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The Best Laid Plans: Examining the Conditions Under Which a Planning Intervention Improves Learning and Reduces Attrition

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Planning plays an instrumental role in prominent self-regulation theories (e.g., action regulation, control, goal setting), yet as a scientific community we know little about how people carry out their learning plans. Using an experimental field study, we implemented a repeated-measures intervention requiring trainees to create a plan for when, where, and how much time they intended to devote to training before each of 4 online modules and examined the conditions under which the planning intervention improved learning and reduced attrition. Trainees benefited from the planning intervention when it was paired with another intervention—prompting self-regulation—targeting self-regulatory processes that occur subsequent to planning (e.g., monitoring, concentration, learning strategies). Trainees' learning performance was highest and attrition lowest when they received both interventions. The planning intervention was also advantageous for enhancing learning and reducing attrition when trainees followed through on the amount of time that they planned to devote to training. Finally, the relationship between planned study time, time on task, and learning performance was cyclical. Planned study time had a positive effect on time on task, which, in turn, had a positive effect on learning performance. However, trainees planned to devote less time to training following higher rather than lower learning performance. The current study contributes to our theoretical understanding of self-regulated learning by researching one of the most overlooked components of the process—planning—and examining the conditions under which establishing a learning plan enhances training outcomes.

Keywords: planning, self-regulation, attrition, online training

Scientists and philosophers have taught us that planning is a critical first step for achieving any objective. For example, Benjamin Franklin (1706–1790) once said, "By failing to prepare, you are preparing to fail." Plato (B.C. 427–347) and Confucius (B.C. 551–479) also discussed the criticality of planning in their statements, "The beginning is the most important part of the work" and "A man who does not think and plan long ahead will find trouble right at his door." In preparatory contexts, such as training, forming and implementing a plan are essential for ensuring goal accomplishment (Locke & Latham, 2002). Although there is evidence of the benefits of planning in the workplace (e.g., Brinckmann, Grichnik, & Kapsa, 2010; Claessens, Van Eerde, Rutte, & Roe, 2004, 2010; Frese et al., 2007), we know little as a scientific community about how people form a plan and carry it out over time as they acquire work-related knowledge and skills.

Extensive research has focused on goal setting and the process by which trainees regulate their learning activities to facilitate goal achievement (see Locke & Latham, 2002, for a review of goal setting research). However, researchers studying self-regulated learning have neglected to examine the types of plans that trainees create and how they carry them out over time (Sitzmann & Ely, 2011), despite the fact that prominent self-regulation theories—control (Carver & Scheier, 1981), goal setting (Locke & Latham, 1990, 2002), action regulation (Frese & Zapf, 1994; Hacker, 1982), and self-regulated learning (Pintrich, 2000; Zimmerman, 2000)—suggest that planning is an instrumental component of self-regulation. Only nine studies have examined the correlation between self-reports of whether trainees engaged in planning and objectively assessed learning (e.g., Al-Ansari, 2005; Chen, Thomas, & Wallace, 2005; Heikkilä & Lonka, 2006), and the conclusions drawn from these studies are limited by the questionable assumption that trainees accurately engaged in retrospection regarding their learning plans. Moreover, a recent meta-analysis of this literature found planning does not have a significant effect on learning (Sitzmann & Ely, 2011). Moving beyond correlational research, other studies have manipulated planning as part of an intervention; however, in these studies planning is typically confounded with other self-regulated learning processes (e.g., Harris, 1998; Keith & Frese, 2005). For example, Keith and Frese (2005) implemented an error management intervention that targeted three subcomponents of metacognition—planning, monitoring, and evaluation—simultaneously, making it difficult to isolate the effects of planning from other self-regulatory processes. Moreover, the effect of planning on learning is inconsistent across intervention studies (Ely & Sitzmann, 2009).

Given the importance of planning to self-regulation theories and the inconsistencies in previous research, it is valuable to understand when planning enhances the learning process. The goal of this study is to determine the conditions under which planning,

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initiated through a planning intervention, enhances learning and reduces attrition in learner-controlled online training. Although planning is important across a breadth of tasks, it is particularly important in learner-controlled online training because trainees are given discretion over when and where they complete the course and how much time they devote to learning (Kraiger & Jerden, 2007; Sitzmann, Kraiger, Stewart, & Wisher, 2006). Using an experimental field study with working adults, we implemented a repeated-measures intervention that required trainees to establish a plan before each of four online modules for when, where, and how much time they were going to devote to training. Both control theory and action regulation theory acknowledge that people do not plan very far into the future (Carver & Scheier, 2000; Frese & Zapf, 1994). People typically have a few steps planned out at a time, and the plan evolves as they carry out the task (Frese & Zapf, 1994). Thus, we employed a repeated-measures design to understand how trainees carry out their learning plans and modify them over time. In addition, Berthold, Nuckles, and Renkl (2007) suggested that interventions are most effective when they target a breadth of self-regulatory processes. As such, we examine whether inconsistencies in the planning intervention literature may be due to studies finding stronger effects when the interventions target a broader range of self-regulatory processes. If this is true, we should observe a more positive effect of the planning intervention when other self-regulatory processes are also targeted.

This study makes several theoretical contributions to the extant literature. First, we include separate interventions targeting planning and other self-regulated learning processes. Thus, we can test the unique benefits of a planning intervention with and without the activation of other self-regulatory processes, furthering our understanding of planning's role in self-regulated learning. Second, correlational research typically relies on retrospective reports of planning, making it difficult to differentiate planning from the follow-through process (e.g., Claessens et al., 2004; Heikkilä & Lonka, 2006; Volet & Lund, 1994; see Vancouver & Kendall, 2006, for an exception in the training domain). It is possible that trainees who follow through on their plans are more likely to report that they had created plans than trainees who planned but failed to follow through on those plans. Separating out the plans that trainees create from the actions that they engage in during training allows us to examine the process by which planning enhances learning and reduces attrition. Third, theory suggests that self-regulation is an iterative process and trainees' performance in a course determines future regulatory engagement (Boekaerts, Maes, & Karoly, 2005; Carver & Scheier, 2000; Kanfer & Ackerman, 1989; Winne, 1996; Zimmerman, 2000). Thus, we hypothesize a cyclical relationship between trainees' planned time on task, actual time on task, and learning performance.

In the following section, we provide a theoretical overview of planning and discuss the conditions under which a planning intervention is likely to affect the learning process. We then introduce the theoretical model that will be tested and the study hypotheses.

Theoretical Overview of Planning

Planning is defined as determining the behavioral paths that one could follow for goal achievement (Austin & Vancouver, 1996) and is one of 16 processes that comprise the self-regulated learning domain (Sitzmann & Ely, 2011). Cognitive theory proposes that planning is required to convert thoughts and intentions into action (Frese et al., 2007; Miller, Galanter, & Pribram, 1960). Planning serves several key functions. First, planning provides a means of testing alternative courses of action without utilizing the time and resources necessary to engage in the action (Austin & Vancouver, 1996). For example, if trainees were to think through potential locations for completing online training, they might deduce that their homes are too chaotic, without wasting time attempting to complete the course at home. Second, planning allows one to contemplate the temporal dimensions of goals and the sequence of actions needed to achieve them (Austin & Vancouver, 1996). In the case of self-directed learning, trainees can examine how much time they need to devote to learning as well as the other demands on their time and schedule training over as many days as necessary to complete the course. Third, planning makes goal attainment a more automatic process so that individuals engage in goal-directed behavior without conscious intent (Gollwitzer, 1993; Gollwitzer & Brandstätter, 1997; Webb & Sheeran, 2007). With regards to online training, having training scheduled for a couple of hours on a particular day would allow trainees to immediately log in to the course at the scheduled time, reducing the cognitive effort required to initiate self-directed learning (Webb & Sheeran, 2007).

