UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

STIMULATING EXPLORATION IN COMPLEX TASK LEARNING VIA PRE-PRACTICE AND INTERMITTENT KNOWLEDGE ENRICHMENT

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, OK
2019

STIMULATING EXPLORATION IN COMPLEX TASK LEARNING VIA PRE-PRACTICE AND INTERMITTENT KNOWLEDGE ENRICHMENT

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

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Abstract

A growing body of scholarly literature points to the importance of exploratory behavior in the acquisition of complex skills. The purpose of this laboratory study, in which 257 undergraduate students (64% male) learned to play a complex video game, was to examine the effects of different schedules of presenting knowledge enrichment on learner exploration. Participants were randomly assigned to one of four conditions with differing amounts of pre-practice or intermittent knowledge enrichment. It was predicted that pre-practice knowledge enrichment would lead to higher initial exploration, whereas intermittent knowledge enrichment would prompt sustained exploration throughout practice, both of which would lead to higher levels of task knowledge, acquisition performance, and adaptation performance. In general, the results did not support the hypothesized effects, but instead showed support for a too-much-novelty perspective, which suggests that learners can become overwhelmed with too much information (i.e., knowledge enrichment) and will accordingly engage in less exploratory behavior. The results suggest that intermittent knowledge enrichment can directly benefit knowledge acquisition and indirectly benefit skill acquisition and adaptation via exploratory behavior. However, the indirect effects observed were small in magnitude. Future research is needed to examine the potential of intermittent knowledge enrichment to support self-regulated learning for the acquisition and adaptation of complex skills.

Stimulating Exploration in Complex Task Learning via Pre-Practice and Intermittent Knowledge Enrichment

Technological advances in recent years have coincided with an increased use of computer-based training and synthetic learning environments (SLEs) such as computer simulations, games, and virtual environments as efficient methods of training for organizations (Cannon-Bowers & Bowers, 2010; Wilson et al., 2009). These training methods offer unique opportunities to grant learners considerable control over their learning while engaging in rich and dynamic learning environments that provide timely feedback (Bedwell & Salas, 2010). Accordingly, there has been a sizeable increase in research surrounding the maximization of computer-based training and SLEs with some empirical evidence supporting their effectiveness (Bedwell, & Salas; Cuevas, Fiore, Bowers, & Salas, 2004; Sitzmann, 2011). In particular, active learning is one of the more prominent theoretical approaches that is suitable to understanding the effectiveness of computer-based training and SLEs.

Active learning reconciles discovery-based and proceduralized approaches to instruction by giving learners a large degree of autonomy over their own learning environment while simultaneously incorporating training design elements to support their self-regulation as they engage training content and practice opportunities (Bell & Kozlowski, 2008). The present study emphasizes the role of behavioral exploration in the active learning process. In general, there is a rich literature on the critical role played by exploration in the learning process (Berlyne, 1960, 1966; Bruner, 1961; Grief & Keller, 1990), and more recent research has provided evidence that exploration is a key component to active-learning training with positive effects on both the acquisition and adaptive transfer of skill-based learning (Hardy, Day, & Arthur, 2019; Hardy, Day, Hughes, Wang, & Schuelke, 2014; Westlin, Day, & Hughes, 2017). Despite the positive link between exploration and skill-based learning, few studies (e.g., Frese et al., 1991) have endeavored to examine the direct links between training design elements, exploratory behavior, and skill-based learning in complex task environments (Hardy et al., 2014).

When it comes to complex tasks, novice learners can be overwhelmed by the open-endedness of the environment and equifinality of performance effectiveness. These features of complex environments can undermine exploration, often leading learners to settle prematurely on performance strategies that are sub-optimal (Gopher, Weil, & Siegel, 1989; Seagull & Gopher, 1997). Accordingly, the present study examined the extent to which training design elements that provide learners with elaborated task information (i.e., knowledge enrichment) stimulate exploratory behavior during the active learning of a complex task. I compared four conditions that varied the amount and timing of elaborated task information presented to learners. One was a control condition that involved only presenting basic task information to learners in a training presentation prior to practice (i.e., no knowledge enrichment [NKE]). The other three conditions all presented learners with the elaborated task information in addition to the same basic information in the control condition. Although the amount of elaborated task information was the same, these three experimental conditions differed in terms of the timing of this information. In one experimental condition, all of the elaborated information was presented prior to practice (i.e., 100% pre-practice [P] knowledge enrichment [PKE). The other two experimental conditions presented elaborated information intermittently during practice. They differed, however, in that one presented half of the elaborated information prior to practice (i.e., 50% pre-practice [P], 50% intermittent [I] knowledge enrichment PIKE), whereas the other presented all of the elaborated information intermittently (i.e., 100% intermittent [I] knowledge enrichment [IKE]). The comparison of these conditions is based on recent correlational research demonstrating greater pre-practice task-related knowledge is associated with higher levels of exploratory behavior in early skill acquisition trials as well as less of a decrease in (i.e. better sustained) exploratory behavior in later skill acquisition trials (Hardy et al., 2014). This combination of conditions allowed me to disentangle effects of timing versus amount of knowledge enrichment with respect to both initial levels of exploratory behavior and the sustainment of exploratory behavior in practice.

The Role of Exploratory Behavior in Active Learning

Over the last few decades, active learning has emerged as a prominent approach to training. Active learning reflects a constructivist perspective with the premise that learning is primarily an inductive process in which learners explore and infer rules, principles, and strategies for effective performance (Bell & Kozlowski, 2008). Active-learning training is most often used to train individuals on open-ended, complex tasks (Hardy et al., 2019). As such, active-learning training relies on the utilization of training design elements that best facilitate a learner's acquisition of knowledge and skills (Hardy, Day, & Steele, 2017). Researchers have identified a number of learner-controlled approaches and learner-centric interventions that effectively develop learner knowledge and skills (Debowski, Wood, & Bandura, 2001; Frese et al., 1991; Keith & Frese, 2005; Kozlowski, 2008; Kozlowski, Gully, et al., 2001; Wood, Kakebeeke, Debowski, & Frese, 2000). Accordingly, active learning can be couched as a general framework for enhancing the inductive learning process.

One of the key aspects of active learning is self-regulation. Self-regulated learning is defined as the "modulation of affective, cognitive, and behavioral processes throughout a learning experience to reach a desired level of achievement" (Sitzmann & Ely, 2011, p. 421). Although a growing body of research supports self-regulation and active-learning training (Keith

& Wolff, 2015), especially with respect to computer simulations and games (Sitzmann, 2011), the vast majority of the research has focused on the cognitive, motivational, and affective components of self-regulation with very little attention to the behavioral components. In fact, Sitzmann and Ely's (2011) meta-analysis of self-regulated learning included very few studies that directly measured the behavior of learners. Hardy and colleagues (2014; Hardy et al., 2019) argue that although behavioral self-regulation in learning is minimally understood, it may be more readily accessible to researchers than cognitive or motivational self-regulation because behaviors are more observable.

One such behavioral component in the learning process is exploration. Much like active learning itself, exploration is best suited to complex tasks in which there are dynamic elements and a breadth of knowledge and skill to be acquired (Hardy et al., 2018). Exploration has been well demonstrated to positively contribute to the learning process (Berlyne, 1960, 1966; Bruner, 1961; Grief & Keller, 1990), but in the training literature has primarily been examined as an instructional design element, rather than a behavioral process (Bell & Kozlowski, 2008; Hardy et al., 2018; Hardy et al., 2014; Hardy et al., 2019). Because of this, exploration has often been studied as a distal predictor of learner performance that is mediated through more proximal self-regulatory processes such as metacognition (Ford & Kraiger, 1995; Frese, Albrecht, Altmann, & Lang, 1988), intrinsic motivation (Debowski et al., 2001), and willingness to make errors (Keith & Frese, 2005). However, more recent research has focused on exploration as a behavioral component of the learning process (e.g., Hardy et al., 2014; Hardy et al., 2018).

Exploratory behavior is 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). Examples of exploratory behavior include information search, strategy variation, risk-taking, experimentation, and discovery (Hardy et al., 2018; March, 1991). Importantly, these and other exploratory behaviors are crucial to initial and sustained learning efforts. Particularly in complex tasks, to which exploration is most suited, individuals do not know all that can or should be tried during practice without constraining themselves. Therefore, exploratory behavior is fundamental to both initial and sustained learning.

Recently, a few studies (e.g., Hardy et al., 2014; Hardy et al., 2018) directly linked exploratory behavior to both immediate and distal learning outcomes. Specifically, these studies showed exploration during practice yielded positive relationships with practice performance, task knowledge, analogical transfer performance, and adaptive transfer performance (Hardy, 2015; Hardy et al., 2014; Westlin et al., 2017). Further, Hardy, Day, and Steele (2015) found that exploratory behavior predicted these outcomes above and beyond the effects of self-efficacy and metacognition, which are considered to be key motivational and cognitive variables, respectively, in self-regulation and active learning.

Among the examined learning outcomes, exploratory behavior is thought to be especially beneficial to adaptive performance compared to other skill-based outcomes. Hardy et al. (2018) argue that exploration creates a breadth and repertoire in the knowledge and skill of learners, which in-turn provides them with more options and strategies to select when presented with novelty (i.e., change in task demands). This notion is further illustrated through the study of elaborative rehearsal. Elaborative rehearsal is defined as a function of working memory which involves processes that more deeply encode and store information for later retrieval (Craik & Lockhart 1972, Craik & Tulving, 1975). These elaborative rehearsal processes necessitate that the learner actively engages to-be-learned material to develop a more comprehensive understanding of the material and related concepts. As such, exploratory behavior engages learners in elaborative rehearsal, which in-turn leads to effective retrieval in later learning and performance contexts. In other words, there is empirical evidence that increases in learner exploration when practicing a complex skill lead to greater acquisition of both immediate and distal knowledge and skill (e.g., Hardy et al., 2014), in part due to elaborative processes that are engaged during exploration.

Despite these advantages, exploration decreases as practice progresses (Hardy et al., 2014; Hardy et al., 2018). Learners engage in the greatest amount of exploration during the earliest stages of the learning process, as they acquire the basic knowledge and skill required for task performance (Hardy et al., 2014; Hardy et al., 2018). Then, learners begin shifting their focus away from the acquisition of a diverse knowledge and skill set, instead focusing on the consolidation and refinement of a limited number of performance strategies in an attempt to maximize decision-making utility (Hardy et al., 2018; Hardy et al., 2019; Gonzalez & Dutt, 2016).

Although this shift may be useful, the evidence that positively links exploratory behavior with learning outcomes suggests that perhaps learners are shifting away from exploration too quickly, and are failing to maximize their own knowledge and skill acquisition. Further, learners may not recognize the need to balance the refinement of current skills with exploration throughout training. It can therefore be argued that active-learning training necessitates instructional design elements which are aimed at increasing and sustaining exploratory behavior and, in turn, learning outcomes (Hardy et al., 2015; Hardy et al., 2019).

Exploration-Exploitation Trade-offs

Exploratory behavior declines when learners identify and utilize a limited set of strategies they deem most effective for task performance (Hardy et al., 2019). This shift represents movement along a continuum, with exploration on one end, and exploitation on the other. *Exploitation*, in contrast with exploration, “involves staying with a single option (or a limited set of alternatives) with the purpose of maximizing the potential of a preferred solution, and encompasses behaviors like refinement, implementation, and execution” (March, 1991). In an active-learning environment, learners are not limited by the amount to be learned, but are instead limited by the cognitive resources that can be invested into learning tasks (Norman & Bobrow, 1975). As such, learners will not be able to fully explore and exploit simultaneously, and will thus need to select the use of more exploratory or exploitative behaviors at any given time.

Exploration-exploitation tradeoffs have been studied in both animal and human behavior in risk choice, foraging, individual learning, and organizational learning (Mehlhorn et al., 2015). At an organization level, organizations may invest more or less resources into the research and development of new products/systems (exploration) versus maximizing existing products/systems (exploitation) (Gupta, Smith, & Shalley, 2006; March, 1991). As March (1991) states, “the problem of balancing exploration and exploitation is exhibited in distinctions made between refinement of an existing technology and invention of a new one” (p. 72).

At an individual level, this exploration-exploitation tradeoff involves the shift from making the most of where you are (exploitation) to another option, strategy, or behavior, in an attempt to get a better outcome (Mehlhorn et al., 2015). It can be argued that these tradeoffs occur in an individual’s learning process, but this notion has not been well studied. At both the organizational and individual levels, a balance must be struck between exploration and exploitation.

Over-utilization of either exploration or exploitation can be problematic for individual learners. Adopting a purely exploratory approach to learning can inhibit the development of knowledge and skill depth, ultimately inhibiting task performance. Likewise, strictly emphasizing exploitation of a single or small set of strategies can inhibit adaptation to changes in the problem or task (Hardy et al., 2017). Effective learners transition back and forth from exploration and exploitation. They practice newly discovered strategies (Schunn, McGregor, & Saner, 2005) and exploit/master simpler ones (Donner & Hardy, 2015). Over time, the explored strategies become simpler to perform and are then exploited, creating an opportunity for additional exploration. The back and forth transition from exploration to exploitation should yield a diverse repertoire of learner skills, which can be applied to a variety of situations (Schunn et al., 2005).

As learners become more proficient, they show a general trend moving from more exploration to more exploitation. Accordingly, one would expect greater emphasis on exploration early in training, and a more heavy emphasis on exploitation later in training. Optimal learning, however, necessitates a continual mix of both exploration and exploitation. So as learners transition to more exploitation-focused strategies, instructional design elements should be implemented to promote sustained exploration.

The Information-Knowledge Gap

One explanation for how individuals approach the exploration-exploitation tradeoff is through the information-knowledge gap. Originally articulated by Loewenstein (1994), the information-knowledge gap can be described as discrepancies between two individual sets of perceptions. The first, which Hardy et al. (2019) call *competency beliefs*, are the beliefs an individual has about what they know/can do. The second set of perceptions are *novelty motives*, which are essentially what learners *want* to know/be able to do, based on their perceptions of what is available within the learning environment. When individuals perceive a discrepancy between their competency beliefs and their novelty motives, an information-knowledge gap is created. That is, when individuals perceive a large gap between their own competency and what they *want* their competency to be, it cues uncertainty, which signals to learners that exploration is needed. This, in-turn, should lessen the information-knowledge gap through the acquisition of new knowledge and skills.

