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## Guiding Learners through Technology-Based Instruction: The Effects of Adaptive Guidance Design and Individual Differences on Learning over Time

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## Abstract

Adaptive guidance is an instructional intervention that helps learners to make use of the control inherent in technology-based instruction. The present research investigated the interactive effects of guidance design (i.e., framing of guidance information) and individual differences (i.e., pre-training motivation and ability) on learning basic and strategic task skills over time. 130 participants were randomly assigned to one of two types of adaptive guidance (autonomy-supportive, controlling) or a no-guidance condition while learning to perform a complex simulation task over nine consecutive trials. Results indicated that participants receiving controlling guidance acquired strategic task skills at a faster rate than participants receiving autonomy-supportive guidance or no-guidance. The design of adaptive guidance also moderated the effects of pre-training motivation and cognitive ability on learners' acquisition of basic and strategic task skills. Specifically, autonomy-supportive guidance enhanced the positive effects of pre-training motivation on the acquisition of basic task skills, and controlling guidance enhanced the positive effects of cognitive ability on the acquisition of strategic task skills. Implications for research and practice are discussed.

## Keywords

learning, technology, guidance, individual differences, performance

## Disciplines

Human Resources Management | Performance Management

## Comments

### Required Publisher Statement

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### Suggested Citation

Kanar, A. M., & Bell, B. S. (2013). *Guiding learners through technology-based instruction: The effects of adaptive guidance design and individual differences on learning over time*. Retrieved [insert date], from Cornell University, ILR School site: <https://digitalcommons.ilr.cornell.edu/articles/1291>

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### Abstract

Adaptive guidance is an instructional intervention that helps learners to make use of the control inherent in technology-based instruction. The present research investigated the interactive effects of guidance design (i.e., framing of guidance information) and individual differences (i.e., pre-training motivation and ability) on learning basic and strategic task skills over time. 130 participants were randomly assigned to one of two types of adaptive guidance (autonomy-supportive, controlling) or a no-guidance condition while learning to perform a complex simulation task over nine consecutive trials. Results indicated that participants receiving controlling guidance acquired strategic task skills at a faster rate than participants receiving autonomy-supportive guidance or no-guidance. The design of adaptive guidance also moderated the effects of pre-training motivation and cognitive ability on learners' acquisition of basic and strategic task skills. Specifically, autonomy-supportive guidance enhanced the positive effects of pre-training motivation on the acquisition of basic task skills, and controlling guidance enhanced the positive effects of cognitive ability on the acquisition of strategic task skills. Implications for research and practice are discussed.

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Guiding Learners through Technology-Based Instruction: The Effects of  
Adaptive Guidance Design and Individual Differences on Learning over Time

Over the past decade, a number of different forces, including technological advances, economic pressures, and globalization, have spurred significant growth in technology-based instruction in both higher education and corporate settings. For instance, the National Center for Education Statistics estimates that from 2000 to 2008 the percentage of undergraduates enrolled in at least one distance education course grew from 8% to 20% (Radford, 2011). Similarly, the American Society for Training and Development estimates that the percentage of learning delivered through technology in work organizations has increased from 8.8% in 2000 to 38.5% in 2011 (Miller, 2012; Van Buren & Erskine, 2002).

One important implication of this trend in learning delivery is that technology-based instruction often provides learners with significant control over different aspects (e.g., content, sequence, pace) of their learning (DeRouin, Fritzsche, & Salas, 2005). Kraiger and Jerden (2007), for example, note that many modern forms of technology-based instruction follow a learner-centered format in which the software serves as a learning portal and individuals must make choices about both what and how to learn. When compared to conditions in which instructional software controls most or all of the learning decisions (i.e., program control), learner control often has a positive, albeit small, effect on student outcomes (Kraiger & Jerden, 2007; Reeves, 1993). Yet, researchers have also noted that instruction that offers high levels of learner control often proves ineffective because learners experience resource depletion, fail to come into contact with important information, and make poor learning decisions (Brown, 2001; Kirschner, Sweller, & Clark, 2006; Mayer, 2004).

These findings highlight the need for instructional strategies that can assist learners in making effective use of the control offered by technology-based instruction. One approach that has been examined involves supplementing learner control with adaptive guidance, which provides learners with diagnostic and interpretive information designed to help them make more effective learning decisions (Bell & Kozlowski, 2002). Although research has shown that adaptive guidance leads to better learning outcomes than either total learner or program control (e.g., Bell & Kozlowski, 2002; Corbalan, Kester, & Merriënboer, 2008), the issue of how adaptive guidance should be designed to optimize student learning in technology-based instruction remains largely unexplored.

One instructional design feature that may have an important impact on student achievement is the framing of guidance information. Prior research has demonstrated that how learning instructions and activities are framed can have a significant impact on learning (e.g., Kozlowski & Bell, 2006; Rawsthorne & Elliot, 1999). For instance, drawing on self-determination theory (SDT), investigators have shown that learning contexts that are framed as autonomy-supportive lead to higher levels of motivation and learning than contexts that are framed as controlling (e.g., Black & Deci, 2000; Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004). These findings suggest that guidance information should be framed so as to minimize perceptions of external control and emphasize learners' autonomy and freedom. Resource allocation theories of self-regulation (e.g., Kanfer & Ackerman, 1989), however, suggest that providing greater autonomy and choice may deplete learners' cognitive resources and impede skill acquisition, particularly in learning contexts that impose substantial demands on attentional resources. Thus, guidance that is framed as more controlling and restrictive may reduce the burden on learners, allow them to direct more of their attentional resources to learning, and

increase the likelihood that learners' come into contact with important learning content (Mayer, 2004).

The current study explores these different perspectives through an examination of the effects of two forms of adaptive guidance - autonomy-supportive and controlling – on learning during a complex simulation-based training program. This effort advances the existing literature in at least three ways. First, using SDT and resource allocation theory, we propose that the effects of different adaptive guidance designs may vary across different learning outcomes. To test this prediction, we examine the effects of autonomy-supportive and controlling guidance on multiple indicators of learning, namely the acquisition of basic and strategic task skills. Second, recent studies suggest that individual differences often moderate the effects of interventions designed to improve learning during technology-based instruction, such that a specific intervention will be more effective for some learners than others (e.g., Sitzmann, Bell, Kraiger, & Kanar, 2009). Building on and extending these findings, we examine how different forms of guidance interact with individual differences related to effort (i.e., pre-training motivation) and resource availability (i.e., cognitive ability) to influence learning. Finally, we use a longitudinal design and latent growth modeling to examine the effects of the two forms of adaptive guidance over time. Whereas most research has treated the effects of guidance as static, our longitudinal approach examines the impact of the different types of adaptive guidance on individuals' learning trajectories over the course of instruction, which provides further insight into how different forms of guidance influence the acquisition of different types of task skills. The conceptual model examined in this research is presented in Figure 1. In the following sections, we discuss the theory that underlies the relationships outlined in the model.

### **Adaptive Guidance**

Although there is some evidence that learner control can enhance student motivation and satisfaction (e.g., Reeves, 1993), research suggests that individuals often do not make effective use of the control they are given over their instruction (Steinberg, 1977, 1989). Learners frequently misinterpret feedback and are poor judges of their performance and progress, which can lead to poor learning choices and misdirected effort. Brown (2001), for example, studied learner choices during online instruction and found that learners commonly skipped critical practice opportunities and some spent less than 50% of the available time in the course. He concluded, “Results suggest that, despite the appeal of computer-based training as a way to make learning more efficient, employees may not use control over their learning wisely” (p. 290). Mayer (2004) leveled similar criticisms against discovery learning, in which students are free to work in the learning environment with little or no guidance. He reviewed research that compared pure and guided discovery methods and concluded that guided methods help ensure that students come into contact with to-be-learned material and better support the cognitive processes necessary for constructivist learning. Finally, Kirschner et al. (2006) argue that unguided environments create a heavy working memory load that is detrimental to learning.

Although guided instruction can take many forms (c.f., Kirschner et al., 2006), in the current study we focus on adaptive guidance, which was designed for more complex learning environments that leverage technology (Bell & Kozlowski, 2002). Adaptive guidance was developed based on a foundation provided by learner control research (e.g., Tennyson, 1980; Tennyson & Buttrey, 1980), but was also designed to extend to more complex learning domains that require learners to acquire not only basic but also strategic task skills. Basic task skills involve a trainees’ ability to perform fundamental task operations that must be learned in order to



develop more advanced skills (Bell & Kozlowski, 2002). Individuals utilize their declarative knowledge (e.g., knowledge of facts) and procedural knowledge (e.g., knowledge of rules) when performing basic skills. Through practice and experience, declarative knowledge is compiled or proceduralized, which allows trainees to execute basic operations more quickly and with fewer errors (Anderson, 1983). Strategic skills involve carrying out more difficult operations that require trainees to understand the underlying complexities of a task and integrate task concepts. In addition, trainees must develop contextual knowledge that informs why, when, and where to apply their strategic skills (Ford & Kraiger, 1995). Thus, strategic performance involves selectively retrieving and integrating specific knowledge from one's knowledge base and applying the resulting constructions to varying task contingencies (Tennyson & Breuer, 2002). In environments that require both basic and strategic skills, learning is a function of not only effort (e.g., time on task) but also the quality of study and practice activities. Thus, adaptive guidance uses learners' past performance to provide evaluative and diagnostic information that assists them in judging their progress toward task mastery, which should influence the amount of effort they invest in learning. In addition, it provides individualized suggestions for what learners should study and practice, based on progress, which should influence the allocation of attention and lead to better learning choices.