Despite the theoretical rationale for why planning should be beneficial, planning does not consistently have a positive impact on performance (Sitzmann & Ely, 2011; Smith, Locke, & Barry, 1990; Weingart, 1992). Rather, the beneficial effects of planning should be enhanced when trainees also self-regulate as they carry out their plans and follow through on the plans that they establish. Self-regulation is a cyclical process by which trainees establish learning plans, develop learning strategies, channel their attention toward learning, monitor their learning performance, and subsequently modify their self-regulatory processes over time (Carver & Scheier, 2000; Hacker, 1978; Kanfer & Ackerman, 1989; Pintrich, 2000; Tubbs & Ekeberg, 1991; Zimmerman, 2000). Thus, planning is one of the self-regulatory processes that occurs as trainees self-direct their learning, but a breadth of strategies (e.g., time management and environmental structuring) must be implemented for trainees to successfully carry out their plans (Locke & Latham, 2002; Sitzmann & Ely, 2011).

Furthermore, action regulation theory acknowledges that plans may be abandoned shortly after they are formed (Frese & Zapf, 1994). A habitual routine may divert someone from carrying out a plan or people may forget their plans, reducing the benefits of engaging in planning activities. Moreover, distractions or alternative goal pursuits may pull trainees' attention away from their training plans (Carr, 2000; Tyler-Smith, 2006), causing them to fail to act on their plans. Thus, planning should be more beneficial when trainees exert the self-discipline necessary to carry out their plans, and we must investigate the follow-through process to understand when trainees benefit from establishing a learning plan.

In the following sections, we hypothesize that requiring trainees to establish a plan will enhance learning and reduce attrition from training. We then suggest that the beneficial effects of a planning intervention will be greatest when combined with a second intervention that targets other self-regulatory processes or when trainees follow through on the plans that they generate.

Effects of the Planning Intervention on Learning and Attrition

According to action regulation theory (Frese & Zapf, 1994; Hacker, 1985), the action process begins with setting a goal and developing a prognosis of the likelihood of reaching the goal. People then generate plans, and these plans are the immediate motivational causes of most human behavior (Frese & Zapf, 1994). Indeed, research suggests that plans effectuate behavior (Brandstätter, Lengfelder, & Gollwitzer, 2001; Gollwitzer & Brandstätter, 1997; Trötschel & Gollwitzer, 2007). In a learning context, Al-Ansari (2005) demonstrated that planning is associated with higher scores on exams and papers as well as better grades in college courses. Trainees who plan for the long-term use of training material have greater training transfer than those who fail to generate a plan (Frese & Zapf, 1994). Planning also reduces the likelihood that trainees will get distracted and fail to complete the course. Bayer, Gollwitzer, and Achtziger (2010) found that having plans for when, where, and how one intends to achieve a goal buffered against distractions from goal pursuit on a variety of tasks. Further, Alfred (1973) found college students' plans for continuing their education predicted whether they remained enrolled in college the next semester or dropped out. Therefore, implementing an intervention that requires trainees to engage in planning should increase learning and reduce attrition in online training.

> *Hypothesis 1:* The planning intervention will have a positive effect on learning, such that learning performance will be higher for trainees in the planning condition than the control condition.

> *Hypothesis 2:* The planning intervention will have a negative effect on attrition, such that the probability of dropping out will be lower for trainees in the planning condition than the control condition.

Moderating Role of Prompting Self-Regulation

Self-regulation may be trainees' most essential asset (Sitzmann & Ely, 2011). Yet trainees do not consistently engage in self-regulation during training (Butler & Winne, 1995; Sitzmann & Ely, 2010). Although a planning intervention targets the initial phase of the self-regulated learning process, trainees must subsequently monitor their learning performance, use effective learning strategies, and channel their cognitive resources toward training to maximize their learning performance (Carver & Scheier, 2000; Kanfer & Ackerman, 1989; Pintrich, 2000; Zimmerman, 2000). Directing attentional resources toward the task at hand is particularly important when the task is cognitively demanding, as is the case with self-directed learning (Kanfer & Ackerman, 1989; Sitzmann, Bell, Kraiger, & Kanar, 2009). Thus, the beneficial effects of a planning intervention may be enhanced when paired with another intervention that targets a breadth of self-regulatory processes and enables trainees to overcome obstacles to successfully completing the course (e.g., making poor learning decisions and failing to concentrate).

One intervention that targets several self-regulatory processes is prompting self-regulation, or asking trainees reflective questions regarding whether there are gaps in their understanding of the course material, if they are concentrating on learning the material, and if their study strategies are effective (Sitzmann et al., 2009). As evidence of the efficacy of prompting self-regulation, Sitzmann and Ely (2010) demonstrated that implementing the intervention throughout training resulted in a 5 percentage point increase in test scores and a 17 percentage point reduction in attrition, relative to the control condition. Trainees who received the intervention also increased their self-regulated learning activity following feedback indicating poor learning performance, suggesting that they were effectively regulating their learning. Conversely, trainees in the control condition mentally disengaged from training or dropped out following poor learning performance. Several other studies have confirmed that prompting self-regulation has a positive effect on learning (Berthold et al., 2007; Hübner, Nückles, & Renkl, 2006; Sitzmann et al., 2009). The current study moves beyond previous self-regulation prompts research by examining how the intervention acts in concert with a planning intervention to enhance learning and reduce attrition.

In summary, the beneficial effects of a planning intervention may be enhanced when other self-regulatory processes are also activated during training. Prompting self-regulation should ensure that trainees employ a breadth of self-regulatory strategies as they carry out their learning plans.

> *Hypothesis 3:* Prompting self-regulation will moderate the effect of the planning intervention on learning. The planning intervention will have a more positive effect on learning performance when it is implemented in conjunction with prompting self-regulation.

> *Hypothesis 4:* Prompting self-regulation will moderate the effect of the planning intervention on attrition from training. The planning intervention will have a more negative effect on attrition when it is implemented in conjunction with prompting self-regulation.

Following Through on Trainees' Plans

Forming a plan does not guarantee a change in trainees' behavior. Rather, trainees may fail to follow through on their plans if they revert to habitual behavior, forget their plans, or redirect their attention toward alternative goal pursuits (Carr, 2000; Frese & Zapf, 1994; Tyler-Smith, 2006). In the current study, trainees created a plan for when, where, and how much time they would devote to learning before each of four training modules. We expect that plans are more beneficial when they are followed through upon (see Figure 1). Follow-through is conceptualized as the extent to which the amount of time spent in training is consistent with trainees' planned time on task and whether trainees completed the training on the planned dates (i.e., match planned and actual dates).