Recent research has been conducted in the pursuit of increasing learners' exploratory behavior. Error-framing instructions and exploration encouragement have both been examined and proposed as a means to increase exploratory behavior. Error-framing instructions encourage learners to make errors during training. Error encouragement instructions are thought to benefit learning through the exploration of the causes of learner errors (Dormann & Frese, 1994; Keith & Frese, 2005, 2008). Keith et al. (1991) found that during computer training, learners benefitted from making errors. However, Hardy et al. (2014) did not find a direct effect between error framing and positive learning outcomes. Instead, they found that the error framing instructions moderated the relationship between general mental ability (GMA) and exploration, such that those with higher GMA explored more in response to error-framing instructions, and those with lower GMA explored less in response to the same instructions. Hardy et al. (2014) suggested that this finding may be due to training design elements having differential impacts on learners based on learner characteristics. Further, they stated that error management is an indirect attempt at increased exploratory behavior.

A more direct approach to increasing exploratory behavior (i.e., encouraging exploration) has also been examined, but with limited success. Hardy (2015) did not find a direct effect between his manipulation and exploratory behavior when openly encouraging learners to explore their learning environment. Because of this, Hardy (2015) argued that "the antecedents of exploratory behavior (i.e., learner perceptions of novelty and the information-knowledge gap) rather than the behavior itself may be more effective at shaping and supporting learner exploration" (p. 47). In essence, Hardy (2015) suggested that learners must know what needs to be explored rather than simply knowing that exploration is beneficial. A key premise of the present study is that exploration during practice can be stimulated initially and sustained via instructional design elements that spur novelty motives and widen the information-knowledge gap.

Declarative and Procedural Knowledge, and Exploration

Exploration plays a larger role in initial knowledge and skill development due to high novelty perceptions. Likewise, as novelty perceptions decrease, so too does exploratory behavior (Hardy et al., 2019). Novelty spurs information-knowledge gaps, which in turn spur exploration and in turn knowledge and skill development. By providing learners with declarative knowledge, they are given the tools to develop procedural knowledge. Declarative knowledge, defined as knowledge of facts and things (Anderson, 2005; Kanfer & Ackerman, 1989), provides learners with an awareness of what exists and how things work. Declarative knowledge is typically the first type of knowledge acquired by learners.

However, performance of complex skills requires learners to develop procedural knowledge, defined as knowledge of how to perform activities (Anderson, 2005; Kanfer & Ackerman, 1989). Typically, procedural knowledge is acquired during the middle and later stages of learning respectively. As it pertains to the information-knowledge gap, declarative knowledge alerts learners to the to-be learned procedural knowledge. As such, learners with more declarative knowledge of the task will have larger information-knowledge gaps, in that they know that they do not have the procedural knowledge for most effective performance. In essence, providing learners with facts about the task creates the information part of the information-knowledge gap (i.e., information-*procedural* knowledge gaps). This information informs learners that they do not have adequate procedural knowledge, stimulating novelty motives and widening the information-knowledge gap, ultimately stimulating exploration. Accordingly, one objective of the present study was to examine the influence of knowledge enrichment on exploratory behavior. As such, I tested the following hypothesis.

> *Hypothesis 1:* Knowledge enrichment will lead to more exploratory behaviors during practice.

As previously stated, learner exploration decreases over time as learners acquire and focus on a limited number of strategies (Hardy et al., 2018). This shift towards an exploitative approach is sometimes premature, as evidenced by a direct positive link of exploration to learning outcomes even in later acquisition trials (Hardy et al., 2014; Hardy, 2015; Hardy et al., 2019). Therefore, sustaining task exploration is important to skill acquisition, and knowledge enrichment should lead to better sustained exploration via increased novelty perceptions and widened information-knowledge gaps. This proposed benefit of knowledge enrichment is consistent with Hardy et al.'s (2014) correlational finding that task-related knowledge was associated with better sustained exploratory behavior in practice. Accordingly, I tested the following hypothesis.

> *Hypothesis 2:* Knowledge enrichment will reduce the rate at which exploratory behaviors decrease during practice.

Stimulating Initial Exploration via Pre-Practice Knowledge Enrichment

Novelty motives reflect the degree to which learners want to know more or be able to do better. Increased novelty motives create an information-knowledge gap between what is known and what is wanted to be known. In-turn, learners will seek to minimize this gap by engaging in more exploratory behavior. Thus, one practical way to increase or make salient the information-knowledge gap might be to simply provide learners with more declarative knowledge about what is available within their learning environment prior to practice. Indeed, pre-practice task-related knowledge has been found to be positively linked to exploration (Hardy 2015; Hardy et al., 2014; Hardy et al., 2019). That is, those who know more about the task are more likely to engage in exploratory behavior at the onset of practice. Related, those with greater task expertise are better able to recognize and perceive novelty within their learning environment, and thus are better able to explore (Haerem & Rau, 2007). As such, links between pre-practice knowledge, exploration, expertise, and exploitation have implications for instructional design. Specifically, augmenting learners' base of knowledge before active practice may stimulate their exploration.

It can be argued that when they are informed of the novelty in their environment prior to practice, learners are more likely to explore, especially at the onset of practice. Providing learners with more declarative knowledge should alert learners to novelty. As such, a second objective of the present study was to examine the influence of presenting learners with an elaboration of basic training information prior to practice on initial levels of task exploration in practice. It was expected that pre-practice knowledge enrichment would stimulate greater initial exploration among learners. Accordingly, I tested the following hypothesis.

> *Hypothesis 3:* Pre-practice knowledge enrichment will lead to more exploratory behaviors at the onset of acquisition than no enrichment. That is, greater amounts of pre-practice task information will be associated with more exploration at the onset of practice.

However, it should be noted that moderate levels of novelty invoke the largest amount of exploratory behavior (Berlyne, 1966). Too much novelty is associated with anxiety, which is detrimental to learning as anxiety taxes cognitive resources and undermines exploratory behavior (Csikszentmihalyi, 1990; Loewenstein, 1994). In the present study, incorporating two pre-practice knowledge enrichment conditions with different amounts of elaborated information—one with all (i.e., PKE) and the other half (i.e., PIKE)—along with a purely intermittent condition (i.e., IKE) allowed me to examine this issue. Hypothesis 3 predicts exploration will be greater with PKE than PIKE early in acquisition, whereas a *too-much-novelty perspective* predicts exploration will be greater with PIKE compared to PKE if there is in fact too much information in the PKE condition.

Sustaining Exploration via Intermittent Knowledge Enrichment

As learners engage more with the training task, the information-knowledge gap often gets smaller as a function of reducing uncertainty and novelty through exploration (Hardy et al., 2018). Learners develop competence in the things they explore, and therefore explore less over the course of skill acquisition. The third objective of the present study was to examine the influence of intermittently presenting learners with elaborated task information during practice on the sustainment of exploration. That is, providing learners with information about what is available within their learning environment should stimulate novelty perceptions and lessen the decrease in the information-knowledge gap. These intermittent presentations should also allow for greater elaborative rehearsal during skill acquisition, as learners have a greater number of opportunities to integrate and expand on their pre-practice knowledge as well as the knowledge gained from practice. Overall, the benefit of intermittent knowledge enrichment to sustained exploration is predicated on the assumption that it lessens the decrease in the information-knowledge gap. Put another way, intermittent knowledge enrichment provides learners with new information of to-be explored elements of the task. Accordingly, I tested the following hypothesis.

> *Hypothesis 4:* Intermittent knowledge enrichment will reduce the rate at which exploratory behavior decreases across skill acquisition trials compared to no intermittent

> knowledge enrichment. That is, the more elaborated task information is disbursed intermittently, the better exploration will be sustained.

Indirect Effects of Knowledge Enrichment on Learning via Exploration

As previously discussed, there is a direct link between higher amounts of exploratory behavior with task-based knowledge, analogical transfer, and adaptive transfer. Exploratory behavior involves the use of elaborative rehearsal, and provides learners with a more diverse knowledge and skill set from which to retrieve appropriate strategies. Therefore, exploration serves as a mediating mechanism between the knowledge enrichment manipulations and learning outcomes: knowledge acquisition, skill acquisition, and reacquisition (adaptive performance following unexpected changes in task demands). Accordingly, I tested the following hypotheses.

> *Hypothesis 5:* Exploratory behavior will mediate the relationship between knowledge enrichment and (a) knowledge acquisition, (b) skill acquisition, and (c) reacquisition adaptation.

Exploration and Adaptive Performance

Adaptive performance, defined as one’s response to a changing task environment, has become a focal point for both researchers and organizations (Hardy et al., 2019; Healy, Wohldman, Kole, Schneider, Shea, & Bourne, 2013; Huang, Shoss, & Jundt, 2017). Exploration has been suggested as one means by which individuals can prepare themselves for change. Exploration leads to a greater breadth of knowledge and skill which can be applied to novel contexts (Hardy et al., 2019). Knowledge and skills acquired pre-change that may not have had importance before, may suddenly be required. As such, those with a greater repertoire of knowledge and skills are more likely to perform better after a change in task demands than those with more limited repertoires. Moreover, the learning that has taken place from exploration may not be fully captured by pre-change performance (i.e., skill acquisition). Instead, some learned skills may only be exhibited after a change to the environment. Therefore, I tested the following hypothesis.

> *Hypothesis 6:* Exploratory behavior during skill acquisition will predict reacquisition adaptation even after controlling for skill acquisition.

Method

Participants

Recruitment of participants was open to males and females via the Department of Psychology at the University of Oklahoma's participant pool. Participants received research credit hours towards their Elements of Psychology course for their participation. Two hundred seventy-three individuals participated in this study. Data from 16 participants were removed for not following instructions (n = 9) or incomplete data (n = 7), resulting in a final sample of 257 (164 males, 93 females). Participants ranged from 17 to 33 years of age (M = 19.06, SD = 1.73). One hundred eighty-three participants reported their ethnicity as Caucasian (71.2%), 21 as Black/African American (8.2%), 19 as Asian (7.4%), 16 as Hispanic (6.2%), eight as Native American (3.1%), and ten as other (3.9%).

Performance Task

The experimental task used in this study was Unreal Tournament 2004 (UT2004; Epic Games, 2004), a commercially available first-person shooter computer game that has been used in previous research on active learning and complex skill acquisition (e.g., Hardy et al., 2014; Hughes et al., 2013). The objective of the task is to destroy computer-controlled opponents while minimizing the destruction of one's own character. Participants can collect new weapons or resources (i.e., power-ups) during each trial to increase their character's health or offensive and defensive capabilities. When a participant's character or opponent is destroyed, it reappears in a random location with the default weapons and capabilities. The game was "every character for him- or herself," meaning that the computer-controlled characters are in competition with each other as well as the participant. UT2004 is a fast-paced, dynamic task involving cognitive and perceptual-motor demands. Participants use a mouse and keyboard simultaneously to move and control their character, all while learning the strengths and weaknesses of different weapons and strategies, and quickly deciding which to use given the current situation.

Design

A four-condition between-persons design was used to examine the hypothesized effects of knowledge enrichment. Specifically, participants were randomly assigned to one of four conditions—no knowledge enrichment (NKE), pre-practice knowledge enrichment only (PKE), intermittent knowledge enrichment only (IKE), and both pre-practice and intermittent knowledge enrichment (PIKE). It is important to note that although the experimental conditions (PKE, IKE, and PIKE) were presented with elaborated task information in different manners (pre-practice, intermittently, or both), participants in each were presented with the same exact content. See Appendix A for a visual representation of the four conditions.

Pre-practice knowledge enrichment only (n = 64, male = 64%). All conditions viewed an audio and visual presentation which explained the performance task. Those randomly assigned to the control condition (i.e., NKE: n = 66, male = 68 %) were provided with basic task information about the controls and functions within the performance task. Those in the pre-practice knowledge enrichment condition (PKE) received the same information as those in the control condition, but also received additional information about the weapons, items, and strategies that can be used during practice. The scripts for these presentations can be found in Appendix B.

Intermittent knowledge enrichment only (n = 63, male = 51%). Participants randomly assigned to the intermittent knowledge enrichment condition (IKE) received the same pre-practice audio and visual presentation as those in the control condition (i.e., NKE). They also received the same additional information about the weapons, items, and strategies as those in the pre-practice knowledge enrichment only condition (PKE), but received it through six shorter audio and visual presentations after each practice session.

Pre-practice and intermittent knowledge enrichment (n = 64, male = 72%). Participants randomly assigned to the pre-practice and intermittent knowledge enrichment condition (PIKE) received a pre-practice audio and visual presentation that was the same as the control condition (NKE) but also contained *half* of the additional information presented in the PKE condition. The other half of the additional information was provided intermittently after each session. Thus, the intermittent presentations received by those within this condition was shorter than the intermittent presentations received by those in the PIKE condition.

Procedure

Individuals participated in cohorts of no more than seven, and were told that the purpose of the study was to investigate how people learn to play a dynamic and complex videogame. They first completed an informed consent form followed by a battery of self-report measures to serve as control variables. Participants were told that they would be entered into a lottery to win one of five, $25 gift cards, for each trial in which their score was in the top 50% of all study participants for that given trial. At this point, participants watched their respective training presentations. Participants were randomly assigned to their conditions as a cohort. The length and content of this presentation was dependent upon the experimental condition to which participants were randomly assigned (NKE and IKE or PIKE and PKE). They then received a 1-minute familiarization trial without any opponents in order to become familiar with the controls, display, and the game environment. After this familiarization trial, participants completed a series of self-report measures.

Participants then completed 14 sessions each consisting of two 4-minute trials. Sessions 1 through 7 were acquisition (pre-change) sessions. Sessions 8 through 14 were reacquisition adaptation (post-change) sessions. Following each session, participants completed self-report measures of information-knowledge gap perceptions, and exploration. For the first seven sessions (i.e., pre-change), participants competed against two computer-controlled opponents at a difficulty setting of 4 (on a 1-to-8 scale). After the seventh session, participants completed the same self-report measures, as well as a declarative knowledge multiple-choice test. Following a task-change paradigm (see Lang, & Bliese, 2008), the eighth session and those thereafter (i.e., the midway point; 15th of 28 trials) included several key changes to the performance task (Hughes et al., 2013). Participants competed against nine computer-controlled opponents at a difficulty setting of 5. In addition, the game environment (i.e., map) was much larger, with wider spaces, multiple levels of platforms, and edges over which characters could fall to their death. Participants were debriefed following the 14th session (i.e., 28th trial).

