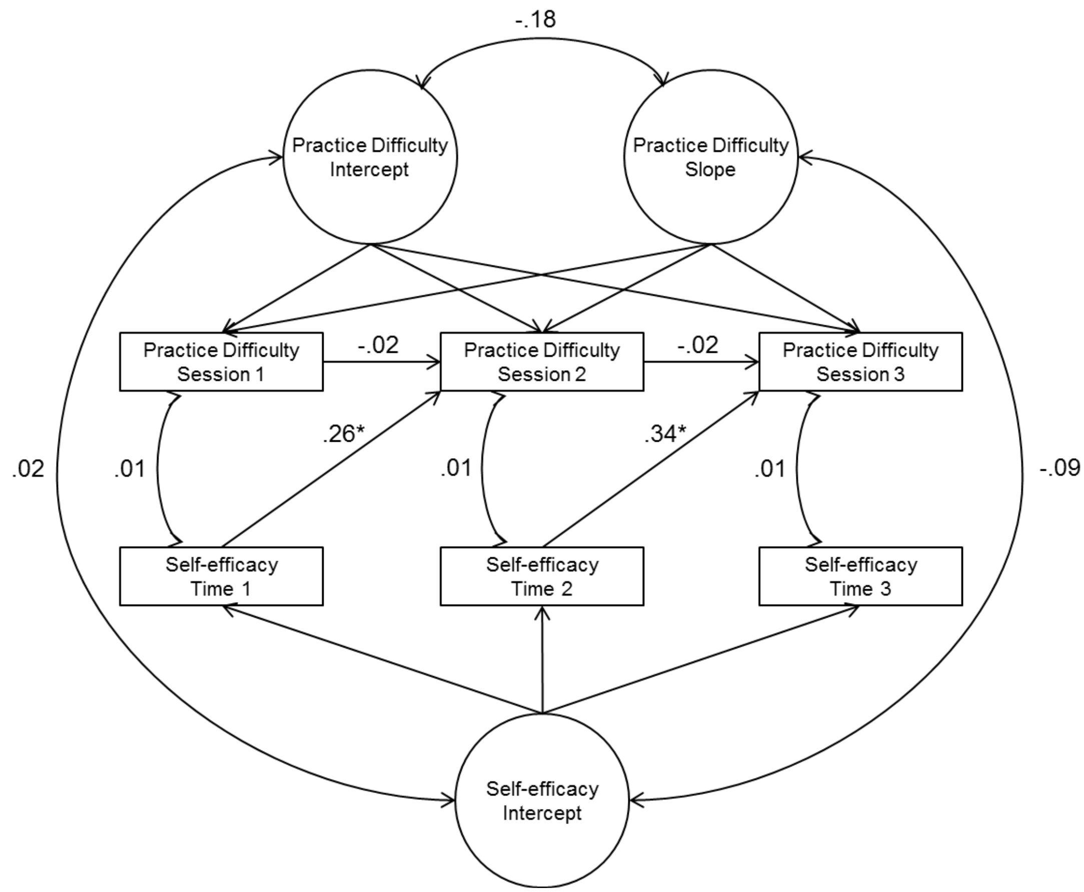
Best-fitting Cross-lagged Latent Growth Model between Practice Difficulty and Metacognition



Note. Parameter estimates are standardized. Indicator coefficients for the latent intercepts are fixed to 1. Indicator coefficients for the latent slopes are fixed to 1, 2, and 3 for the first, second, and third observations, respectively. Curved arrows linking manifest indicators represent correlated error terms. Not shown in the figure are correlations between the practice difficulty intercept and metacognition slope ($\gamma = -.15$, $p > .05$), and practice difficulty slope and metacognition intercept ($\gamma = -.31$, $p > .05$). Also not shown are the effects of the self-imposed challenge manipulation and individual difference variables on the latent intercepts and slopes.
† $p < .10$, * $p < .05$ (two-tailed).