Following Through on Time

Time on task reflects the amount of effort that trainees devote to learning (Fisher & Ford, 1998; Sitzmann & Ely, 2011). Vancouver and Kendall (2006) found trainees' planned study time had a positive effect on time on task at the within-subject level of

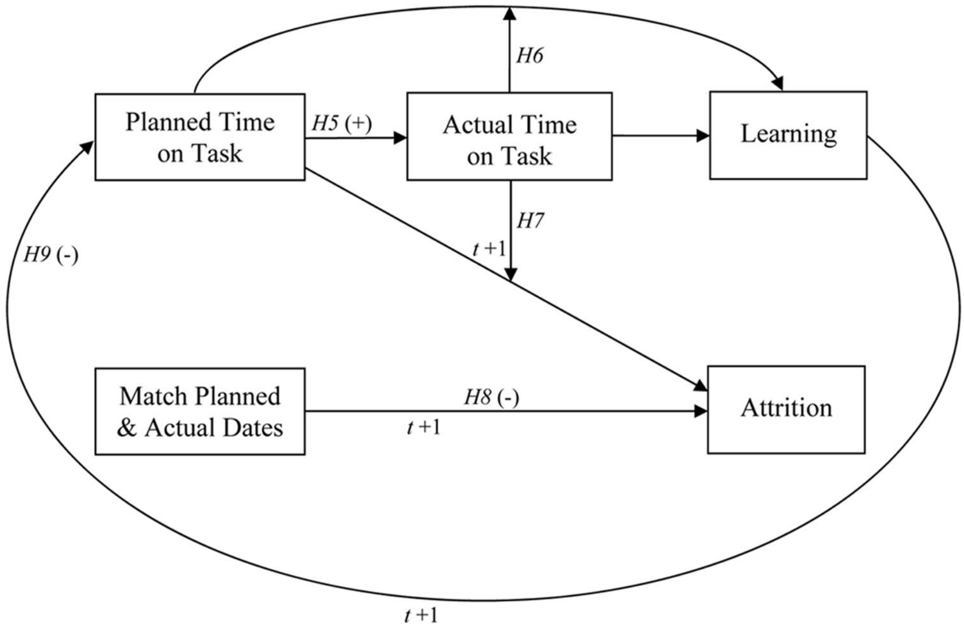

Figure 1. Model of the effect of following through on trainees' plans on the learning process. Match planned and actual dates refers to the extent to which trainees completed the training on the planned training dates. Hypotheses 1–4, which are between-subjects comparisons of the training conditions, are not included in the model on follow-through. Positive hypothesized effects are indicated by (+); negative hypothesized effects are indicated by (−). Time-lagged effects are indicated by $t + 1$. H = hypothesis.

analysis but left about 80% of the variance in time on task unexplained. When trainees establish plans for the amount of time that they need to devote to training, they think about their current knowledge level and how much time they need to spend reviewing to achieve their training goals (Winne, 1996). As such, trainees plan to spend more time reviewing when their current knowledge level is low rather than high. However, family and work constraints may severely restrict the amount of time available to devote to training (Bean & Metzner, 1985; Tyler-Smith, 2006) and may explain some of the variance in time on task. Failing to devote the time that one plans for studying may have deleterious effects. Specifically, trainees may be insufficiently prepared for the upcoming exam, impairing their learning performance. Thus, trainees' planned time on task should only have a positive effect on learning performance when their actual time on task is high.

> *Hypothesis 5:* Trainees' planned time on task will only have a positive effect on their actual time on task.

> *Hypothesis 6:* Time on task will moderate the effect of the amount of time that trainees plan to devote to training on learning. Trainees' planned time on task will only have a positive effect on learning performance when their actual time on task is high.

Failing to follow through on one's planned study time may also signal a lack of commitment to the plan or to the goal itself (Gollwitzer, 1999; Sheeran, Webb, & Gollwitzer, 2005). The cumulative demands of multiple goals may exceed available time (Schmidt & Dolis, 2009). At this point, people rely on their expectancies for goal attainment to determine whether to persist or disengage from each of the goals competing for their time (Bandura, 1991; Carver & Scheier, 1998; Locke & Latham, 1990; Schmidt & Dolis, 2009). When trainees plan to devote a lot of time to reviewing but actually devote little time, they may realize that time constraints are going to impair their ability to fully achieve their goal of mastering the course content. Rather than continuing to devote time to training when they have insufficient time to complete the course, trainees may abandon their learning goal altogether, ultimately dropping out before or during the next module. Thus, planning to devote substantial time to training should only reduce attrition when trainees follow through on their plans, meaning their actual time on task is high.

> *Hypothesis 7:* Time on task will moderate the effect of the amount of time that trainees plan to devote to training on attrition from the subsequent module. Trainees' planned time on task will only have a negative effect on attrition when their actual time on task is high.

Following Through on Dates

We also examined the extent to which trainees reviewed the material on the dates specified in their training plans and expect that a strong match between trainees' planned and actual training dates will reduce attrition from training. Our rational for this prediction is similar to our justification for why planned and actual time on task should interact when predicting attrition. One of the benefits of establishing the specific days and times that one intends to complete training is that it makes goal attainment a more automatic process, such that people engage in the behavior on the intended days because it is scheduled (Gollwitzer, 1999). However, scheduling time for training is unlikely to be sufficient for completing a course unless people follow through and complete training on the dates specified in their plans. Nevertheless, work and family obligations may interfere with trainees' attempts to follow through and complete training on the scheduled days (Sitzmann, 2012). If people's schedules do not permit them to meet all their obligations, they may abandon one of their goals (Schmidt & Dolis, 2009), potentially causing them to drop out of training.

Hypothesis 8: The degree of similarity between trainees' planned and actual dates for participating in the course will have a negative effect on attrition from training, such that trainees will be less likely to drop out if they complete training on the dates specified in their plans.

Revising Training Plans

Self-regulation is a dynamic process that unfolds over time as trainees make decisions about the level of resources that they need to devote to training (Kanfer & Ackerman, 1989). Thus, trainees may periodically reevaluate their training plans based on feedback received during the learning process. In the current study, trainees received feedback on their learning performance at the end of each module, allowing us to examine the effects of learning on trainees' plans for the subsequent module. On the basis of control theory (Carver & Scheier, 1998), we expect trainees' performance will influence their planned time on task in the subsequent module. However, there is no theoretical reason to believe trainees' performance will influence their planned dates for training.

Specifically, we expect that receiving positive feedback will cause trainees to plan to decrease subsequent efforts, whereas receiving negative feedback will cause trainees to plan to increase subsequent efforts (Lord, Diefendorff, Schmidt, & Hall, 2010). According to Vancouver and Kendall (2006), trainees may reduce the amount of time that they plan to spend reviewing when they successfully learned the material in the previous section of the course. Under certain conditions, superior performance causes one to allocate less effort to that task (Carver & Scheier, 1998; Schmidt & DeShon, 2010; Vancouver, Thompson, Tischner, & Putka, 2002). Indeed, positive feedback can result in a decrease in effort and motivation (Campion & Lord, 1982; Podsakoff & Farh, 1989; Walker & Smither, 1999). Thus, when trainees perform well in the course, they may reallocate their time to other demands and reduce the amount of time that they plan to spend in the subsequent section of training (Vancouver & Kendall, 2006).

Hypothesis 9: Trainees' learning performance will have a negative effect on the amount of time that they plan to spend reviewing in the subsequent module.

Method

Participants

Four-hundred eighty-eight adults were recruited online and received free training in exchange for research participation. The majority of participants were employed full or part time (71%), whereas 22% were unemployed, 4% were retired, and 3% were students. There was also variability in participants' educational backgrounds: 2% had not completed high school, 16% had a high school diploma or general education diploma, 29% had completed some college, 14% had an associate's or technical degree, 28% had a bachelor's degree, and 11% had a graduate or professional degree. Forty-nine percent of trainees indicated that they enrolled in the course to improve their skills for their current job, 38% were hoping to improve their potential to secure a new job, 12% were planning to use the skills in their personal lives, and 1% signed up for other reasons. The average age of participants was 47 years (SD = 11.5; ages ranged from 18 to 74), and 63% were female.