Measures

Covariates. Self-reported ACT scores was used as an index of general mental ability. A 4-item scale was used to measure prior videogame experience, which served as a proxy for pre-training videogame knowledge. For the first two items, participants responded using a 5-point Likert scale (*1 = not at all, 2 = rarely, just a few times, 3 = monthly, 4 = weekly, 5 = daily*) to the following questions: (a) "*Over the last 12 months, how frequently have you typically played video/computer games?*" (*M* = 2.95, *SD* = 1.38) 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 = 2.41, SD = 1.31). For the second two items, participants indicated how many hours per week they typically play video/computer games (M = 4.27, SD = 6.08, *range* = 0-30) and more specifically, first-person shooter video/computer games (M = 2.36, SD = 4.47, *range* = 0-25). Scores for these four items were standardized and then averaged to create a composite score (α = .74).

Exploration. Exploratory behavior was coded in each pre-change trial (Sessions 1-7) from video playbacks by me and five coders familiar with common video-game environments and strategies. Every trial video was coded by me and at least one other coder, and the scores were then averaged to create trial scores. Session scores were then computed by averaging these trial scores for each session's pair of trials. Coders underwent approximately 20 hours of frame-of-reference training in which they were introduced to the UT2004 training environment and the same exploration scales validated by Hardy et al. (2014). Coders independently viewed gameplay videos for each participant and rated exploratory behavior using four 5-point scales. Video files were stored in a way such that access to the videos would ensure the coders were blind to all information regarding predictor and criterion variables. Intraclass correlation coefficients (ICCs) were used to examine interrater reliability at the trial level, which were then averaged across trials (Shrout & Fleiss, 1979). As recommended by Cicchetti (1994), ICCs between .60 and .74 are considered good interrater reliability and ICCs 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 other research using this task (e.g., Hardy et al., 2014). Three of the scales measure exploratory behavior in three major game domains: (a) combat strategies (*1 = very few strategies tried, 5 = a great deal of strategies tried;* (average

ICC = .77), (b) weapons (*1 = very few weapons tried, 5 = a great deal of weapons tried*; average ICC = .84), and (c) map (*1 = very little map visited, 5 = entire map visited;* average ICC = .90). The fourth scale measures overall exploratory behavior and thus account for behavior not captured by the other scales (i.e., what was explored in this trial that was not explored in previous trials; *1 = very little exploratory behavior, 5 = a great deal of exploratory behavior;* average ICC = .74). Support for the content-related validity and construct-related validity (i.e., the sensitivity of scale scores to manipulated changes in exploration) for this operationalization of exploratory behavior has been provided by Hardy and colleagues (2014). Together these scales were 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. Coefficient alphas range from .62 to .96 (average = .82).

Exploration was also measured using a 3-item scale used in previous research (Day et al., 2017). After Sessions 1-7, participants were asked to respond using a 11-point Likert scale (*0 = Not at all, 10 = Extremely Hard*) to the following questions after each session: "*How hard did you try to learn something new in the previous two games*?", "*How hard did you try to better understand Unreal Tournament during the previous two games?*"; "*How hard did you try to experiment with different strategies and techniques during the previous two games?*". Coefficient alphas ranged from 0.77 to 0.93 (average = 0.88). I examined the relationship between the scores from this self-report scale with those of the behavioral measure of exploration as a check on the construct-related validity of the behavioral measure. Results of a mixed-effects growth model showed that although the scores on this self-report measure of exploration were not related to behavioral exploration at the between-person level ($t(252) = -0.56$, $B = 0.01$, $SE = -0.01$), there was a statistically significant within-person effect ($t(1539) = 3.08$, $B = 0.01$, $SE = 0.005$, $p < 0.01$). In other words, increases in self-report scores were associated with increases in behavioral exploration coded from the video playbacks.

Task knowledge. Task knowledge was assessed using a 25-item multiple-choice test. Fifteen items were derived from information covered in the experimental conditions presentation(s). Ten items were taken from a previous measure of task knowledge (Hardy et al., 2014), and assessed knowledge that was not included in the information provided to participants, but could be acquired through practice. A copy of this multiple-choice test can be found in Appendix C.

Task performance. Task performance scores for each trial were calculated using the same index as Hardy and colleagues (2014): player kills (i.e., number of times a participant destroyed an opponent) divided by the quantity of kills plus deaths (i.e., number of kills plus the number of times a participant's own character was destroyed) plus player rank (i.e., the participant's rank relative to the computer opponents in that trial). For ease in interpretability, performance scores were then multiplied by 100. Performance for each session was calculated by taking the average of the scores for both trials in that session.

Information-knowledge gap. Information-knowledge gaps were measured before every session (two-trials) using a 4-item scale used in previous research (Day et al., 2017). Participants were asked to rate the extent to which certain features of UT2004 (e.g., primary and secondary weapons functions) still need to be discovered on a 0-100 percent scale. Items include "*What percentage of the weapons and approaches to using weapons in Unreal Tournament remain to be discovered, tried, and understood?*", "*What percentage of the map and approaches to interacting with the map in Unreal Tournament remains to be discovered, tried, and* *understood?*", "*What percentage of the strategies to performing well in Unreal Tournament remain to be discovered, tried, and understood?*", and "*In general, what percentage of the overall Unreal Tournament game remains to be discovered, tried, and understood?*". Coefficient alphas ranged from 0.84 to 0.94 (average = 0.89). I examined the relationship between scores from this self-report scale and the experimental manipulations as a check on the logic underlying how knowledge enrichment might spur novelty motives. To do so, I conducted a 4 (condition: NKE, IKE, PIKE, PKE) by 14 (session) mixed analysis of covariance controlling for ACT scores, sex, and videogame experience on these scores and plotted the adjusted means. Figure 1 shows the plot of these adjusted means. Consistent with general expectations regarding changes in perceptions of information-knowledge gaps over the course of acquisition and adaptation (Hardy et al., 2019), scores decreased over the course of acquisition, sharply increased immediately after the task change, and then decreased again over the course of adaptation. However, the results showed that information-knowledge gaps did not differ by condition ($F(3, 253) = 1.02$, $p = .39$). In particular, the knowledge enrichment manipulation did not yield any effect on information-knowledge gaps during acquisition (pre-change sessions). This result is counter to expectations. The proposed logic of the manipulation was that additional declarative knowledge should expose gaps in knowledge and prompt greater exploratory behavior (i.e., trying something new). In contrast to the pre-change results, the post-change adjusted means showed lower scores in the IKE condition versus the other conditions immediately following the change in task demands (i.e., Session 8) and in the last three post-change sessions. I speculate that this reflects how those in the IKE condition were less overwhelmed or surprised by the task change than other conditions, presumably due to a greater breadth of understanding of the task.

Results

Table 1 shows means, standard deviations, and correlations for all the substantive study variables. Before examining the hypotheses, it is important to consider the covariates and learning outcomes associated with said hypotheses. ACT scores, the standardized videogame experience composite, and sex were all examined as covariates for learning outcomes. A one-way analysis of variance ($F(3,253) = 0.30$, $p = 0.83$) showed that ACT scores did not significantly differ by condition. Likewise, a one-way analysis of variance ($F(3,253) = 1.32$, $p = 0.27$) showed that videogame experience did not significantly differ by condition. Nevertheless, they were included in my hypothesis testing given their significant relationships with the learning outcomes.

With regards to the 25-item knowledge test, a one-way analysis of covariance ($F(3,253) = 16.22$, $p < 0.001$) showed that those in the NKE condition ($M_{adj} = 12.87$, $SE = 0.35$) scored significantly lower than all other conditions when controlling for ACT scores ($F(1,256) = 26.55$, $p < 0.001$), sex ($F(1,256) = 49.62$, $p < 0.001$), and videogame experience ($F(1,256) = 16.46$, $p < 0.001$). Those in the PKE condition ($M_{adj} = 15.14$, $SE = 0.35$) scored significantly lower than those in both the IKE ($M_{adj} = 16.62$, $SE = 0.36$) and PIKE ($M_{adj} = 17.51$, $SE = 0.35$) conditions. Those in the IKE and PIKE conditions did not significantly differ in their knowledge test scores. A depiction of these findings can be found in Figure 2.

As shown in Figure 3, the performance curve of this study is similar to that found in studies using a comparable design (e.g., Lang, & Bliese, 2008), showing a gradual increase in performance over acquisition sessions, a large performance loss after the task change, and another gradual increase in adaptation sessions. To provide an overview of the performance effects, I conducted a 4 (condition: NKE, IKE, PIKE, PKE) by 14 (session) mixed analysis of covariance controlling for ACT scores, sex, and videogame experience and plotted the adjusted means. Figure 4 shows this plot of the adjusted mean performance scores. The results showed no condition main effect ($F(3, 253) = 0.68$, $p = .56$), a significant session main effect ($F(13, 243) = 2.10$, $p < .05$), and a significant condition by session interaction ($F(18, 239) = 1.87$, $p < .05$). With respect to the interaction, the graph shows lower scores in in Sessions 6 and 10 in the PIKE condition versus all the other conditions, but no condition differences in any other sessions. In general, scores in the PIKE condition were relatively lower versus scores in the other conditions in post-change sessions than in pre-change sessions. This pattern of effects was not expected.

Exploratory Behavior

Before testing the hypotheses, and to get an overview of the effects for behavioral exploration, I conducted a 4 (condition: NKE, IKE, PIKE, PKE) by 7 (session) mixed analysis of covariance controlling for ACT, sex, and videogame experience and plotted the adjusted means. Figure 5 shows the plot of these adjusted mean behavioral exploration scores. As expected, exploratory behavior decreased across sessions ($F(6, 250) = 2.69$, $p < .05$). The results did not show a main effect for condition ($F(3, 253) = 1.84$, $p = .14$), nor a statistically significant condition by session interaction ($F(18, 239) = 1.36$, $p = .14$). As shown in Figure 5, exploration in the IKE condition increased across Sessions 1 and 2 while exploration in the other conditions decreased across Sessions and 2. In general, thereafter, scores in all the conditions decreased across sessions.

To test Hypothesis 1, which predicted that knowledge enrichment would lead to more exploratory behavior during practice, dummy-coded multiple regression controlling for ACT, videogame experience, and sex, was used to compare those who received knowledge enrichment (i.e., PKE, IKE, PIKE conditions) to those who did not receive knowledge enrichment (NKE condition) on average exploration across Sessions 1-7. Condition (knowledge enrichment versus no enrichment) did not significantly predict exploration above and beyond the covariates of ACT ($t(255) = 1.12$, $p = 0.26$), sex ($t(255) = 5.52$, $p < .001$), and videogame experience ($t(255) = 1.65$, $p = 0.10$). Thus, the results did not support Hypothesis 1. There was no significant effect of knowledge enrichment versus no enrichment ($t(255) = 1.02$, $p = 0.31$; $B = 0.17$, $SE = 0.17$), although the overall model was significant ($F(2, 255) = 16.34$; $p < .05$, $R^2 = 0.21$).

I used mixed-effects growth modeling to test Hypotheses 2 through 4 depending on whether the plot of the adjusted means (Figure 5) from the aforementioned ANCOVAs were consistent with the hypothesized pattern of effects. R, an open source software, was used to conduct the modeling and analyses (Pinheiro, Bates, DebRoy, & Sarkar, 2016; R Development Core Team, 2016). Level 1 models accounted for autocorrelation in error structures (AR1). I tested a series of models following recommendations by Bliese and Lang (2016). I started by testing the basic growth model. The random intercept model was tested to estimate the intraclass correlation coefficient (ICC), which indicates the proportion of variance that resides within- and between-persons. In Step 1, I included the growth variables.

$$Y_{ij} = \gamma_{00} + \gamma_{10}\text{Session} + \gamma_{20}\text{Session}^2 + \varepsilon_{ij}$$

Session was centered at Session 1 (i.e., 0, 1, 2, 3, 4, 5, 6). The results indicated a significant decrease in exploration ($t(1540) = -7.62$, $B = -0.12$, $p < .001$) across pre-change sessions, and a significant quadratic trend for exploration was also significant, ($t(1540) = 2.58$, $B = 0.01$, $p < .01$), which was indicative of smaller decreases in later scores.

In Step 2, I added the covariates (sex, ACT, videogames experience; see Table 2). ACT and videogame experience were grand-mean centered. The main effects of ACT ($t(250) = -0.84$, $B = 0.00$, $p = .89$) and videogame experience ($t(250) = 0.40$, $B = 0.02$, $p = .69$) on exploration were non-significant. The main effect of sex was negative and significant ($t(250) = -2.91$, $B = -0.30$, $p < .01$), reflecting that females exhibited lower levels of exploration than males. Table 2 summarizes the results of Steps 1 and 2. In Step 3, the dummy-coded main effect of knowledge enrichment was added, and in Steps 3 and 4 the condition by linear and quadratic interactions, respectively, were added.

To test Hypothesis 2, which predicted that knowledge enrichment would reduce the rate at which exploratory behaviors decreased during practice, dummy coding was used to compare the conditions where no knowledge enrichment was provided (NKE) to those who received knowledge enrichment (IKE, PIKE, and PKE). Results indicated that there was no main effect for knowledge enrichment ($t(249) = -0.63$, $B = -0.05$, $p = .53$), and no significant interactions between knowledge enrichment and either the linear or quadratic trajectories ($t(1536) = -0.03$, $B = -0.00$, $p = .98$; see Table 3). Thus, Hypothesis 2 was not supported.

