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

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Abstract
Planning plays an instrumental role in some of the most prominent self-regulation theories (e.g., action regulation, control, goal setting); yet as a scientific community we know little about how people institute and carry out their learning plans. Using an experimental field study with working adults, we implemented a repeated measures intervention requiring trainees to create a plan for when, where, and how much time they would devote to training before each of four 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 greatest and attrition lowest when they received both interventions. The planning intervention was also advantageous for enhancing learning and reducing procrastination and attrition when trainees followed through on their learning plans. Finally, the relationship between planned study time, time on task, and learning performance was cyclical, such that trainees planned to devote less time to training following higher 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; procrastination
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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 (BC 427-347) and Confucius (BC 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., Claessens, van Eerde, Rutte, & Roe, 2004, 2010; Frese et al., 2007), we know very little as a scientific community about how people institute 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 in order to facilitate goal achievement (see Locke & Latham, 2002, for a review of goal setting research). However, the plans that trainees create and how they carry them out over time are neglected components of the self-regulated learning process (Sitzmann & Ely, in press), despite the fact that some of the most 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)—all suggest that planning is an instrumental component of self-regulation. Only nine studies have examined the correlation between planning and learning outcomes (e.g., Al-Ansari, 2005; Chen, Thomas, & Wallace, 2005; Heikkila & Lonka, 2006) and the conclusions drawn from these correlational studies are limited by the questionable assumption that trainees can accurately
report their internal processes. Moreover, a recent meta-analysis of this literature found planning did not have a significant effect on learning (Sitzmann & Ely, in press). Studies in which planning is manipulated as part of an intervention often confound planning with other self-regulated learning processes (e.g., Harris, 1998; Keith & Frese, 2005), making it difficult to differentiate the effects of planning. Moreover, the effect of planning on learning has been inconsistent across intervention studies (Ely & Sitzmann, 2009).

Given the theoretical importance of planning to self-regulation theories and the inconsistencies in previous research, it is important to understand when planning enhances the learning process. The goal of this study is to determine the conditions under which planning, 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 where trainees are given control 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. Requiring trainees to create a learning plan should provide tremendous insight as to how trainees carry out their learning plans and modify them over time. Consistent with Tubbs and Ekeberg’s (1991) integration of goal setting theory and the theory of planned behavior, we propose that planning positively influences training outcomes only insofar as trainees follow through on their plans. In addition, Berthold, Nuckles, and Renkle (2007) suggest that interventions are most effective when they target a breadth of self-regulatory processes. Thus, we examine whether inconsistencies in the planning intervention literature may
be due to studies finding stronger effects for the interventions when they target a broader range of self-regulatory processes. If this is true, we should only observe a positive effect of the planning intervention when other self-regulatory processes are also activated.

In doing so, the current study makes several theoretical contributions to the extant research. First, our study includes 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 the role of planning in the self-regulated learning process. Second, correlational research on planning typically relies on retrospective reports of the planning process, making it difficult to differentiate planning from the follow-through process (e.g. Classens et al., 2004; Volet & Lund, 1994; see Vancouver & Kendall, 2006, for an exception). It is possible that individuals who follow through on their plans are also more likely to report that they had created plans than individuals 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 (Boekaerts, Maes, & Karoly, 2005; Kanfer & Ackerman, 1989; Winne, 1996; Zimmerman, 2000) and trainees’ performance in the course determines future regulatory engagement (Carver & Scheier, 2000). Thus, we hypothesize a cyclical model in which trainees’ learning performance influences their plans in the subsequent module. In the following section, we provide a theoretical overview of planning and discuss the conditions under which a planning intervention is likely to have an effect on the learning process. We then introduce the theoretical model that will be tested and the study hypotheses.