Bell and Kozlowski (2002) showed that adaptive guidance helps learners to make better learning decisions in a learner-control environment. Learners who received guidance studied and practiced training material in a more appropriate sequence than those who received no guidance. Guidance also had a positive effect on trainees' self-efficacy early in training, when learning is most challenging and errors are common. The result was that learners who received adaptive guidance exhibited higher levels of basic and strategic knowledge and performance and were

better able to transfer their skills than those who were given learner control without guidance (Bell & Kozlowski, 2002). Accordingly, we expect that learners receiving adaptive guidance will exhibit greater positive change in their performance relative to those in a no guidance condition.

H1: Participants who receive adaptive guidance will exhibit more positive change in basic and strategic performance skills than participants who do not receive guidance.

### **Autonomy-Supportive and Controlling Guidance**

The issue of how adaptive guidance should be designed to optimize student learning in technology-based instruction has received limited research attention. Adaptive guidance seeks to provide the direction learners need to avoid making poor learning decisions while retaining the motivational benefits of autonomy. Self-determination theory (SDT; for a review see Ryan & Deci, 2000) is a theory of motivation that assumes high-quality motivation is inherently human and is expressed to different degrees depending on the context that influences the process of making choices. Initial conceptualizations of motivation quality distinguished between motivations stemming from an internal locus of causality (e.g., interest and enjoyment) and those stemming from an external locus of causality (e.g., rewards and punishments) (Vansteenkiste, Lens, & Deci, 2006). A more recent conceptualization, however, distinguished among various types of extrinsic motivation that differ in their degree of autonomy, which shifted the focus to differences between autonomous motivation, which involves the experience of volition and choice, and controlled motivation, which involves the experience of being pressured or coerced (Vansteenkiste et al., 2006). Prior research has shown that learning contexts that provide choice and options for self-direction tend to facilitate autonomous motivation and enhance learning, whereas controlling environments that pressure learners to think or act in a particular way often

diminish autonomous motivation and lead to poorer learning (Ryan & Deci, 2000; Vansteenkiste et al., 2004).

A common means of operationalizing autonomy-supportive and controlling learning environments is through the framing of instructions. For example, a number of laboratory and field studies have found that verbal or written instructions containing primarily autonomy-supportive phrases (e.g., “you may” or “if you choose”) lead to higher levels of autonomous motivation and learning than instructions with more controlling phrases (e.g., “you should” or “you have to,” Vansteenkiste et al., 2004). Thus, presenting adaptive guidance instructions using autonomy-supportive language may capitalize on these motivational benefits and lead to greater learning performance than guidance instructions incorporating controlling language.

As previously noted, however, prior learner control research has found that greater autonomy does not always translate into higher levels of learning, and in fact sometimes leads to poorer performance (e.g., Pollock & Sullivan, 1990). A closer examination of this research suggests that these mixed findings may be due, at least in part, to differences in the learning outcomes examined across studies. For example, a meta-analysis by Patall, Cooper, and Robinson (2008) found small and positive effects of choice on simple task performance (i.e., quantity and accuracy), but they did not find a significant relationship between choice and subsequent measures of learning that assessed skill acquisition. Overall, they concluded that research examining the effects of choice on learning has yielded findings that have been “somewhat inconsistent” (Patall et al., 2008, p. 294). Accordingly, it may be important to consider how different forms of guidance potentially impact different types of learning outcomes. Ackerman (1987), for instance, found that motivation and effort are the primary determinants of learners’ acquisition of declarative knowledge and performance on simple tasks.

Learners' motivation influences performance on basic tasks because, through practice and experience, learners develop knowledge of facts (declarative knowledge) and rules (procedural knowledge) and thus are able to perform tasks quicker and with fewer errors (Anderson, 1983). Thus, the motivational benefits of autonomy-supportive guidance should be evident on basic task components, where performance is determined primarily by effort (Bell & Kozlowski, 2002). Accordingly, we expect that learners receiving autonomy-supportive guidance will acquire basic skills at a faster rate than learners receiving controlling guidance.

H2: Participants in the autonomy-supportive condition will exhibit more positive change in basic performance skills than participants in the controlling condition.

The positive effects of choice in learner-controlled training, however, may not extend to learning outcomes that are a function of a trainee's ability to process and integrate complex information. Acquisition of more complex task skills is closely tied to processes related to learners' attention such as choices made during training (e.g., sequence of study) and the quality of practice (Bell & Kozlowski, 2002; Brown, 2001), and guidance that is more controlling may increase the likelihood that trainees engage in appropriate study and practice activities. In addition, guidance design features that facilitate (rather than restrict) a learner's sense of autonomy increase the number of potential problem solutions and amount of information that needs to be processed. As the total amount of information increases, people must rely on less information to make choices, resulting in simplified problem-solving and decision-making processes and sub-optimal outcomes (Chua & Iyengar, 2008; Payne, Bettman, & Johnson, 1993). For example, Iyengar and Lepper (2000) found that a greater number of options decreased people's ability to think about multiple solution combinations. By directing learners' attention to key elements of the task and limiting learners' choices, controlling guidance may enhance the

acquisition and integration of skills for performing more complex components of the task. Thus, we expect that learners receiving controlling guidance will acquire strategic skills at a faster rate than learners receiving autonomy-supportive guidance.

H3: Participants in the controlling condition will exhibit more positive change in strategic performance skills than participants in the autonomy-supportive condition.

### **Interactive Effects of Guidance Design and Individual Differences**

Although autonomy may yield motivational benefits during training, it is also important to consider trainees' motivation when entering a training program (i.e., pre-training motivation). Pre-training motivation describes trainees' initial attitudes and intentions to exert effort toward learning the content of a training program (Noe, 1986). Pre-training motivation is different from motivation quality constructs because pre-training motivation implies attitudes and personal action (activation) directed toward learning; motivation quality constructs address the beliefs and reasons underlying different types of motivation (Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). Motivated action theories have shown that attitudes and intentions provide the link between beliefs and behaviors (Heckhausen & Kuhl, 1985). Indeed, learning orientation strongly and positively predicts trainees' pre-training motivation levels (Colquitt & Simmering, 1998; Klein, Noe, & Wang, 2006), and motivation to learn has been shown, in turn, to positively relate to learning outcomes (Colquitt, LePine, & Noe, 2000).

Although pre-training motivation has been shown to be a positive predictor of training outcomes, research has also found that individual characteristics often interact with training design to influence learning (i.e., aptitude x treatment interactions). Gully, Payne, Koles, and Whiteman (2002), for example, found that trainees higher in openness to experience had, in general, higher declarative knowledge, training performance, and self-efficacy. In addition, they

found that when the training was designed to encourage exploratory behaviors consistent with this dispositional characteristic, the positive relationship was strengthened. However, when the training was designed to restrict exploration, the positive effect of openness on the training outcomes was nullified. In the current study, we propose that guidance design may play a similar role in either enhancing or constraining the positive relationship between pre-training motivation and skill acquisition. In particular, autonomy-supportive guidance should support trainees' desire to take personal action toward learning the training content, thus strengthening the relationship between pre-training motivation and learning. On the other hand, guidance that is framed as controlling should contradict trainees' positive attitudes and intentions toward the training, thus weakening the relationship between pre-training motivation and learning. Consistent with our earlier arguments, we expect the interaction between guidance design and trainees' pre-training motivation will be observed for basic skill acquisition, which is determined primarily by trainees' motivation and effort.

H4: Pre-training motivation will be positively related to basic performance growth for participants receiving autonomy-supportive guidance, and this relationship will be weaker for participants receiving controlling guidance.

In more complex learning environments, it is important to design training to support not only trainees' motivation but also their cognition (Bell & Kozlowski, 2008). Cognitive ability, which is an individual's intellectual capacity, has been shown to be a potent predictor of learning (Colquitt et al., 2000; Ree & Earles, 1991). In general, individuals with higher levels of cognitive ability have greater attentional resources to devote to learning, which means they are able to absorb and retain more information than lower ability individuals. The challenge in learner controlled environments is ensuring that trainees allocate their attentional resources to

study and practice activities that facilitate learning. DeRouin et al. (2004, p. 154) suggest that when trainees are given too much control, “they may be unable to focus the majority of their attention on the subject matter of the instructional program,” which can cause learning to suffer. Niederhauser, Reynolds, and Salmen (2000), for example, examined the effects of hypertext navigation features on learning. They found that students who made extensive use of compare and contrast links, which were designed to provide alternate paths to information, exhibited impaired learning, whereas students that read the text in a systematic and sequential manner performed significantly better. Niederhauser et al. (2000) suggest that the compare and contrast links impeded learning because they required learners to make decisions about what to read and the order in which to read information, which likely absorbed attentional resources that could no longer be directed to integrating new knowledge. Consistent with these findings, we expect that by providing learners with a clear and unambiguous path for navigating the training, controlling guidance should enable trainees to devote more of their attentional resources to learning. This should strengthen the positive relationship between cognitive ability and performance, particularly on strategic task components that require deeper comprehension and integration of task concepts. In contrast, the relationship between cognitive ability and strategic performance should be weakened when trainees are given autonomy-supportive guidance because the greater choice options may increase the chances that attentional resources are misdirected or absorbed by instructional decisions.

H5: Cognitive ability will be positively related to strategic performance growth for participants receiving controlling guidance, and this effect will be weaker for participants receiving autonomy-supportive guidance.