Experimental Design and Procedure

Advertisements for free Microsoft Excel training were posted on popular search engine websites to recruit research participants. People who responded to an advertisement were sent a username, a password, and a link to a website with information on navigating the course as well as the course login page. The training consisted of four modules that covered a variety of Excel functions including formulas, graphing, pivot tables, and macros. The instruction was text based and included screen shots demonstrating how to perform various functions in Excel. The data used in the examples were available for trainees, and they were encouraged to practice as the functions were demonstrated. Trainees' goals were the same across experimental conditions—to improve their knowledge and skills related to Microsoft Excel. After finishing each module, trainees completed a multiple-choice test to assess their knowledge of the material and reviewed feedback that explained the correct answers to the test questions.

The course was designed to take approximately 4 hr to complete, but trainees were given control over the pace of instruction—they could determine the amount of time spent on each module and choose to complete the course in a single day or spread it out over several weeks. However, trainees were required to review the content in a predetermined order and were given the deadline of completing the course 2 weeks after the date when they enrolled. If trainees missed the 2-week deadline, they were given an extension but were also informed of the firm deadline of the date when we were ceasing data collection. All trainees had access to the course for at least a month before the final deadline.

Before beginning the course, trainees were randomly assigned to one of six conditions for a 2 (planning intervention, no planning intervention) × 3 (self-regulation prompts, interrupting questions control, no prompts control) experimental design. The first manipulation was the planning intervention; half of trainees received an intervention requiring them to develop a plan for when, where, and how much time they were going to devote to training before each module, whereas the other half did not receive the planning intervention. At the beginning of the course, trainees in the planning intervention condition read the following message:

> Research suggests that creating a plan enhances learning and assists people in completing training. The primary reason people drop out is they lack the self-discipline necessary to succeed in online training. The barriers to success that many people succumb to include failing to set aside enough time for training and completing the course in an environment full of distractions such as TV, e-mail, colleagues, and family members. Let's take a moment and develop a plan for how you can overcome these barriers to completing online training.

Trainees were then informed that they would need to complete the course within 2 weeks of the date they enrolled and that, on average, each module would take about 1 hr to complete, but the amount of time that they spent reviewing would be completely up to them. They then viewed a calendar and selected the dates when they were planning to log in to the course and reported how many hours they were planning to spend reviewing. The final component of the planning worksheet informed trainees that they needed to choose a study environment that is quiet and free from distractions. They were then asked to check a box next to the locations where they were planning to participate in training. The options available were home, work, library, friend's house, coffee shop, metro/bus/train, and other (please specify). Finally, trainees were encouraged to print a copy of their plan for the next module.[1]

The second manipulation was a self-regulation prompts intervention and included three levels. The first group of trainees was asked self-regulation prompt questions designed to stimulate self-regulated learning. Trainees viewed the following message before starting the course:

> Research has shown that asking yourself questions about whether you are concentrating on learning the training material will increase how much you learn during training. The training program will periodically ask you questions about where you are directing your mental resources and whether you are making progress toward learning the training material. Honestly respond to these questions and use your responses to direct your learning during training.

Trainees were asked three self-regulation prompt questions periodically per module, for a total of 12 prompt questions during the course. The questions were the same as those used by Sitzmann and Ely (2010) and included the following: "Do I understand all of the key points of the training material?", "Am I concentrating on learning the training material?", and "Are the study strategies I'm using helping me learn the training material?" Trainees responded to the questions on a 5-point Likert scale (1 = *not at all* to 5 = *definitely*).

One of the limitations noted by both Sitzmann et al. (2009) and Sitzmann and Ely (2010) is the possibility that periodic breaks during training while trainees responded to the prompt questions, rather than the having trainees reflect on their self-regulatory processes, may have caused subsequent changes in the learning process. Thus, the second level of the self-regulation prompts manipulation asked trainees questions about their training experience periodically throughout training, but the questions were not designed to stimulate self-regulated learning. The questions asked in the interrupting questions condition were parallel in both the number of words and characters to the self-regulation prompt questions and asked trainees about their satisfaction with the course format, the training platform, and the overall course, as well as the utility of training. Example questions were "I am enthusiastic about what I learned in this online training module," "The online system made it easy for me to review the material," and "This online Microsoft Excel course will have a positive impact on my job performance." Trainees responded to the questions on a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*).

The final level of the self-regulation prompts manipulation was a second control condition. These trainees did not receive the intervention and were not asked questions during training, other than the measures that all trainees completed at the end of each module.

Measures

Trainee demographics were assessed pretraining. After finishing each module, trainees completed a test to assess their learning performance. Time on task, the dates for completing the modules, and attrition were captured by the learning management system. Finally, trainees in the planning condition provided information on their planned amount of time for training and the dates when they planned to complete the modules as they filled out the planning intervention worksheets.

Learning. A 12-item multiple-choice assessment of declarative and procedural knowledge was administered to trainees at the conclusion of each module. Some test questions measured trainees' capacity to recall factual information presented during training, whereas others measured trainees' capacity to recall sequences of actions for executing Excel functions. The average learning performance scores across the four modules ranged from 60% to 68% correct.

Attrition. Data from the learning management system were used to assess attrition. Of the 488 trainees who enrolled in the course, 155 (32%) dropped out in Module 1, 99 (20%) dropped out in Module 2, 64 (13%) dropped out in Module 3, and 23 (5%) dropped out in Module 4. Thus, 147 (30%) trainees who began training also completed the course.

Planned and actual time on task. Trainees' planned time on task reflects the number of hours that they planned to spend reviewing for the upcoming module. The average amount of time that trainees planned to dedicate to training ranged from 1.61 to 2.30 hr per module. Trainees' actual time on task reflects the number of hours that they spent reviewing the course material and was captured by the learning management system. The actual amount of time that trainees dedicated to training ranged from an average of 0.85 to 1.07 hr per module.

Match between planned and actual training dates. We calculated the percent match between trainees' planned and actual dates for participating in the course. Matches indicate that trainees logged in on a date included in their plans; mismatches indicate either that there was a date included in trainees' plans when they did not log in or that trainees logged in on a date that was not included in their plans. For example, if trainees planned to complete Module 1 on December 2 and 3, but they actually completed the module on December 1, 2, and 3, their date match score would be 0.67. The average date match across the four modules ranged from 0.52 to 0.73.

Control variable. Age was included as a control variable in each of the analyses because prior research has found that it is related to learning in online training (Sitzmann et al., 2006).

[1] At the end of each module, trainees self-reported where they reviewed the training material. Trainees' planned and actual study locations were the same between 94% and 97% of the time across the four modules, limiting our ability to model the effects of following through on where trainees were planning to complete the course. Thus, we focus exclusively on trainees' planned and actual study time and dates in the analyses examining the effects of following through on one's plans.

Data Analysis

Hierarchical linear modeling with full maximum-likelihood estimates was used to analyze the within-subject results for the continuous outcomes—time on task, learning, and planned time on task in the subsequent module. SAS PROC MIXED was used to run the analyses following the model-building procedure specified by Bliese and Ployhart (2002). Hierarchical generalized linear modeling was used to predict attrition. Generalized linear models are extensions of mixed-effect models to cases where standard linear model assumptions are violated (Littell, Milliken, Stroup, Wolfinger, & Schabenberger, 2006). We ran the analyses with SAS PROC GLIMMIX following the procedure outlined by Littell et al. (2006) and Raudenbush and Bryk (2002).

In each of the analyses, module was included as a covariate because time-dependent analyses can be sensitive to order effects. Module was centered such that the intercept represents scores in the first module of the course. The planning intervention was dummy coded such that trainees who received the intervention (coded 1) were compared with trainees who did not receive the intervention (coded 0). Two dummy codes were created to compare the self-regulation prompts conditions; the self-regulation prompts (coded 1) and interrupting questions (coded 1) conditions were compared with the control condition (coded 0). All the other predictors were grand-mean centered. Attrition was coded such that trainees received a 0 in modules that they completed and a 1 in the module where they dropped out.

