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Exploratory behavior in active learning: A between- and within-person examination ☆

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ABSTRACT

Despite being central to active learning theory, surprisingly little research has directly examined the antecedents and outcomes of exploratory behavior. This laboratory study addressed this gap using repeated measures to examine the role and dynamics of exploration in complex task learning. Findings showed task exploration was beneficial across a variety of learning outcomes. Dynamic effects were also observed: (a) exploration was positively related to practice performance at both between- and within-person levels, (b) exploration decreased across practice trials, and (c) decreases in exploration were mitigated by pre-training task-related knowledge. Although general mental ability (GMA) and pre-training task-related knowledge both exhibited effects on exploration, effects were stronger for pre-training task-related knowledge. Neither moderated the link between exploration and learning. Error framing moderated the GMA–exploration relationship such that higher-GMA learners explored more under approach versus avoid conditions. Results are discussed with respect to criticisms of discovery-based learning and implications for active learning.

Introduction

Exploration has a rich history in the psychological literature as a fundamental behavioral information-gathering process central to human development and learning (Berlyne, 1954a, 1954b, 1955; Piaget & Cook, 1952). In a training context, the centrality of *exploratory behavior*—defined as an active interaction on the part of the trainee with the training environment through attempts at multiple solutions to the problem at hand (Dormann & Frese, 1994)—is an important tenet of the constructivist theory of learning (Bruner, 1961). Constructivism posits that learning is an active and inductive process whereby individuals explore to assimilate rules, principles, and strategies into knowledge and skill. This perspective has since come to serve as the foundation for a modern, learner-centered training paradigm known as the active learning approach (Bell & Kozlowski, 2008, 2010).

In general, empirical research has supported the notion that learners should be actively involved in the learning process (Bell & Kozlowski, 2008, 2010; Keith & Frese, 2008; Keith, Richter, & Naumann, 2010). However, despite the prominence of exploration in active learning theory (Bell & Kozlowski, 2010), its outcomes in these contexts are often debated. Early research on active learning found that exploratory behavior facilitated higher levels of learning and performance (Dormann & Frese, 1994). However, later findings suggested that learners in conditions that allow for task exploration often show better analogical and adaptive transfer outcomes but worse training performance relative to learners in proceduralized conditions that limit exploration (Bell & Kozlowski, 2008; Hesketh, 1997). Many attribute this pattern of findings to the implied relationship between exploration and the making of errors (Keith & Frese, 2008) or to varying degrees of guidance and structure in exploration-based interventions (Debowski, Wood, & Bandura, 2001; Smith, Ford, & Kozlowski, 1997). Critics of exploration-based interventions go even further, arguing that the utility of discovery and active learning approaches is limited for low ability or inexperienced learners due to high information-processing demands (Kirschner, Sweller, & Clark, 2006) or because inexperienced learners miss important material in exploration-based learning (Mayer, 2004). Often, these criticisms allude to the exploratory nature of discovery environments as the cause of such

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limitations and call for restrictions on trainee exploration (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011).

In this paper, we argue that conflicting conclusions regarding effects of exploration on performance in active learning can be addressed by resolving a level of analysis problem concerning the theoretical conceptualization and study of exploratory behavior in learning contexts. Specifically, most studies examining the role of exploration in active learning have not directly measured task exploration during the learning process but rather infer its effects through comparisons of exploration-based versus proceduralized interventions. Although there are clear advantages to manipulation-based (i.e., experimental) approaches, relying solely on such a design provides a limited examination of learner self-regulatory processes. Accordingly, many calls have been made for more studies that directly examine (e.g., via behavioral observation) mechanisms that account for active learning effects (Bell & Kozlowski, 2010; Debowski et al., 2001; Gully, Payne, Koles, & Whiteman, 2002), and several cognitive and motivational self-regulatory processes, such as metacognition, emotion control, self-efficacy, and goal setting have since been studied directly (e.g., Bell & Kozlowski, 2008; Keith & Frese, 2005; Kozlowski & Bell, 2006). However, the measurement of exploratory behavior during training has been generally overlooked. This omission from the literature is problematic for several reasons. First, and most central, is that by relying solely on manipulation-based operationalizations of exploration, active learning research diverges from its constructivist origins by studying exploration as a component of an intervention rather than as a behavioral process of the learner. Such an approach carries the untenable assumption that all trainees engage equally in task exploration when participating in active learning. Second, exploration-based interventions are inherently multi-faceted with multiple design and informational components influencing a variety of self-regulatory processes. This makes it difficult to isolate exploration as a mechanism facilitating or inhibiting learning outcomes. Consequently, when research points to potential problems with exploration-based interventions, it is difficult to identify the specific causes of the problems (Bell & Kozlowski, 2010). Without direct measurement, one cannot be sure if exploratory behavior *per se* is to blame for problems that might arise in discovery learning (cf. Charney, Reder, & Kusbit, 1990), thus limiting the development of targeted solutions. Third, by definition, self-regulation theory speaks to within-person, dynamic phenomena (Vancouver, Weinhardt, & Vigo, 2014). As such, repeated, direct measurements of exploration during the learning process are necessary to examine how exploration changes over time and to identify factors related to these changes. Finally, despite being identified as an important self-regulatory pathway that benefits learning (Kozlowski, Toney, et al., 2001), trainee behavior during practice has been relatively understudied in active learning research in favor of a stronger focus on more cognitive- and emotion-based mechanisms. Although cognition and emotion are certainly important, by overlooking trainee behavior, researchers are neglecting key processes by which learners interact with their environment.

Accordingly, our purpose was to examine the role and dynamics of exploration in complex task learning by using repeated, direct measurements of exploratory behavior across practice trials. Taking the perspective of curiosity theory, which views exploration as a dynamic, information-gathering process concerning how individuals approach and engage the complexity and novelty of task stimuli (Berlyne, 1960, 1966; Loewenstein, 1994), we tested and compared two proposed pathways by which the capability-based individual difference variables of general mental ability (GMA) and pre-training task-related knowledge (i.e., a composite of prior experience and baseline performance) are linked to learning outcomes via exploration. First, we examined a common proposition of critics of discovery learning that learner capabilities moderate the relationship between exploration and learning outcomes such that the positive relationships between exploration and learning outcomes are stronger for higher-capability individuals (Kirschner et al., 2006). Second, we examined the extent to which GMA and task-related knowledge *directly* and positively influence exploratory behavior, which in turn positively relates to learning outcomes. Furthermore, we compared whether the effects of exploration are related more to GMA versus task-related knowledge by testing similar pathways for both. With respect to the second pathway, we also examined how error framing instructions in error management training (EMT)—a common active learning intervention—directly influences exploration and moderates the influence of GMA and task-related knowledge on exploration. Finally, we expected that the underlying processes driving exploratory behavior's effects would fluctuate across practice trials. As such, we contend that exploration is dynamic and should be studied accordingly. Research has demonstrated that dynamic constructs can show differential effects depending on the between- and within-person levels of analysis (Vancouver, Thompson, Tischner, & Putka, 2002; Yeo, Loft, Xiao, & Kiewitz, 2009; Yeo & Neal, 2006). Therefore, we tested for dynamic trends during practice and took a nuanced approach by examining if effects on practice performance are similar or different at the between- and within-person levels. Fig. 1 summarizes these propositions and shows the model that served as our guiding framework.

The effects of exploratory behavior on learning

When examining learning outcomes, it is important to consider both proximal (i.e., knowledge and skill) and distal (i.e., adaptation) outcomes (Kraiger, Ford, & Salas, 1993). Accordingly, in this study, we examined multiple learning outcomes including task knowledge, practice performance, and analogical and adaptive transfer performance. *Task knowledge* is composed of both basic task knowledge, defined as the comprehension of basic task features and critical tasks, and strategic task knowledge, defined as the understanding necessary for situational assessment and prioritization (Kozlowski, Toney, et al., 2001). Skill-based outcomes included *practice performance*, defined as effectiveness during training, and *analogical transfer* (i.e., near transfer), defined as the capability to be effective in familiar performance situations after training. Skill adaptability or *adaptive transfer* (i.e., far transfer) is defined as the capability to use one's existing knowledge and skill in response to novel (e.g., more difficult, complex, and dynamic) performance demands (Ivancic & Hesketh, 2000).