Figure 6

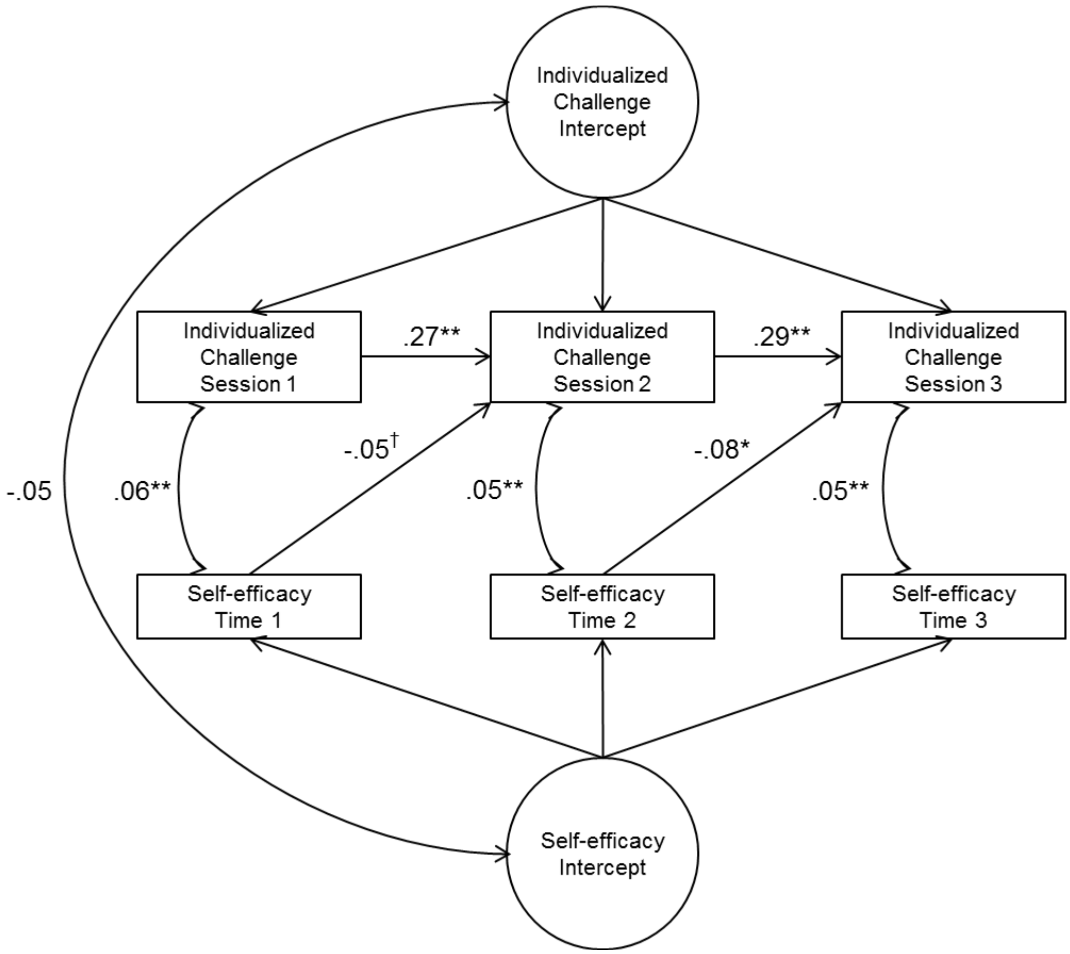
Best-fitting Cross-lagged Latent Growth Model between Practice Difficulty and Self-efficacy



Note. Parameter estimates are standardized. Indicator coefficients for the latent intercepts are fixed to 1. Indicator coefficients for the practice difficulty latent slope are fixed to 1, 2, and 3 for the first, second, and third observations, respectively. Curved arrows linking manifest indicators represent correlated error terms. Not shown in the figure are the effects of the self-imposed challenge manipulation and individual difference variables on the latent intercepts and practice difficulty slope.
* p < .05 (two-tailed).

Figure 7

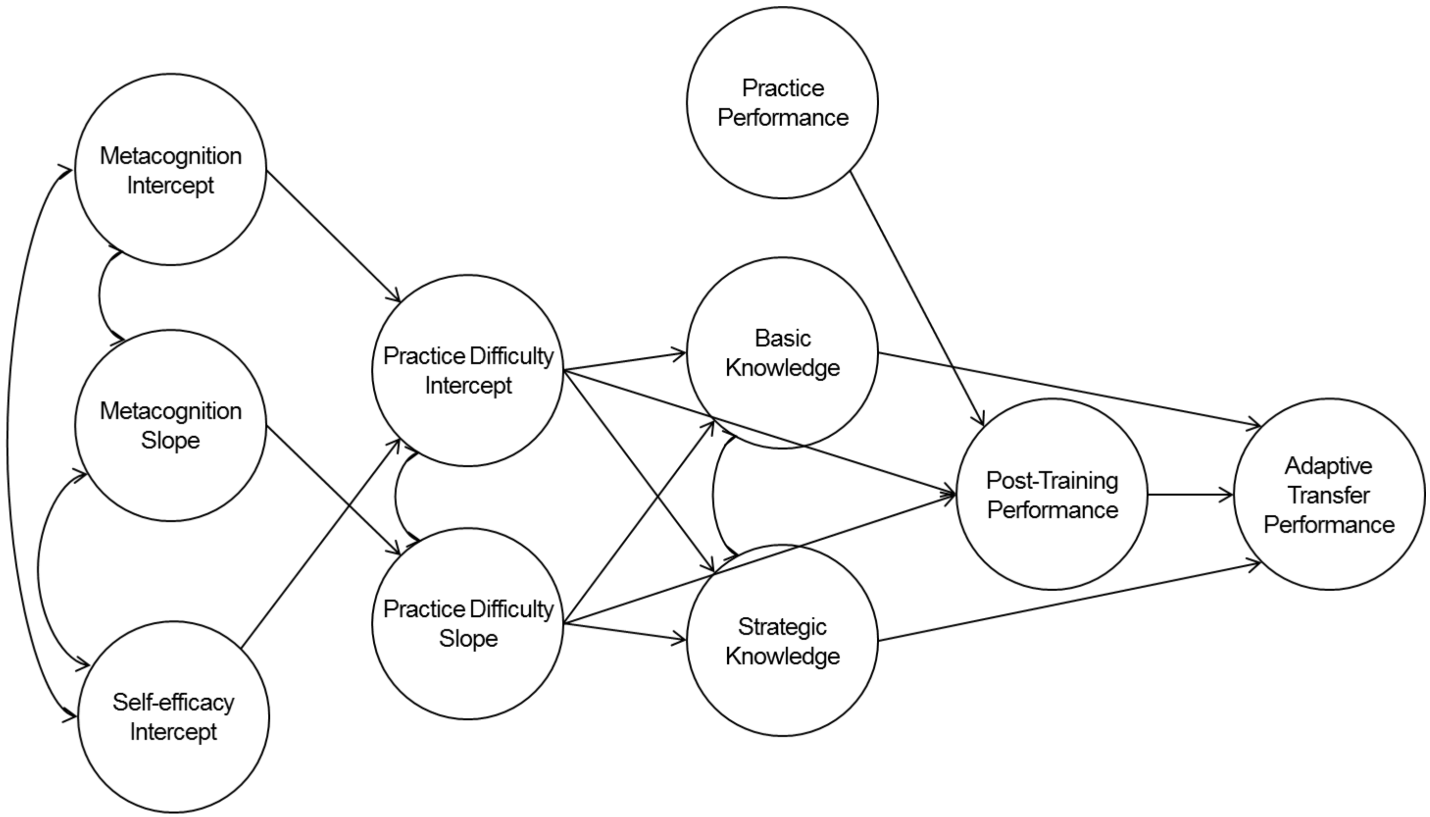
Best-fitting Cross-lagged Latent Growth Model between Individualized Challenge and Self-efficacy