Following the recommendation of Cohen, Cohen, West, and Aiken (2003), we used the significance values from the Type III sums of squares when interpreting main effects; we used the significance values from the Type I sums of squares when interpreting interactions to test the unique contribution of the interaction terms over the main effects in the model. Due to the directional nature of the hypotheses and reduced statistical power caused by the high attrition rate, we used one-tailed tests of significance for the hypothesized effects. Two-tailed tests were used for the nonhypothesized effects.

One of the advantages of hierarchical linear modeling and hierarchical generalized linear modeling with repeated-measures data is the robustness in calculating parameters with all available data, despite missing data points (Bryk & Raudenbush, 1992; Ployhart, Holtz, & Bliese, 2002). Thus, if trainees dropped out in a module, their learning performance scores from the modules that they completed were included in the analyses predicting learning. However, the analyses require complete data for all between-subjects variables (i.e., age). Thus, 25 trainees were excluded from the analyses because they failed to report their age. As such, 463 trainees, rather than the overall sample size of 488 trainees, were included in the analyses predicting attrition. One-hundred fifty-five trainees dropped out before completing the first exam, so 308 trainees were included in the analyses predicting learning. Finally, the analyses focusing on following through with one's plans use data from the 231 trainees who reported their age and were assigned to the planning condition, which is approximately half of the 463 trainees who provided demographic data.

Results

The intraclass correlation coefficients, descriptive statistics, and correlations among study variables are presented in Table 1. It is noteworthy that, on average, trainees planned to devote 1.90 hr (SD = 1.33) to reviewing the material per module, but the mean of their actual time on task was 0.95 hr (SD = 0.81). Thus, on average, trainees devoted nearly an hour less time per module than they had planned. Time on task was significantly correlated with learning at the within- and between-subjects levels of analysis (r = .16, .25, respectively) and with attrition at the between-subjects level of analysis (r = –.28). However, trainees who planned to

Table 1
Intraclass Correlation Coefficients, Descriptive Statistics, and Correlations Among Study Variables at the Within- and Between-Subjects Levels of Analysis

Variable	ICC	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Age		46.51	11.54	—								
2. Planned time on task	.48	1.90	1.33	.04	—	.02	−.18*				−.05	
3. Time on task	.36	0.95	0.81	.14*	.13	—	.01				.16*	
4. Match planned and actual dates		0.65	0.38	.02	−.23*	.00	—				−.02	
5. Planning intervention		0.47	0.50	.08				—				
6. Prompting self-regulation condition		0.32	0.47	.00	.03	.04	−.03	.04	—			
7. Interrupting questions condition		0.34	0.47	−.03	−.07	−.09	.03	−.01	−.49*	—		
8. Learning	.35	0.63	0.21	−.05	−.17*	.25*	.10	.04	.04	−.03	—	
9. Attrition	.20	0.70	0.46	−.16*	−.10	−.28*	.08	−.03	−.05	.00	−.08	—

Note. Between-subjects correlations are below the diagonal and within-subject correlations are above the diagonal. The planning intervention was dummy coded such that trainees who received the intervention (coded 1) were compared with trainees who did not receive the intervention (coded 0). There were three conditions in the prompting self-regulation manipulation: trainees who were asked self-regulation prompt questions, trainees who were asked questions designed to interrupt learning but not stimulate self-regulatory activity, and trainees in a control condition who were not asked questions throughout training. These conditions were dummy coded such that the self-regulation prompts (coded 1) and interrupting questions (coded 1) conditions were compared with the control condition (coded 0). Attrition was coded such that 1 indicates that trainees withdrew from the course and 0 indicates that trainees completed the course. The between-subjects correlations with planned amount of time for training, time on task, and match planned and actual dates were calculated for the 231 trainees in the planning condition; due to missing data, *N*s ranged from 171 to 231. The remaining between-subjects correlations used data from all 488 trainees; due to missing data, *N*s ranged from 329 to 488. *N*s for the within-subjects correlations ranged from 377 to 461. ICC = intraclass correlation coefficient.
* $p < .05$ (two-tailed).

Table 2
Results Examining the Effects of the Planning and Self-Regulation Prompts Interventions on Learning and Attrition

Variable	H1 Learning[a]	H3 Learning[b]	H2 Attrition[a]	H4 Attrition[b]
Intercept	0.64† (0.02)	0.67† (0.02)	−0.66† (0.14)	−0.68† (0.17)
Module[c]	−0.03† (0.01)	−0.03† (0.01)	−0.24† (0.06)	−0.23† (0.06)
Age[d]	0.00 (0.00)	0.00 (0.00)	−0.02† (0.01)	−0.02† (0.01)
Planning intervention[d]	0.02 (0.02)	−0.03 (0.03)	−0.07 (0.13)	−0.02 (0.23)
Prompting self-regulation condition vs. control[d]	0.02 (0.02)	−0.03 (0.03)	−0.14 (0.16)	0.04 (0.22)
Interrupting questions condition vs. control[d]	0.00 (0.02)	−0.03 (0.03)	−0.01 (0.16)	−0.12 (0.22)
Planning Intervention × Prompting Self-Regulation Condition		0.10* (0.05)		−0.39* (0.33)
Planning Intervention × Interrupting Questions Condition		0.05 (0.05)		0.22 (0.32)

Note. Mixed-effects modeling was used to predict learning, and hierarchical generalized linear modeling was used to predict attrition. In the analyses predicting learning, the values are fixed effects, with standard errors in parentheses. In the analyses predicting attrition, the values are logits, with standard errors in parentheses. H = hypothesis.
[a] Analyses with main effects. [b] Analyses with main effects and interactions. [c] Within-subject predictor. [d] Between-subjects predictor.
† $p < .05$ (two-tailed for nonhypothesized effects). * $p < .05$ (one-tailed for hypothesized effects).

devote more time to training performed worse on the exams ($r = -.17$, $p < .05$).

Next, we examined the effects of the planning intervention on learning and attrition from training (see Table 2). Hypotheses 1 and 2 predicted that learning performance would be higher and attrition lower for trainees in the planning intervention condition than trainees in the control condition, respectively. However, learning and attrition did not significantly differ across experimental conditions ($\gamma = 0.02$; logit $= -0.07$), failing to support the hypotheses. Age had a significant effect on attrition (logit $= -0.02$), such that the probability of dropping out was 8 percentage points greater for younger than older trainees, when comparing trainees 1 *SD* above and below the mean in terms of their age.

Hypothesis 3 predicted that prompting self-regulation would moderate the effect of the planning intervention on learning, such that the planning intervention would have a more positive effect on learning when implemented in conjunction with prompting self-regulation. In support of Hypothesis 3, the two-way interaction between the planning and prompts interventions was significant ($\gamma = 0.10$; see Figure 2). Trainees' learning performance was between 6 and 8 percentage points greater in the condition that received both interventions than in the conditions that received only one or neither intervention.

Hypothesis 4 suggests the planning and prompts interventions would interact when predicting attrition, such that the planning intervention would have a more negative effect on attrition when implemented in conjunction with prompting self-regulation. Supporting the hypothesis, the interaction was significant (logit $= -0.39$; see Figure 3). The probability of dropping out was between 5 and 6 percentage points less in the condition that received both the planning and prompts interventions than in the conditions that received only one or neither intervention.