Hypothesis 3 predicted that pre-practice knowledge enrichment would lead to more exploratory behavior at the onset of training. However, the aforementioned adjusted means in Figure 5 showed a different pattern of effects. Specifically, behavioral exploration in Session 1 in the two pre-practice knowledge enrichment conditions (i.e., PKE and PIKE) was not higher than behavioral exploration in the conditions that did not involve pre-practice knowledge enrichment (i.e., NKE and IKE). Thus, the results did not support Hypothesis 3. As described above, the plot of the adjusted means suggests that participants in the IKE condition explored more across Sessions 1 and 2 than participants in all the other conditions. This pattern of results is consistent with a *too-much-novelty perspective*. That is, the amount of information in both pre-practice knowledge enrichment conditions may have been overwhelming and not likely to spur exploration. Rather, additional information appears to have been facilitative toward spurring more exploration when presented after two performance trials. Accordingly, I conducted a 2 (condition: IKE vs. NKE, PIKE, and PKE collapsed) by 2 (Session 1 and Session 2) mixed analysis of covariance as a follow-up test. The condition main effect showed overall higher scores in the IKE condition (M_{adj} = 3.45, SE = 0.06), and a statistically significant interaction confirmed that the change in scores across Sessions 1 and 2 was different for the IKE condition than in the other conditions (M_{adj} = 3.28, SE = 0.32; $t(252) = 8.67$, $p < .01$). Thus, the results were consistent with a *too-much-novelty perspective*.

To test Hypothesis 4, which predicted that intermittent knowledge enrichment would reduce the rate at which exploratory behavior decreased across skill acquisition trials, dummy coding was again used to compare the intermittent knowledge enrichment condition (IKE) to the condition with both pre-practice and intermittent knowledge enrichment (PIKE), and also to the no intermittent knowledge enrichment conditions (NKE and PKE). As seen in Table 4, three models were tested. First, the condition variable was added to the base model, followed by the condition-linear trajectory interaction and finally the condition-quadratic trajectory interaction. Results indicated the condition-only model was the best fitting of these three models, and that the main effect of this dummy-coded comparison was only significant when the condition-linear trajectory interaction was included in the model (B = 0.11, $t(249) = 2.37$, $p < 0.05$). Because of the pattern of effects displayed in Figure 5 and as described in the preceding paragraph, I then tested a dummy-coded comparison of just the IKE condition compared with the three other conditions collapsed as a follow-up test. The same procedures in the previous analysis were used, adding the condition effect first, followed by the interaction terms. As seen in Table 5, the main effect of the dummy-coded condition was significant at all steps of analysis, indicating a significantly higher amount of exploration by the IKE condition compared to the three other conditions. Furthermore, the condition-only model was the best fitting of these three models.

Hypothesis 5, which predicted that exploratory behavior would mediate the relationship between knowledge enrichment and the learning outcomes, was tested via a bootstrapping approach (Preacher & Hayes, 2008) in which point estimates of the indirect effect (*ab*) of exploration on reacquisition adaptation with pre-change scores as the mediating mechanism, and bias corrected 95% confidence intervals were derived from the mean of 5,000 estimates. Results showed that there was no indirect effect from condition to any of the three learning outcomes (knowledge: *ab* = .02, 95% CI = -.02, .08, pre-change performance: *ab* = .001, 95% CI = -.002, .005, and post-change performance: *ab* = .001, 95% CI = -.001, .005).

However, based on the aforementioned findings concerning the too-much-novelty perspective and the follow-up tests for Hypotheses 3 and 4, I conducted a follow-up test in which conditions were dummy coded such that the IKE condition was compared with all three other conditions collapsed. Results showed that exploration did mediate the relationship between this dummy-coded condition and learning outcomes (knowledge: *ab* = .11, 95% CI = .004, .32, pre-change performance: *ab* = .01, 95% CI = .002, .02, and post-change performance: *ab* = .01, 95% CI = .001, .02).

Hypothesis 6, which predicted that exploratory behavior during practice would predict reacquisition adaptation (i.e., average post-change performance) after controlling for acquisition performance, was examined through hierarchical regression. Step 1 included the covariates (ACT, sex, and videogame experience) to predict post-change performance scores. In Step 2, the dummy-coded (comparing each condition to one another) condition variable was added. In Step 3, exploration was added, and finally, in Step 4, pre-change performance scores were added.

Results showed that exploration did not significantly predict reacquisition adaptation above and beyond the effect of practice performance ($\Delta R^2 = 0.00$, $p = 0.75$). However, it should be noted that in Step 3, exploration did significantly predict exploration ($\Delta R^2 = 0.03$, $p < 0.01$) above and beyond the effects of condition and the covariates. Thus, Hypothesis 6 was not supported. However, I conducted another analysis and examined exploration as an indirect predictor of reacquisition adaptation via pre-change performance. The same bootstrapping approach (Preacher & Hayes, 2008) used to test Hypothesis 5 was again used. Results showed that there was in fact a significant indirect effect from exploration to post-change performance scores via pre-change performance scores ($ab = .08$, 95% CI = .05, .11). Supplemental analyses also showed that among the four conditions in this study, exploration significantly predicted pre-change performance scores and post-change performance scores for each of the experimental conditions above and beyond the covariates (IKE $\Delta R^2 = 0.08$, $p < .001$, $\Delta R^2 = 0.08$, $p < .001$; PIKE $\Delta R^2 = 0.07$, $p < 0.01$, $\Delta R^2 = 0.08$, $p < .001$; PKE $\Delta R^2 = 0.07$, $p < 0.01$, $\Delta R^2 = 0.03$, $p < .001$;), but not for the control condition ($\Delta R^2 = 0.00$, $p = 0.95$, $\Delta R^2 = 0.00$, $p = .95$;).

Discussion

Computer-based and synthetic learning environments continue to become more commonplace in training and education, and as such, there has been a growing body of research concerning how learners might best maximize their learning in such environments (Bedwell, & Salas; Cuevas et al., 2004; Sitzmann, 2011). Specifically, active learning, which grants learners a large degree of autonomy over their own learning while supporting self-regulatory processes, has become a theoretical focal point for researchers (Bell & Kozlowski, 2008). Among these self-regulatory processes, there is ample evidence that task exploration is positively related to a variety of learning outcomes (Hardy, 2015; Hardy et al., 2014; Westlin, Day, & Hughes, 2017).

This laboratory study investigated two approaches to knowledge enrichment—pre-practice and intermittent—to prompt exploratory behavior at the onset of and during the practice of a complex task. The findings of the present study are nuanced, with partial support for knowledge enrichment as a means of promoting exploratory behavior. Although initial exploration was not found to be influenced by pre-practice knowledge enrichment, the intermittent knowledge enrichment manipulation was found to have a meaningful impact on the exploration of those in the IKE condition, but not in the PIKE condition. Additionally, knowledge enrichment had a direct effect on task knowledge, and an indirect effect for participants in the IKE condition on all learning outcomes through exploratory behavior. Further, although exploration did not directly influence adaptation performance, there was an indirect relationship from exploration to adaptation through acquisition.

To interpret the findings from this study, we must look at the pattern of expected effects of knowledge enrichment. That is, it was expected that the knowledge enrichment manipulations would lead to larger information-knowledge gaps. These gaps would prompt learners to explore their environment, which would in turn lead to increased knowledge as well as pre and post-change task performance. Accordingly, it is important to discuss each of these expected relationships, as well as the indirect versus direct relationships of the manipulation to the learning outcomes (knowledge, pre-change performance, and post-change performance). In the following sections I further discuss and explain these findings, attempt to address the partial impact of knowledge enrichment on both proximal and distal outcomes, and conclude by discussing the study limitations and directions for future research.

Knowledge Enrichment and the Information-Knowledge Gap

Knowledge enrichment was expected to lead to increased information-knowledge gaps in learners. As seen in Figure 1, none of the conditions differed significantly from one another in initial or overall information-knowledge gaps during acquisition (pre-change sessions). The theory behind this expectation was that if learners were provided with more task-related declarative knowledge, it would inform them that they do not have adequate procedural knowledge for effective task performance and would thus prompt exploration. However, this link was not supported, particularly at the onset of practice. Assuming all of the information presented prior to practice was novel to the participants, participants had little to no frame of reference or understanding of the abundance of task-related information that was available within their environment. Instead, participants were likely to view the initial presentation as simply declarative knowledge about the task, rather than guiding information about what remained unexplored within the task environment. This would lead to similar information-knowledge gaps at the onset of practice as all learners were equally unaware of how much remained to be learned about the task.

Similarly, previous research has shown that exploratory behavior generally begins high and starts to decrease as learners become more familiar with to-be-learned material and turn to exploit what they know (Hardy et. al., 2019). Accordingly, the intermittent conditions were designed to mitigate the transition from exploration to exploitation through increases in the information-knowledge gap via intermittent knowledge enrichment. However, learners in all conditions had similar information-knowledge gaps throughout acquisition, indicating that intermittent knowledge enrichment was not stimulating these information-knowledge gaps. It could be the case that the presented information did not prompt learners to recognize novelty in their environment, but rather the information was viewed as closing their existent information-knowledge gaps. Additionally, the measure of information-knowledge gaps may not have fully captured the construct, as it did not ask learners the extent to which they wished to *learn* more about the task.

Unexpectedly, those in the IKE condition, which received the most intermittent knowledge enrichment, reported lower information-knowledge gaps than all other conditions in the first session after the task change and in other post-change sessions. This finding suggests that although pre-change perceptions of information-knowledge gaps were similar among conditions, those in the IKE condition may have been better able to utilize their intermittent knowledge enrichment in such a way that they were less overwhelmed by task demands in the novel (post-change) environment. This trend continued after the task change, with those in the IKE condition having smaller information-knowledge gaps than other conditions. In addition, although not statistically significant, participants in the IKE condition did have the highest performance scores of all the conditions in the final three post-change sessions.

Because the conditions did not differ in their pre-change information-knowledge gaps, it is unclear if knowledge enrichment as a whole is ineffective, or if it could be effective if instituted differently. One unexplored avenue of knowledge enrichment is presenting more new information later in acquisition. As shown in Figure 5, learners were at their lowest levels of task exploration near the end of practice. This implies that learners have shifted towards an exploitation mindset, focusing more on refinement of existing strategies rather than discovering new ones. This is also the point in the study that learners have the smallest information-knowledge gaps. If the goal of knowledge enrichment is to increase the information-knowledge gap, presentation of additional task-related information later in acquisition should stimulate learners' information-knowledge gaps, and lead to more sustained exploratory behavior.

Knowledge Enrichment and Exploratory Behavior

The benefits of sustained exploration to the learning process should not be discounted. Empirical research demonstrates that learners do in fact benefit from exploration (Berlyne, 1960, 1966; Bruner, 1961; Grief & Keller, 1990; Hardy, 2015; Hardy et al., 2014; Westlin et al., 2017). Researchers have attempted to increase exploratory behavior through error management training and the explicit encouragement of exploration, but only with limited success (Dormann & Frese, 1994; Keith & Frese, 2005, 2008; Hardy et al., 2014). This study attempted to increase exploratory behavior by widening the information-knowledge gaps of learners via the presentation of additional task information beyond core information.

In this study, there were no significant differences in initial learner exploration from the knowledge enrichment manipulation. Similar to the findings for the information-knowledge gaps, this finding suggests that pre-practice knowledge enrichment had no impact on learner exploration. I speculate that participants may have found their first acquisition session overwhelming as they began to explore the most fundamental facets of the task, and thus explored comparably. In this manner, pre-practice knowledge enrichment would not aid in initial exploration. This alone would suggest that knowledge enrichment was ineffective at promoting exploratory behavior. However, there was evidence of a link between intermittent knowledge enrichment and exploration, as there was a significant difference in exploration when comparing the IKE condition to all others. When learners in the IKE condition received their first intermittent knowledge enrichment (after Session 1), their exploratory behavior increased. As seen in Figure 5, the second session for IKE was the only *increase* in exploratory behavior observed across all sessions and conditions. Likewise, as reflected in Table 5, the main effect of the dummy-coded variable of the IKE condition compared to all others showed that those in the IKE did explore more than the other conditions.

Although counter to the hypothesized relationships, this finding is consistent with the too-much-novelty perspective. That is, those in the PKE condition received all task-related knowledge prior to practice. Similarly, those in the PIKE condition received some task-related knowledge prior to practice. Because exploration was lower among these conditions than the IKE condition, it appears that the pre-practice knowledge information was overwhelming at such an early stage in training. In contrast, all the knowledge enrichment in the IKE condition occurred intermittently. One of the basic tenets of curiosity research is that humans have a preference for stimuli that are *slightly* more complex than those which are more familiar or understood (Earl, 1957; Berlyne, 1960). Thus, those in the IKE condition had more opportunity to practice the task before knowledge enrichment, and accordingly, the information was likely more closely related to their current skill level, and thus more easily explored. One might conclude that intermittent knowledge enrichment is in fact beneficial in prompting exploratory behavior, but future research is needed to determine when and how it is most effective to provide intermittent knowledge enrichment, and more importantly, if intermittent knowledge enrichment can impact the amount of skill acquired during training, particularly in complex tasks.

Altogether, the results of this study showed partial support for the notion of knowledge enrichment having a positive impact on exploratory behavior over the course of acquisition, but only when presented intermittently. The findings of the present study suggest that pre-practice knowledge enrichment does not spur learner exploration, but additional research is needed to determine if this finding was a function of learners in this particular setting being overwhelmed prior to practice, or if similar findings would occur in other learning environments.

Knowledge Enrichment and Learning Outcomes

Knowledge, pre-change performance, and post-change performance were all key learning outcomes in this study. Results showed that those who received knowledge enrichment scored significantly higher on the knowledge test than those in the control condition (NKE), and that those who received intermittent knowledge enrichment (IKE and PIKE) scored significantly higher than those who received all the knowledge enrichment before practice (PKE). This finding indicates that the manipulation was in fact effective at enhancing knowledge acquisition, in that learners that received more information generally had higher task knowledge than those who did not. Moreover, intermittent knowledge enrichment led to more knowledge than pre-practice knowledge enrichment, which is consistent with the distributed practice effect (Benjamin & Tullis, 2010; Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006).

As mentioned above, although pre-change information-knowledge gaps did not differ among conditions, as seen in Figure 1, those in the IKE condition had smaller information-knowledge gaps after the task change than all other conditions, implying that perhaps their higher amount of declarative knowledge could have decreased the amount of novelty they perceived when elements of the performance demands changed. I speculate that through task practice, comprehension of declarative knowledge presented intermittently was more easily retained, as learners were better able to build on their prior knowledge acquired in pre-change sessions.