It is particularly important to examine both proximal and distal outcomes when studying exploration given that manipulation-based approaches sometimes show crossover effects such that trainees in exploration conditions perform worse during practice but better on post-training tests of skill retention and adaptability (Bell & Kozlowski, 2008; Hesketh, 1997; McDaniel & Schlager, 1990). However, these findings are in reference to the comparison of interventions that are inherently multifaceted without measurements of exploratory behavior to link intervention effects to learning outcomes. Consequently, these findings are limited in the extent to which they can speak directly to how variability in exploratory behavior is associated with variability in both proximal and distal performance. For instance, trainees in proceduralized conditions are often provided with step-by-step task solutions during practice, whereas those in exploration-based conditions are not (e.g., Bell & Kozlowski, 2008; Dormann & Frese, 1994; Frese et al., 1991). This additional instruction and guidance directly affects performance scores during practice. Accordingly, many of the negative practice performance effects attributed to

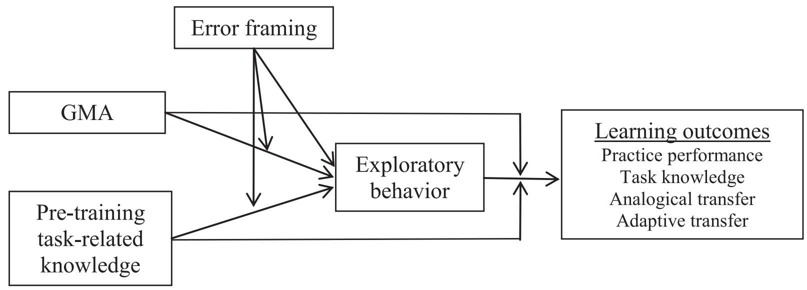

Fig. 1. Guiding theoretical model of the antecedents, outcomes, and interactions associated with exploration in active learning.

exploration are relative to proceduralized conditions in which practice performance may not solely reflect the volition of trainees. Although this approach can be informative in the evaluation of interventions as a whole, such comparisons do not allow one to draw conclusions regarding the effectiveness of exploration as a behavioral mechanism in active learning, as trainee decisions and behavior are not the sole determinates of practice performance scores. Accordingly, we turn to theories of curiosity and exploratory behavior for guidance in developing our predictions for the direct effects of exploratory behavior on learning.

Curiosity theorists postulate that exploration begins with perceptions of novelty (Berlyne, 1966; Harrison, 2012; Litman, 2005; Loewenstein, 1994). Experiencing novelty exposes a gap between information relevant to effectively dealing with the environment and one's current level of understanding (Loewenstein, 1994). This gap motivates learners to improve their effectiveness in dealing with the environment (White, 1959), ultimately leading them to explore in an effort to resolve perceived deficiencies. Along these lines, we believe that exploratory behavior will offer two primary benefits in active learning contexts. First, as a benefit of resolving environmental novelty, learners who explore more will cultivate a deeper and more complete understanding of the relative effectiveness of a variety of different approaches in response to dynamic stimuli. Second, exploratory behavior should enable learners to be more flexible and intentional in the approaches they attempt. By building upon existing knowledge and skill, exploration allows for increased responsiveness to novelty in the immediate, context-specific demands of complex and dynamic task environments. In other words, learner exploration is not random behavior. Rather, it represents a systematic process whereby individuals identify, seek out, and resolve novelty relevant to immediate task performance (Loewenstein, 1994). In this regard, exploration can mitigate the premature adopting of an overly narrow task focus and settling on suboptimal strategies (Gopher, Weil, & Siegel, 1989; Stafford & Dewar, 2013; Yechiam, Erev, & Gopher, 2001). On the other hand, when learning simple tasks in which novelty is limited and optimal approaches are readily available, continuous exploration is often unnecessary and may inhibit the automation of optimal strategies. In these instances, practice may be better spent repeating and overlearning the correct approach. However, tasks typically used in adaptive training (e.g., active learning training) are characterized by complex and dynamic decision-making characteristics (Kozlowski, Toney, et al., 2001) that are well suited for exploratory behavior given that they typically have no single, simple task solution or optimal strategy. Accordingly, we expected that when learning a complex task, positive effects of task exploration on learning would be found at the within-person level such that fluctuations in exploration in an active learning context would be positively associated with changes in episodic practice performance. These benefits cumulate over the course of practice as individuals build their knowledge and skill, leading to positive effects at the between-person level as well.

Hypothesis 1. Exploratory behavior will be positively related to (a) practice performance at the between-person and within-person levels and (b) post-training learning outcomes (i.e., task knowledge, analogical transfer, and adaptive transfer).

The moderating role of general mental ability and pre-training task-related knowledge

Cognitive resources are required to incorporate new information into knowledge to be applied in future performance instances (Kanfer & Ackerman, 1989). Trainees encounter a large amount of nuanced information when exploring, which requires attentional resources on the part of the trainee (Kahneman, 1973; Treisman & Gelade, 1980). Although some researchers (e.g., Keith et al., 2010) argue that active learning environments are suitable for both low- and high-ability learners, critics of discovery-based approaches argue that the cognitive load incurred by exploration puts limits on its potential benefits to individuals who have the requisite ability to handle such demands (Ivancic & Hesketh, 1995, 2000; Kirschner et al., 2006). Analogical and problem-solving processes are likely to be important for converting and combining information learned from exploration into a framework that facilitates future performance. Accordingly, one might predict interactions such that (a) GMA and (b) pre-training task-related knowledge equip trainees with the requisite cognitive capacity to better process information from exploration.

Hypothesis 2. The positive relationships between exploration and practice performance, and exploration and post-training outcomes will be moderated by (a) GMA and (b) task-related knowledge such that the relationships will be larger for trainees with higher-GMA and pre-training task-related knowledge.

The dynamics of exploratory behavior

As we alluded to earlier, curiosity theory proposes that exploratory behavior is a dynamic process whereby learners continually assess and reassess discrepancies between novelty in the environment and their current level of competence (Loewenstein, 1994). Accordingly, trends in one's motivation to resolve novelty (White, 1959) and consequently exploratory behavior should reflect changes in novelty perceived by learners relative to changes in their levels of competence. As such, when performing a complex task early in practice, perceived novelty will be relatively high. As a result, learners will expend considerably more effort exploring novel stimuli early in training in order to resolve the wider information-knowledge gaps initially perceived. However, as training progresses, learners begin to resolve novelty as they become more knowledgeable and skilled. The longer trainees engage in practice, the narrower their information-knowledge gap becomes.

Therefore, we expected that exploratory behavior would be highest early in practice but would gradually decline over the course of practice.

Hypothesis 3. Exploratory behavior will decline across practice trials.

Antecedents of exploratory behavior

Thus far, we have focused primarily on overall trends of exploration during practice. However, it is important to note that levels of novelty perceived at the onset of training are not the same in all learners, even in similar performance contexts. Furthermore, Berlyne argued that the mechanism of increased complexity also plays an important role in curiosity theory because it allows for sustained levels of exploratory behavior (Berlyne, 1960, 1966, 1970). In particular, Berlyne proposed that increased complexity results in elevated levels of novelty (Berlyne, 1966), which slows the rate at which the information-knowledge gap is closed in response to increasing levels of competence. Indeed, early research has supported the notion that individuals generally prefer sources of novelty slightly more complex than their current levels of competence (Earl, Franken, & May, 1967; May, 1963). Together, novelty and complexity operate in an adaptive feedback process that allows explorers to continue to learn and grow, even as they resolve initial sources of novelty.

However, not everyone will increase task complexity at the same rate, resulting in variations in the trends of exploratory behavior across practice and across learners. The implication of this dynamic process is that factors that influence (a) overall levels of perceived novelty and (b) one's willingness to increase complexity following changes in task knowledge or skill will also influence overall levels and trends in exploratory behavior (Greif & Keller, 1990; Loewenstein, 1994). Along these lines, we expected that capability-based individual differences would contribute to overall levels of exploration and to the trajectory of exploratory behavior across practice trials such that trainees who perceive greater levels of novelty and those willing to increase the complexity of their interactions with the task environment would be more likely to explore more and to continue exploring in active learning contexts. Although a wide range of antecedents to exploration are plausible (e.g., goal orientations, metacognition, openness, self-efficacy, and emotional regulation), we elected to focus on capability-based individual difference antecedents for which the relationships with novelty and complexity have been demonstrated in the extant literature; namely GMA and pre-training task-related knowledge.

General mental ability

Theorists have long considered GMA and exploration to be closely related. As such, the relationship has been examined in research on animal behavior (e.g., Matzel et al., 2003, 2006), human infants (e.g., Berg & Steinberg, 1985; Bornstein & Sigman, 1986), and in educational contexts (e.g., Coie, 1974; Maw & Magoon, 1971). Voss and Keller (1983) emphasized the importance of the GMA–exploration relationship in human development when they noted that, "exploration is a form of intelligent behavior" (p. 122). Research in the cognitive literature suggests that higher-GMA individuals are able to recognize and engage a greater amount of novelty in the environment given their greater availability of cognitive resources (Norman & Bobrow, 1975). Accordingly, higher-GMA learners naturally perceive a relatively larger information-knowledge gap because they are able to perceive greater amounts of novelty in a complex environment relative to lower-GMA learners. Given their higher levels of perceived novelty, higher GMA learners engage in more exploratory behavior overall during practice. Furthermore, research has shown that when given control over the level of task complexity to practice in an active learning environment, higher-GMA trainees select higher levels compared to lower-GMA trainees (Hughes et al., 2013). By engaging complexity, higher-GMA trainees are continually exposed to novelty, which leads to maintenance of the information-knowledge gap and to more sustained exploration across practice trials.

Hypothesis 4. GMA will be (a) positively related to average exploration and (b) inversely related to the decline in exploration across practice trials.