It is interesting that the interrupting questions condition (i.e., a control condition that provided trainees with a mental break from training as they responded to survey questions, but where the questions were not designed to increase self-regulatory activity) did not significantly differ from the no prompts control condition in learning or attrition. Also, this condition never interacted with the planning intervention when predicting learning or attrition. This adds support to research conclusions indicating that the

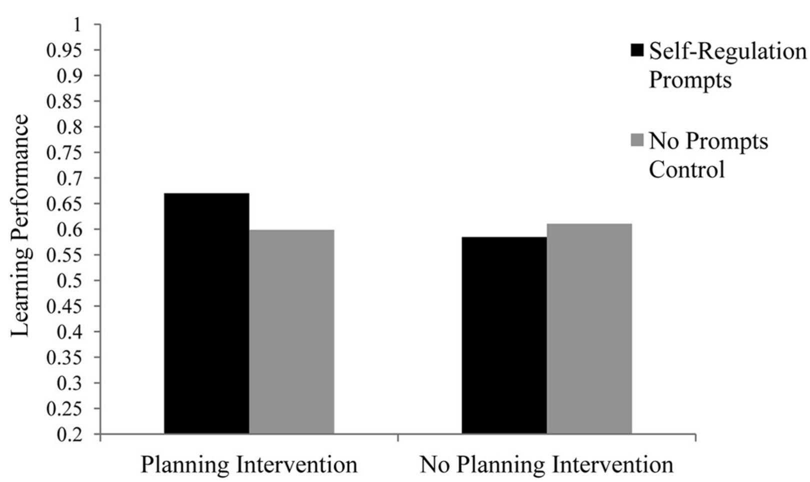

Figure 2. Graph of the interaction between the planning and self-regulation prompts interventions when predicting learning.

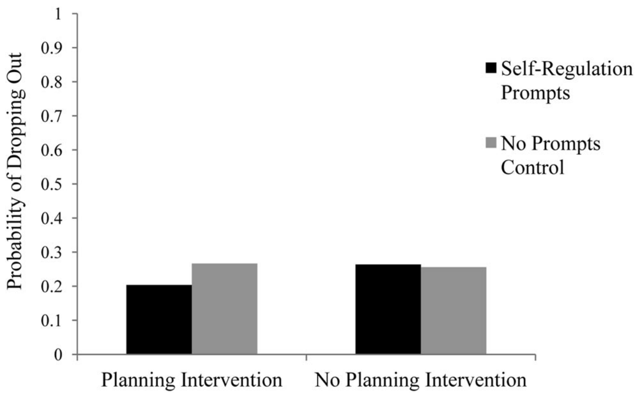

Figure 3. Graph of the interaction between the planning and self-regulation prompts interventions when predicting attrition.

beneficial effects of prompting self-regulation are driven by changes in self-regulatory activity rather than periodic breaks from training (Sitzmann et al., 2009; Sitzmann & Ely, 2010).

The next set of analyses examined the implications of following through on one's plans on learning and attrition for the 231 trainees in the planning condition (see Table 3). In support of Hypothesis 5, the amount of time that trainees planned to devote to training had a significant, positive effect on time on task (γ = 0.05), such that time on task was 14 min longer when trainees planned to spend a longer rather than a shorter amount of time reviewing. Moreover, time on task had a positive effect on learning ($\gamma = 0.05$, $p < .05$). Trainees' learning performance was 8 percentage points greater when they spent a longer rather than a shorter amount of time reviewing the course material.

Hypothesis 6 predicted that trainees' planned time on task would only have a positive effect on learning performance when their actual time on task is high. The interaction between time on task and planned time on task was significant ($\gamma = 0.03$). In support of Hypothesis 6, planning to spend more time reviewing only had a positive effect on learning when trainees' actual time on task was high (see Figure 4). Trainees' learning performance was 14 percentage points greater when they followed through with their plan to devote a lot of time to training than when they failed to follow through on this plan.

Hypothesis 7 suggested that planning to devote more time to training would only reduce attrition when trainees' actual time on task is high. Supporting the hypothesis, planned time on task only had a negative effect on attrition from the subsequent module when trainees' actual time on task was high (logit = –0.39, $p < .05$; see Figure 5). When trainees planned to devote a lot of time to reviewing, the probability of dropping out was 24 percentage points greater when their time on task was lower rather than higher.

The match between trainees' planned and actual training dates had a positive effect on attrition (logit = 0.73, $p < .05$). Thus, the results are in the opposite direction of Hypothesis 8. The probability of dropping out was 9 percentage points less when trainees had a weaker rather than a stronger date match.

Finally, we tested Hypothesis 9, which predicted that trainees' learning performance would have a negative effect on the amount of time that they planned to devote to the subsequent module. The results support this hypothesis ($\gamma = -0.89$, $p < .05$). The amount of time that trainees planned to devote to reviewing was 20 min less following higher rather than lower learning performance.

Discussion

The goal of this study was to address the disconnect between prominent theoretical claims regarding the value of planning (e.g., Carver & Scheier, 1981; Locke & Latham, 2002) and empirical evidence suggesting that planning does not have a significant effect on learning (Sitzmann & Ely, 2011). Specifically, using an experimental field study, we implemented a repeated-measures intervention that required trainees to create a plan for when, where, and how much time they were going to devote to training before

Table 3
Results Examining the Effects of Following Through on Trainees' Plans

Variable	H5 Time on task[a]	Learning[a]	H6 Learning[b]	H8 Attrition (subsequent module)[a]	H7 Attrition (subsequent module)[b]	H9 Planned time (subsequent module)[a]
Intercept	0.97[†] (0.09)	0.63[†] (0.02)	0.63[†] (0.02)	−0.97[†] (0.28)	−1.02[†] (0.29)	2.02[†] (0.15)
Module[c]	0.02 (0.03)	−0.03[†] (0.01)	−0.04[†] (0.01)	−0.05 (0.19)	0.00 (0.20)	−0.20 (0.10)
Age[d]	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.03[†] (0.01)	−0.03[†] (0.01)	−0.01 (0.01)
Prompting self-regulation condition vs. control[d]	0.06 (0.11)	0.08[†] (0.03)	0.07[†] (0.03)	−0.60 (0.37)	−0.56 (0.38)	0.25 (0.17)
Interrupting questions condition vs. control[d]	−0.17 (0.12)	0.04 (0.03)	0.03 (0.03)	−0.38 (0.38)	−0.31 (0.39)	0.36 (0.18)
Planned time on task[c]	0.05[*] (0.03)	0.00 (0.01)	−0.01 (0.01)	0.10 (0.12)	0.09 (0.12)	0.78[†] (0.06)
Time on task[c]		0.05[†] (0.01)	0.05[†] (0.01)	−0.27 (0.21)	−0.33 (0.22)	0.10 (0.09)
Match planned and actual dates[c]		0.02 (0.02)	0.02 (0.03)	0.73[*] (0.42)	0.73[*] (0.43)	
Learning[c]						−0.89[*] (0.43)
Planned Time on Task × Time on Task			0.03[*] (0.01)		−0.39[*] (0.24)	

Note. Mixed-effects modeling was used to predict time on task, learning, and planned time in the subsequent module. In these analyses, the values are fixed effects, with standard errors in parentheses. Hierarchical generalized linear modeling was used to predict attrition; the values are logits, with standard errors in parentheses. H = hypothesis.
[a] Analyses with main effects. [b] Analyses with main effects and interactions. [c] Within-subject predictor. [d] Between-subjects predictor.
[†] $p < .05$ (two-tailed for nonhypothesized effects). [*] $p < .05$ (one-tailed for hypothesized effects).