Note. Parameter estimates are standardized. Indicator coefficients for the latent intercepts are fixed to 1. Curved arrows linking manifest indicators represent correlated error terms. Not shown in the figure are the effects of the self-imposed challenge manipulation and individual difference variables on the latent intercepts.
† $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Figure 8

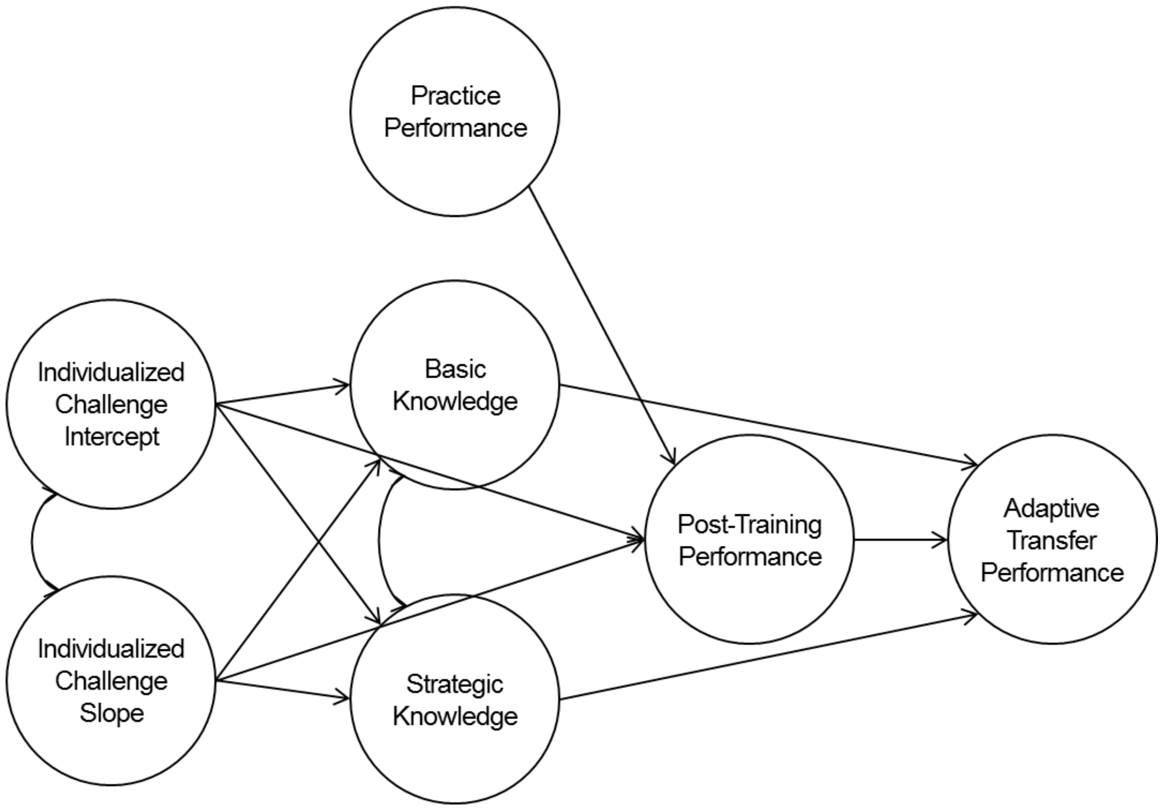
Baseline Model for Practice Difficulty with Training Outcomes



Note. For clarity, manifest indicators for the latent growth models, training outcomes, and practice performance are not shown. Additionally, correlations between learner-controlled practice difficulty and practice performance indicator errors at same time points were modeled. Similarly, correlations between self-efficacy and practice performance indicator errors at same time points were also modeled.