Pre-training task-related knowledge

When it comes to the acquisition of skill on the type of open, complex tasks, common in active learning contexts, variability in performance between learners often increases over the course of practice and instruction in a fan-spread pattern such that those with higher levels of knowledge and skill at the onset of training improve at a faster rate than those with less knowledge and skill (Ackerman, 2007). This phenomenon is sometimes referred to as the "Matthew Effect" in that the 'rich' get 'richer' whereas the 'poor' do not (Ackerman, 2007; Stanovich, 1986). Research suggests that this effect is prevalent in active learning environments such that more experienced learners benefit more from active learning environments than do novices (Kalyuga, 2007; Kalyuga, Chandler, & Sweller, 2001; Scheiter & Gerjets, 2007). We propose that the fan-spread effect in active learning environments can be partially explained by differences in trainee willingness and capability to explore. When encountering complex tasks, individuals with greater expertise are better able to recognize novelty because they pay attention to different aspects of the task, are less distracted by superficial characteristics, and see unfamiliar task exceptions as more analyzable (Haerem & Rau, 2007). These advantages allow trainees higher in pre-training task-related knowledge to better identify meaningful sources of novelty, leading to a larger information-knowledge gap to resolve via exploration. Furthermore, research has shown that when given the opportunity, trainees with more pre-training experience select higher overall levels of task complexity to practice in an active learning environment (Hughes et al., 2013). Collectively, like the preceding rationale for GMA, these findings suggest that trainees higher in pre-training task-related knowledge are better equipped to explore in active learning.

Hypothesis 5. Pre-training task-related knowledge will be (a) positively related to exploration and (b) inversely related to the decline in exploration across practice trials.

Error framing

Main effect

Active learning interventions involve the use of design elements to guide trainee self-regulatory processes (Debowski et al., 2001; Keith & Frese, 2005; Kozlowski, Gully, et al., 2001). Error management training (EMT) is one such intervention that has received notable attention and empirical support (Keith & Frese, 2008). In EMT, error-framing instructions are used to influence how trainees interact with the training environment by encouraging and facilitating exploratory behavior (Keith & Frese, 2008). Error-approach instructions frame errors as a beneficial part of the learning process, whereas error-avoid instructions frame errors as mistakes to be avoided. Error-approach instructions are thought to facilitate learning by encouraging trainees to seek out the causes of their errors through exploration (Dormann & Frese, 1994; Keith & Frese, 2005, 2008).

Despite the importance of exploration in EMT theory, to our knowledge, only one study has directly examined the impact of error-framing instructions on exploration during training. Dormann and Frese (1994) found that error-approach training was related to greater levels of exploration relative to proceduralized learning when teaching 30 psychology students to use statistical software. Furthermore, they found that exploration was positively related to learning. Interestingly, Dormann and Frese (1994) noted that when trainees ignored instructions and explored in the proceduralized condition, they demonstrated performance levels similar to those in the error-approach condition. However, because the training content substantially differed between the two conditions, exploration was operationalized differently in each condition. Consequently, exploratory behavior between the two conditions could not be compared. To allow for a clearer examination of the effects of error-framing instructions on task exploration, we sought to replicate the findings of Dormann and Frese (1994) using consistent training content and a consistent operationalization of exploration across conditions.

Hypothesis 6. Error-approach instructions compared to the error-avoid instructions will lead to higher levels of exploration during practice.

Attribute-treatment interactions

The interaction between ability and training structure on learning outcomes is one of the most commonly purported attribute-treatment interactions (ATI) in the training and educational literatures (Cronbach & Snow, 1969; Goldstein & Ford, 2002; Pashler, McDaniel, Rohrer, & Bjork, 2008; Snow & Lohman, 1984). The logic is that lower-ability trainees need and do better in more structured (e.g., proceduralized) instructional programs, whereas higher-ability trainees prefer and do better in less structured instructional programs. Structure is thought to inhibit the natural learning strategies (e.g., exploration) used by higher-ability trainees (Goldstein & Ford, 2002). In this vein, Gully et al. (2002) found that higher-GMA trainees benefited more from error encouragement than lower-GMA trainees. Negative error framing was thought to impose a certain degree of structure on trainees whereas positive error framing represented a more open, unstructured environment (Gully et al., 2002). Although less work has focused on task-related knowledge, it is likely to interact in a similar fashion as GMA with elements of the training environment to influence behavior and outcomes (Gully & Chen, 2010). We propose that trainee exploratory behavior can help explain Gully et al.'s (2002) ATIs such that trainees higher in GMA and pre-training task-related knowledge will see errors as a source of novelty and consequentially explore more in error-approach environments than error-avoid environments. In contrast, trainees lower in GMA and pre-training task-related knowledge are less likely to see the novelty in errors. As a result, their decisions to engage in exploration will be less affected by error-framing instructions.

Hypothesis 7. The beneficial effect of error-approach instructions on exploration will depend on trainee (a) GMA and (b) pre-training task-related knowledge such that the effect will be larger for trainees with higher GMA and pre-training task-related knowledge.

Method

Participants

Participants were 128 undergraduate males attending a large, public university in the southwestern U.S. Due to computer problems, data from seven participants were missing, resulting in complete data from 121 participants. Participants ranged in age from 18 to 28 ($M = 19.16$, $SD = 1.30$). Participants were randomly assigned to one of three error-framing conditions: error-approach ($n = 39$), error-avoid ($n = 41$), or no error framing ($n = 41$). Participants received research credit for a psychology course research participation requirement.

Performance task

The performance task was Unreal Tournament 2004 (UT2004; Epic Games, 2004), a commercially available first-person-shooter computer game with many dynamic decision-making characteristics (Kozlowski, Toney, et al., 2001); that is, UT2004 contains technology-mediated, shifting, ambiguous, and emergent task-qualities which are important criterion-task features for studies of active learning. In UT2004, participants compete against computer-controlled opponents from the perspective of their character, which they move and manipulate in a fast-paced dynamic setting. Using weapons, the objective is to destroy the opponents while minimizing the destruction of one's character. Participants start with a basic weapon and can collect new weapons or resources (i.e., pick-ups) to increase their character's health, basic offensive and defensive capabilities, and advanced capabilities (i.e., power-ups). The game environment (i.e., the map) is arranged such that weapons and pick-ups appear in consistent locations. A few special pick-ups are available in locations only accessible by deliberate choice. When an opponent or the participant's character is destroyed, that character reappears in a new location with the basic weapons and capabilities. A trial (i.e., a game) ends when time runs out.

UT2004 involves a high degree of both psychomotor and cognitive demands. Participants use a mouse and keyboard simultaneously to move and control their character. Participants must learn how each weapon works, consider weapon strengths and weaknesses, and be able to quickly decide which to use given the circumstances. Moreover, participants must learn and remember weapon and resource locations and, in some cases, use problem solving to access those items. Although some approaches to task performance are generally more effective than others, there is no single optimal strategy in UT2004 for maximizing task performance in all situations. The best tactics in each situation will depend on the combination of several important and dynamic task parameters. For example, depending on the range and location of their opponents, their surroundings, and their character's health, participants must decide whether to move to find more health resources or other pick-ups, change their weapon choice and combat tactics, or move to find a more advantageous position.

Procedures

All participants were told that the purpose of the study was to examine how people learn to play a dynamic and complex videogame. Participants first completed an informed consent form followed by a measure of videogame experience. They then watched a 15-min training video on UT2004 explaining the basic game controls, rules, and resources, followed by 3 min for practice and familiarization with the basic controls, display, and game environment without any opponents. Then, participants performed two 5-min baseline trials against two opponents for which they were instructed to "do your best." UT2004 allows an objective level of computer-controlled opponent difficulty that ranges from 1 to 8. For the baseline trials, the opponents were set to perform at a moderate level of difficulty (5) as determined by pre-study pilot testing.

Next, error-framing instructions were read aloud and all participants underwent three learner-guided practice sessions, each consisting of five 5-min trials against two opponents set at the same difficulty as the baseline trials for a total of 15 practice trials. All participants were instructed to view the practice sessions as learning opportunities and to advance at their own pace. Detailed performance feedback was available on the game screen during and after every trial. Participants were also given a game log to record their performance and make game-related notes throughout practice.

Immediately following the last practice session, a manipulation check of the error-framing instructions was administered. Next, participants played two 5-min trials against two opponents at the same difficulty and on the same map as the practice trials, testing their post-training performance (i.e., analogical transfer). Participants were instructed to "do your best" on each of these two trials. Following the post-training test trials, participants entered a period of non-use during which they completed a measure of GMA and a test of task knowledge.

Finally, participants played two 5-min adaptive transfer trials. Unlike the previous trials, tests of adaptive transfer included nine opponents and were played on a map that was structured differently from the previous map, containing new interactive features, and introducing the chance of being destroyed by environmental hazards. In addition, the difficulty was raised one setting to 6 on the 1-to-8 scale. At this elevated difficulty, opponents were faster, more elusive, made better decisions, and were more unpredictable. Participants were informed of these changes prior to testing and were once again told to "do your best." Participation in the study lasted approximately 4 h.