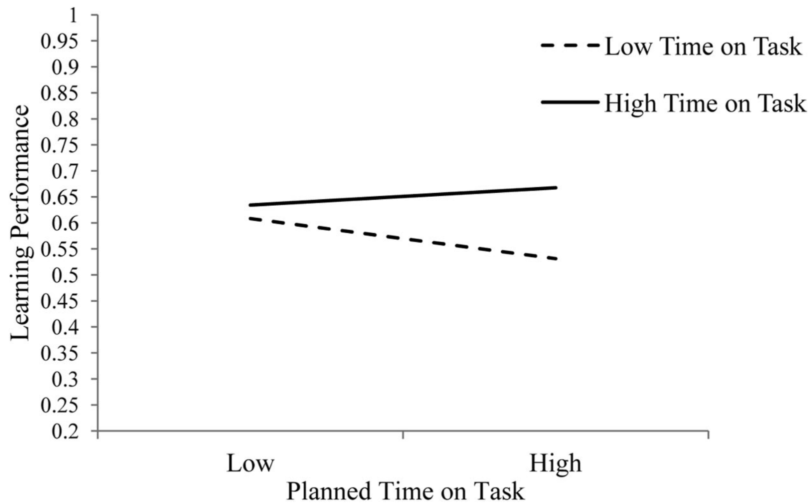

Figure 4. Graph of the interaction between trainees' planned and actual time on task when predicting learning.

each of four online modules. The repeated nature of the intervention is imperative due to evidence that trainees do not plan very far into the future and that plans evolve as they carry out tasks (Anderson, 1990; Carver & Scheier, 2000; Frese & Zapf, 1994). Furthermore, the intervention required trainees to create a learning plan, whereas previous interventions research has taught trainees about the value of engaging in planning activities, provided them with tools to encourage planning activities, or encouraged self-reflection on trainees' plans (e.g., Azevedo & Cromley, 2004; Corliss, 2005; Keith & Frese, 2005). Thus, our study provides insight as to the impact of the plans that trainees create on learning and attrition as well as how trainees' plans evolve over time in response to learning performance feedback. In the following sections, we discuss the theoretical implications of the results followed by recommendations for practitioners, study limitations, and directions for future research.

Theoretical Implications

Corroborating our predictions, the planning intervention enhanced learning and reduced attrition when paired with another self-regulatory intervention or when trainees followed through on their plans. The planning intervention did not, however, have a main effect on learning or attrition. This finding is consistent with meta-analytic evidence suggesting that planning does not have a significant effect on learning (Sitzmann & Ely, 2011) but is inconsistent with research and theory suggesting that planning has a direct impact on behavior (Al-Ansari, 2005; Carver & Scheier, 1981; Gollwitzer, 1999; Locke & Latham, 2002). It is possible that self-directed learning necessitates that other self-regulatory processes are also activated for planning to have its intended effects.

Indeed, the planning intervention was advantageous for enhancing learning and reducing attrition when trainees were also

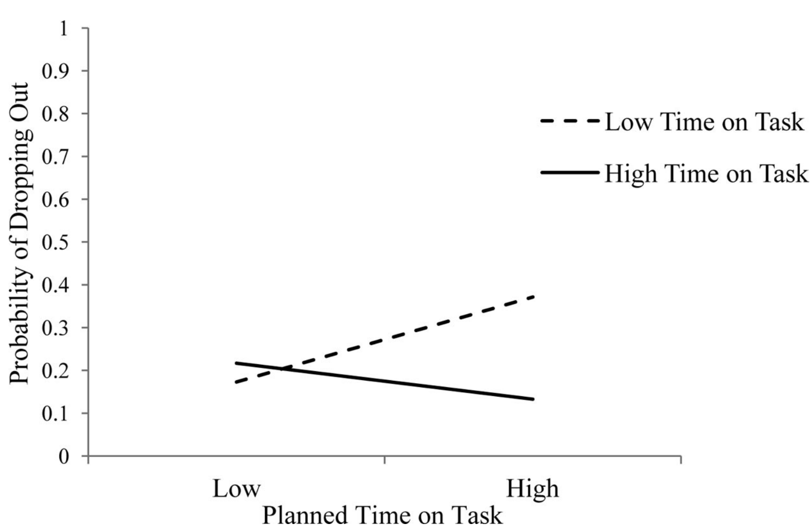

Figure 5. Graph of the interaction between trainees' planned and actual time on task when predicting attrition from the subsequent module.

prompted to self-regulate during training. Prompting self-regulation proved ideal for pairing with the planning intervention because it targets trainees' monitoring, concentration, and learning strategies, which are self-regulatory processes that occur subsequent to planning and are instrumental for learning (Gollwitzer & Sheeran, 2006; Pintrich, 2000; Zimmerman, 2000). Via targeting a breadth of self-regulatory processes, it may be possible to assist trainees in avoiding the vast majority of pitfalls that can impede their progress in online training. Specifically, the planning intervention should remind trainees to set aside time for training, whereas the prompts intervention should remind trainees to concentrate during training, monitor their learning progress, and use effective learning strategies. Thus, in concert, the interventions provide trainees with a repertoire of self-regulated learning strategies that they can employ to enhance their understanding of the course topic and complete online courses.

Trainees also benefited from the planning intervention when they followed through on their plans for the amount of time they intended to spend reviewing. When repeated efforts are needed to accomplish a task, planning may not have a significant main effect on performance because many individuals fail to follow through on their plans over time (Buehler, Peetz, & Griffin, 2010). Consistent with Vancouver and Kendall (2006), we found trainees' plans for the amount of time that they were going to devote to learning had a positive effect on the amount of time that they actually spent reviewing. However, we also extended these findings by investigating the two-way interaction between trainees' planned and actual time on task when predicting learning and attrition from the subsequent module. Learning was highest and attrition lowest when trainees both planned to and spent a lot of time in training. When trainees establish plans, they self-assess their knowledge level and contemplate how much time they would need to devote to reviewing to learn the material (Winne, 1996). Thus, trainees plan to devote more time to training when they have a poor understanding of the course topic. Following through on the decision to devote substantial time to training may indicate that trainees are committed to their goal of mastering the course content (Gollwitzer, 1999; Sheeran et al., 2005), ultimately enhancing learning and reducing attrition from the subsequent module. In contrast, failing to devote the time that one planned for studying had deleterious effects on the learning process—trainees were insufficiently prepared for the upcoming exam and were more likely to drop out of training.

One puzzling finding is that attrition from the subsequent module was greater following a high rather than a low level of fit between trainees' planned and actual dates for training. A potential explanation for this finding is the course website indicated that trainees were expected to complete all four modules within 2 weeks of the day that they enrolled. It is possible that some trainees assumed this was a firm deadline and completed multiple consecutive modules as the deadline approached but also dropped out when they ran out of time for training. Additional research is needed to explore potential negative side effects of following through on one's plans and imposing deadlines for course completions.

Finally, theory suggests and research demonstrates that self-regulation is a recursive process and trainees' learning performance influences subsequent self-regulation (Carver & Scheier, 2000; Kanfer & Ackerman, 1989; Sitzmann & Ely, 2010; Vancouver & Kendall, 2006). This study established that trainees planned to allocate less time to the subsequent module following higher than lower learning performance. On one hand, this is a functional aspect of regulating multiple competing goals, because people can free up time for other goal pursuits. However, planning to devote less time to training may have dysfunctional consequences for training outcomes—planning to devote less time to reviewing resulted in trainees spending less time reviewing, which, in turn, resulted in lower learning performance. Future research should investigate whether certain trainees are capable of devoting the bare minimum time to training while still ensuring content mastery and the individual differences that predict this capability.