## **Method**

### **Participants**

Participants were 130 undergraduate students enrolled in an introductory human resource management course at a large northeastern university who earned course credit for participation. Fifty-nine percent of the participants were male and most (93.1 percent) were between 18 and 21 years old.

### **Task**

The task used in this study was a version of TANDEM (Dwyer, Hall, Volpe, Cannon-Bowers, & Salas, 1992), a computer-based radar-tracking simulation designed for assessing judgment and decision making in complex task environments. The object of the simulation was to make correct decisions about unknown— and potentially hostile—contacts appearing on a simulated radar screen and to prevent contacts from crossing defensive perimeters. Participants were required to detect, identify, and act upon the multiple contacts on the screen using a number of basic and strategic skills (Bell & Kozlowski, 2002; Kozlowski & Bell, 2006). All participants had access to an online instruction manual that contained complete information on all important aspects of the simulation.

Basic skills involved making decisions about contacts on the radar screen. After engaging a contact, participants could access cue information from pull-down menus, with 3 cues available for each of three component decisions regarding the Type (air, surface, submarine), Class (civilian or military), and Intent (hostile or peaceful) of the contact. After making the three component decisions, participants needed to decide whether to take action against the contact (if hostile) or clear it from the radar screen (if peaceful). Participants received points for correct decisions and lost points for incorrect decisions.



The basic skills serve as the foundation for developing more strategic skills focused on perimeter defense and contact prioritization. Specifically, there are two defensive perimeters located within the task and participants lose points for perimeter intrusions. The inner defensive perimeter is clearly marked and easy for participants to identify. However, the outer perimeter is beyond the initial viewing range of the radar display and is not clearly marked. Thus, participants must learn how to “zoom out” and locate “marker contacts” that serve to identify the outer boundary. Participants must also learn how to prioritize contacts by determining which constitute the greatest threats to the defensive perimeters. There are often multiple contacts approaching both the inner and outer perimeter, so participants need to monitor both perimeters and gather information on the speed and distance of contacts in order to determine those that are the highest priority. Trainees also have to make strategic decisions about trade-offs between contacts approaching the inner and outer perimeters, based on the number of contacts at each perimeter and their “cost” if they penetrate.

### **Manipulations**

Learners can be given control over a number of different aspects of their instruction, including content, sequence, and pace (Kraiger & Jerden, 2007). In the current study, all trainees were given control over what they chose to study and practice (content) and the order in which they chose to study and practice the material (sequence). In addition, they were given some control over the pace of their learning, such as being able to exit the online manual early; however, for design reasons we set maximum time limits on the study and practice periods. Thus, trainees in all conditions were given the same level of objective learner-control.

At the beginning of the training session, participants in the no-guidance control condition were given a list of learning topics. They were told that the list covered all important aspects of

the simulation and that they may want to focus on these topics during training, but what they chose to study and practice was at their discretion. Trainees in the no-guidance condition did not receive any guidance information.

Trainees in the guidance conditions received the list of learning topics, along with guidance information that could be used to help them evaluate their current progress and improve their deficiencies in the different aspects of the simulation. As described below, the framing of this information depended on whether trainees were assigned to the controlling or autonomy-supportive condition. The guidance information was delivered following the last screen of feedback presented after each trial. The guidance manipulations created for the current study were modeled from prior research (Bell & Kozlowski, 2002). The guidance was “adaptive” because the suggestions for study and practice were tailored to participants’ proficiency in the simulation.<sup>1</sup> The guidance focused on helping learners build basic skills early in training, before proceeding later in training to developing more strategic competencies which build on the fundamental skills.

The two guidance manipulations were created by framing the instructions for study and practice using language that either (a) was coercive and controlling (controlling guidance) or (b) emphasized choice and self-initiated behaviors (autonomy-supportive guidance). The specific phrases were identical to those used in a number of earlier studies that manipulated autonomy-supportive or controlling contexts through task instructions (e.g., Vansteenkiste et al., 2004). Specifically, the controlling guidance manipulation used explicitly controlling language through phrases such as “you have to,” “you must,” “you should,” and “you had better.” For example, participants might be told, “You must study the material in your manual on prioritization strategies.” The autonomy-supportive guidance manipulation used instruction phrases such as,

“you can,” “you might,” “you may,” and “if you choose.” For example, participants in the autonomy-supportive guidance condition might be told, “You may want to study the material in your manual on prioritization strategies.” Other than the differences in the use of autonomy-supportive or controlling phrases, the two types of adaptive guidance were identical.

## Measures

**Pre-training motivation.** At the beginning of the experimental session, participants’ pre-training motivation was measured using 7-items developed by Noe and Schmitt (1986).<sup>2</sup> Items were modified to be consistent with our learning setting and were rated on a five-point scale ranging from “strongly disagree” (1) to “strongly agree” (5). Sample items are “I am motivated to learn the skills emphasized in this training program” and “If I can’t understand something in the training program I will try harder.” Internal consistency reliability of the scale was .86.

**Cognitive ability.** At the beginning of the experimental session, participants provided their SAT or ACT scores. Research has shown that the SAT and ACT have a large general cognitive ability component (Frey & Detterman, 2004). In addition, the publishers of these tests report high internal consistency reliabilities for their measures (e.g., KR-20 = .96 for the ACT composite score; American College Testing Program, 1989) and self-reported SAT/ACT scores have been shown to correlate highly with actual scores. For example, Gully et al. (2002) found that self-reported SAT scores correlated .95 with actual scores. Individuals’ ACT or SAT scores were standardized using norms published by ACT and the College Board, and this standardized score was used as a measure of cognitive ability (College Board, 2011).

**Basic and strategic task performance.** Using measures that have been established in previous research using the TANDEM simulation (e.g., Bell & Kozłowski, 2002) data were

collected during each training trial that allowed assessments of participants' performance on basic and strategic aspects of the task. Basic task performance was calculated based on the number of correct and incorrect decisions during the trials; the two fundamental components of participants' score. Performance on these two aspects of the task is the result of knowledge of basic task components (e.g., decision-making cues and procedures). This measure is similar to task performance measures of accuracy often found in studies of choice effects on motivation (Patall et al., 2008). Strategic task performance was composed of the number of times participants zoomed out, the number of markers hooked in an effort to identify the location of an invisible outer perimeter, and the number of high priority contacts processed during the practice trials. These indicators capture the two major elements of strategic performance: perimeter defense and contact prioritization. Past cross-sectional research supports the two-factor structure for the performance data using TANDEM (e.g., Bell & Kozlowski, 2002).

### **Procedure**

Training was conducted in a single three-hour session with groups of one to four participants. During this session, participants learned to operate the radar-tracking simulation described above. Participants were randomly assigned to one of three experimental conditions: controlling guidance, autonomy-supportive guidance, or a no-guidance control condition.

**Familiarization.** Trainees were first presented with a brief demonstration of the simulation that described its features and decision rules and were shown the online instruction manual that contained complete information on all important aspects of the simulation. They then had an opportunity to familiarize themselves with the instruction manual for 3-min and were able to practice the task in a 5-min "familiarization" trial. The goal of this preliminary trial was

to ensure that participants understood how to operate the instruction manual and were familiar with the equipment.

**Training.** After the familiarization trial, trainees began the training session, which was divided into nine 10.5-min trials. Each training trial consisted of a cycle of study, practice, and feedback. Trainees had 3-min to study the online instruction manual. They then had 5-min of hands-on practice. The nine trials possessed the same general profile (e.g., same difficulty level, rules, number of contacts), but the configuration of contacts (e.g., location and characteristics of contacts) was unique to each trial. Immediately after each practice trial, trainees reviewed veridical descriptive feedback on all aspects of the task relevant to both basic and strategic performance. Trainees in all conditions received feedback, but only trainees in the guidance conditions received the adaptive guidance information following the last screen of feedback in each trial. Trainees in all conditions were given the same amount of time (2.5-min) after each practice trial to review their feedback and, if available, guidance information. Participants were given a 5-min break following the third and ninth trials.

### **Manipulation Checks**

At the end of training, all participants responded to a three-item measure of autonomous motivation adapted from Vansteenkiste et al. (2004). The items were assessed on a 5-point Likert scale that ranged from 1 (*not at all true*) to 5 (*very true*). A sample item is “I practiced the task because it was very interesting.” The reliability (coefficient alpha) of the measure was .93. We ran a hierarchical regression analysis, controlling for participant’s pre-training motivation, to determine whether there were differences across the three conditions on the measure of autonomous motivation. We employed one-tailed tests of significance due to the directional nature of our predictions. As expected, participants in the controlling condition ( $M = 2.73$ ,  $SD =$

1.21) reported significantly lower levels of autonomous motivation than participants in the no guidance condition ( $M = 3.28$ ;  $SD = 1.19$ ),  $t(129) = -2.19$ ,  $p < .05$ , and marginally significant lower levels of autonomous motivation than participants in the autonomy-supportive condition ( $M = 3.01$ ;  $SD = 1.11$ ),  $t(129) = -1.46$ ,  $p < .10$ . Autonomous motivation did not differ significantly across the autonomy-supportive and no guidance conditions ( $t(129) = .92$ ,  $p > .10$ ), which is consistent with the fact that participants in both conditions were told they could choose what to study and practice.