Error-framing manipulation

Error-framing instructions were read aloud to participants at the start of the first 5-trial practice session. Error-framing instructions were reiterated at the top of the game logs and abridged error-framing instructions were read aloud before the second and third practice sessions. All participants were told to view the practice trials as learning opportunities and that practice is beneficial for learning. Error-approach instructions also communicated that errors are beneficial for learning and encouraged participants to make errors during the practice sessions. In contrast, error-avoid instructions communicated that errors are detrimental to learning and instructed participants to avoid making errors during practice. Participants in the control condition received no error-framing instructions. Following the last practice trial, participants responded to two questions about their willingness to make errors during practice. Participants in the error-approach condition indicated they were more willing to make errors ($M = 3.51$, $SD = 0.73$) compared to participants in the error-avoid condition ($M = 2.66$, $SD = 1.13$, $t = 4.31$, $p < .01$, $d = 1.16$) and the no error-framing condition ($M = 3.12$, $SD = 0.71$, $t = 1.98$, $p < .05$, $d = 0.53$). Furthermore, indicating a greater willingness to make errors, participants in the error-approach condition destroyed their own character more, on average, during practice ($M = 12.10$, $SD = 6.64$) than participants in the error-avoid condition ($M = 9.46$, $SD = 4.80$, $t = 2.05$, $p < .05$, $d = 0.73$) and the no error-framing condition ($M = 9.54$, $SD = 5.21$, $t = 2.11$, $p < .05$, $d = 0.71$).

Measures

GMA

The 12-item short form (Arthur & Day, 1994) of the Advanced Progressive Matrices (Raven, Raven, & Court, 1998) was used to measure GMA. A Spearman–Brown odd–even split-half reliability of .71 was obtained in the present study.

Pre-training task-related knowledge

We used a composite index of videogame experience and baseline performance for our measure of pre-training task-related knowledge. A 4-item scale was used to measure videogame experience; a proxy for domain knowledge. For the first two items, participants responded using a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*daily*) to the following questions: (a) "Over the last 12 months, how frequently have you typically played video/computer games?" ($M = 3.50$, $SD = 1.02$) and (b) "Over the last 12 months, how frequently have you typically played first-person shooter video/computer games (e.g., Call of Duty, Half-Life, Halo, Unreal Tournament)?" ($M = 3.02$, $SD = 1.18$). For the second two items, participants indicated how many hours per week they typically play video/computer games ($M = 4.57$, $SD = 4.83$, min. = 0.00, max. = 30.00) and how many hours per week they typically play first-person shooter video/computer games ($M = 2.81$, $SD = 4.01$, min. = 0.00, max. = 30.00). Scores for these four items were standardized and then averaged into a single videogame experience score. Scores for the two baseline performance trials were averaged ($M = 0.26$, $SD = 0.11$) and then standardized. Finally, the standardized index of videogame experience and the standardized index of baseline performance were averaged to yield a composite index of overall pre-training task-related knowledge. Following recommendations outlined by Wang and Stanley (1970), a composite reliability of .81 was obtained for this index of task-related knowledge.

Exploratory behavior

Exploratory behavior was coded in each practice trial from video playbacks by the first author and one undergraduate coder experienced with common videogame environments and strategies. Coders underwent approximately 20 h of frame-of-reference training in which they were familiarized with the UT2004 training environment and the exploration scales. Coders independently viewed game videos for each participant and rated exploratory behavior using four 5-point scales. Video files were recorded and stored in a way such that access to the videos ensured the coders were blind to the experimental condition as well as information regarding all predictor and criterion variables. Of the 1815 trial videos coded (151.25 h of game play across 121 participants) a random sample of 300 trial videos (20 participants) were rated by both coders to examine interrater reliability. Intraclass correlation coefficients (ICCs) were used to examine interrater reliability (Shrout & Fleiss, 1979). As recommended by Cicchetti (1994), ICC's between .60 and .74 are considered good interrater reliability and ICC's above .75 are considered excellent interrater reliability.

The exploration scales were developed via a content analysis of UT2004 in relation to how exploration has been conceptualized in the extant literature on emphasis change exploration (Erev & Gopher, 1999; Gopher et al., 1989; Yechiam et al., 2001), child exploration (Hutt, 1966; Jennings, Harmon, Morgan, Gaiter, & Yarrow, 1979), animal exploration (Dashiell, 1925; Nissen, 1930), and active learning (Dormann & Frese, 1994). Because exploratory behavior is defined in reference to specific task stimuli, developing scales of exploration in the context of the specific task domain is important for understanding how exploration operates in a practical learning context (Loewenstein, 1994). Therefore, three of the scales in the current effort measured exploratory behavior in three major game domains: (a) combat strategies, (b) weapons, and (c) map. The fourth scale measured overall exploratory behavior. Exploratory behavior was defined as an active interaction on the part of the trainee with the training environment through the trainee's attempts at multiple solutions to the problem at hand (Dormann & Frese, 1994).

The variety of combat strategies scale (ICC = .70) ranged from 1 (*very few strategies tried*) to 5 (a *great deal of strategies tried*). The variety of weapons used scale (ICC = .69) ranged from 1 (*very few weapons tried*) to 5 (*a great deal of weapons tried*). The amount of map visited scale (ICC = .81) ranged from 1 (*very little map visited*) to 5 (*entire map visited*). Each of these three scales were designed to capture how thoroughly trainees were exploring various sources of novelty in each of the major game domains. The overall exploratory behavior scale (ICC = .77) provided a rating of exploration similar to that used in previous research on active learning (i.e., Dormann & Frese, 1994) and accounted for characteristics of exploratory behavior not captured by the other scales. For this scale, coders were instructed to rate exploratory behavior in the context of participant behavior up until the trial being coded. In this way, the overall exploration scale captured exploration in the context of the other trials and took into consideration uniqueness in each learner's approaches relative to previous trials. This scale ranged from 1 (*very little exploratory behavior*) to 5 (*a great deal of exploratory behavior*). Correlations among the exploration scale scores ranged from .52 to .65. Together these scales combined to capture both the overall amount (i.e., the total variety of solutions explored during each trial) and uniqueness (i.e., the frequency of brand-new approaches explored during each trial) of participant exploration during practice. A confirmatory factor analysis indicated the four scales loaded on a single factor. Therefore, the four scale scores were averaged for each trial to create an overall trial-level exploration index. Coefficient alpha for this measure was .89.

Content validity of the individual exploration scales was examined using an approach similar to that recommended by MacKenzie, Podsakoff, and Podsakoff (2011). Five graduate students unfamiliar with the purpose of the study served as subject matter experts (SMEs) and were trained on the definition and core aspects of exploration. SMEs then independently rated how well each exploration scale definition and accompanying benchmarks captured the core aspects of exploration on a scale ranging from 0 (*Not at all*) to 4 (*Very much*). The mean SME ratings across the four scales ranged from 3.00 to 3.70, showing support for the content validity of the scales in reference to the conceptualization of exploratory behavior.

To examine the sensitivity of the exploration scale scores to detect variations in exploratory behavior, we used a video-based construct validation procedure recommended by Podsakoff, Podsakoff, MacKenzie, and Klinger (2013). The purpose of the video-based construct validation procedure is to determine if variations in the construct of interest cause corresponding variations in the scores of the measures utilized. First, script manipulations were developed to reflect various levels of exploration and trends in exploration across trials. Next, video manipulations of exploration based on the scripts were produced, refined, and validated. Finally, the video manipulations were viewed and coded by nine undergraduate student raters unfamiliar with the purpose of the study to examine if ratings are sensitive to variations of the construct represented in the video manipulations. Hierarchical linear modeling (HLM) blocking on coder, confirmed that the manipulation of exploration was strongly related to mean ratings of exploratory behavior ($B = 2.86$, $t(33) = 55.85$, $p < .01$). Furthermore, the trial by exploration manipulation interaction was significant ($B = 0.56$, $t(142) = 16.25$, $p < .01$) indicating that exploration ratings reflected manipulated changes in exploration across trials.

Learning outcomes

Scores for baseline skill, practice performance, analogical transfer performance, and adaptive transfer performance were calculated using an identical function of multiple in-game statistics. Specifically, performance scores were computed by dividing participant kills (i.e., number of times a participant destroyed an opponent) by the quantity of kills plus deaths (i.e., number of times a participant's own character was destroyed) plus participant rank (i.e., finishing in first, second, or third place relative to the opponents in the trial) all of which were displayed on-screen during and at the end of every trial. Scores could range from 0 to approximately 1. This formula is similar to the one used by the creators of UT2004 to create an index of efficiency and was used in this study because it accounts for multiple aspects of performance. Task knowledge was measured with a 20-item multiple-choice test reflecting a mix of basic, procedural, and strategic knowledge.