Recommendations for Practitioners

Adults are capable of succeeding in online training, but they often succumb to distractions in their training environment, procrastinate, choose not to devote enough time to training, fail to accurately assess their knowledge levels, and use ineffective learning strategies, which prevent them from achieving their full learning potential (Brown, 2001; Derouin, Fritzsche, & Salas, 2005; Kanfer & Ackerman, 1989; Sitzmann, Ely, Bell, & Bauer, 2010; Sitzmann, Ely, Brown, & Bauer, 2010; Steel, 2007). Training practitioners owe it to the people who participate in their learner-controlled online courses to provide them with the support that they need to successfully complete training.

Trainees' learning performance will be maximized and attrition minimized when two interventions are implemented in concert during training. First, trainees should be asked to fill out a planning worksheet at the beginning of each training module so that they think through how much time they will need and when they will find time to complete the course. Second, trainees should be asked self-regulation prompt questions periodically throughout training so that they remember to monitor their learning performance, concentrate on learning, and use effective learning strategies. Enabling the success of all trainees will ensure that employees have the skills they need to successfully perform their jobs.

The amount of time that trainees plan to devote to training also holds tremendous potential for diagnosing whether they are spending sufficient time reviewing. Trainees' learning performance was impaired and attrition from the subsequent module increased when trainees planned to devote substantial time to training but their actual time on task was low. Therefore, trainers could compare how much time trainees planned to set aside for training to objective time on task data collected by the learning management system. Paying careful attention to these predictors of training success may help organizations intervene before trainees drop out or fail to achieve their learning goals.

Study Limitations and Directions for Future Research

Approximately a third (n = 155) of trainees who began training dropped out before completing the first module. This precluded an assessment of the extent to which the planning and prompts interventions impacted learning for those trainees. Future research should continuously measure learning as trainees progress through the course to investigate the effect of training interventions on learning for all trainees. Moreover, it is likely that the effect sizes reported in the current study were attenuated due to the reduced control typical of a field study.

We failed to find a main effect of the planning intervention on learning and attrition. Although this is consistent with recent meta-analytic results (Sitzmann & Ely, 2011), theory suggests that planning should impact training outcomes (Carver & Scheier, 1981; Frese & Zapf, 1994; Gollwitzer, 1999; Locke & Latham, 2002). There are several possible explanations for these inconsistencies. It is possible that some people in the control condition also engaged in planning, reducing observed differences between the experimental conditions. Because we manipulated planning and did not measure planning in the control condition, our study could not account for the degree of planning among trainees in the control condition. Also, the intervention used in this study is quite different from interventions used in previous research. The planning interventions used in past research confounded planning with other self-regulated learning processes. For example, Keith and Frese (2005) established the effectiveness of an intervention that targeted planning, monitoring, and evaluation, suggesting that the positive effects of planning may be strongest when other self-regulatory processes are also activated. Likewise, we found planning was beneficial when combined with another self-regulatory intervention.

Further, the duration of time over which trainees needed to carry out their plans may have reduced the benefits of planning in the current study. The tasks used in previous planning research often involved a concrete course of action (e.g., create a resume, push a button when a number appears on a screen, write a brief report over Christmas break, or engage in a 15-min negotiation) that required a single, continuous act (Brandstätter et al., 2001; Gollwitzer & Brandstätter, 1997; Trötschel & Gollwitzer, 2007). In the current study, trainees had to review about 4 hr of material and complete four exams to establish an effect of the planning intervention. Indeed, Buehler et al. (2010) found the effects of planning on behavior are strongest when task completion occurs in a single, continuous session. When repeated efforts are needed to accomplish a task, planning may not have a significant effect on performance because many individuals fail to follow through on their plans over time.

It is also possible that our operationalization of planning impacted the results. Planning is a broad construct and can involve a wide range of activities not studied here (Frese & Zapf, 1994). For example, planning can involve reflecting on one's intended course of action (Keith & Frese, 2005) or finding ways to balance multiple goals (Köpetz, Faber, Fishbach, & Kruglanski, 2011), both of which are very different from establishing a plan for when, where, and how much time one will spend reviewing course material. It is possible that other types of planning could have main effects on performance. Indeed, research on entrepreneurial success has shown positive effects of planning on performance outcomes (Brinckmann et al., 2010). As additional research on planning continues, current models of planning should be enhanced by including moderators of the effect of planning on behavior, such as characteristics of the task (e.g., cognitive complexity, length of time required to complete), the research methodology (e.g., whether planning is self-reported or objectively measured, whether planning is measured as it occurs or retrospectively), the intervention (e.g., whether multiple self-regulatory processes are activated), and the plan itself (e.g., specificity, quality).

We also failed to find a main effect for prompting self-regulation on learning and attrition. Three previous studies have found a significant effect of prompting self-regulation on learning at the within-subject level of analysis (Sitzmann et al., 2009, who reported the results of two studies; Sitzmann & Ely, 2010), and two previous studies have found a significant effect on learning at the between-subjects level of analysis (Berthold et al., 2007; Hübner et al., 2006). Furthermore, Sitzmann and Ely (2010) found that prompting self-regulation reduced attrition by 17 percentage points, relative to a no prompts control condition. However, there is also evidence that the effect of prompting self-regulation on training outcomes is moderated by cognitive ability and self-efficacy, such that trainees benefit from the intervention only if their cognitive ability is high and they are confident in their ability to achieve their training goals (Sitzmann et al., 2009). Indeed, 61% of trainees in this study did not have a 4-year college degree, whereas trainees tended to be more educated in previous prompts research. It is possible that difference in education levels or self-efficacy for learning may have caused our results to differ from previous results. Additional research is needed to examine boundary conditions for when prompting self-regulation as well as other self-regulatory interventions are effective for enhancing learning and reducing attrition.

Research is also needed to develop and test the effects of an adaptive planning intervention. Specifically, the current results revealed deleterious effects when trainees planned to devote a lot of time to training but their subsequent time on task was low. In many organizations, hundreds, if not thousands, of trainees complete each online course. Thus, there is tremendous potential to create a database of how much time, on average, trainees spend on each section of the course. The amount of time that trainees spend reviewing could then be compared with their learning plans and a database of how much time is needed for the current section of training. An adaptive intervention could target trainees at the point when their planned time on task is high and actual time on task is low relative to other trainees. The intervention could warn trainees' supervisors that they need more time during the workday to devote to learning activities or inform trainees that learning requires a substantial time investment and remind them of the benefits of completing the course. Via targeting trainees when they are most at risk of dropping out, an adaptive intervention may enable all trainees to succeed in online training.

Conclusions

Planning is one of the least frequently researched components of the self-regulated learning process (Sitzmann & Ely, 2011), despite the fact that prominent self-regulation theories—goal setting, control, action regulation—advocate for the instrumental role of planning in understanding how people regulate goal-directed behavior. To enhance our understanding of planning, we used an experimental design to examine the plans that trainees create and how they carry them out over time. We conclude that implementing a planning intervention is advantageous for enhancing learning and reducing attrition when combined with another intervention—prompting self-regulation—or when trainees followed through on the amount of time that they planned to devote to training. Examining the process by which trainees carry out their learning plans may hold the key to understanding why self-regulated learning does not always produce optimal training outcomes.

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Correction to Mathieu, Aguinis, Culpepper, and Chen (2012)

The article "Understanding and Estimating the Power to Detect Cross-Level Interaction Effects in Multilevel Modeling," by John E. Mathieu, Herman Aguinis, Steven A. Culpepper, and Gilad Chen (*Journal of Applied Psychology*, Advance online publication. May 14, 2012. doi:10.1037/a0028380), contained production-related errors in a number of the statistical symbols presented in Table 1, the Power in Multilevel Designs section, the Simulation Study section, and the Appendix. All versions of this article have been corrected.

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