Figure 9

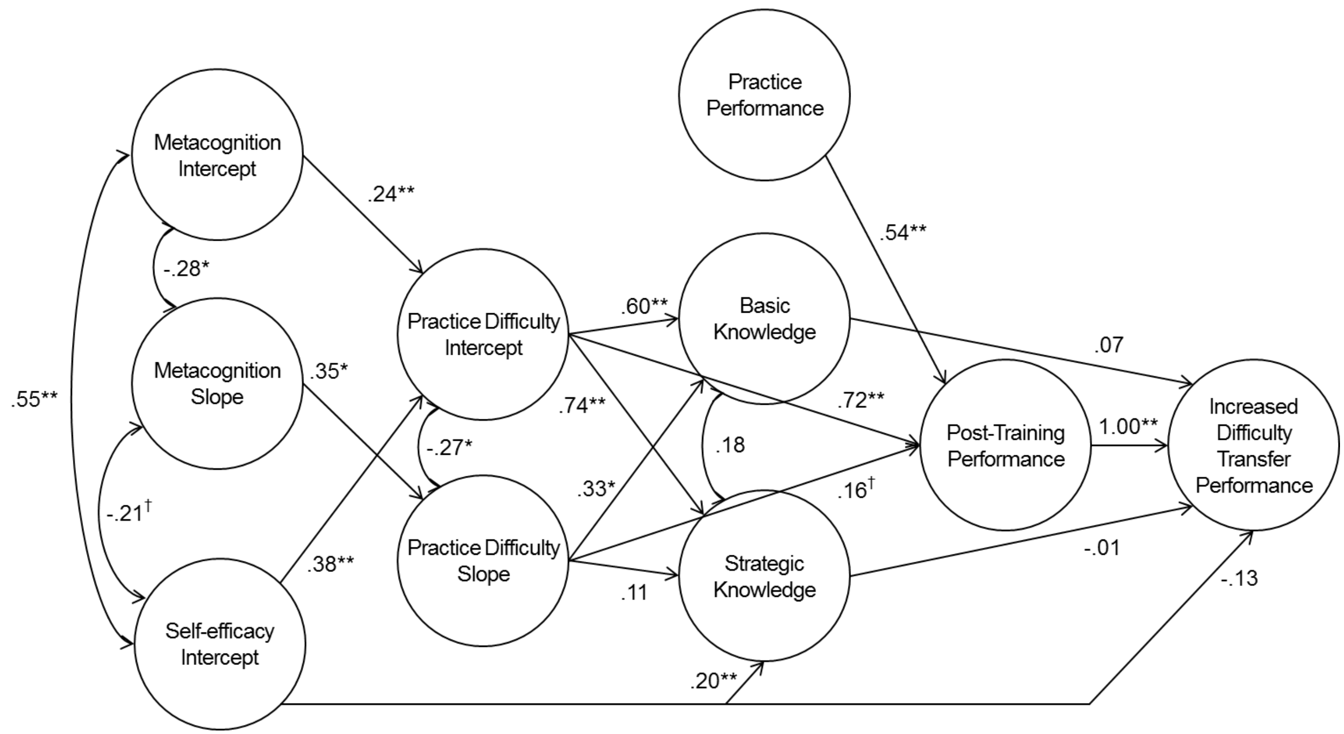
Baseline Model for Individualized Challenge with Training Outcomes



Note. For clarity, manifest indicators for the individualized challenge latent growth model, training outcomes, and practice performance are not shown. Additionally, correlations between individualized challenge and practice performance indicator errors at same time points were modeled.

Figure 10

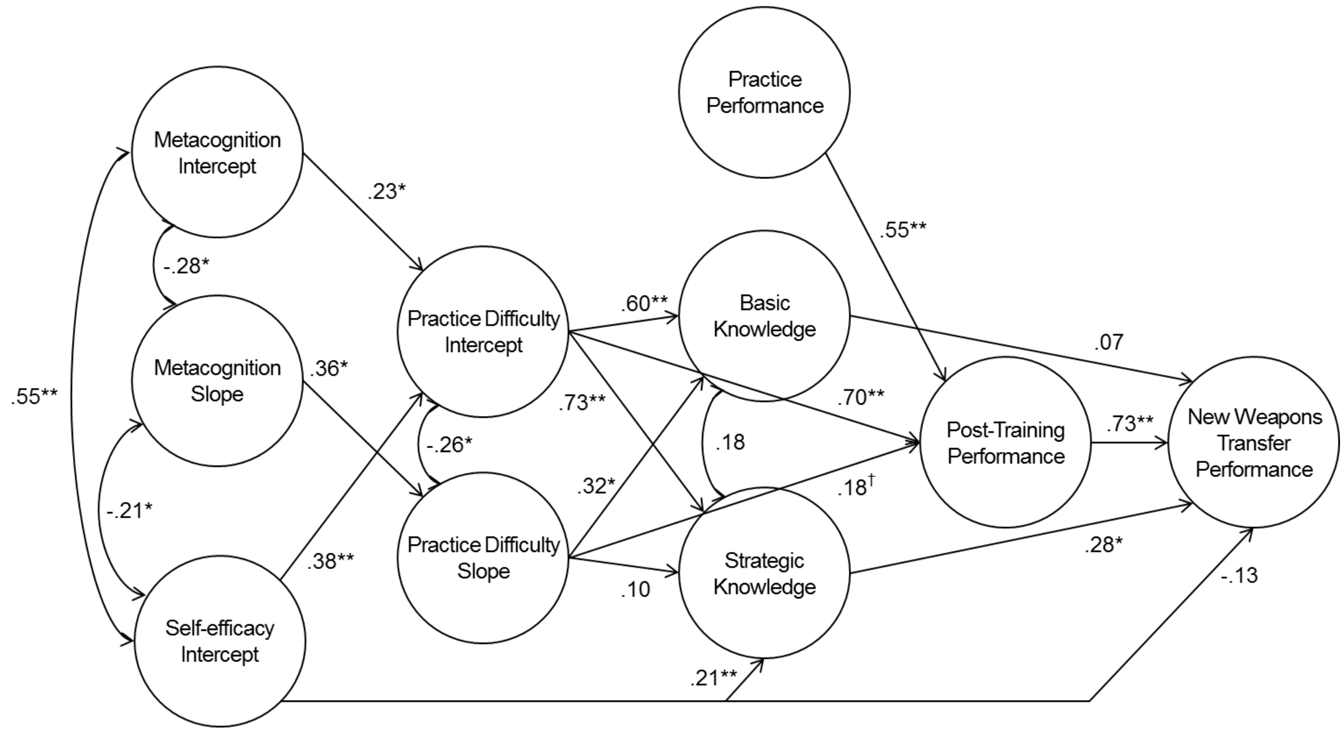
Best-fitting Model for Practice Difficulty with Transfer Performance entailing Increased Difficulty