Results

Exploration as a predictor of learning outcomes

Practice performance

Means, standard deviations, and intercorrelations for the between-person and within-person variables are presented in Table 1. We used HLM (Raudenbush & Bryk, 2002) to examine the between- and within-person effects of exploration on practice performance. Consistent with previous research (e.g., Gully et al., 2002), condition was dummy coded with the error-approach condition set 0,0 as the comparison group. GMA, pre-training task-related knowledge, and between-person exploration were grand-mean centered. Within-person exploration was person-mean centered. To facilitate interpretation of the average main effects in the presence of dynamic trends, the practice trial trajectory was centered on the middle (eighth) practice trial. The linear and quadratic trajectories of practice trial (i.e., performance over practice trials), within-person exploration, and the linear practice trial × within-person exploration interaction were Level 1 predictors. GMA, pre-training task-related knowledge, condition, between-person exploration, and the capability × between-exploration interactions were Level 2 predictors.

The ICC of the practice performance unconditional model indicated that 50% of the variance in practice performance was between participants and 50% of the variance was within participants. As can be seen in Model 1 of Table 2, the linear ($\beta = .03$, $p < .01$) and quadratic ($\beta = -.01$, $p < .01$) trajectories of practice performance were significant, indicating that practice performance in this task followed a classic skill-acquisition curve (Fitts & Posner, 1967). Task-related knowledge ($\beta = .54$, $p < .01$) was positively related to average practice performance. Additionally, as shown by the linear practice trial × condition interactions in Model 2 of Table 2, error framing had dynamic effects on practice performance (Fig. 2) such that the performance among participants in the error-approach condition was worse early in practice, but improved at a faster rate relative to those in the error-avoid condition ($\beta = -.02$, $p < .05$) and the no error instructions condition ($\beta = -.02$, $p < .05$).

Hypotheses 1a was supported. As shown in Model 3 of Table 2, both between-person exploration ($\beta = .13$, $p < .01$) and within-person exploration ($\beta = .04$, $p < .01$) were positively associated with practice performance. In contrast, Hypotheses 2a and 2b were not supported. As shown in Model 4 of Table 2, neither GMA nor task-related knowledge moderated the between- or within-person exploration effects on practice performance.

Post-practice learning outcomes

To examine the relationships between exploration and post-practice learning outcomes, we conducted a series of moderated hierarchical regression analyses. We entered GMA and pre-training task-related knowledge first, followed by the dummy-coded training conditions, followed by exploration, followed by the GMA and pre-training task-related knowledge interactions with exploration. Hypothesis 1b was supported. As shown in Table 3, exploration was positively related to all proposed learning outcomes including

Table 1
Means, standard deviations, and intercorrelations of study variables at the between-person and within-person levels.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
Between-person level											
1. Error approach	0.32	0.47									
2. Error avoid	0.34	0.48	−.49**								
3. Control	0.34	0.48	−.49**	−.51**							
4. GMA	7.41	2.35	−.07	.05	.02						
5. Pre-training task-related knowledge	0.00	0.84	.04	−.09	.05	.20*					
6. Exploration	3.02	0.45	−.04	−.12	.16†	.22*	.33**				
7. Practice performance	0.33	0.12	.05	−.04	−.01	.26**	.76**	.42**			
8. Task knowledge	11.53	2.65	.03	.02	−.05	.38**	.50**	.39**	.57**		
9. Analogical transfer	0.38	0.15	.07	.00	−.07	.23**	.66**	.38**	.79**	.58**	
10. Adaptive transfer	0.21	0.09	.02	.01	−.03	.24**	.61**	.41**	.77**	.40**	.64**

Variable	ICC	*M*	*SD*	1	2
Within-person level					
1. Practice trial	–	0.00	4.32		
2. Exploration	.66	3.02	0.71	−.27**	
3. Practice performance	.50	0.33	0.16	.14**	.18**

Note. N between-person = 121. N within-person = 1815. GMA = general mental ability. ICC = intraclass correlation coefficient. Pre-training task-related knowledge is a composite of pre-training task-related experience and baseline skill.
† $p < .10$ (two-tailed).
* $p < .05$ (two-tailed).
** $p < .01$ (two-tailed).

Table 2
HLM results for the prediction of practice performance.

Variable	Model 1			Model 2			Model 3			Model 4		
	B	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Intercept (γ_{00})	.341**	.007	.00	.346**	.012	.00	.347**	.012	.00	.347**	.012	.00
Linear practice trial trajectory (γ_{10})	.005**	.001	.03	.008**	.001	.05	.008**	.001	.05	.008**	.001	.05
Quadratic practice trial trajectory (γ_{20})	−.001**	.000	−.01	−.001**	.000	−.01	−.001**	.000	−.01	−.001**	.000	−.01
GMA (γ_{01})	.006†	.003	.08	.006*	.003	.08	.004	.003	.06	.005	.003	.07
Pre-trng. task-related knowledge (γ_{02})	.101**	.008	.54	.102**	.008	.54	.094**	.008	.50	.094**	.008	.49
Linear practice trial × GMA (γ_{11})	.000	.000	.00	.000	.000	.00	.000	.000	.00	.000	.000	.00
Linear practice trial × pre-trng. task-related knowledge (γ_{12})	.002†	.001	.01	.002†	.001	.01	.001	.001	.01	.001	.001	.00
Dummy control (γ_{03})				−.012	.017	−.07	−.017	.016	−.11	−.017	.017	−.10
Dummy error-avoid (γ_{04})				−.002	.017	−.01	.000	.016	−.00	.000	.017	.00
Linear practice trial × dummy control (γ_{13})				−.004*	.002	−.02	−.004*	.002	−.02	−.004*	.002	−.02
Linear practice trial × dummy error-avoid (γ_{14})				−.004*	.002	−.02	−.004*	.002	−.02	−.004*	.002	−.02
Between-person exploration (γ_{05})							.047**	.016	.13	.047**	.016	.13
Within-person exploration (γ_{30})							.012**	.005	.04	.013**	.005	.05
Linear practice trial × between-person exploration (γ_{15})							.001	.002	.00	.001	.002	.00
Linear practice trial × within-person exploration (γ_{40})							.001	.001	.00	.001	.001	.00
Between-person exploration × GMA (γ_{06})										.004	.006	.03
Within-person exploration × GMA (γ_{31})										.000	.002	.00
Between-person exploration × pre-trng. task-related knowledge (γ_{07})										−.012	.017	−.03
Within-person exploration × pre-trng. task-related knowledge (γ_{32})										−.011	.006	−.03

Note. N between-person = 121. N within-person = 1815. The error-approach condition was set as the comparison group. Dummy control: Error approach = 0, Control = 1. Dummy error avoid: Error approach = 0, Error avoid = 1.
† $p < .10$ (two-tailed).
* $p < .05$ (two-tailed).
** $p < .01$ (two-tailed).

practice performance ($\beta = .19$, $p < .01$, $\Delta R^2 = .029$), task-knowledge ($\beta = .23$, $p < .01$, $\Delta R^2 = .042$), analogical transfer ($\beta = .21$, $p < .01$, $\Delta R^2 = .030$), and adaptive transfer ($\beta = .23$, $p < .01$, $\Delta R^2 = .047$). However, again, Hypotheses 2a and 2b were not supported. Neither GMA nor task-related knowledge moderated the effects of exploration on any of the learning outcomes.

Dynamics and antecedents of exploration

The dynamics of exploration and the effects of GMA, task-related knowledge, error framing, and the error framing × GMA and task-related knowledge interactions on exploratory behavior were tested using a series of HLMs with exploration as the dependent variable. GMA and pre-training task-related knowledge were grand-mean centered. The linear trajectory of exploration over practice trials was set as a Level 1 predictor and was centered on the middle (eighth) practice trial. GMA, pre-training task-related knowledge, condition, and the condition × individual difference interactions were set as Level 2 predictors.

The ICC of the exploration unconditional model indicated that 66% of the variance in exploration was between-person and 34% was within-person. As shown in Model 1 of Table 4, the linear trajectory of exploration over the practice trials supported Hypothesis 3. On average, exploratory behavior decreased across the practice

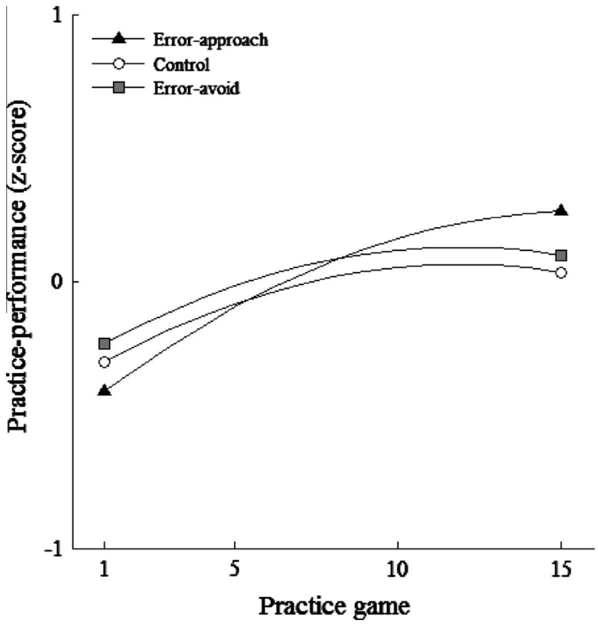

Fig. 2. Effect of error framing on practice performance over practice.