Given the subtle nature of the manipulation, we also examined the amount of time participants spent in the feedback sessions. Following each trial, participants could spend up to 2.5-min reviewing their feedback and, if available, guidance information. Participants in the no-guidance condition received only feedback, whereas participants in the controlling and autonomy-supportive conditions received both feedback and adaptive guidance information. Thus, if participants in the controlling and autonomy-supportive conditions reviewed the guidance information, we would expect them to spend more time overall in the feedback sessions. The amount of time (in seconds) participants spent reviewing the pages containing feedback and guidance (if available) information across the nine trials was automatically recorded by the computer and was subjected to regression analysis, once again using one-tailed tests of significance. The results revealed that participants in the autonomy-supportive condition ( $M = 616.10$ ,  $SD = 18.90$ ) spent significantly more time in the feedback sessions than participants in the control condition ( $M = 418.77$ ,  $SD = 23.26$ ),  $t(129) = 6.58$ ,  $p < .01$ , as did participants in the controlling condition ( $M = 600.33$ ,  $SD = 21.23$ ),  $t(129) = 5.77$ ,  $p < .01$ . Time spent in the feedback sessions did not significantly differ across the two guidance conditions,  $t(129) = -.55$ ,  $p > .10$ . Further, analyses examining time spent on only the pages containing

feedback information revealed that participants in autonomy-supportive condition (378.47, SD = 14.37) spent significantly less time than participants in the no-guidance condition reviewing feedback (M = 418.77, SD = 17.69),  $t(129) = -1.77, p < .05$ , as did participants in the controlling condition (M = 356.41, SD = 16.14),  $t(129) = -2.61, p < .01$ . The two guidance conditions did not significantly differ in amount of time spent reviewing feedback,  $t(129) = -1.02, p > .10$ .

Together, these findings show that participants in the guidance conditions spent more time in the feedback sessions and this increase was due to the time they spent reviewing the guidance, rather than feedback, information.

### **Analyses**

We used latent growth curve analysis (LCA) to analyze the repeated measures performance data. Latent growth curve analysis is an extension of covariance structure analysis that invokes a confirmatory factor analytic structure on the repeated variables measured over time, where the factor loadings for the latent growth constructs determine the shape of the growth trajectories. This approach can give identical results to other growth modeling approaches (e.g., hierarchical linear modelling) but allows greater flexibility (Curran, 2003). In particular, the latent growth curve framework allowed us to (a) test measurement invariance assumptions across time and (b) estimate growth across the three experimental conditions simultaneously by specifying a multiple-group growth curve model. Hypotheses were tested by sequentially imposing constraints on latent means (Hypotheses 1, 2, & 3) and structural paths (Hypotheses 4 & 5) and comparing nested models with the chi-square difference test (Bentler & Bonett, 1980). M-Plus was used to conduct all analyses (Muthén & Muthén, 2007). Performance measures were standardized across the nine trials. For all models, we specified autocorrelated

error terms for performance scores at each time period because scores at adjacent time periods were non-independent.

## Results

Table 1 reports descriptive statistics and intercorrelations among the study variables. Inspection of the means for the basic and strategic performance outcomes shows that participants improved over time but at a decreasing rate. Table 2 presents the basic and strategic task performance means for each condition for each of the nine training trials.

### Nature of Performance Trajectories

The first step in latent growth curve analysis is to describe the nature of change for all participants in the sample. Table 3 presents fit statistics and nested comparisons for alternate growth trajectories (i.e., no-growth, linear, and quadratic growth) and error structures (i.e., homogeneous or heterogeneous) for basic and strategic performance. The no-growth model included only a latent intercept mean and error term, while additional mean and error terms are included in the linear (i.e., intercept and linear terms) and quadratic (intercept, linear, and quadratic terms) models. Consistent with other longitudinal research on learning and performance during skill acquisition (e.g., Chen & Mathieu, 2009), the nested models in Table 3 show that the quadratic growth specification best fit the longitudinal data.

Table 4 presents the parameter estimates for the quadratic growth curve models. The latent factor means describe the average shape of performance growth across the nine trials for all participants. The positive linear factor means for basic ( $\mu = 0.31$ ,  $t = 9.52$ ,  $p < .001$ ) and strategic ( $\mu = 0.34$ ,  $t = 11.17$ ,  $p < .001$ ) performance suggest that, on average, participants scored 0.31 and 0.34 standardized points higher in each subsequent performance trial for basic and strategic performance, respectively. However, the significant negative quadratic factor means for



basic ( $\mu = -0.02, t = -4.44, p < .01$ ) and strategic ( $\mu = -0.02, t = -5.33, p < .001$ ) performance suggest that the marginal rates of performance improvement were declining over time.

Importantly, Table 4 also shows significant variation around the intercept, linear, and quadratic factors. Thus, we next specified conditional latent curve models in order to predict the individual-level variation in performance trajectories and test the study hypotheses.

### **Modeling Variation in Change**

We modeled variation in participants' growth trajectories as functions of the experimental design (i.e., condition) and two time-invariant individual-difference factors (i.e., pre-training motivation and cognitive ability). Separate multiple-group growth curve models were estimated for basic and strategic performance. Cognitive ability was a single-indicator factor where we set the loading to the latent variable to the square root of the scale's reliability and set the error variance for the single indicator to one minus the reliability multiplied by the observed variance of the scale (Fornell & Larcker, 1981). We used random-item parcels to reduce the number of items on the pre-training motivation scale (Landis, Beal, & Tesluk, 2000) from seven to two items. The multiple-group models for basic  $\chi^2(df = 171, N = 130) = 238.63$ , CFI = 0.941, TLI = 0.932, RMSEA = 0.096, SRMR = 0.095) and strategic  $\chi^2(df = 176, N = 130) = 226.96$ , CFI = 0.946, TLI = 0.939, RMSEA = 0.082, SRMR = 0.114) performance met conventional standards for fit statistics.

Table 5 presents the parameter estimates across the three experimental conditions. A visual inspection of Table 5 shows that pre-training motivation was significantly related to basic growth trajectories, while cognitive ability was a significant predictor of strategic growth. For both basic and strategic task performance outcomes, learners in all three conditions showed

significant and positive linear performance improvements, and significant and negative quadratic performance declines (Figure 2).

Hypothesis 1 predicted that learners receiving adaptive guidance would show greater gains in basic and strategic performance than learners receiving no guidance. Table 5 presents the means for basic and strategic performance outcomes across experimental conditions. We tested Hypothesis 1 by sequentially constraining growth factor means as equal—first across the no-guidance and autonomy-supportive guidance conditions and second across the no-guidance and controlling guidance conditions—and examining the associated change in the chi-squared fit statistics between the nested models (Bentler & Bonett, 1980). Contrary to our expectations, all chi-squared difference tests for linear and quadratic mean differences across basic and strategic performance models revealed non-significant differences between the autonomy-supportive and no guidance conditions (all  $p$ 's > .10).

Next, we compared the growth trajectories across participants receiving controlling guidance to those receiving no guidance. As predicted, participants receiving controlling guidance showed more positive linear growth in strategic performance ( $\mu = 0.44$ ) than participants receiving no guidance ( $\mu = 0.26$ ;  $\Delta\chi^2 = 19.44$ ,  $\Delta df = 1$ ,  $p < .001$ ). However, results of the chi-squared difference tests showed no other significant differences in performance trajectory means across the controlling guidance and no guidance conditions for basic or strategic performance (all  $p$ 's > .10). In sum, results showed that learners receiving controlling guidance had more positive strategic linear performance trajectories than participants receiving no guidance, yet no other differences in performance trajectories were evident. Accordingly, Hypothesis 1 received partial support.

Hypothesis 2 predicted that participants receiving autonomy-supportive guidance would exhibit greater basic performance growth than participants receiving controlling guidance. Figure 2 shows that, contrary to our prediction, we found that participants receiving controlling guidance exhibited marginally more positive linear basic performance trajectories ( $\mu = 0.38$ ) than participants receiving autonomy-supportive guidance ( $\mu = 0.28$ ;  $\Delta\chi^2 = 3.51$ ,  $\Delta df = 1$ ,  $p < .10$ ). Hypothesis 2 was not supported. However, because the quadratic factor means were negative, indicating a decelerating trend, a negative relationship between a predictor and a quadratic growth factor suggests that higher levels of a predictor are associated with less deceleration in performance over time. The quadratic factor mean for participants receiving autonomy-supportive guidance ( $\mu = -0.01$ ) was marginally less-negative than for participants receiving controlling guidance ( $\mu = -0.02$ ;  $\Delta\chi^2 = 3.18$ ,  $\Delta df = 1$ ,  $p < .10$ ), suggesting that learners' receiving autonomy-supportive guidance improved in their basic task skills at a more consistent rate than did participants receiving controlling guidance. Figure 2 shows that the basic performance differences between participants receiving autonomy-supportive guidance and controlling guidance become smaller over time.

Hypothesis 3 predicted that participants receiving controlling guidance would exhibit greater strategic performance growth than participants receiving autonomy-supportive guidance. Figure 2 (lower figure) shows that, as expected, participants receiving controlling guidance ( $\mu = 0.44$ ) showed greater linear growth in strategic performance than participants receiving autonomy-supportive guidance ( $\mu = 0.32$ ;  $\Delta\chi^2 = 8.79$ ,  $\Delta df = 1$ ,  $p < .01$ ). The strategic quadratic factors for controlling guidance ( $M = -0.02$ ) and autonomy-supportive guidance ( $\mu = -0.02$ ) were not different ( $\Delta\chi^2 = 0.42$ ,  $\Delta df = 1$ ,  $ns$ ). Thus, Hypothesis 3 was supported.