Note. Parameter estimates are standardized. For clarity, manifest indicators for the latent growth models, training outcomes, and practice performance are not shown. Additionally, correlations between learner-controlled practice difficulty and practice performance indicator errors at same time points were modeled (*r*'s < -.37, *p*'s < .01). Similarly, correlations between self-efficacy and practice performance indicator errors at same time points were also modeled (*r*'s > .05, *p*'s < .05). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with *t*-values ranging from 1.34 to 5.22, $df = 151$. † $p < .10$, * $p < .05$, ** $p < .01$ (two-tailed).

Figure 11

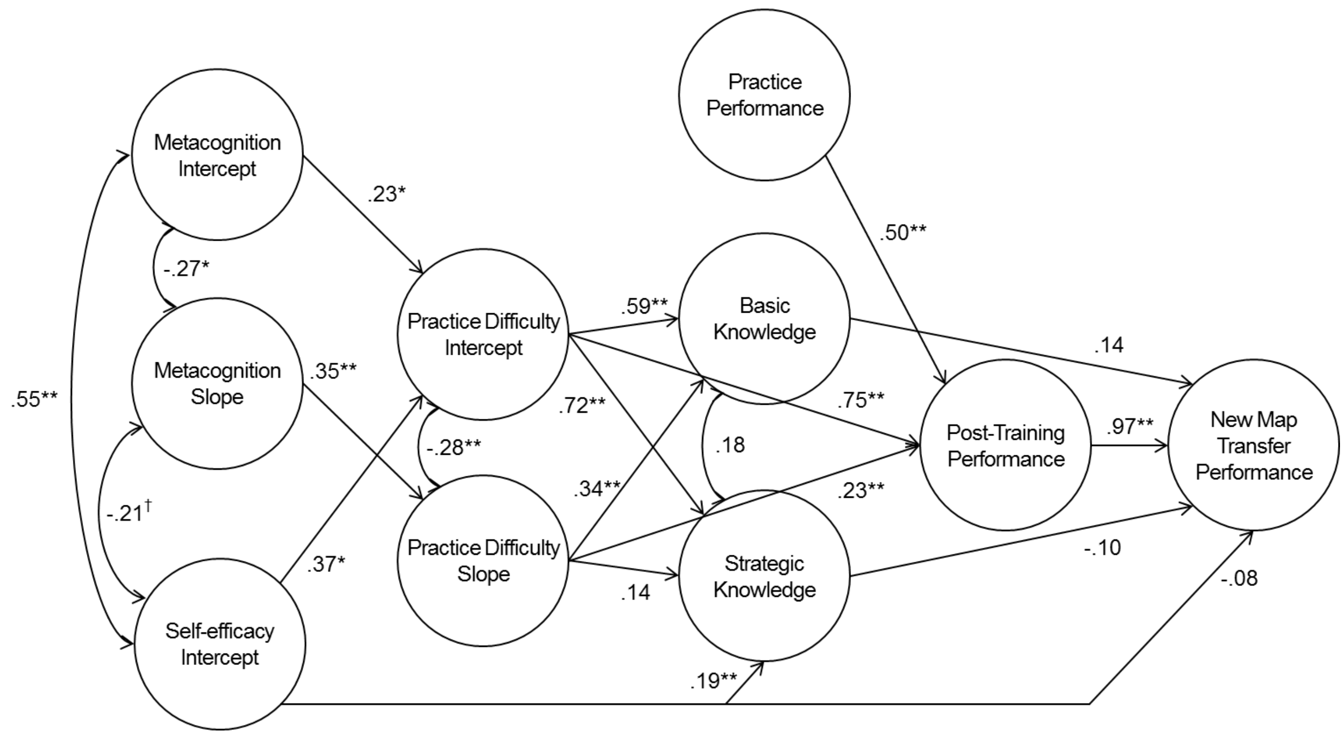
Best-fitting Model for Practice Difficulty with Transfer Performance entailing New Weapons