To test this speculation, I conducted a mediation analysis, having dummy coded to compare those that received intermittent knowledge (IKE and PIKE) enrichment to those who did not (PKE and NKE) Results showed that there was a significant indirect relationship between knowledge enrichment and post-change performance through task knowledge, while controlling for videogame experience, ACT, and sex (*ab* = .007, 95% CI = .003, .013), which was consistent with my speculation. This means that knowledge enrichment led to higher scores on the knowledge test, which in turn led to great post change performance. As such, although the knowledge enrichment did not directly lead to greater skill performance, it may have better equipped participants to adapt to the task changes through a more comprehensive understanding of the task. More broadly, every experimental (knowledge enrichment) condition had significantly higher knowledge scores than the no knowledge enrichment control (NKE) condition. This suggests that even if there were minimal benefits to skill acquisition, participants did benefit more distally from the knowledge enrichment in acquisition.

Ultimately, the goal of any skill-based training is that learners become more proficient at the criterion task, and that their newly acquired skills can be translated to novel performance demands. Exploration is fundamental to this learning process (Berlyne, 1960, 1966; Bruner, 1961; Grief & Keller, 1990, Hardy et al., 2018). Task exploration is especially meaningful when it aids in the adaptive performance of a task. Within this study, performance did not differ significantly by condition, nor did exploratory behavior significantly predict reacquisition adaptation after controlling for pre-change performance. However, supplemental analyses showed that there may be a viable explanation for this finding. Above and beyond the influence of the covariates, exploratory behavior was found to be predictive of both pre-change and post-change performance in all knowledge enrichment conditions, but not in the control condition. I speculate that these findings together reflect how there was a difference in the manner in which participants were developing skill.

Specifically, the declarative knowledge received by those in knowledge enrichment conditions may have been practiced, but not to the extent that they continued to use the learned strategies more effectively throughout practice. In essence, learners may have attempted to utilize the information in the knowledge enrichment, but they did not develop the depth of procedural knowledge necessary for highly effective performance. This speculation is consistent with the distinction between implicit and explicit learning. Implicit learning involves learning complex systems without much executive control or conscious effort, whereas explicit learning involves more executive control and deliberate conscious effort (Deshon and Alexander, 1996). It may be that those in the NKE condition were engaging in more implicit learning whereas those in the knowledge enrichment conditions were engaging in more explicit learning. Thus, participants in the NKE condition might have developed a depth in select strategies which facilitated their skill performance. For the knowledge enrichment conditions, the exploration of new information might have inhibited development of strategy depth, and their skill improvements might have been due more to breadth of strategies.

Limitations and Future Research

There are a number of limitations that must be considered in the interpretation of these findings. First, the context involved learning a computer video game over just a few hours of practice, and was characterized by learning at one's own pace without explicit instructions for optimal performance. Accordingly, the findings might not generalize to other contexts, particularly those involving more time in training or more proceduralized learning.

Additionally, the manipulation itself had a number of limitations. First, we must look at the manipulations individually. The results from this study showed that learners who were provided with information prior to practice did not explore more than those who received no pre-practice knowledge enrichment, indicating that this manipulation was ineffective in producing the hypothesized effects. The pre-practice knowledge enrichment condition (PKE) provided learners with all task-related information prior to practice. As previously mentioned, learners can become overwhelmed if presented with content that is beyond their current skill level (Berlyne, 1960), which will result in learners utilizing known skills rather than engaging in exploratory behavior. Perhaps the pre-practice knowledge enrichment condition overwhelmed learners with content, such that they utilized mostly the basic information presented at the onset of training. Because participants did not differ by condition in their initial exploration, it could be that only the basic training information was utilized at the onset of training.

With regard to intermittent knowledge enrichment, one of the key assumptions made was in the order of the information received by participants. This information was intermittently presented in a hierarchical order deemed logical by the researcher. For example, information about weapon uses was presented earlier in training while some gameplay strategies were presented later in training. However, this assumes that participants learned the task in a similar manner. But as previously mentioned, complex tasks have equifinality with no clear performance ceiling, and active learning environments such as this provide learners with a large degree of autonomy while simultaneously promoting self-regulatory processes (Hardy, et. al., 2018). Accordingly, although learners may acquire similar skillsets during practice, they may do so in different ways, and as such, the information presented in the intermittent knowledge enrichment may be overwhelming or underwhelming, depending on the learner. In essence, the ordering of the intermittent knowledge enrichment may not have been well-suited to prompt exploratory behavior. Had learners been able to select which content to learn intermittently, perhaps the selected content would have been more beneficial to learner exploration.

At a broader level, knowledge enrichment may be an ineffective way to promote exploratory behavior. Within the error management literature, learners have been found to occasionally ignore instructions and behave in a way they found most natural (Dormann & Frese, 1994). There were no instructions regarding exploration within this study, and it might be that learners did not fully utilize the additional information in the knowledge enrichment conditions.

Another possible explanation for the limited support of the hypotheses directly pertains to the information-knowledge gap. The information-knowledge gap is characterized by the difference between what individuals can do and what they *want* to do (Loewenstein 1994). The information provided to the control condition was designed to be limited in scope, providing only the fundamentals of gameplay. However, learners may have found this information equally overwhelming in comparison to the participants that received the pre-practice knowledge enrichment. The PKE condition was intended to prompt more initial exploratory behavior because participants were provided more information about gameplay and what to explore. If, however, all participants were provided too much information prior to practice, one would not expect to find differences in initial exploration. Thus, the information-knowledge gap among participants may have been larger, and more similar to one another than intended. Although minimal support was found for knowledge enrichment's impact on exploratory behavior, future research is needed to investigate if knowledge enrichment can indeed be an effective means of stimulating exploratory behavior through widening information-knowledge gaps. One avenue for future research would be to investigate how information-knowledge gaps are impacted if learners are granted control over the content or topics of their knowledge enrichment. One might expect the selection of one's own intermittent knowledge enrichment content would aid in widening information-knowledge gaps, as learners would likely select content which they would be more inclined to explore in practice. Additionally, future research should investigate if learners will explore more if actively encouraged or instructed to utilize information from knowledge enrichment within practice rather than simply being presented with it. Regardless, this study's findings demonstrate that knowledge enrichment may not be the most effective way to spur exploratory behavior. As such, researchers should search for more effective ways to promote exploration.

Conclusion

The results of the present study can be examined in relation to each of the two manipulations. It was clear that pre-practice knowledge enrichment was ineffective in producing increases in information-knowledge gaps, exploratory behavior, or task performance. Likewise, although pre-practice knowledge enrichment led to greater task knowledge than no knowledge enrichment, those that received intermittent knowledge enrichment acquired the most task knowledge. As such, it can be concluded that pre-practice knowledge enrichment should not be used in the design of training when intermittent knowledge enrichment can be used instead.

With regard to intermittent knowledge enrichment, the results are more nuanced. Clearly, intermittent knowledge enrichment had little impact on either acquisition or adaptation performance. However, those that received some degree of intermittent knowledge enrichment (PIKE and IKE) acquired the most declarative knowledge, and when only intermittent knowledge enrichment was provided (IKE), learners engaged in more exploratory behavior in comparison to other conditions. Additional research is needed to determine if intermittent knowledge enrichment can be more effectively administered to support self-regulated learning, and moreover, if it can produce stronger benefits to skill performance through exploratory behavior.

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Table 1

Means, Standard Deviations, and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6
1. Sex								
2. ACT	26.40	1.20	-.10					
3. Videogame experience	0.00	1.00	-.55	.04				
4. Exploration	3.10	0.43	-.44	.10	.37			
5. Knowledge test	15.51	3.95	-.48	.26	.41	.37		
6. Pre-change performance	0.37	0.18	-.69	.21	.62	.58	.52	
7. Post-change performance	0.30	0.16	-.66	.17	.60	.52	.93	.48

Note. Sex: male = 0, female = 1. Videogame experience was a standardized composite. Pre-change performance = average performance across pre-change sessions (i.e., Session 1-7). Post-change performance. = average performance across post-change sessions (i.e., Session 8-14). Exploration = average composite exploratory behavior score across pre-change sessions (i.e., Sessions 1-7).

$N = 257$. $r > |.11| = p < .10$; $r > |.13| = p < .05$; $r > |.16| = p < .01$. All tests are two-tailed.

Table 2

Mixed-Effects Growth Models of Exploratory Behavior

	Model 1			Model 2		
Variable	*B*	*SE*	*t*	*B*	*SE*	*t*
Intercept, γ_{00}	3.50	0.05	77.58**	3.62	0.05	79.12**
Linear trajectory (Session), γ_{10}	-0.12	0.02	-7.62**	-0.12	0.02	-7.62**
Quadratic trajectory (Session squared), γ_{20}	0.01	0.00	2.58**	0.01	0.00	2.58**
Sex, γ_{01}				-0.35	0.06	-5.94**
ACT, γ_{02}				0.01	0.01	0.23
Videogame experience (VGE), γ_{03}				0.06	0.03	0.07
AIC		*1288.92*			*1250.41*	

Note. Sex: male = 0, female = 1. *N*= 257. †*p* < .10, **p* < .05, ***p* < .01.

Table 3

Mixed-Effects Growth Model of Exploratory Behavior as a Function of Knowledge Enrichment

	Model 3		
Variable	*B*	*SE*	*t*
Intercept, γ_{00}	3.64	0.05	72.53**
Linear trajectory (Session), γ_{10}	-0.12	0.02	-7.44**
Quadratic trajectory (Session squared), γ_{20}	0.01	0.00	2.58**
Sex, γ_{01}	-0.36	0.06	-5.97**
ACT, γ_{02}	0.01	0.01	1.25
Videogame experience (VGE), γ_{03}	0.06	0.03	1.77
Knowledge enrichment (KE), γ_{04}	-0.04	0.08	-0.60
KE × Session, γ_{14}	-0.00	0.01	-0.10
KE × Session squared, γ_{24}			
AIC	*1264.40*		

Note. Sex: male = 0, female = 1. KE: NKE = -1; IKE = 0.33, PIKE = 0.33, PKE = 0.33).
N= 257. †p < .10, *p < .05, **p < .01.

Table 4

Mixed-Effects Growth Model of Exploratory Behavior as a Function of Intermittent Knowledge Enrichment versus Both Pre-Practice and Intermittent Knowledge Enrichment versus Pre-practice Knowledge Enrichment and No Knowledge Enrichment

	Model 3			Model 4			Model 5		
Variable	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*
Intercept, γ_{00}	3.63	0.05	79.25**	3.63	0.05	79.07**	3.63	0.05	79.18**
Linear trajectory (Session), γ_{10}	-0.12	0.02	-7.62**	-0.12	0.02	-7.60**	-0.12	0.02	-7.62**
Quadratic trajectory (Session squared), γ_{20}	0.01	0.00	2.58**	0.01	0.00	2.58**	0.01	0.00	2.59**
Sex, γ_{01}	-0.36	0.06	-6.10**	-0.36	0.06	-6.10**	-0.36	0.06	-6.10**
ACT, γ_{02}	0.01	0.01	1.18	0.01	0.01	1.18	0.01	0.01	1.18
Videogame experience (VGE), γ_{03}	0.06	0.03	1.84	0.06	0.03	1.84	0.06	0.03	1.84
Intermittent knowledge enrichment (INTKE), γ_{04} (INTKE), γ_{04}	0.05	0.03	1.60	0.10	0.05	2.13*	0.03	0.06	0.57
INTKE x Session, γ_{14}				-0.01	0.01	-1.40	0.03	0.02	1.32
INTKE x Session squared, γ_{24}							-0.01	0.00	-1.95†
AIC	*1254.80*			*1262.70*			*1270.42*		

Note. Sex: male = 0, female = 1. INTKE: NKE = -0.5, PKE = -0.5; PIKE = 0; IKE = 1. *N*= 257. †*p* < .10, **p* < .05, ***p* < .01.

Table 5

Mixed-Effects Growth Model of Exploratory Behavior as a Function of Intermittent Knowledge Enrichment versus All Other Conditions

	Model 3			Model 4			Model 5		
Variable	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*
Intercept, γ_{00}	3.63	0.05	79.33**	3.63	0.05	79.22**	3.63	0.05	79.32**
Linear trajectory (Session), γ_{10}	-0.12	0.02	-7.62**	-0.12	0.02	-7.61**	-0.12	0.02	-7.62**
Quadratic trajectory (Session squared), γ_{20}	0.01	0.00	2.58**	0.01	0.00	2.58**	0.01	0.00	2.57**
Sex, γ_{01}	-0.37	0.06	-6.17**	-0.37	0.06	-6.17**	-0.37	0.06	-6.17**
ACT, γ_{02}	0.01	0.01	1.21	0.01	0.01	1.21	0.01	0.01	1.21
Videogame experience (VGE), γ_{03}	0.06	0.03	1.89†	0.06	0.03	1.89†	0.06	0.03	1.89†
Intermittent knowledge enrichment γ_{04} (IKE), γ_{04}	0.09	-0.04	2.20*	10.11	-0.06	2.00*	0.04	0.07	0.51
INTKE x Session, γ_{14}				-0.01	-0.01	-0.56	0.04	0.03	1.55
INTKE x Session squared γ_{24}							0.01	0.00	-1.87†
AIC		*1252.14*			*1261.24*			*1268.83*	

Note. Sex: male = 0, female = 1. INTKE = NKE = -0.33 PKE = -0.33 and PIKE = -0.33, IKE = 1. *N*= 257. †$p < .10$, *$p < .05$, **$p < .01$.