trials ($\beta = -.06$, $p < .01$). Although the relationship between GMA and average exploration was positive as predicted, the magnitude of this effect was close to but did not reach conventional levels of statistical significance in Model 1 ($\beta = .10$, $p = .07$). Thus, the results in this model did not support Hypothesis 4a. However, the results in Model 1 supported Hypothesis 5a, showing that task-related knowledge ($\beta = .19$, $p < .01$) was positively related to average exploration. Hypothesis 4b was not supported; GMA was not related to the changes in exploration across practice trials. However, Hypothesis 5b was supported. There was an interaction between task-related knowledge and the linear exploration trajectory ($\beta = .02$, $p < .05$) such that participants higher in task-related knowledge were more likely to continue exploring in later practice trials whereas those lower in task-related knowledge exhibited a steeper decline in exploratory behavior (Fig. 3). As shown in Model 2, Hypothesis 6 was not supported. No statistically significant main effects were found for error framing on exploration. Hypothesis 7a received mixed support. As shown in Model 3 of Table 4, the moderating effect of error framing on the GMA–exploration relationship (Fig. 4) was close to, but did not reach conventional levels of statistical significance ($\beta = -.19$, $p = .09$). However, given the likelihood of multicollinearity resulting from the relationship between GMA and task-related knowledge and the similarities in both proposed interactions with error framing, we tested each interaction in separate models following the recommendations of Appelbaum and Cramer (1974). After removing the suppressing effects of task-related knowledge, the main effect of GMA was positive and significant ($\beta = .14$, $p < .01$) showing support for Hypothesis 4a, and the interaction between GMA and error framing was also statistically significant ($\beta = -.27$, $p < .05$) showing support for Hypothesis 7a. Specifically, higher-GMA trainees (+2z) explored more in the error-approach condition than in the error avoid condition ($t(115) = 2.40$, $p < .05$), whereas for low GMA train-

Table 3
Hierarchical multiple regression results for the prediction of learning outcomes.

Model/variable	B	SE	β	R^2	ΔR^2
Practice performance					
1. GMA	.005	.003	.09	.584**	
Pre-training task-related knowledge	.093**	.009	.67		
2. Dummy control	−.019	.017	−.08	.586**	.002
Dummy error-avoid	−.002	.017	−.01		
3. Exploration	.049**	.017	.19	.614**	.029**
4. GMA × exploration	.004	.006	.04	.622**	.007
Pre-training task-related knowledge × exploration	−.025	.018	−.09		
Task knowledge					
1. GMA	.014**	.005	.25	.329**	
Pre-training task-related knowledge	.059**	.013	.38		
2. Dummy control	−.032	.025	−.12	.336**	.006
Dummy error-avoid	.002	.025	.00		
3. Exploration	.069**	.024	.23	.378**	.042**
4. GMA × exploration	−.002	.009	−.01	.381**	.002
Pre-training task-related knowledge × exploration	−.015	.026	−.05		
Analogical transfer					
1. GMA	.003	.004	.05	.451**	
Pre-training task-related knowledge	.098**	.012	.59		
2. Dummy control	−.046†	.024	−.15	.462**	.011
Dummy error-avoid	−.008	.024	−.03		
3. Exploration	.066**	.023	.21	.492**	.030**
4. GMA × exploration	−.008	.009	−.07	.503**	.011
Pre-training task-related knowledge × exploration	−.026	.024	−.08		
Adaptive transfer					
1. GMA	.003	.003	.09	.387**	
Pre-training task-related knowledge	.057**	.008	.53		
2. Dummy control	−.012	.016	−.07	.392**	.005
Dummy error-avoid	.011	.016	.06		
3. Exploration	.047**	.016	.23	.439**	.047**
4. GMA × exploration	.002	.006	.03	.441**	.002
Pre-training task-related knowledge × exploration	.008	.017	.03		

Note. $N = 121$. The regression weights shown are from the final model. Dummy control: Error approach = 0, Control = 1. Dummy error avoid: Error approach = 0, Error avoid = 1.

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

† $p < .10$ (two-tailed).

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

Table 4
HLM results for the prediction of exploratory behavior.

Variable	Model 1			Model 2			Model 3		
	B	*SE*	β	*B*	*SE*	β	*B*	*SE*	β
Intercept (γ_{00})	2.999^{**}	.044	.00	3.002^{**}	.065	.00	3.001^{**}	.065	.00
Linear exploration trajectory (γ_{10})	-0.046^{**}	.005	−.06	-0.041^{**}	.009	−.06	-0.041^{**}	.009	−.06
GMA (γ_{01})	$0.030^{\dagger}$	.016	.10	$0.030^{\dagger}$	.016	.10	0.061^{*}	.026	.20
Pre-training task-related knowledge (γ_{02})	0.162^{**}	.045	.19	0.155^{**}	.045	.18	0.223^{**}	.067	.26
Linear exploration × GMA (γ_{11})	0.000	.002	.00	0.000	.002	.00	0.000	.002	.00
Linear exploration × pre-training task-related knowledge (γ_{12})	0.019^{**}	.006	.02	0.018^{**}	.006	.02	0.018^{**}	.006	.02
Dummy control (γ_{03})				0.110	.091	.15	0.110	.090	.15
Dummy error avoid (γ_{04})				−0.040	.092	−.06	−0.046	.090	−.06
Linear exploration × dummy control (γ_{13})				−0.007	.013	−.01	−0.007	.013	−.01
Linear exploration × dummy error avoid (γ_{14})				−0.008	.013	−.01	−0.008	.013	−.01
GMA × dummy control (γ_{05})							−0.042	.037	−.14
GMA × dummy error avoid (γ_{06})							$-0.059^{\dagger}$	.035	−.19
Pre-training task-related knowledge × dummy control (γ_{07})							−0.141	.103	−.17
Pre-training task-related knowledge × dummy error avoid (γ_{08})							−0.133	.099	−.16

Note. *N* between-person = 121. *N* within-person = 1815. The error-approach condition was set as the comparison group. Dummy control: Error approach = 0, Control = 1. Dummy error avoid: Error approach = 0, Error avoid = 1.
† $p < .10$ (two-tailed).
* $p < .05$ (two-tailed).
** $p < .01$ (two-tailed).

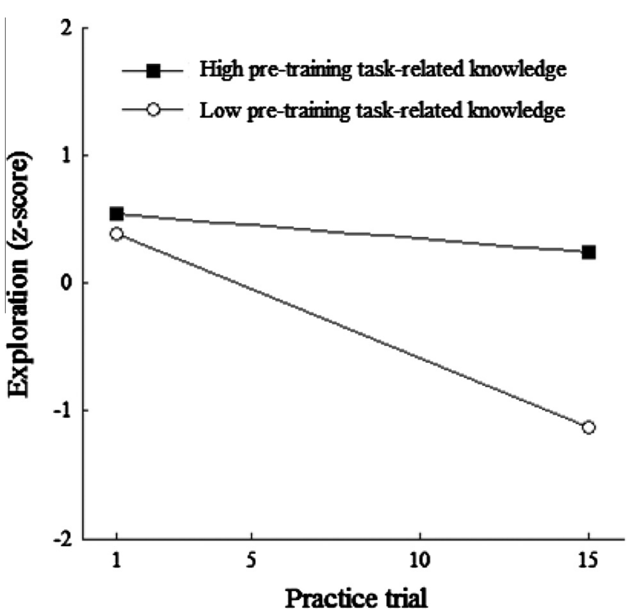

Fig. 3. Decrease in exploration across practice trials by pre-training task-related knowledge. High and low = ±2*z*. Slopes (βs): high pre-training task-related knowledge = −.01, $p > .05$; low pre-training task-related knowledge = −.10, $p < .01$ (two-tailed).

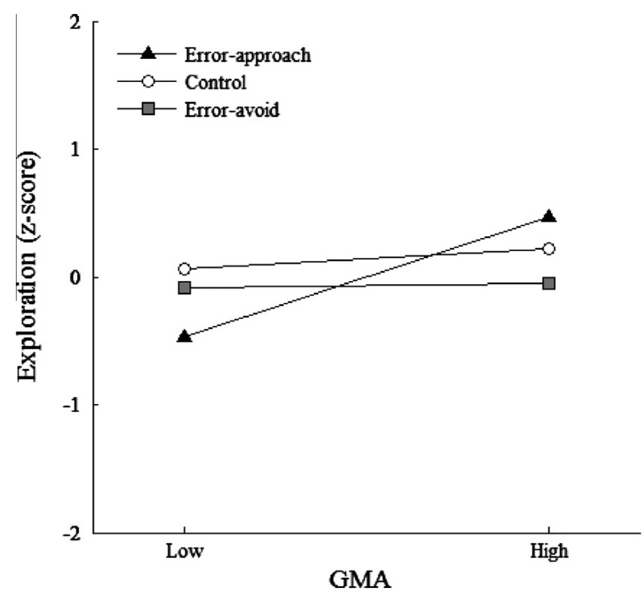

Fig. 4. Interaction of GMA and error framing. High and low = ±2*z*. Slopes (βs): error-approach = .20, $p < .01$; control = .04, $p > .05$; error-avoid = .01, $p > .05$ (two-tailed).

ees (−2*z*) the difference in exploration between the error-approach and error avoid conditions was not statistically significant ($t(115) = -1.64$, $p > .05$). Although the interaction between task-related knowledge and error framing showed a similar pattern such that trainees with higher task-related knowledge (+2*z*) generally explored more in the error-approach than error-avoid condition, this difference ($t(115) = 1.80$, $p > .05$) and its related interaction ($\beta = -.22$, $p > .05$) were not statistically significant. Accordingly, Hypothesis 7b was not supported.