Hypothesis 4 predicted that pre-training motivation will be positively related to basic performance growth for participants receiving autonomy-supportive guidance, and this relationship will be weaker for participants receiving controlling guidance. Table 5 shows that participants' pre-training motivation was positively related to basic linear growth in the autonomy-supportive guidance condition ( $\beta = .27$ ,  $EST/SE = 2.32$ ,  $p < .05$ ) and negatively related to performance growth in the controlling guidance condition ( $\beta = -.28$ ,  $EST/SE = -2.21$ ,  $p < .05$ ). This difference was significant ( $\Delta\chi^2 = 15.84$ ,  $\Delta df = 1$ ,  $p < .05$ ) and is illustrated in Figure 3, where we plotted the interactive effects following Aiken and West's (1991) procedures. Table 5 also shows that participants' pre-training motivation was more strongly and negatively related to quadratic change (i.e., deceleration) for participants receiving autonomy-supportive guidance ( $\beta = -0.03$ ,  $EST/SE = -2.16$ ,  $p < .05$ ) than for participants receiving controlling guidance ( $\beta = 0.02$ ,  $EST/SE = 1.796$ ,  $p < .10$ ;  $\Delta\chi^2 = 13.75$ ,  $\Delta df = 1$ ,  $p < .05$ ). This suggests that participants receiving autonomy supportive guidance with greater pre-training motivation were able to improve their basic performance scores at a more constant rate throughout the training. Finally, as expected, Table 5 shows that participants' pre-training motivation was not significantly related to strategic performance growth in either guidance condition. These results support Hypothesis 4.

Hypothesis 5 predicted that cognitive ability will be positively related to strategic performance growth for participants receiving controlling guidance, and this effect will be weaker for participants receiving autonomy-supportive guidance. Table 5 shows that ability was positively related to linear strategic performance growth for participants receiving controlling guidance ( $\beta = 0.14$ ,  $EST/SE = 2.30$ ,  $p < .05$ ) but negatively and not significantly related to performance for participants receiving autonomy-supportive guidance ( $\beta = -0.05$ ,  $EST/SE = -$

0.60, *ns*). The structural paths between ability and the linear growth factors were marginally different across the experimental conditions ( $\Delta\chi^2 = 3.48$ ,  $\Delta df = 1$ ,  $p < .10$ ). To help interpret the interaction effects across guidance conditions we plotted the interactions using Aiken and West's (1991) procedures (see Figure 4), using one standard deviation differences in participants' ability. There was also a marginally significant negative relationship between ability and the strategic performance quadratic factor for participants receiving controlling guidance ( $\beta = -0.01$ ,  $EST/SE = -1.89$ ,  $p < .10$ ), suggesting that higher ability participants receiving controlling guidance were better able to sustain positive gains in strategic performance throughout the nine trials (see Figure 4). Ability was not related to the quadratic factor for participants receiving autonomy-supportive guidance ( $\beta = .00$ ,  $EST/SE = 0.16$ , *ns*), and the two guidance conditions did not differ in the effect of the ability on quadratic change ( $\Delta\chi^2 = 1.88$ ,  $\Delta df = 1$ , *ns*). Finally, as expected, Table 5 shows that ability was not significantly related to participants' basic performance growth in either guidance condition. Overall, these results provide support for Hypothesis 5.

### Discussion

Although educational institutions and work organizations are increasingly using computers to deliver instruction, learners often do not make good use of the control inherent in modern learning technologies (Brown, 2001). Prior research suggests that adaptive guidance can assist learners in making more effective learning choices and can enhance learning outcomes in technology-based instruction (Bell & Kozlowski, 2002). The current investigation provides further support for the utility of adaptive guidance, but more importantly it advances research in this area by showing that the effects of guidance may vary across different design features,

learning outcomes, and learner profiles. In the following sections, we review the key findings of the current study and discuss their theoretical and practical implications.

### **Key Findings and Theoretical Implications**

Prior research on adaptive guidance has tended to treat its effects on learning as static. To address this limitation, we used a longitudinal design and latent growth curve analysis to examine the effects of adaptive guidance on learning over time. The results revealed that learners who received adaptive guidance exhibited more positive change in their task performance over time than those who received no guidance, but this effect was limited to the effects of controlling guidance on strategic task performance. Adaptive guidance is designed primarily to impact the quality of learning (Bell & Kozlowski, 2002), so it is not surprising that its effects would be most pronounced for strategic performance outcomes, which are closely tied to processes related to learners' attention and require the integration of concepts and the development of task strategies. Further, although we expected that both autonomy-supportive and controlling guidance would lead to more positive strategic task performance change than no guidance, the observed pattern of findings support the argument that increasing the level of direction and constraining learner choices may enhance strategic learning outcomes by reducing demands on learners' attentional resources and making it more likely that learners will come into contact with critical to-be-learned material (Kirschner et al., 2006; Mayer, 2004).

The direct comparison of autonomy-supportive and controlling guidance provided further evidence for the superiority of controlling guidance in the current context. As expected, individuals receiving controlling guidance exhibited greater linear growth in their strategic task performance than those who received autonomy-supportive guidance. Contrary to our predictions, individuals who received controlling guidance also exhibited marginally more

positive basic task performance trajectories than those receiving autonomy-supportive guidance. It is important to note, however, that the basic performance trajectories of those in the controlling guidance condition showed a trend toward greater deceleration in performance growth than those in the autonomy-supportive guidance condition (see Figure 2). Thus, future research may investigate these findings further to determine whether guidance that emphasizes autonomy and choice may lead to higher levels of basic performance when learning is extended over a longer timeframe, perhaps by sustaining individuals' motivation and effort (e.g., Moller, Deci, & Ryan, 2006). Overall, however, these findings suggest that controlling guidance may be a more effective strategy for supporting skill development in more complex learning environments. Future research is needed to replicate and extend these findings, with particular attention devoted to examining the learning processes that may help further elucidate the effects of different guidance designs on various learning tasks.

A final issue examined in the current study was the interactive effects of learner characteristics and guidance design on learning over time. Drawing on SDT and resource allocation theory, we argued that individual differences related to effort (pre-training motivation) and the availability of attentional resources (cognitive ability) may interact with autonomy-supportive and controlling guidance, respectively, to influence learning trajectories. As expected, the results revealed that individuals with high levels of pre-training motivation exhibited greater growth in basic task performance when given autonomy-supportive rather than controlling guidance. Controlling guidance was detrimental to the basic task performance growth of individuals with high levels of motivation (see Figure 3), but interestingly it enhanced the performance of individuals with low levels of pre-training motivation (a finding we discuss more below). Overall, these findings suggest that autonomy-supportive guidance may support

the natural expression of high levels learning motivation, whereas controlling guidance may be effective for inducing effort from those trainees who have less positive initial attitudes and intentions toward training.

We also found that ability interacted with guidance design to impact strategic task performance. Among those who received controlling guidance, there was a positive relationship between ability and strategic performance growth. These findings support our argument that controlling guidance enables learners to allocate more of their attentional resources toward study and practice activities that will allow them to master complex task elements. However, when individuals received autonomy-supportive guidance, ability was unrelated to strategic performance. This is consistent with our hypothesis that increasing learner choice options may absorb or divert attentional resources that could otherwise be directed toward skill acquisition.

### **Practical Implications**

The present study suggests that the relative advantage of autonomy-supportive instructional designs relative to controlling designs may be limited in more complex tasks and motivational guidelines alone are not sufficient for instructional design. Instead, designers should consider the extent to which the instructional program aims to teach basic or strategic skills. For basic task performance, autonomy supportive guidance had an advantage over controlling guidance, but only for learners who possessed high levels of pre-training motivation (i.e., learners 1 SD above the mean; see Figure 3). This is consistent with our argument that autonomy-supportive learning contexts facilitate, and controlling contexts thwart, the beneficial effects of pre-training motivation.

Although controlling instructional designs are less frequently advocated, the present study showed a clear advantage for controlling guidance over autonomy-supportive guidance for



strategic skill acquisition. Learners receiving controlling guidance showed greater gains in strategic performance than participants receiving either autonomy-supportive guidance or no guidance (Figure 2). Further, controlling guidance enhanced the positive relationship between cognitive ability and strategic performance, whereas cognitive ability was not significantly related to performance improvements for those receiving autonomy-supportive guidance. Although unexpected, the greatest growth in basic performance was observed among participants who were low in pre-training motivation who were given controlling guidance instructions. Together, these findings provide several examples of the potential utility of guidance instructions that are controlling instead of autonomy-supportive.

Katz and Assor (2006) point out that self-determination theory is a theory of three human needs—autonomy, competence, and relatedness. Providing choice can have implications for learning if it changes the extent to which any of these needs are or are not satisfied. Katz and Assor (2006) note the potential resource limitations associated with providing learners with autonomy during complex tasks, and suggested that instructional designers might reduce the complexity of the task to match a person's cognitive ability. On complex tasks learners' need for competence may be more salient than their need for autonomy. In the current study, controlling guidance information may have helped to conserve attentional resources that could be directed to learning important material, thus supporting learners' need for competence. Future research can investigate whether tailoring guidance to different needs (autonomy, relatedness, and competence) can enhance the beneficial effects of adaptive guidance on learning and performance across different learning contexts. For example, Katz and Assor (2006) note that providing choice to teams can impact relatedness needs.

### **Limitations and Future Research Directions**

It is important to highlight a few limitations to the present research. First, the synthetic task and student sample may limit the generalizability of our findings. Future research should extend our findings to different tasks, training spanning different lengths of time, and different instructional aids (e.g., intelligent tutors). Further, future research should examine the relationships in other samples with varying levels of motivation and ability. For example, future research extending our findings in a field study employing a sample varying on demographic and individual-difference factors (e.g., age) associated with different levels of motivation and ability would have important practical implications. Alternatively, researchers could attempt to manipulate attentional resources in an experimental study by varying the task demands across performance trials.