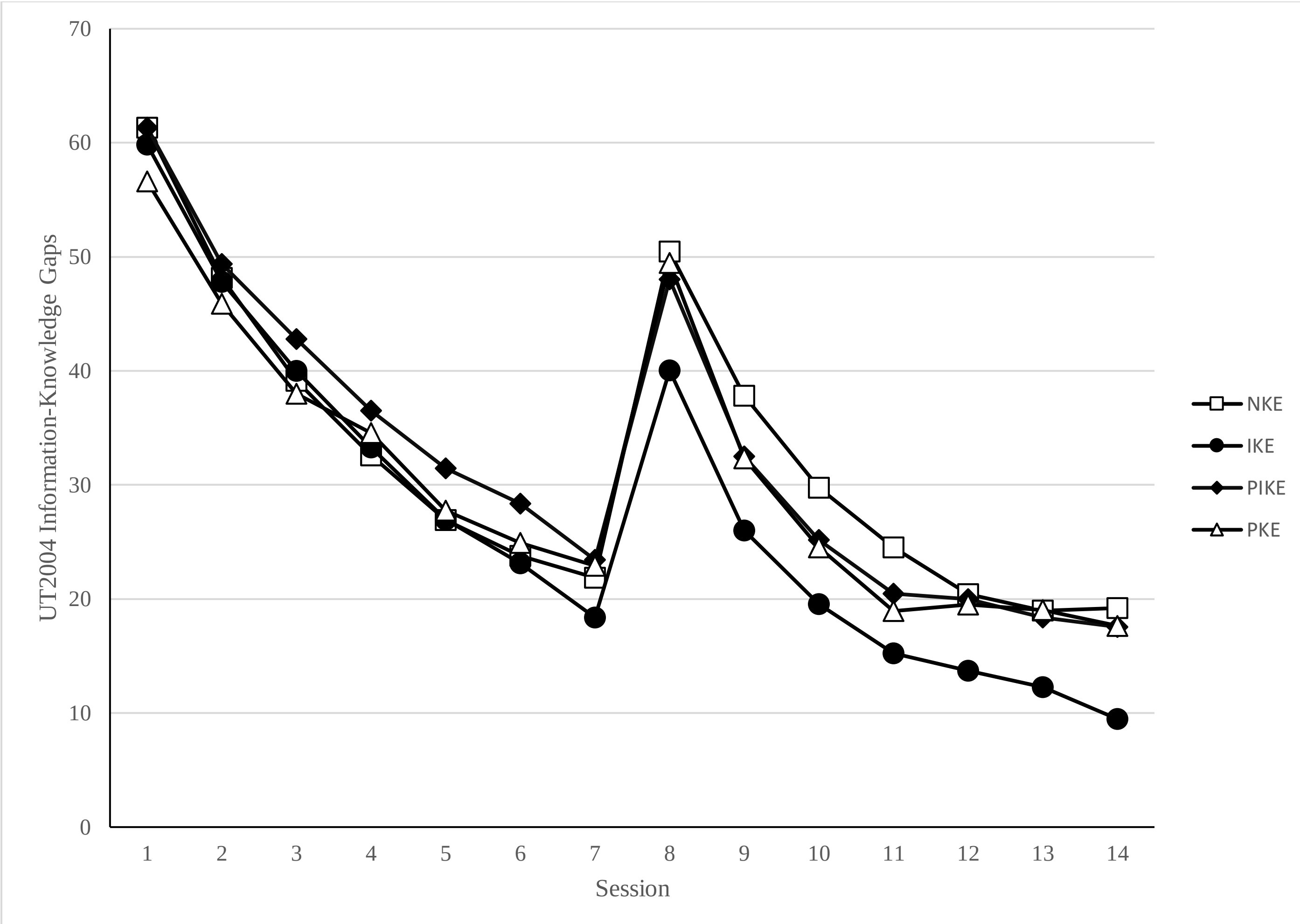


Figure 1. Adjusted means of perceptions of information-knowledge gaps by condition, controlling for ACT scores, sex, and videogame experience. Sessions 1-7 = pre-change. Sessions 8-14 = post-change. NKE = no knowledge enrichment. IKE = intermittent knowledge enrichment. PIKE = pre-practice and intermittent knowledge enrichment. PKE = pre-practice knowledge enrichment.

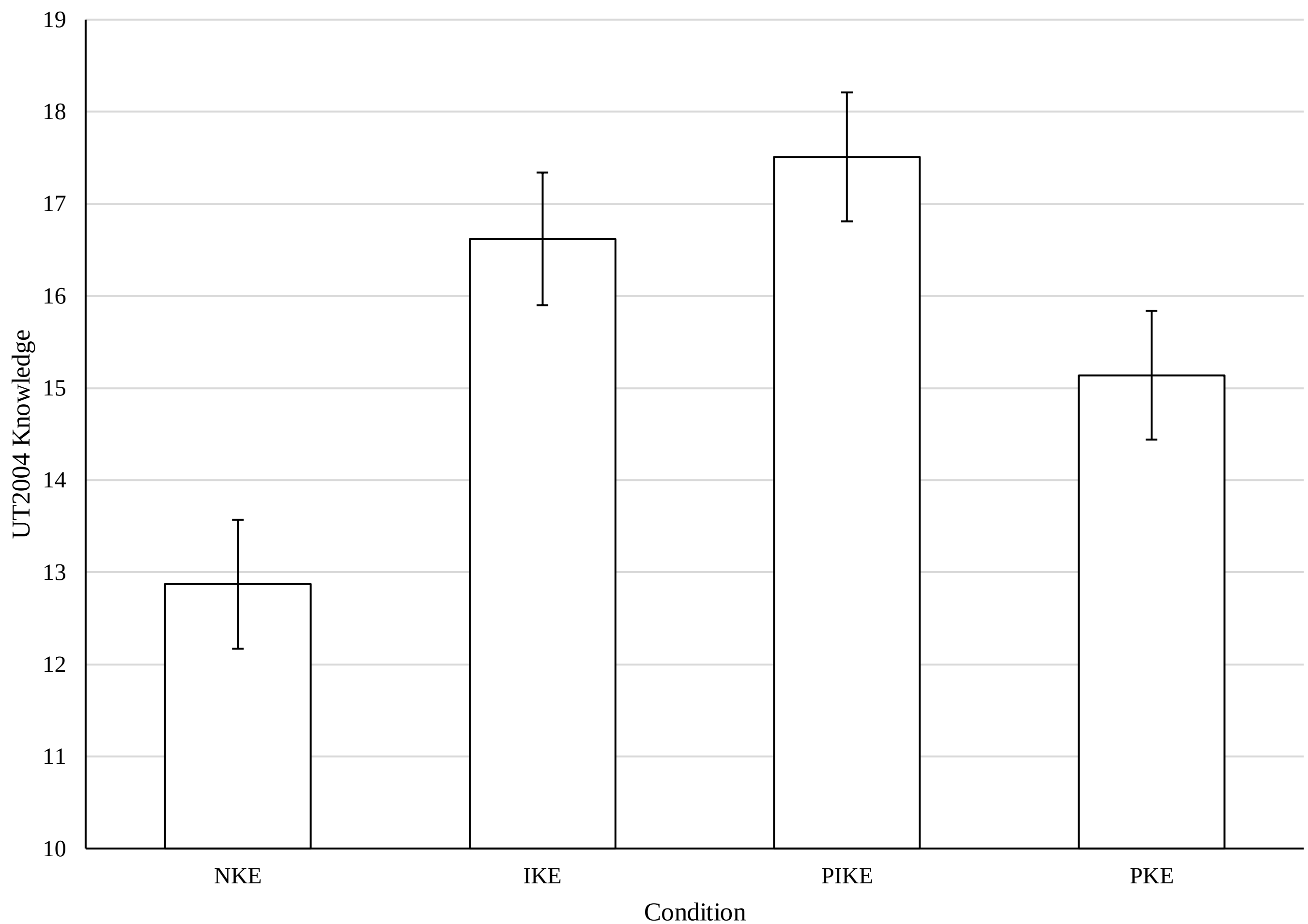


Figure 2. Adjusted means of knowledge test scores by condition controlling for ACT scores, sex, and video game experience. NKE = no knowledge enrichment. IKE = intermittent knowledge enrichment. PIKE = pre-practice and intermittent knowledge enrichment. PKE = pre-practice knowledge enrichment. Error bars = ± 2 SE.

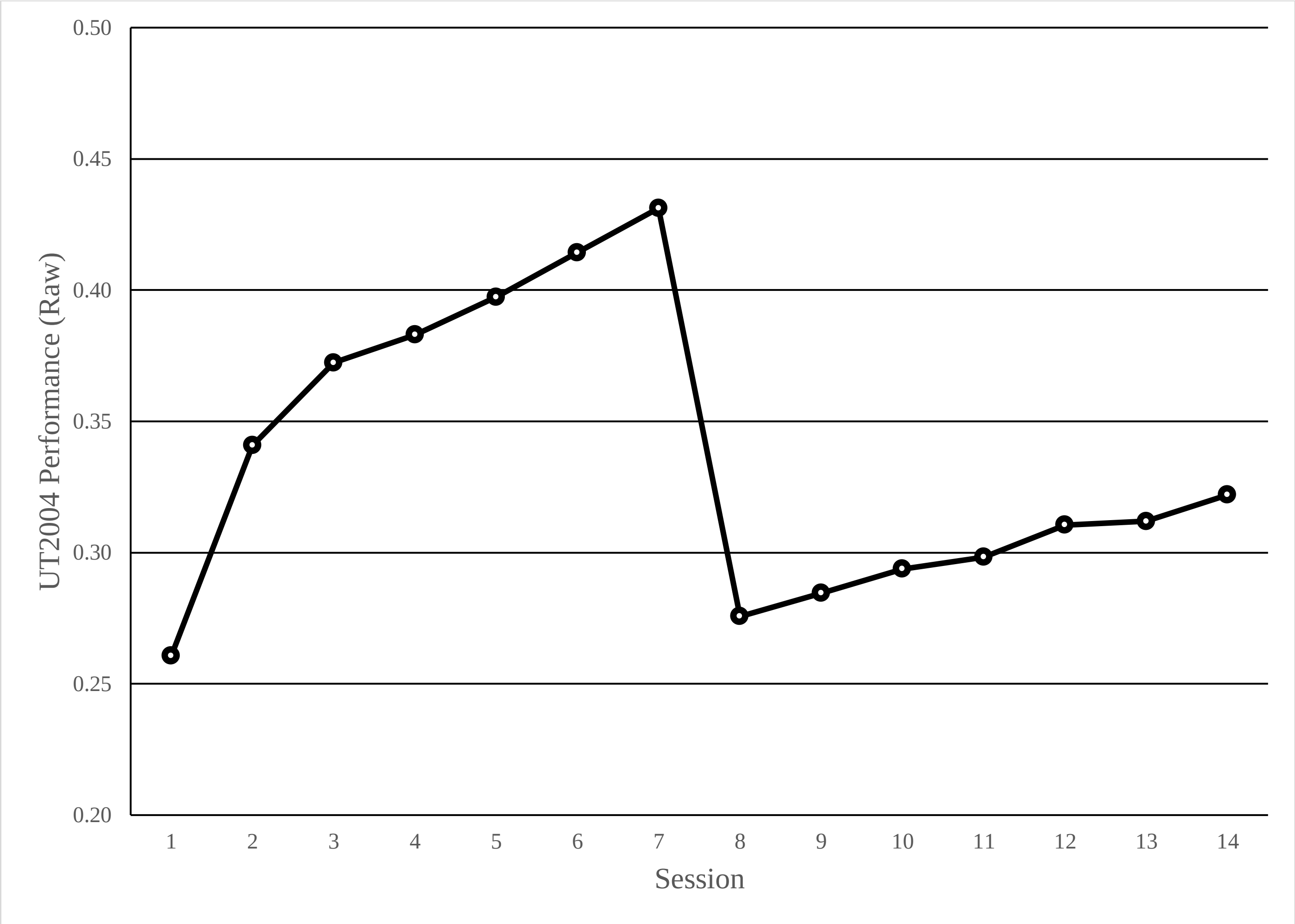


Figure 3. Raw means of skill performance, controlling for ACT scores, sex, and videogame experience. Sessions 1-7 = pre-change. Sessions 8-14 = post-change.

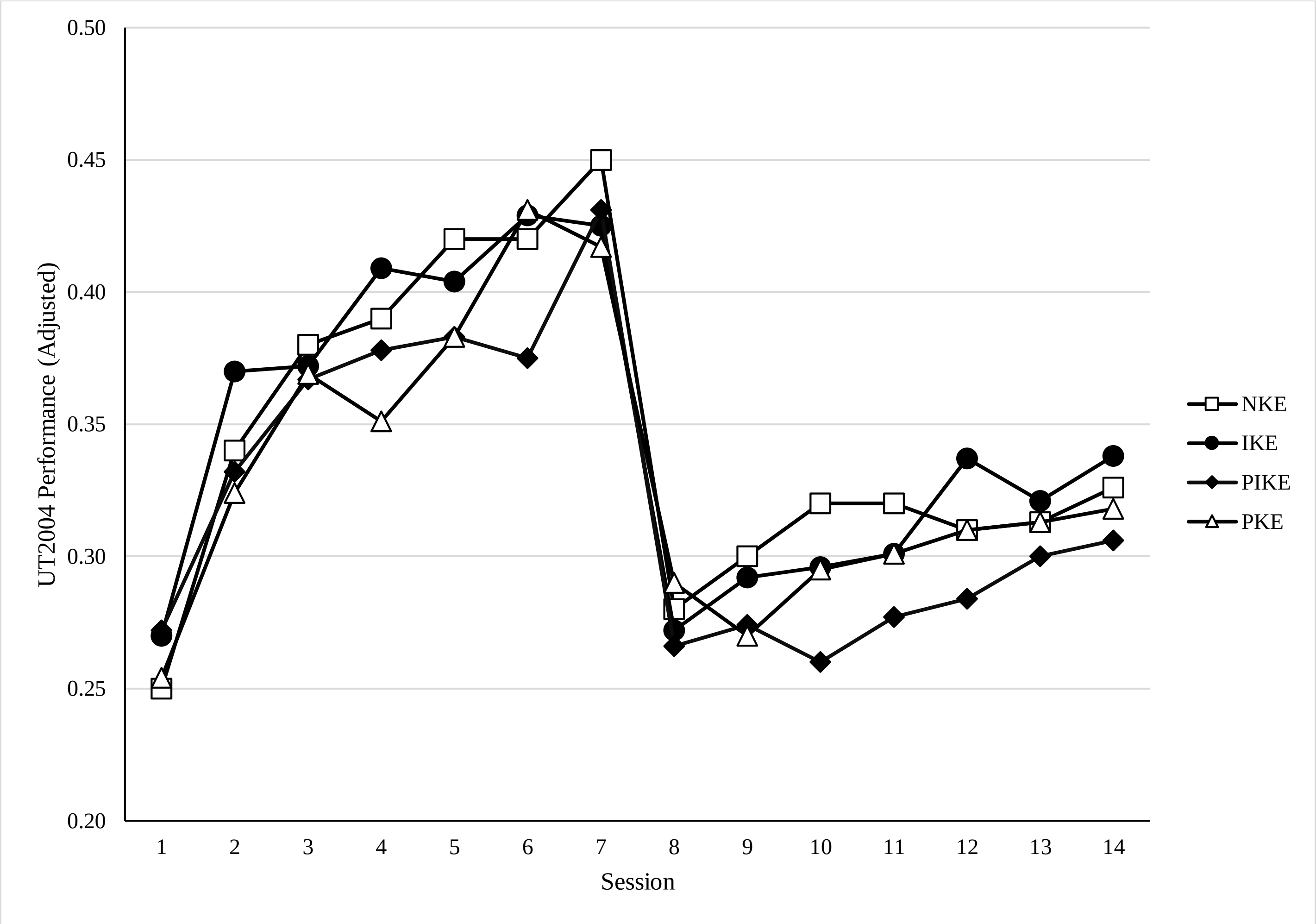


Figure 4. Adjusted means of skill performance by condition, controlling for ACT scores, sex, and videogame experience. Sessions 1-7 = pre-change. Sessions 8-14 = post-change. NKE = no knowledge enrichment. IKE = intermittent knowledge enrichment. PIKE = pre-practice and intermittent knowledge enrichment. PKE = pre-practice knowledge enrichment.