Tests of indirect effects of individual differences on learning through exploration

Our model indicates that exploration is a mechanism through which GMA and pre-training task-related knowledge are linked to learning outcomes. Accordingly, we used the SOBEL macro for SAS developed by Preacher and Hayes (2004) to examine and compare the simple indirect effects of GMA and pre-training task-related knowledge on each of the learning outcomes via exploration. Bootstrapping was used to obtain confidence intervals. Across all learning outcomes, the results showed statistically significant indirect effects through exploration for both GMA (practice performance: $ab = .083$, 95% CI = .007–.180, $R^2_{ab} = .038$; task knowledge: $ab = .071$, 95% CI = .008–.162, $R^2_{ab} = .052$; analogical transfer: $ab = .078$, 95% CI = .009–.177, $R^2_{ab} = .030$, adaptive transfer: $ab = .082$, 95% CI = .005–.180, $R^2_{ab} = .033$) and pre-training task-related knowledge (practice performance: $ab = .063$, 95% CI = .017–.122, $R^2_{ab} = .144$; task knowledge: $ab = .085$, 95% CI = .026–.163, $R^2_{ab} = .096$; analogical transfer: $ab = .060$, 95% CI = .014–.122, $R^2_{ab} = .117$, adaptive transfer: $ab = .076$, 95% CI = .023–.144, $R^2_{ab} = .121$). Furthermore, across all learning outcomes, the indirect effects were larger for pre-training task-related knowledge than for GMA (mean $R^2_{ab} = .119$ versus .038) indicating that learning resulting from exploration is more strongly associated with task-relevant than general information-processing capabilities.

Discussion

Exploration is a fundamental process guiding how people interact with their surroundings and learn. Moreover, exploration is central to active learning, which has garnered growing empirical attention in the organizational training literature (Bell & Kozlowski, 2008, 2010). In the following sections, we review the key findings of the current study in relation to the effects of exploratory behavior on learning outcomes. Next, we discuss the relationships between task exploration and capability-based individual differences with a focus on how the pattern of results speaks to common criticisms of exploration-based training and to the domain-specific nature of exploration. Then, we discuss the effects of error framing on exploratory behavior and the similarities of the ATI found in the current study to those found in previous research. Finally, we emphasize the importance of measuring exploration directly and discuss how exploratory behavior fits in theories of self-regulated learning. We finish with a discussion of the limitations to the current study and outline areas of future research.

The relationship between exploration and learning outcomes

The value of active learning centers on the proposition that task exploration is beneficial to learning outcomes. However, much of the research on exploration in active learning has operationalized exploration as an intervention or a design element (Bell & Kozlowski, 2008) rather than as a dynamic information-gathering behavioral self-regulatory process. The current study contributes to this literature by directly measuring exploratory behavior and examining a variety of exploration–learning relationships in an active learning context. Furthermore, by adopting a between- and within-person approach, we were able to examine how learning is associated with fluctuations in exploratory behavior during practice.

Overall, the results showed consistent support for the predictions of active learning theory regarding the benefits of exploration. Exploration incrementally predicted practice performance and post-practice knowledge, performance, and adaptability outcomes beyond the influence of GMA and pre-training task-related knowledge. Furthermore, the positive effect of exploration found at the within-person level suggests that exploration can also benefit episodic performance when learning dynamic, complex, open tasks. Thus, it may be more appropriate to conceptualize exploration as a proximal self-regulation pathway to performance improvement and adaptability rather than as a training design element (cf. Bell & Kozlowski, 2008).

Nevertheless, the benefits of exploration found in the present study may not translate to all training contexts. For example, one could expect that encouraging exploration in simple tasks or tasks with clearly defined protocols might be distracting or counterproductive. Furthermore, it would be unwise to encourage learners to explore in dangerous situations when risks cannot be reduced within the relative safety of the training environment. As such, although targeting exploration shows promise in complex task training, trainers should always carefully consider if the task to be learned is amenable to exploratory behavior and ensure it is appropriate for active learning interventions.

Capability-based individual differences and exploration

Direct versus moderating effects and the criticisms of discovery learning

In the present study, we examined two pathways by which capability-based individual differences might be associated with learning in relation to exploration; namely (a) a direct effect in which capability stimulates the occurrence of exploration and (b) a moderating effect such that capability influences the extent to which trainees are able to learn from exploration. Each pathway carries important implications for training design. For example, a direct effect would suggest that some learners (i.e., low-capability learners) may need additional support, guidance, or encouragement to prevent them from settling prematurely on suboptimal strategies and missing important information in discovery (i.e., exploration-based) learning environments (Mayer, 2004). Alternatively, a moderating effect would suggest that the value of discovery approaches would ultimately be limited for learners with limited cognitive resources and that encouraging additional exploratory behavior may serve to further overwhelm low-capability learners (Kirschner et al., 2006).

Collectively, our findings supported direct effects of capability on exploratory behavior, but not moderating effects of capability on the exploration–learning relationship. Thus, problems associated with discovery environments may be attributable to differences in exploratory tendencies among learners rather than to excessive cognitive demands required to process information gathered during exploration. In this regard, we argue that a problem with discovery learning is in the assumption that all trainees will elect to explore as much as they should when given the opportunity. In the present study, we demonstrated that this assumption is perhaps untenable, which can help explain why some trainees miss important content when given control over the learning process (Mayer, 2004). In this respect, we found that lower-GMA trainees and trainees with less pre-training task-related knowledge were most at risk.

Accordingly, our findings support the recommendations of Mayer (2004), Kirschner et al. (2006), and others (Bell & Kozlowski, 2002, 2008; Debowski et al., 2001) who argue that guidance should be provided to some learners during exploration-based learning. However, we hope to help clarify theory regarding the role of guidance in two ways. First, we argue that guidance should encourage continuous, systematic exploration. Specifically, guidance should provide a coherent mental framework to allow trainees to make sense of and explore the training environment. Such knowledge structures come naturally to some trainees but not to others depending on their pre-training abilities and experiences (Gitomer, 1988; Kraiger, Salas, & Cannon-Bowers, 1995). Second, our findings showed that, on average, exploration declined across practice trials. However, trainees higher in pre-training task-related knowledge maintained higher levels of exploration, even in later practice sessions. These results corroborate the findings of van der Linden, Sonnentag, Frese, and Van Dyck (2001) who found that experienced participants were better able to overcome manipulated mental fatigue and use systematic exploration relative to inexperienced participants when performing a complex task. Perhaps if trainees are made aware of their tendency to settle into relatively ineffective strategies as training progresses (Seagull & Gopher, 1997), they will be more likely to continue exploring. Thus, the encouragement of exploratory behaviors and feedback on trainee exploratory tendencies might be especially beneficial for trainees low in pre-training task-related knowledge. In this manner, guidance may not need to be tailored to meet individual performance deficiencies *per se*. For example, if knowledge of results are provided across different performance components during the training process, trainees should be better able to compare and contrast the effectiveness of the strategies they attempt, allowing for more systematic exploration (Debowski et al., 2001). Furthermore, it may be beneficial to provide trainees with a degree of proceduralized instruction early in training to allow them to develop the requisite knowledge structures to engage in purposeful exploration upon entering an active learning environment.

The domain-specific nature of exploration

By comparing similar pathways by which GMA and pre-training task-related knowledge are linked to learning outcomes in relation to exploration, our findings suggest that exploration is largely a domain-specific rather than a general phenomenon. In other words, exploration may be more a product of experience, knowledge, and capability in a domain than general information-processing ability. Thus, individuals who explore prolifically in one context may not explore in another. Nevertheless, it is important to acknowledge that GMA is an important predictor of task-related knowledge (Schmidt & Hunter, 1992). Therefore, many of the effects of GMA on exploration may operate through task-related knowledge, which is more proximal to exploration. Moreover, our results showed that GMA uniquely predicted exploration beyond its relationship with pre-training task-related knowledge. Thus, when identifying individuals to take part in active learning, it is important to ensure that trainees have the capability to engage in exploration during practice.

Error framing and exploration

In the present study, we looked to isolate the effects of error framing—an intervention designed to influence trainee motivational self-regulatory processes—on trainee exploratory behavior. In doing so, we did not replicate the positive main effect of error management training (EMT) on exploration found by Dormann and Frese (1994). This finding runs contrary to the common but rarely tested assumption that error framing influences learning outcomes through increased trainee willingness to engage in exploratory behavior.