Second, Figure 3 reveals a negative relationship between motivation and basic performance for learners in the controlling guidance condition, which implies that the least motivated participants were acquiring basic skills at the fastest rate. This was an unexpected finding and suggests that controlling guidance did not thwart the positive effects of motivation on basic performance acquisition, but reversed the motivational effect (i.e., it was beneficial for unmotivated learners). We speculate that learners who lack the motivation to engage in study decisions may have defaulted to compliance, while learners with moderate levels of motivation may have reached a level of motivation that was sufficient to channel attentional resources away from the task. Future research is needed to first replicate and then extend this finding. Building on this finding, research may also consider other situations where external control is preferable to intrinsic motivation to learn (c.f., Pintrich, 2003).

In addition, our study design did not allow us to examine attrition from the training, which is an important practical problem for learner-control instructional designs (Sitzmann & Ely, 2010). This is an important consideration because scholars have found that controlling instructional designs may be associated with less task persistence than autonomy designs (e.g., Vansteenkiste et al., 2004). Therefore, it is important that future research include measures of attrition. Future research examining the impact of design features on attrition may also benefit by examining the type of motivation induced by the design features. For example, controlling guidance instructions may facilitate motivation that is introjected (e.g., internal control such as avoiding guilt) or external (compliance, satisfying external demands), and the difference may be important for measures of persistence. Finally, future research may want to examine instructional designs that shift the focus of guidance over time. For example, guidance designs that shift from controlling to autonomy-supportive as training progresses may facilitate the acquisition of complex skills while also sustaining learners' motivation and effort over extended timeframes.

### **Conclusion**

A central issue facing learner-controlled educational technologies is that learners often make poor use of the control they are given. Thus, instructional strategies such as adaptive guidance aim to help learners to better use the control by facilitating key motivational (e.g., effort) and cognitive (e.g., learning choices) processes. This article suggests that slight changes in the design of adaptive guidance interact with individual differences in pre-training motivation and cognitive ability to impact the rate at which learners acquire basic and strategic task skills. Specifically, guidance that was autonomy-supportive appeared to facilitate (while controlling guidance reversed) the positive effects of pre-training motivation during basic skill acquisition. Guidance that was controlling was better for learning strategic skills, and appeared to facilitate

the positive effects of cognitive ability on strategic skill acquisition. In contrast, when learners received guidance was autonomy-supportive, higher cognitive ability was not significantly related to the acquisition of strategic task skills. These findings highlight the importance of aligning the guidance design, individual differences, and skill outcome in learner-controlled environment.

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## Footnotes

<sup>1</sup> The guidance was adaptive based on three levels of performance. Pilot data was used to set cutoff scores at the 50<sup>th</sup> and 85<sup>th</sup> percentiles to differentiate among low, medium, and high performance on different task components. Learners were not aware of the cutoff scores. If individuals scored below the 50<sup>th</sup> percentile, the guidance informed them that they had not yet learned how to perform the necessary skill or strategy and provided practice and study suggestions for improvement. For those scoring between the 50<sup>th</sup> and 85<sup>th</sup> percentile, the guidance informed them that they had reached a level of minimal performance, but needed to become more proficient. The guidance also provided suggestions on what they should study and practice to improve. For individuals exceeding the 85<sup>th</sup> percentile, the guidance informed them that they had mastered the skill or strategy and should focus on other areas in which they were still deficient.

<sup>2</sup> Pre-training motivation was assessed with eight items adapted from Noe and Schmitt (1986). Prior to modeling the latent growth trajectories, we conducted an exploratory factor analysis for the scales. One reverse-coded item “My primary goal for this experiment is just to finish it so I get my credit” yielded loadings less than .20 on the pre-training motivation factor. Thus, this item was dropped from the measure. The utility of reverse-coded items is frequently debated among psychometric scholars (Hinkin, 1998). In addition to internal item quality issues, dropping the item is also justified based on judgmental item quality concerns, given that the measure was adapted to the context and the item may have had different meaning with the respondent population (see Stanton, Sinar, Balzar, and Smith, 2002).

Table 1

*Descriptive Statistics and Correlations*

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	M	SD
Autonomy-supportive <sup>a</sup>	0.41	0.49		- <b>0.57</b> **	<b>0.12</b>	- <b>0.08</b>	- <b>0.17</b>	- <b>0.08</b>	- <b>0.16</b>	- <b>0.12</b>	- <b>0.07</b>	- <b>0.07</b>	- <b>0.08</b>	- <b>0.09</b>	- <b>0.11</b>	--	--
Controlling <sup>b</sup>	0.32	0.47	- 0.57 **		- <b>0.06</b>	<b>0.06</b>	<b>0.16</b>	<b>0.18</b> **	<b>0.16</b>	<b>0.27</b> **	<b>0.26</b> **	<b>0.29</b> **	<b>0.35</b> **	<b>0.33</b> **	<b>0.40</b> **	--	--
Ability (standardized)	2.81	0.85	0.12	- 0.06		- <b>0.04</b>	<b>0.08</b>	<b>0.10</b>	<b>0.17</b>	<b>0.21</b>	<b>0.15</b>	<b>0.04</b>	<b>0.12</b>	<b>0.05</b>	<b>0.05</b>	--	--
Pre-training motivation	3.33	0.62	- 0.08	0.06	- 0.04		- <b>0.11</b>	- <b>0.03</b>	<b>0.03</b>	<b>0.11</b>	<b>0.08</b>	<b>0.02</b>	<b>0.10</b>	- <b>0.04</b>	<b>0.08</b>	--	--
Performance trial 1	- 0.92	0.60	0.00	- 0.02	0.30 **	0.06		<b>0.45</b> **	<b>0.28</b> **	<b>0.23</b> **	<b>0.22</b> **	<b>0.24</b> **	<b>0.25</b> **	<b>0.34</b> **	<b>0.30</b> **	- <b>0.97</b>	<b>0.50</b>
Performance trial 2	- 0.52	0.79	- 0.03	0.08	0.32 **	0.05	0.41 **		<b>0.58</b> **	<b>0.48</b> **	<b>0.44</b> **	<b>0.43</b> **	<b>0.37</b> **	<b>0.34</b> **	<b>0.31</b> **	- <b>0.60</b>	<b>0.46</b>
Performance trial 3	- 0.27	0.91	- 0.03	0.15	0.21 *	- 0.11	0.27 **	0.69 **		<b>0.60</b> **	<b>0.56</b> **	<b>0.45</b> **	<b>0.39</b> **	<b>0.27</b> **	<b>0.29</b> **	- <b>0.43</b>	<b>0.71</b>
Performance trial 4	- 0.10	0.93	0.03	0.06	0.17	- 0.05	0.22 *	0.62 **	0.73 **		<b>0.86</b> **	<b>0.72</b> **	<b>0.67</b> **	<b>0.52</b> **	<b>0.54</b> **	- <b>0.12</b>	<b>0.83</b>
Performance trial 5	0.05	0.92	- 0.03	0.06	0.20 *	0.03	0.18 *	0.52 **	0.64 **	0.73 **		<b>0.81</b> **	<b>0.74</b> **	<b>0.57</b> **	<b>0.66</b> **	<b>0.11</b>	<b>0.85</b>
Performance trial 6	0.26	0.89	- 0.05	0.07	0.22 *	0.02	0.11	0.51 **	0.65 **	0.67 **	0.82 **		<b>0.84</b> **	<b>0.64</b> **	<b>0.73</b> **	<b>0.35</b>	<b>0.96</b>
Performance trial 7	0.41	0.95	- 0.04	0.00	0.22 *	0.04	0.22 *	0.51 **	0.64 **	0.67 **	0.78 **	0.83 **		<b>0.72</b> **	<b>0.77</b> **	<b>0.43</b>	<b>1.03</b>
Performance trial 8	0.49	0.98	- 0.01	0.04	0.25 **	- 0.06	0.26 **	0.55 **	0.57 **	0.60 **	0.74 **	0.76 **	0.79 **		<b>0.77</b> **	<b>0.61</b>	<b>1.03</b>
Performance trial 9	0.59	0.92	0.02	0.05	0.24 **	- 0.03	0.24 **	0.52 **	0.63 **	0.58 **	0.70 **	0.75 **	0.79 **	0.84 **		<b>0.62</b>	<b>1.02</b>

Note. \*\*  $p < 0.01$  (2-tailed). \*  $p < 0.05$  (2-tailed). Basic performance on vertical axis, strategic performance on horizontal axis and bolded.