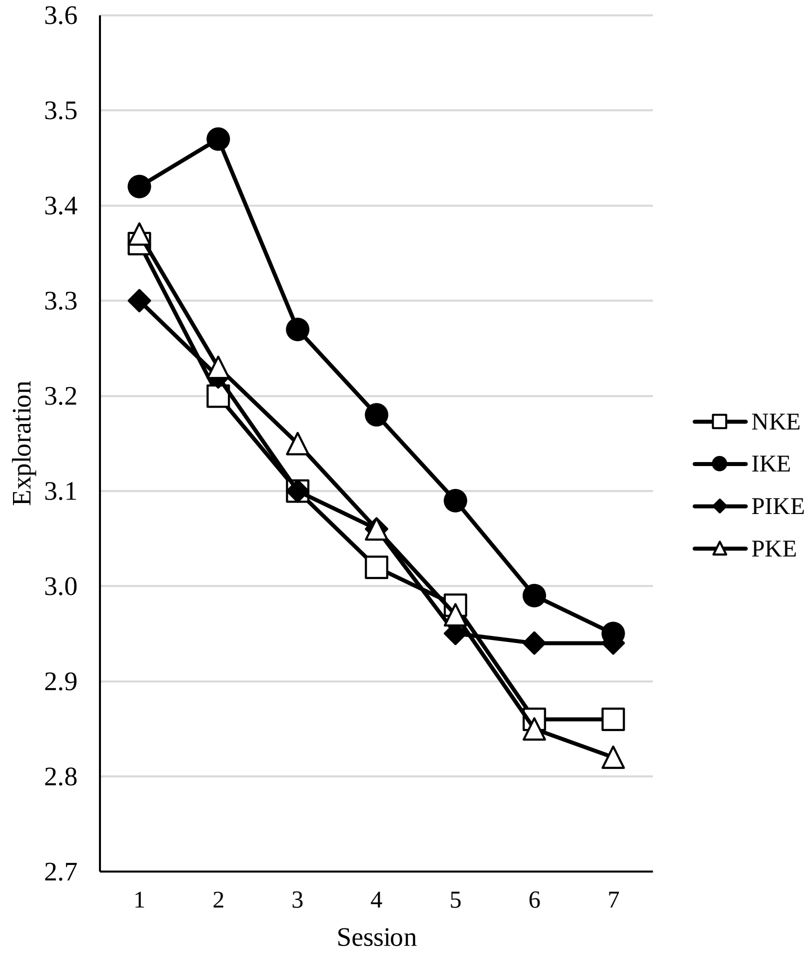
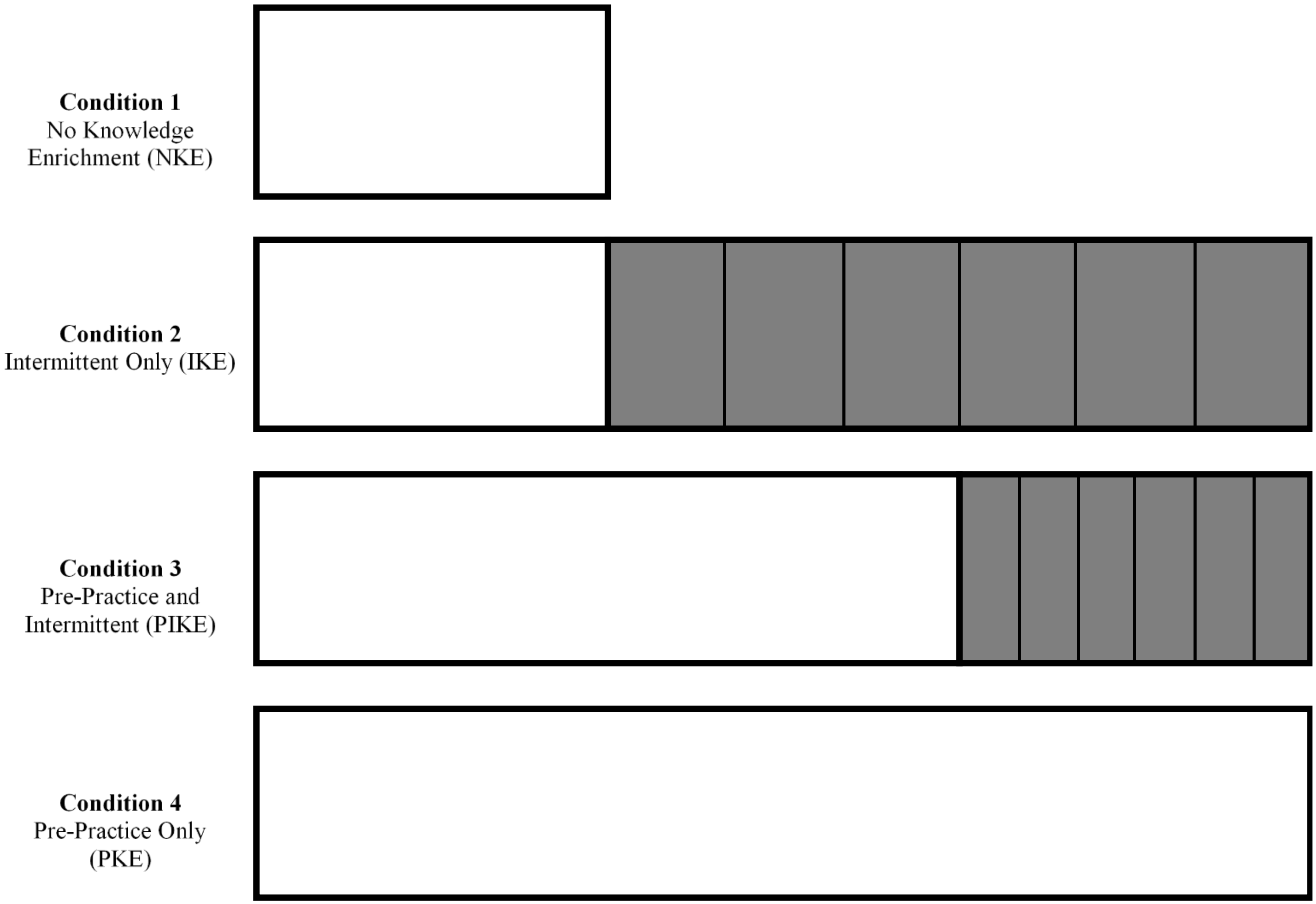


Figure 5. Adjusted means of exploration across pre-change sessions by condition, controlling for ACT scores, sex, and videogame experience. NKE = no knowledge enrichment. IKE = intermittent knowledge enrichment. PIKE = pre-practice and intermittent knowledge enrichment. PKE = pre-practice knowledge enrichment.

Appendix A: Order of Learned Content



Note: White = pre-practice presentation, Grey: intermittent presentations.

Appendix B: Unreal Tournament Training Script

UT Training Script (Pre = presented prior to practice, Numbers = which intermittent presentation information was presented)	
UT01 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	In this training presentation, you will learn about Unreal Tournament 2004, a first-person shooter video game in which each player has control over a different character. Specifically, we will teach you about the game display, the basic game controls, the in-game pick-ups, and the weapons which will be available to your character in today's study.
UT02 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	First we will focus on the on-screen display which you will see while playing Unreal Tournament.
UT03 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The game timer is displayed in the top left corner of the screen. This timer displays the amount of time remaining before the end of each game.
UT04 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The three numbers directly underneath the game timer relate to your game performance. Specifically, the top left number is your current match rank. For instance, first, second, or third.
UT05 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The number below your match rank is the score spread. If you are in first place, the spread will indicate how many more points you have compared to the second-place bot. If you are not in first place, the spread will indicate how many points behind the leader you currently are. Here you can see that this player is 2 points ahead of the second place bot.
UT06 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Finally, the largest of the three numbers is you match score. Your score is determined by the number of times you have destroyed a bot minus the number of times you have destroyed your own character. Each time you destroy a bot you will be awarded one point.
UT07 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Now notice the row of blue boxes running along the bottom of the screen. These display boxes provide information regarding your character's health, weapons, and ammunition. The left-most box is the health display box as indicated by the light blue cross inside. Your character will always begin with 100 health points. As your character takes damage, this number will drop. When it reaches 0, your character will need to respawn.

UT08 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Whenever your character takes damage, red indicators will appear on the sides of the screen to show you where the damage is coming from. For instance, if an enemy bot in front of your character and slightly to the right is attacking you, red indicator lights will appear both on top and to the right of your screen.
UT09 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Now, look at the next series of boxes at the bottom-center of the screen. These are the weapons display boxes. Weapons currently available to your character will be displayed with color images in their respective boxes. Otherwise, black silhouettes will appear in the remaining weapons boxes to indicate that your character does not have those weapons.
UT10 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The weapon which your character is using currently is indicated by the weapon display box that is slightly raised and highlighted in gold. This is the weapon that will appear on the right side of the screen in your character's right hand.
UT11 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Next, notice the display box in the bottom right corner of the screen. This box is your current weapon ammunition display. It shows you how much ammunition remains for the weapon your character currently is using. In this case, this player has 100 ammunition points remaining for the assault rifle. Notice that when the player changes weapons, the ammunition display box changes accordingly. For now, just try to remember how to interpret the weapon and ammunition displays. We will discuss the various weapons and how to use them later on in this training.
UT12 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Now that you have a basic understanding of the on-screen display, we will continue by teaching you the basic controls you will use while playing Unreal Tournament.
UT13 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	First, in order to effectively move your character throughout the game, you must use both the keyboard and the mouse at the same time. The mouse is used to adjust your character's view. On the other hand, the keyboard is used to make your character move around in the game. If you are right-handed, you will likely feel more comfortable with the mouse in your right hand while keeping your left hand on the keyboard. If you are left-handed, you will probably find it more comfortable using the mouse with your left hand and the keyboard with your right. Feel free to move the keyboard and mouse to a position that is most comfortable for you.

UT14 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	You have two options when using the keyboard to move your character. You can place your hand over the arrow keys toward the right side of the keyboard, or you can place your hand over the W, A, S, and D keys toward the left side of the computer. Either position works fine. Now notice how the W, A, S, and D keys are positioned in a similar fashion compared to the arrow keys. Press either the W key or the up arrow to make your character move forward. Press either the A key or the left arrow key to make your character move left. Likewise, pressing the S key or the down key will cause your character to move backward, and pressing the D key or the right arrow key will cause your character to move right. During the practice sessions that follow, try using both keyboard positions to see which one you prefer.
UT15 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The keyboard is also used to make your character jump. Either the Ctrl key or the Spacebar can be used to jump. The jump is most effective when used while moving. For instance, while holding either the W key or the up arrow, you may press either the Ctrl key or Spacebar to jump forward. Another basic maneuver is the crouch. Pressing either the Shift key or the C key will make your character crouch. Your character will crouch for as long as you depress the crouch key but will stand again when the crouch key is released. Also, pressing the crouch key while moving will prevent your character from falling off ledges or other objects.
UT16 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Now we will teach you some more advanced skills which you can use while playing. The first skill we will talk about is dodging. Dodging causes your character to move quickly and sharply in any direction. To dodge, quickly press a move key two times in a row. For example, to make your character dodge forward, quickly press the W key or the up key twice. Similarly, to make your character dodge right, quickly press the D key or the right arrow key twice.
UT17 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Another advanced skill is the double-jump. The double-jump will cause your character to jump higher and farther than a normal jump. To double-jump, you need to press the jump key two times in a row – once to make your character jump initially and then again while your character is still in midair. Like the standard jump, the double-jump is best used while moving.
UT18 NKE- Never IKE- 1 PIKE- Pre PKE- Pre	Now that you have a basic understanding of the game controls, let us focus on the pick-ups that will be available during gameplay.
UT19 NKE- Never IKE- 1 PIKE- Pre PKE- Pre	These are health pick-ups. Walking into any one of these items will increase your character's health. The small blue vials are worth 5 health points each while the floating, light blue crosses are worth up to 25 health points each. Finally, the large white and blue barrels are known as Big Kegs of Health and are worth up to 100 health points.