Note. Parameter estimates are standardized. For clarity, manifest indicators for the latent growth models, training outcomes, and practice performance are not shown. Additionally, correlations between learner-controlled practice difficulty and practice performance indicator errors at same time points were modeled (r's < -.38, p's < .01). Similarly, correlations between self-efficacy and practice performance indicator errors at same time points were also modeled (r's > .05, p's < .05). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with t-values ranging from 1.32 to 5.31, df = 151. † p < .10, * p < .05, ** p < .01 (two-tailed).

Figure 12

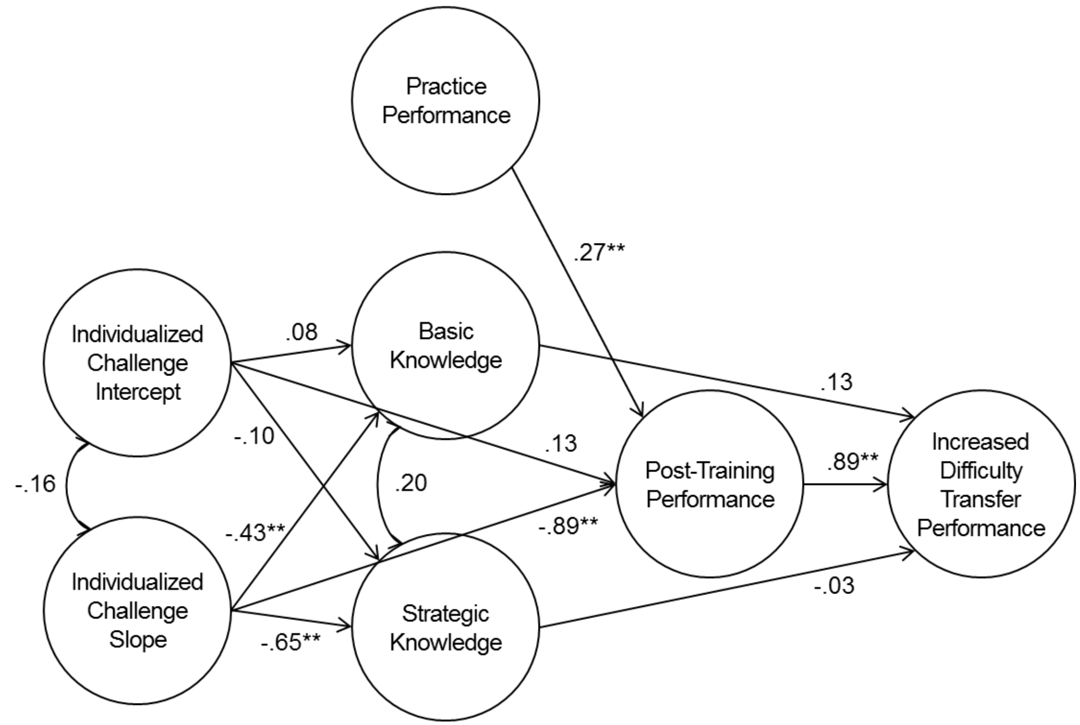
Best-fitting Model for Practice Difficulty with Transfer Performance entailing a New Map



Note. Parameter estimates are standardized. For clarity, manifest indicators for the latent growth models, training outcomes, and practice performance are not shown. Additionally, correlations between learner-controlled practice difficulty and practice performance indicator errors at same time points were modeled (r's < -.37, p's < .01). Similarly, correlations between self-efficacy and practice performance indicator errors at same time points were also modeled (r's > .05, p's < .05). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with t-values ranging from 1.35 to 5.38, df = 151. † p < .10, * p < .05, ** p < .01 (two-tailed).