<sup>a</sup> 1 = Autonomy-Supportive Guidance, 0 = Controlling Guidance and No Guidance; <sup>b</sup> 1 = Controlling Guidance, 0 = Autonomy-Supportive Guidance and No Guidance

Table 2

*Means & Standard Deviations for Performance Dimensions across Time and Experimental Conditions*

Variable	Autonomy-Supportive Guidance			Controlling Guidance			No Guidance		
	n	<i>M</i>	<i>SD</i>	n	<i>M</i>	<i>SD</i>	n	<i>M</i>	<i>SD</i>
Basic task performance									
Time 1	53	-0.92	0.65	42	-0.93	0.60	35	-0.90	0.54
Time 2	53	-0.55	0.87	42	-0.43	0.78	35	-0.58	0.70
Time 3	53	-0.31	0.88	42	-0.08	0.95	35	-0.44	0.89
Time 4	53	-0.07	0.97	42	-0.02	0.87	35	-0.24	0.95
Time 5	53	0.02	1.00	42	0.14	0.90	35	0.01	0.81
Time 6	53	0.21	0.95	42	0.36	0.89	35	0.23	0.80
Time 7	53	0.36	1.07	42	0.40	0.91	35	0.49	0.82
Time 8	53	0.47	1.08	42	0.54	0.98	35	0.44	0.84
Time 9	53	0.61	0.89	42	0.66	0.87	35	0.49	1.03
Strategic task performance									
Time 1	53	-1.07 <sub>a</sub>	0.55	42	-0.85 <sub>b</sub>	0.41	35	-0.95	0.51
Time 2	53	-0.65	0.42	42	-0.49	0.50	35	-0.68	0.46
Time 3	53	-0.57 <sub>a</sub>	0.76	42	-0.27 <sub>b</sub>	0.70	35	-0.43	0.61
Time 4	53	-0.23 <sub>a</sub>	0.81	42	0.20 <sub>b</sub>	0.94	35	-0.33 <sub>a</sub>	0.57
Time 5	53	0.05 <sub>a</sub>	0.85	42	0.43 <sub>b</sub>	0.91	35	-0.17 <sub>a</sub>	0.65
Time 6	53	0.27 <sub>a</sub>	0.96	42	0.76 <sub>b</sub>	0.98	35	-0.03 <sub>a</sub>	0.77
Time 7	53	0.34 <sub>a</sub>	1.02	42	0.96 <sub>b</sub>	0.94	35	-0.05 <sub>a</sub>	0.89
Time 8	53	0.50 <sub>a</sub>	1.01	42	1.10 <sub>b</sub>	1.02	35	0.18 <sub>a</sub>	0.83
Time 9	53	0.49 <sub>a</sub>	0.86	42	1.21 <sub>b</sub>	1.03	35	0.12 <sub>a</sub>	0.90

*Note.* Items are standardized. Means with different subscripts are different at  $p < 0.05$ .

Table 3

*Fit Statistics for Intra-Individual Growth Trajectories*

Model	$\chi^2$	df	CFI	TLI	RMSEA	SRMR
Basic performance						
No-growth heteroscedastic	455.37 ***	35	0.56	0.55	0.30	0.84
No-growth homoscedastic	605.09 ***	43	0.41	0.51	0.32	0.41
Linear heteroscedastic	123.97 ***	32	0.90	0.89	0.15	0.17
Linear homoscedastic	151.96 ***	40	0.88	0.90	0.15	0.16
<b>Quadratic heteroscedastic</b>	<b>47.27 ***</b>	<b>28</b>	<b>0.98</b>	<b>0.97</b>	<b>0.07</b>	<b>0.06</b>
Quadratic homoscedastic	79.18 ***	36	0.96	0.96	0.10	0.09
Strategic performance						
No-growth heteroscedastic	926.92 ***	37	0.00	- 0.01	0.43	2.92
No-growth homoscedastic	733.75 ***	43	0.20	0.33	0.35	0.76
Linear heteroscedastic	178.06 ***	34	0.83	0.82	0.18	0.15
Linear homoscedastic	174.99 ***	40	0.84	0.86	0.16	0.19
<b>Quadratic heteroscedastic</b>	<b>46.25 ***</b>	<b>30</b>	<b>0.98</b>	<b>0.98</b>	<b>0.07</b>	<b>0.08</b>
Quadratic homoscedastic	94.89 ***	36	0.93	0.93	0.11	0.12

*Note.* \*\*\*  $p < 0.001$ ; Bold indicates best-fitting models. The degrees of freedom are different between some basic and strategic performance models. This was necessary since we found the strategic performance models with heteroscedastic error specifications arrived at improper solutions with negative uniqueness estimates for performances at trial nine. Given the small sample size, we followed the recommendations of Gerbing and Anderson (1987) and fixed this residual to zero which has minimal practical influence on parameter estimates or fit statistics.



Table 4

*Growth Curve Parameters for the Quadratic Models*

Growth parameter	Basic performance		Strategic performance	
	Parameter	<i>t</i>	Parameter	<i>t</i>
Intercept				
Mean	- 0.89	- 16.99 ***	- 0.95	- 23.73 ***
Variance	0.20	2.70 **	0.11	1.99 *
Linear				
Mean	0.31	9.52 ***	0.34	11.17 ***
Variance	0.09	4.50 ***	0.09	4.86 ***
Quadratic				
Mean	- 0.02	- 4.44 ***	- 0.02	- 5.33 ***
Variance	0.00	3.91 ***	0.00	5.28 ***
Covariances				
Intercept with linear	- 0.03	- 0.87	- 0.02	- 0.93
Intercept with quadratic	0.00	1.00	0.00	1.14
Linear with quadratic	- 0.01	- 4.24 ***	- 0.01	- 4.76 ***

Note. \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

Table 5

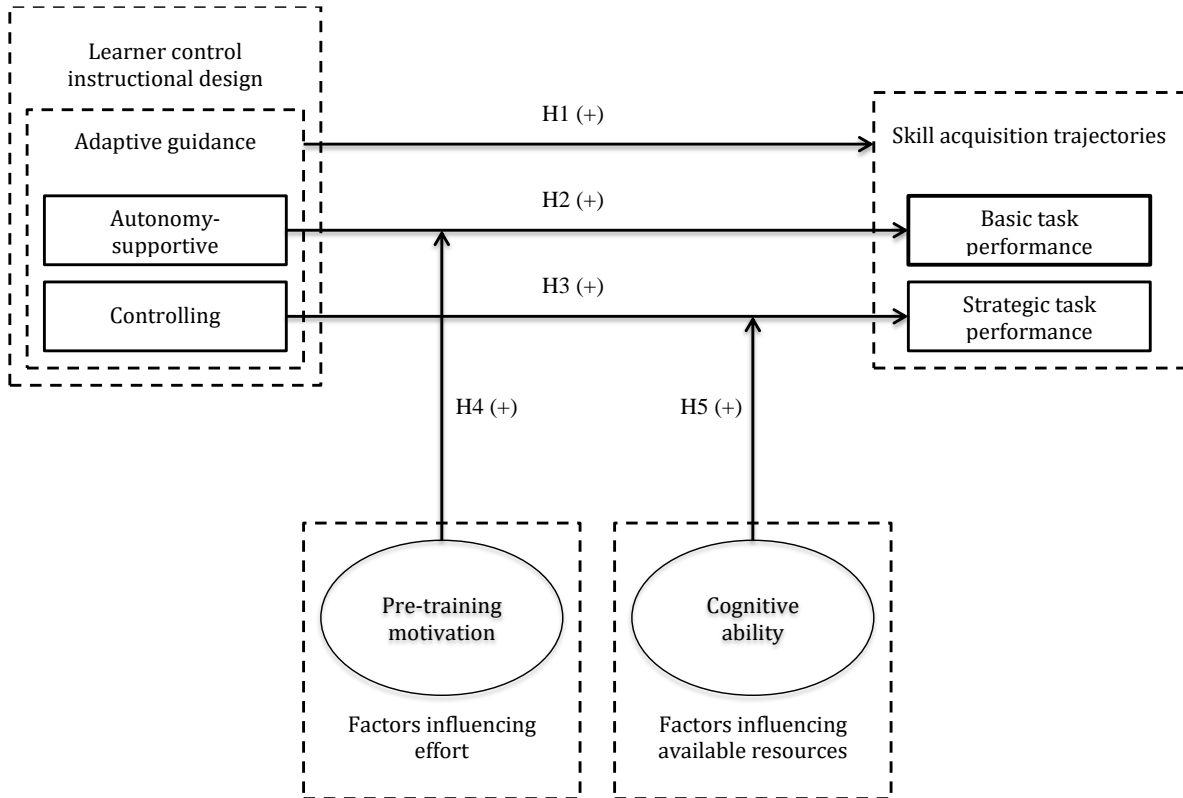
*Parameter Estimates across Experimental Conditions*

	AG	CG	NG
Basic Performance			
Means			
Intercept	- 0.88 *	- 0.82 *	- 0.87 *
Linear	<b>0.28</b> *	<b>0.38</b> *	0.30 *
Quadratic	- <b>0.01</b> *	- <b>0.02</b> *	- 0.02 *
Structural paths			
Pre-training motivation → Basic intercept	- 0.01	0.07	0.02
Pre-training motivation → Basic linear	<b>0.27</b> *	- <b>0.28</b> *	0.07
Pre-training motivation → Basic quadratic	- <b>0.03</b> *	<b>0.02</b> †	- 0.01
Ability → Basic intercept	0.32 *	0.27 *	0.13
Ability → Basic linear	- 0.03	0.07	- 0.04
Ability → Basic quadratic	0.00	- 0.01	0.00
Strategic Performance			
Means			
Intercept	- 0.99 *	- 0.88 *	- 0.93 *
Linear	<b>0.32</b> *	<b>0.44</b> *	0.26 *
Quadratic	- <b>0.02</b> *	- <b>0.02</b> *	- 0.02 *
Structural paths			
Pre-training motivation → Strategic intercept	- 0.22 †	0.12	- 0.04
Pre-training motivation → Strategic linear	0.15	- 0.15	0.06
Pre-training motivation → Strategic quadratic	- 0.01	0.01	- 0.01
Ability → Strategic intercept	0.13	0.03	0.01
Ability → Strategic linear	- <b>0.05</b>	<b>0.14</b> *	0.04
Ability → Strategic quadratic	<b>0.00</b>	- <b>0.01</b> †	0.00

*Note.* \*  $p < .05$  (2-tailed), †  $p < .10$  (2-tailed). Predicted relationships are bolded. CG = Controlling guidance; AG = Autonomy-supportive guidance; NG = No guidance. Basic performance model:  $\chi^2(df = 171, N = 130) = 238.63$ , CFI = 0.941, TLI = 0.932, RMSEA = 0.096, SRMR = 0.095; Strategic performance model:  $\chi^2(df = 176, N = 130) = 226.96$ , CFI = 0.946, TLI = 0.939, RMSEA = 0.082, SRMR = 0.114. Modification indices suggested correlating performance trial two and four residuals in the NG basic model. Performance trial four occurred immediately following a short break and may reasonably have impacted participants not receiving structured guidance. This change improved fit ( $\Delta df = 1, \Delta \chi^2 = 13.71, p < .01$ ) in the basic model, but did not change any results in this study.