UT20 NKE- Never IKE- 1 PIKE- Pre PKE- Pre	Shields are also available during gameplay. Picking up one of these golden crests will provide your character with armor that will absorb 50 points of damage and help preserve your health points.
UT21 NKE- Never IKE- 1 PIKE- Pre PKE- Pre	This next pick-up is a double-damage pick-up. Double-damage pick-ups appear as floating, purple wings, and collecting one of these increases the damage done by all of your character's attacks by two-times. When you walk into a double-damage pick-up, your character's current weapon will turn purple and you will see a timer in the lower right corner of the screen. When the timer expires, so will the double-damage effect. Finally, it is important to know that for all in-game pick-ups, collecting one will mean that it is unavailable for some time and the pick-up will reappear again.
UT22 NKE- Never IKE- 2 PIKE- Pre PKE- Pre	Adrenaline is a special feature in Unreal Tournament 2004, and it is the topic we will discuss next.
UT23 NKE- Never IKE- 2 PIKE- Pre PKE- Pre	During Unreal Tournament games, adrenaline pick-ups will appear scattered throughout the map. Each red and white capsule is worth 2 adrenaline points. Your character can also obtain adrenaline points by destroying enemy bots. The number of adrenaline points your character has is displayed in the top-right corner of the screen.
UT24 NKE- Never IKE- 2 PIKE- Pre PKE- Pre	If you are able to obtain 100 adrenaline points during a match, it will be possible for you to activate one of four special adrenaline abilities for your character. Quickly press 4 move keys in a row to use your adrenaline. We will go over some examples in a moment. You will not lose your adrenaline if your character respawns.
UT25 NKE- Never IKE- 2 PIKE- 1 PKE- Pre	Once you have 100 adrenaline points, pressing up, up, down, down will activate berserk mode, which will be announced by the commentator. Berserk mode increases the rate of fire from weapons, and how much the bots will be knocked back by your fire.
UT26 NKE- Never IKE- 2 PIKE- 1 PKE- Pre	Pressing up, up, up, up will activate speed mode. In speed mode, you can run faster and jump higher than usual. This combo however, drains your adrenaline faster than the other uses of adrenaline.
UT27 NKE- Never IKE- 2 PIKE- 1 PKE- Pre	Pressing right, right, left, left will turn you invisible to your opponents. They will, however, still see the firing of your weapons, regardless of how much adrenaline you have left.

UT28 NKE- Never IKE- 2 PIKE- 3 PKE- Pre	Pressing down, down, down, down will activate your booster. While the booster is active, you will regenerate health up to 199% at a rate of around 5 health per second. Once you have reached full health, booster will generate your shield up to 150%.
UT29 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	Now we will talk about weapons in Unreal Tournament 2004. First, we will show you how to use the weapons in the game.
UT30 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	You may use either the keyboard or mouse to select your character's current weapon. Rolling the mouse wheel up or down will cycle through your character's available weapons. Alternatively, you may use the number keys at the top of the keyboard to select a weapon. Each key corresponds to a different weapon box at the bottom the screen. For instance, pressing the 2 key will choose your character's assault rifle while pressing the 5 key will select the link gun. You may also press forward slash key to scroll through your character's available weapons.
UT31 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	The mouse controls all other weapon functions. Moving the mouse itself will adjust your character's aim. The targeting indicator at the center of the screen shows you what you character is aiming at. Sometimes it can be difficult to see the targeting indicator. However, because the targeting indicator is located at the center of the screen, your character's weapon will always fire towards the center of the screen, as well.
UT32 NKE- Never IKE- 3 PIKE- 2 PKE- Pre	All weapons have both a primary and alternative mode of fire. Left-click to use the weapon's primary mode of fire; right-click to deploy the weapon's alternate mode of fire. Also, you may hold down either the left or right mouse button in order to continuously fire a weapon, or you may click intermittently to fire bursts.
UT33 NKE- Never IKE- 3 PIKE- 2 PKE- Pre	We will now review each of the weapons available to you throughout gameplay. Each weapon, as previously mentioned, has both a primary and alternate use. In some cases, the primary and secondary use are very similar. In other cases, they are very different from one another.
UT34 NKE- Never IKE- 3 PIKE- 2 PKE- Pre	This is the assault rifle. At the start of each game and each respawn, this is the only weapon you begin with. Its primary fire are rapid-firing bullets with moderate accuracy. Its secondary use launches a timed grenade. The longer you hold the right button on the mouse, the farther you will fire the grenade.
UT35 NKE- Never IKE- 3 PIKE- 2 PKE- Pre	This is the rocket launcher. Its primary use fires a single projectile explosive rocket that explodes upon impact for high damage. When used at short range, this explosion can harm you. The secondary use of the rocket launcher is a spiraling fire of three rockets simultaneously. This takes more time to fire than the single rocket.

UT36 NKE- Never IKE- 3 PIKE- 2 PKE- Pre	This is the flak cannon. Its primary use fires white hot chucks of scrap metal, in a spread style, leaving a yellow trail behind them. Shot point-blank, the flak cannon will do extremely high damage, but the damage decreases over distance. The flak cannon's secondary use fires a single grenade full of shrapnel, causing damage to all areas near the grenade.
UT37 NKE- Never IKE- 3 PIKE- 3 PKE- Pre	This is the shock rifle. Its primary use fires a beam of plasma that slightly pushes the target away from whoever fires it. The secondary use of the shock rifle is a slow moving shock ball that deals high damage.
UT38 NKE- Never IKE- 3 PIKE- 3 PKE- Pre	This is the bio rifle. Primary use will launch a series of small, green blobs which will stick to anything or explode on contact with another player. The secondary use requires the user to hold the mouse and charge the bio rifle blobs into a much larger and usually slower-moving charge, but direct contact with a fully-charged shot is fatal, regardless of health and armor.
UT39 NKE- Never IKE- 3 PIKE- 3 PKE- Pre	This is the lightning gun, a high-power energy rifle capable of destroying even the heaviest armor. The weapon's primary use launches an instant-hit lightning bolt with perfect accuracy. Its secondary use zooms in on targets, allowing the user to lock-on and shoot with a high damage electrical shock that doesn't miss.
UT40 NKE- Never IKE- 3 PIKE- 3 PKE- Pre	This is the minigun. Its primary fire mode shoots rapidly but inaccurately, and is a lot more effective at close range. The secondary fire mode shoots a slower but highly accurate stream of bullets which also cause more damage. Each use seems similar to one another in practice, but the secondary use is more beneficial when the target is slightly father away.
UT41 NKE- Never IKE- 3 PIKE- 3 PKE- Pre	This is the link gun. The primary fire consumes 2 ammo per shot and is most powerful at close range, especially against stationary targets. The secondary use fires a single continuous "stream" of damage, so it's best used with a stationary target. As you can see, each weapon that has been discussed has its strengths and weaknesses given a given scenario.
UT42 NKE- Never IKE- 4 PIKE- 4 PKE- Pre	Now we will discuss some effective strategies for gameplay. There are a large number of strategies that can be employed to be more successful in Unreal Tournament. Some of them are more easy to use and some are more challenging. We will now review a few strategies for Unreal Tournament.
UT43 NKE- Never IKE- 4 PIKE- 4 PKE- Pre	The effectiveness of each weapon can depend on the range at which it is used. For example, the lightning gun is not great for closed quarters combat because it takes time to fire, and fires one round at a time.
UT44 NKE- Never IKE- 4 PIKE- 5 PKE- Pre	However, when used at distance, a player can greatly benefit from the precision firing and damage dealt by the lightning gun.

UT45 NKE- Never IKE- 4 PIKE- 5 PKE- Pre	Likewise, the mini gun is of great value when fighting opponents that are close because of its rapid fire and a less need for accuracy.
UT46 NKE- Never IKE- 4 PIKE- 5 PKE- Pre	The mini gun is not, however, useful at long range because the bullets spread out over distance and do not deal high damage. Each weapon has its pros and cons, and not all weapons will be equally effective in all circumstances. It is important to learn when each weapon is best used, and maximize it's potential for both close and long range.
UT47 NKE- Never IKE- 5 PIKE- 5 PKE- Pre	Not all fighting in Unreal Tournament is done face to face. Some strategies allow a player an advantage over an opponent who cannot see them. Other times, fighting is not even the best option. For example, the secondary use of the assault rifle is a grenade that can be ricocheted off of walls. If an opponent is around a corner, but not directly facing you, it may be best to remain unseen and fire a grenade off the wall to explode near the bot.
UT48 NKE- Never IKE- 5 PIKE- 5 PKE- Pre	Likewise, the bio rifle fires a "blob" that sticks to the ground. If being chased, it may be wise to leave a series of blobs for your opponent to step in, as they may attempt to get to you, *or* the blobs may deter the bot from pursuing you further. Sometimes, you may respawn in an area in which bots are already located. Often these bots have better weapons than you, so the best strategy may be to simply run away until you are better equipped. These are just some of the many non-direct strategies for combat you may wish to use during gameplay.
UT49 NKE- Never IKE- 6 PIKE- 6 PKE- Pre	Finally, most maps in Unreal Tournament have special areas which contain rare or special items. The map you will pla has two secret locations. In these secret locations you will find either health, double damage, or shields. In this training we will discuss one of these two secret locations. At the very top of the map, near the lightning gun, there is a high point that one can jump to. You may need to incorporate the double jump to get there. In this area is a keg of health, which provides the most health of any item. This area may also be beneficial as a strategic location. There is only one opening to the area and ranged weapons can be effectively used from here to fire at distant opponents. The other secret location is not as strategically useful, but the items found there are quite beneficial.

UT50 NKE- Pre IKE- Pre PIKE- Pre PKE- Pre	In this presentation, you have learned about the on-screen display in Unreal Tournament 2004. You have also learned about some basic and advanced moves that you can use to control your character. Additionally, we have shown you the different pick-ups that are available in the game. You have also learned about the weapons which will be available to you in today's study, as well as how to use them. Finally, you have learned some useful strategies for effective gameplay. Now you will have some time to practice the skills you have just learned. Please remove your headphones so that the proctor knows you have completed this part of the training.

Note: Pre = presented pre-practice. Numbers indicate which intermittent presentation information appeared (e.g. 3 = third intermittent presentation). Grey text was part of the pre-practice presentation for PIKE and PKE conditions only.

Appendix C: Multiple-Choice Knowledge Test

1. If bots are fighting one another, it may be most effective to _____
    a. Run away
    b. Attack them from a distance
    c. Use that time to collect more weapons
    d. Charge into battle

2. The alternative use of the rocket launcher fires a _______
    a. Slower, but higher-powered rocket
    b. Faster, but weaker rocket
    c. Rocket that does not explode on contact
    d. Set of three rockets at once

3. How many adrenaline points is each adrenaline capsule worth?
    a. 1
    b. 2
    c. 3
    d. 5

4. Which of the following weapons (primary or secondary fire) may NOT be charged?
    a. Assault Rifle
    b. Bio-rifle
    c. Rocket Launcher
    d. All can be charged

5. Which of the following button combinations will activate the "speed" use of adrenaline?
    a. Up, up, up, up
    b. Down, down, down, down
    c. Left, left, right, right
    d. Right, right, left, left

6. Where is the "big keg of health" located?
    a. On top of the bridge
    b. In the tunnel on the lowest level
    c. Right next to the minigun
    d. At the highest point on the map

7. Which of the following weapons zooms in on targets when using its secondary use?
    a. Lightning Gun
    b. Shock Rifle
    c. Flak Cannon
    d. Bio Rifle

8. If there were only 10 seconds left in a match that you were winning, which of the following pickups would be most helpful?
a. Adrenaline Capsule
b. Big Keg of Health
c. Double Damage
d. New Weapon

9. Double tapping a direction followed by pressing the space bar allows your character to ______
a. Leap in that direction
b. Jump higher
c. Run more quickly
d. Fire multiple weapons at the same time

10. Which weapon's primary use is most similar to its secondary use?
a. Assault Rifle
b. Flak Cannon
c. Mini Gun
d. Link Gun

11. If you needed to conserve ammunition but wanted to deal a lot of damage with one shot, which of the following primary weapon attacks would be best?
a. Lightning Gun
b. Bio Rifle
c. Mini Gun
d. Link Gun

12. Which of the following weapons would give you the best chance of damaging a bot that was in midair?
a. Rocket Launcher
b. Shock Rifle
c. Lightning Gun
d. Mini Gun

13. Where would be a good place to visit if you were low on health and wanted to collect adrenaline pickups?
a. Top of the tower
b. Underneath the bridge in the center
c. Long tunnel on the lower level
d. Canyon behind the tower

14. Which of the following weapons would NOT be good for firing at a distant enemy?
a. Rocket Launcher
b. Shock Rifle
c. Mini Gun
d. Lightning Gun

15. If you respawn near enemy bots that have strong weapons for the given location, your best strategy may be to ________
    a. Use the Assault Rifle to fight
    b. Gather as much health as you can
    c. Use your grenades to fight
    d. Run away

16. Which of the following weapons has a fire that will stick to the ground and deal damage to enemies that walk through it?
    a. Lightning Gun
    b. Shock Rifle
    c. Flak Cannon
    d. Bio Rifle

17. One can move side to side without turning by doing what?
    a. Moving the mouse left or right
    b. Double tapping the space bar
    c. Scrolling the mouse wheel
    d. Double tapping left or right

18. Firing a weapon that explodes on contact is especially useful when ________
    a. Enemies are close to one another
    b. You are close to the enemy
    c. You are far from the enemy
    d. You are in a location with lots of walls

19. Which of the following can NOT be found in one of the two secret locations on this map?
    a. Sniper Rifle
    b. Double Damage
    c. Shield
    d. Big Keg of Health

20. Which weapon fires in a spread-style and leaves a yellow trail behind it?
    a. Lightning Gun
    b. Shock Rifle
    c. Flak Cannon
    d. Bio Rifle

21. If you wanted to charge a weapon while waiting for a bot, which of the following weapons would give you the best chance to damage it?
    a. Assault Rifle
    b. Flak Cannon
    a. Rocket Launcher
    b. Shock Rifle

22. If your character had 100 health points and 25 armor points, which of the following pick-ups would be WORST to collect?

a. Big Keg of Health
b. Health Cross
c. Health Vial
d. Shield

23. What was one strategy available to you that the enemy bots did not attempt?

a. Double jumping and dodging to avoid shots
b. Collecting the double damage pickups to increase damage
c. Collecting the shield to increase damage resistance
d. Using the combination of the Shock Rifle primary and secondary capabilities

24. When firing the rocket launcher at a non-moving enemy, where is the most effective place to aim?

a. At their mid-section
b. At the nearest wall that they are facing
c. At their head
d. At the ground under them

25. A disadvantage of staying in one secluded spot was that it would ________

a. Allow enemy bots to earn more kills by fighting one another, hurting my final rank
b. Prevent me from being able to test out the capabilities of my current weapon
c. Make it more difficult to fire most of the weapons accurately
d. Make it more difficult to predict where the enemy bots came from