Figure 13

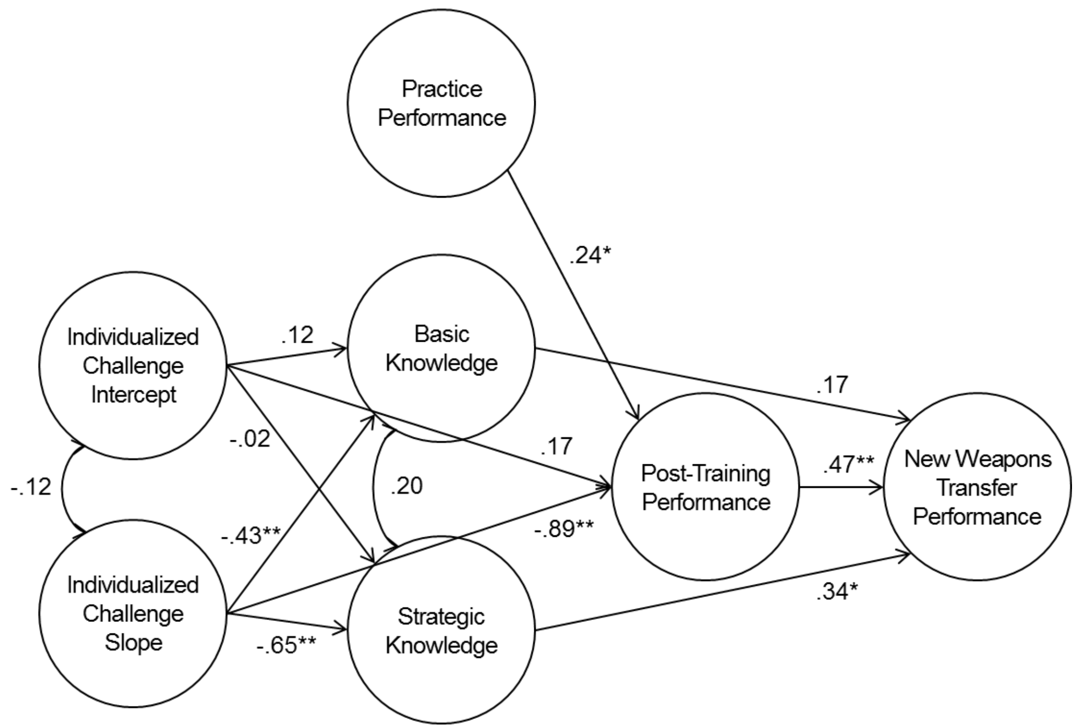
Best-fitting Model for Individualized Challenge with Transfer Performance entailing Increased Difficulty



Note. Parameter estimates are standardized. For clarity, manifest indicators for the individualized challenge latent growth model, training outcomes, and practice performance are not shown. Additionally, correlations between individualized challenge and practice performance indicator errors at same time points were modeled ($r_{\text{time 1}}$ = .01, p > .05; $r_{\text{time 2}}$ = -.14, p < .05; $r_{\text{time 3}}$ = -.35, p < .01). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with t-values ranging from 1.67 to 5.14, df = 151.
** p < .01 (two-tailed).

Figure 14

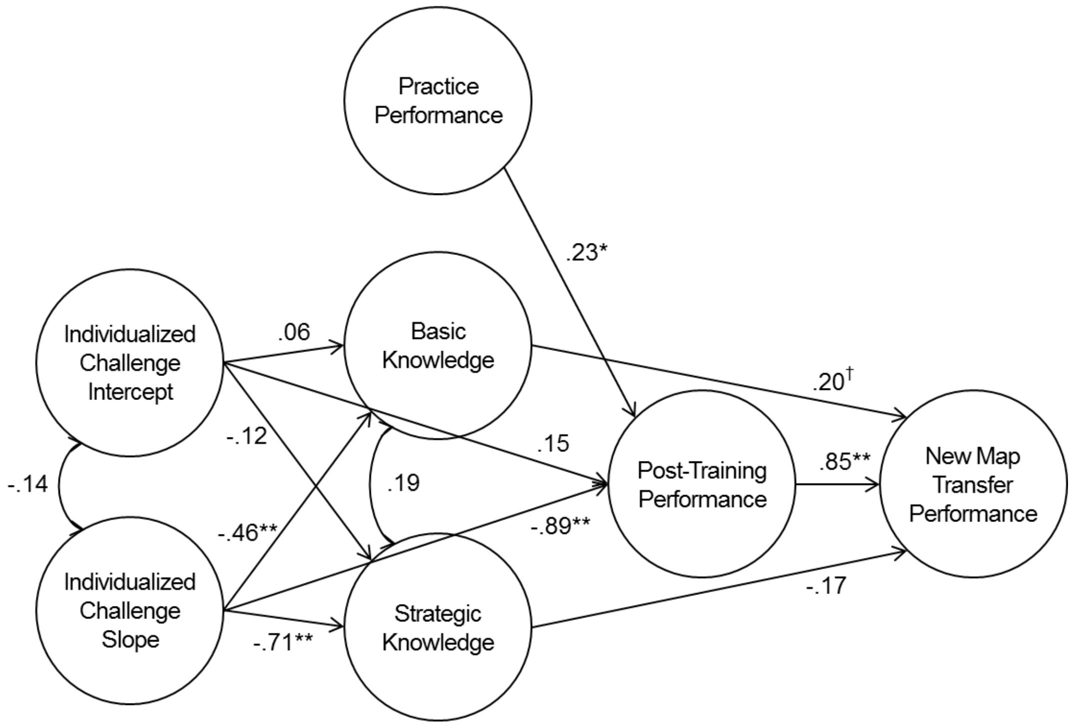
Best-fitting Model for Individualized Challenge with Transfer Performance entailing New Weapons



Note. Parameter estimates are standardized. For clarity, manifest indicators for the individualized challenge latent growth model, training outcomes, and practice performance are not shown. Additionally, correlations between individualized challenge and practice performance indicator errors at same time points were modeled ($r_{\text{time 1}} = .01$, $p > .05$; $r_{\text{time 2}} = -.14$, $p < .05$; $r_{\text{time 3}} = -.36$, $p < .01$). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with *t*-values ranging from 1.40 to 5.39, *df* = 151.
* $p < .05$, ** $p < .01$ (two-tailed).