Figure 1.

*Conceptual model of predicted relationships between adaptive guidance design, individual difference factors, and performance trajectories.*



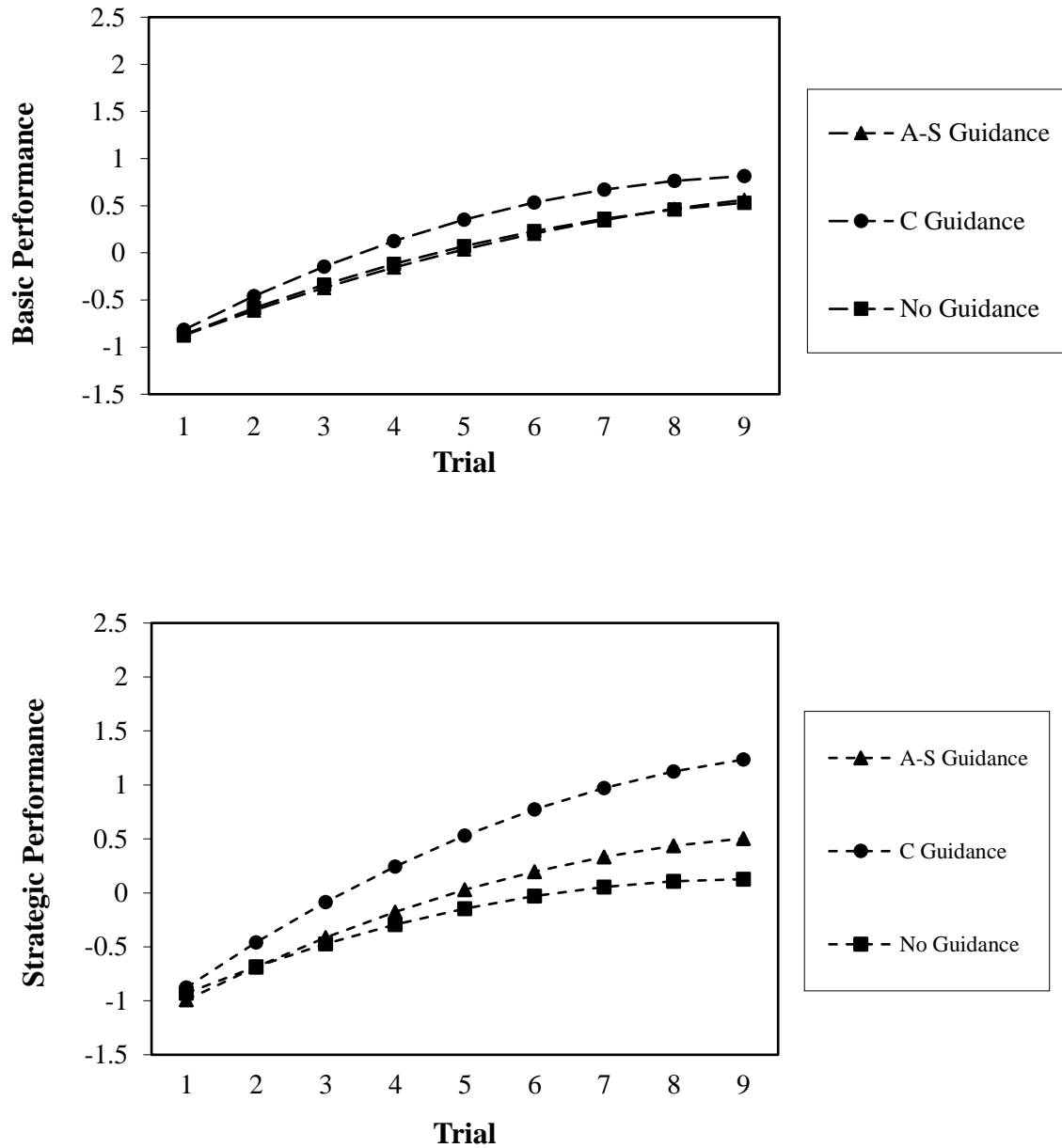
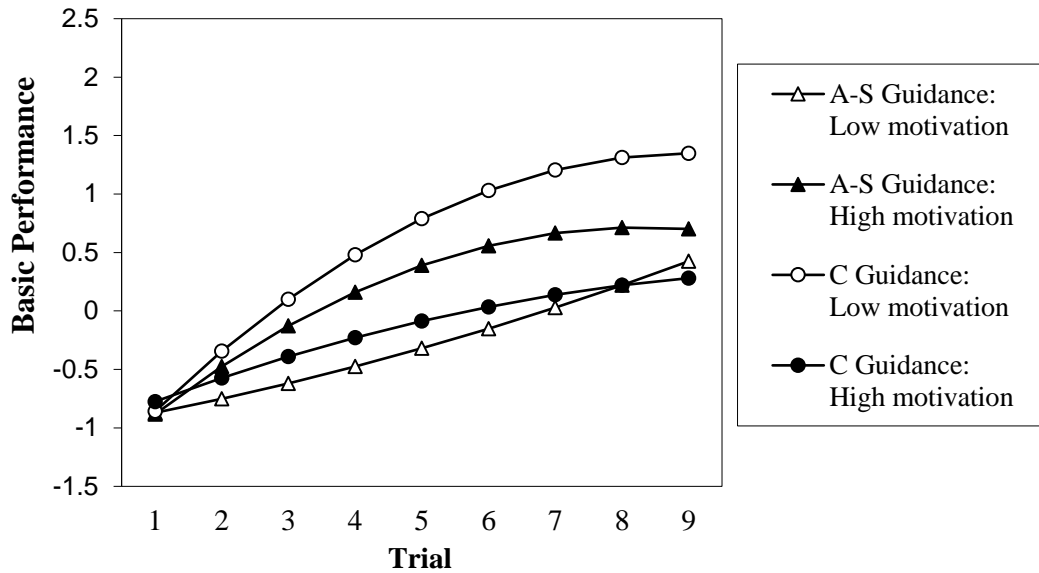


Figure 2. Mean basic and strategic performance trajectories across experimental conditions. A-S Guidance = Autonomy-Supportive Guidance; C Guidance = Controlling Guidance



*Figure 3.* Influence of pre-training motivation on basic performance trajectories across experimental conditions. A-S Guidance = Autonomy-Supportive Guidance; C Guidance = Controlling Guidance

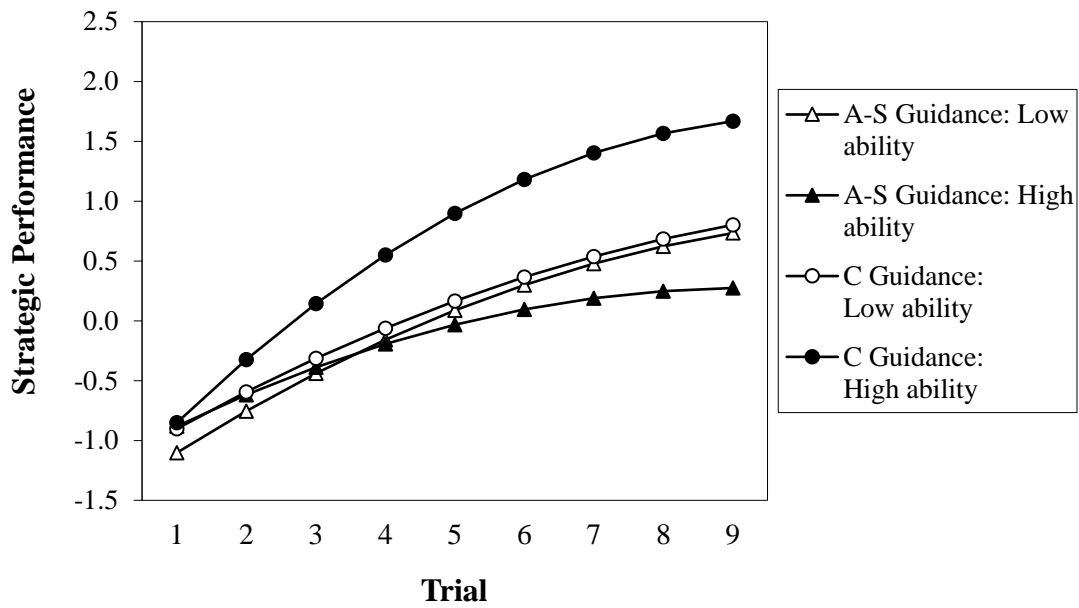


Figure 4. Influence of ability on strategic performance trajectories across experimental conditions. A-S Guidance = Autonomy-Supportive Guidance; C Guidance = Controlling Guidance.