One explanation for the discrepancy between our findings and those of Dormann and Frese is that in Dormann and Frese (1994) other aspects of EMT training besides the framing of errors (e.g., instructor involvement or task commands) may have affected how trainees explored. By isolating the error-framing component of EMT rather than comparing EMT as a whole to an alternative proceduralized-learning approach (cf. Dormann & Frese, 1994), our conclusions speak to the effects of error-framing instructions, specifically, on exploration and not other aspects of EMT. Another explanation pertains to our finding that the effect of error framing on exploration was one of moderation involving an interaction with GMA. Thus, error framing had differential effects on tendencies to explore, such that higher-GMA participants explored more under error-approach than error-avoid instructions. This interaction, shown in Fig. 4, is similar to the ATIs found by Gully et al. (2002) for GMA on performance and self-efficacy outcomes. This convergence in the pattern of ATIs implies that differences in trainee willingness to explore under error-approach relative to error-avoid instructions may help explain differences in learning outcomes found in previous research. Accordingly, trainers should consider alternatives to error framing for fostering exploration in trainee populations that cover a wide range of GMA.

Direct measurement of exploration and the importance of behavioral self-regulation

One may question if a behavioral focus is appropriate when defining exploration and if doing so ignores the cognitive aspects of learning (Mayer, 2004). Clearly cognitive, motivational, and emotional self-regulation processes are important in active learning theory (Bell & Kozlowski, 2008, 2010). Accordingly, there is a relatively well-developed empirical literature on these topics (e.g., Brown & Ford, 2002; Debowski et al., 2001; Keith & Frese, 2005). However, less research attention has been given to understanding behavioral self-regulatory processes. Yet, as Kozlowski, Toney, et al. (2001) noted, "doing, thinking, and feeling all affect each other" and that "all three are engaged concurrently, such that whenever a trainee has an experience which stimulates her to practice more, she will simultaneously become more cognizant about her practice behaviors" (p. 94). When instruction and training are designed to encourage individuals to engage in various cognitive, motivational, and emotion-based self-regulation activities during practice, it is expected that many benefits can be attributed to some change in behavior (Kozlowski, Toney, et al., 2001). Thus, a focus on exploration provides additional insights into learning processes by drawing attention to the behavioral component of self-regulated learning that is often missing in the empirical literature. By measuring exploratory behavior directly in relation to key antecedent and mediating variables articulated in models of active learning, researchers will be better able to pinpoint how to leverage specific training elements and eliminate those that are redundant or detrimental to learning.

Limitations

It is important to acknowledge several limitations of the present study when looking ahead to future research. First, the training task used in the present study involved a combination of cognitive and psychomotor demands characteristic of many synthetic learning environments (SLEs; Cannon-Bowers & Bowers, 2010) that may differ from more traditional training programs that focus on the development of declarative and procedural knowledge. Yet, with the increasing use of technology in training (American Society for Training and Development, 2010), the entrance of a more technologically savvy generation into the workplace (Alsop, 2008), and a shift away from only emphasizing procedural knowledge (Ford, Kraiger, & Merritt, 2010), computer simulations and games are becoming more common in training. To date there is little empirical research examining learning processes and outcomes for SLE training environments (Wilson et al., 2009). The present study contributes much needed theoretical development regarding learning processes in SLEs. Nevertheless, as we discussed earlier, the benefits of exploration are not likely to translate to simple task learning in which an optimal approach is readily available, as learner effort would likely be better spent practicing and automating optimal approaches. In general, more research including more diverse samples and tasks across a variety of real-world training contexts is needed to establish the types of tasks and learning environments for which exploration and active learning is beneficial to learning.

In addition, it is important to note that the present study lacked a direct manipulation of exploration. As such, one is limited in the causal conclusions one can make regarding the direction of the relationship between exploration and practice performance. Rather, our findings for this relationship are descriptive of a learner's natural exploratory tendencies given that exploration and practice performance were assessed concurrently. However, the precise direction of this relationship remains uncertain. Future research should combine training interventions intended to influence exploratory behavior during practice with direct measures of exploration and its mechanisms (i.e., novelty, complexity, and information-knowledge gaps) and use more advanced statistical approaches (e.g., cross-lagged latent growth modeling; Curran & Bollen, 2001) in order to make stronger causal conclusions regarding the impact of exploratory behavior on training performance and distal learning outcomes.

Future directions

In general, future research should focus on expanding, testing, and refining theoretical models of curiosity and exploration in training and development contexts. Although recent research highlights their predictive potential and centrality in the learning process (e.g., Kang et al., 2009; von Stumm, Hell, & Chamorro-Premuzic, 2011), curiosity and exploration are often overlooked in the organizational sciences. Specifically, future work should include direct measurements of perceptions of novelty and complexity as antecedents to exploration as these perceptions are central underlying mechanisms to theories of exploration (Berlyne, 1966; Litman, 2005; Loewenstein, 1994). Such an approach would help training researchers develop a fuller understanding of the constraints that inhibit learners from exploring before and after novelty and complexity are perceived. For example, fatigue has been shown to inhibit exploration, particularly for low-experience learners (van der Linden, Frese, & Sonnentag, 2003). Thus, future research could study the effect of distributed versus massed practice on learner fatigue, exploration, and perceptions of novelty and complexity and the extent to which these relationships help explain the learning advantages of spaced practice (Donovan & Radosevich, 1999). Furthermore, future research should identify instances where the relationships between exploration and task-related knowledge may be negative or curvilinear (i.e., inverted-U shaped). When learning simple and repetitive tasks, high-capability individuals may explore more initially but then exhaust sources of novelty and thus decrease exploration more rapidly relative to low-capability individuals (Berlyne, 1970). This is a pattern characteristic of the exploration/exploitation tradeoff whereby learners transition from exploring to a greater emphasis on utilizing learned knowledge and skill once a large proportion of novelty in a task domain has been resolved (Stafford & Dewar, 2013). Under these conditions, the effect of pre-training task-related knowledge on exploration may show a negative trajectory interaction with exploratory behavior such that individuals higher in task-related knowledge engage in more exploration early in practice but less later in practice. In general, more research should utilize direct measurements of exploration in an effort to develop a greater understanding of the boundary conditions and contingencies on the dynamics and effects of exploration.

Along these lines, learners encounter a wide range of information in exploration-based environments and must make decisions on which pieces of information to explore and which to ignore. There is evidence that learners prefer information that will help them discriminate between two hypotheses over information that helps reduce more general levels of uncertainty (Gureckis & Markant, 2012). However, learners may use multiple strategies depending on their familiarity with the learning content and if they are in more of a declarative, compilation, or proceduralized stage of learning (Anderson, 1982; Kanfer & Ackerman, 1989). Research should clarify the processes and patterns by which learners choose to explore specific information and how exploration is related to and distinct from hypothesis-driven experimentation. In this regard, think aloud protocols (Ericsson & Simon, 1980) show promise as a methodology that can provide insights into trainee decisions to explore (e.g., van der Linden et al., 2003).

Furthermore, a greater empirical focus on the dynamics of cognitive, motivational, emotional, and behavioral self-regulatory processes in active learning training will help cultivate an important theoretical foundation for facilitating the design and implementation of evidence-based dynamic interventions. For example, research utilizing repeated measures designs coupled with sophisticated analytical methods that allow for the establishment of directional relationships would help to disentangle the complex patterns of cause-and-effect between exploration and other self-regulatory processes (e.g., metacognition, self-efficacy, and emotion control). Moreover, future research should take into consideration the complexities and interrelationships of self-regulatory processes (Kozlowski, Toney, et al., 2001; Sitzmann & Ely, 2011) as they change in relation to each other and as a function of skill progression. Research has only begun to scratch the surface of this topic, however the design and testing of adaptive and dynamic interventions offers great potential for advancing training theory and practice toward the goal of increasing the responsiveness of training to the changing needs of learners as skill progresses (Anderson et al., 2004).

Finally, there are a number of individual differences beyond GMA and task-related knowledge that may be related to exploration via trainee perceptions and preferences for novelty and complexity, such as goal orientations (Dweck, 1986), typical intellectual engagement (Goff & Ackerman, 1992), openness (Costa & McCrae, 1992), trait affect (Judge, 1992), and interests and trait complexes (Ackerman, 2003). Future research should examine how these and other individual differences influence novelty and complexity in the exploration process in order to determine the extent to which exploration is driven by trainee information-processing capabilities relative to characteristics involving their attitudes and motivations in the learning process. Given the differences in effects obtained in the present study concerning GMA versus pre-training task-related knowledge, future research should distinguish between the effects of general versus more task-relevant individual differences in attitudes and motivations on exploratory behavior.

Conclusion

Research on the role of exploration in adult learning shows promise for improving our understanding of active learning processes and outcomes. By examining between- and within-person effects, this study (a) illustrates the benefits of exploration in the context of complex task learning, (b) calls into question a common assumption that all trainees explore when given the opportunity, and (c) addresses some criticisms of exploration in active learning environments. In addition, the findings highlight the dynamic and domain-specific nature of exploration as well as its importance as a behavioral self-regulatory mechanism. We hope this study prompts future research to include repeated behavioral measurements of exploration to better identify the processes by which learner differences and instructional design elements facilitate effective active learning for a wide range of learners.

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