Figure 15

Best-fitting Model for Individualized Challenge with Transfer Performance entailing a New Map



Note. Parameter estimates are standardized. For clarity, manifest indicators for the individualized challenge latent growth model, training outcomes, and practice performance are not shown. Additionally, correlations between individualized challenge and practice performance indicator errors at same time points were modeled ($r_{\text{time 1}}$ = .02, p > .05; $r_{\text{time 2}}$ = -.14, p < .05; $r_{\text{time 3}}$ = -.37, p < .01). Finally, to avoid an inadmissible solution resulting from multicollinearity, the correlation between basic and strategic knowledge was modeled by correlating the indicator error terms of the two latent factors. The value shown in the figure represents the average of these correlations with t-values ranging from 1.42 to 5.09, df = 151.

† p < .10, * p < .05, ** p < .01 (two-tailed).

Appendix A

Study Procedures

Task
Goal orientation measure
GMA measure
Training PowerPoint presentation
Practice game (3 min)
Pre-training skill assessment, games 1 and 2 (5 min each)
Difficulty 2 game (5 min)
Difficulty 6 game (5 min)
Pre-training self-efficacy measure
Self-confidence measure (self-imposed challenge), time 1
Self-imposed challenge manipulation
Session 1, practice games 1-5 (5 min each)
Self-evaluation measure, time 1
Self-efficacy measure, time 1
Metacognition measure, time 1
5 min break
Self-confidence measure (self-imposed challenge), time 2
Self-imposed challenge refresher
Session 2, practice games 6-10 (5 min each)
Self-evaluation measure, time 2
Self-efficacy measure, time 2
Metacognition measure, time 2
Self-confidence measure (self-imposed challenge), time 3
Self-imposed challenge refresher
Session 3, practice games 11-15 (5 min each)
Self-evaluation measure, time 3
Self-efficacy measure, time 3
Metacognition measure, time 3
Task knowledge test
Post-training performance test, games 1 and 2 (5 min each)
Videogame experience measure
5 min break
Adaptive transfer performance test – increased difficulty, games 1 and 2 (5 min each)
Transfer game perceptions measure
Adaptive transfer performance test – new weapons, games 1 and 2 (5 min each)
Adaptive transfer performance test – new map, games 1 and 2 (5 min each)

Note. The order of the adaptive transfer test games was counterbalanced by type. Thus, the order of transfer games shown above does not reflect the administered order for all participants.

Appendix B

Self-imposed Challenge Manipulation

Condition	Instructions
Matched	During practice, always select games that will be moderately challenging. Choose difficulty levels at which you are uncertain whether you will succeed or fail. Therefore, you should practice only on games that are matched to your own skill level and at which you will have a 50/50 chance of beating at least one of the bots. For example, if you believe your personal Unreal Tournament skill level is a 4, you should choose difficulty 4. As you feel like you are improving, continue to raise the difficulty level accordingly. Always raise the difficulty if you have won more than once at a previous level. Finally, challenge can be frustrating at times. However, because practicing this way will help you learn and acquire the most knowledge and skill, try to think positively about the challenges you experience. Ultimately, by challenging yourself this way during practice, you will be better prepared for the test games, and better at Unreal Tournament in the end.
Outmatched	During practice, always select games that will be extremely challenging. Choose difficulty levels at which you are certain that you will not succeed. Therefore, you should practice only on games that are far above your own skill level and at which you will have a 0-percent chance of beating either bot. For example, if you believe your personal Unreal Tournament skill level is a 4, you should choose difficulty 6. As you feel like you are improving, continue to raise the difficulty level accordingly. Always raise the difficulty if you beat just one bot at a previous level. Finally, challenge can be frustrating at times. However, because practicing this way will help you learn and acquire the most knowledge and skill, try to think positively about the challenges you experience. Ultimately, by challenging yourself this way during practice, you will be better prepared for the test games, and better at Unreal Tournament in the end.

Appendix C

Self-confidence Measure

For the upcoming practice session, think about how confident you are that you can succeed at each of the 7 difficulty levels. Then, in the boxes below, indicate your confidence at (a) beating only **one bot** and (b) beating **both bots** for each level of difficulty. Make your ratings using a scale from 0 (*no confidence at all*) to 10 (*total confidence*).

0..……1..……2..……3..……4..……5..……6..……7..……8..……9..……10
No confidence at all…………………………………………*Total confidence*

Difficulty	*(a) Confidence at beating **one bot***	*(b) Confidence at beating **both bots***
1		
2		
3		
4		
5		
6		
7		

Appendix D

Example Basic and Strategic Task Knowledge Items

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

2. Which weapon's *primary* fire has the <u>fastest</u> rate of fire?
   a. Assault Rifle
   b. Grenade Launcher
   c. Lightning Gun
   d. Rocket Launcher

3. Which of the following weapons' *alternate* fire modes is <u>least</u> effective for attacking far-away bots?
   a. Assault Rifle
   b. Minigun
   c. Rocket Launcher

4. Which adrenaline ability would be <u>most</u> effective when paired with the Double-Damage pickup?
   a. Increased accuracy
   b. Increased damage
   c. Health boost
   d. Invisibility

Note. Items 1 and 2 assessed basic knowledge, and items 3 and 4 assessed strategic knowledge. Correct answers are in boldface.