_Theoretical Overview of Planning_
Planning refers to determining the behavioral paths that one could follow for goal achievement (Austin & Vancouver, 1996). Cognitive theory proposes that planning is required to convert thoughts and intentions into action (Miller, Galanter, & Pribram, 1960; Frese et al., 2007). Planning serves several key functions. First, planning provides a means of testing alternative courses of action without actually 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 actually 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 place training on their schedule over as many days as necessary in order to make learning a priority. Third, planning helps to make goal attainment a more automatic process so that individuals can engage in goal-directed behavior without conscious intent (Gollwitzer, 1993; Gollwitzer & Brandstatter, 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 (Smith, Locke, & Barry, 1990; Sitzmann & Ely, in press; Weingart, 1992). Planning alone may not effectively increase learning and reduce attrition for at least two reasons. First, a planning intervention may be insufficient for influencing the breadth of self-regulatory processes that must occur in order to enhance the learning process.
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 many self-regulatory processes that must occur as trainees are self-directing their learning experience. Second, in light of the theory of planned behavior and goal setting theory, planning should only be beneficial when trainees follow through on the plans that they establish (Tubbs & Ekeberg, 1991). 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 and limiting the value of the training plan. Thus, we may only observe a positive effect of the planning intervention among those trainees who display the self-discipline necessary to follow through on the plans that they establish. In the following sections, we present hypotheses suggesting 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.

_Moderating Role of Prompting Self-Regulation_

Self-regulation may be employees’ most essential asset (Porath & Bateman, 2006); 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, utilize effective learning strategies, and channel their cognitive resources toward training after establishing their plans in order for planning to have a substantial effect on the learning process (Carver & Scheier, 2000; Kanfer & Ackerman, 1989; Pintrich; 2000; Zimmerman, 2000).
Moreover, logging on to training at a scheduled time is unlikely to be sufficient for improving the learning process if trainees neglect to pay attention as they are viewing the course material and make poor learning decisions, such as failing to practice as skills are demonstrated. Directing attentional resources toward the task at hand is particularly important when the task is cognitively demanding (Kanfer & Ackerman, 1989), as is the case in self-directed learning. Thus, the beneficial effects of a planning intervention may only be observed when paired with another intervention that targets a breadth of self-regulatory processes and enables trainees to overcome obstacles (e.g., making poor learning decisions and failing to concentrate on learning) to successfully completing the course.

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. 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—whereas 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 during training has a positive effect on learning (Berthold et al., 2007; Hübner, Nückles, & Renkl, 2006; Sitzmann, Bell, Kraiger, & Kanar, 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 only be observed when other self-regulatory processes are also activated during training. Together, planning and prompting self-regulation should ensure that trainees employ a breadth of self-regulated learning strategies and channel their cognitive resources toward training as they carry out their learning plans.

**H1:** Prompting self-regulation will moderate the effect of the planning intervention on learning. The planning intervention will only enhance trainees’ learning performance if it is implemented in conjunction with prompting self-regulation.

**H2:** Prompting self-regulation will moderate the effect of the planning intervention on attrition from training. The planning intervention will only reduce attrition if it is implemented in conjunction with prompting self-regulation.

**Following Through on Trainees’ Plans**

Although there is evidence that planning alone can elicit behavior, Buehler, Peetz, and Griffin (2010) found the effects of planning on behavior are strongest when task completion occurs in a single, continuous session. However, when repeated efforts are needed to accomplish a task, planning does not have a significant effect on performance because many individuals fail to follow through on their plans over time. In order to capture the importance of following through on one’s plans, Tubbs and Ekeberg (1991) include an intermediate step (called action) in their model of goal intentions, highlighting the need to better understand the action component of the goal striving process.

In the current study, trainees needed to repeatedly access the training material over time, suggesting that the planning intervention should not have a significant main effect on behavior (Buehler et al., 2010) and following through on one’s plans may explain essential variance in
determining who benefits from the intervention. Specifically, trainees created a plan for when, where, and how much time they would devote to learning before each of four one-hour training modules. In the current study, trainees followed through on their planned study location over 95% of the time. Thus, our hypotheses will focus on the amount of time and the dates that trainees set aside for training. We expect that plans are only beneficial to the extent that they are followed through upon and procrastination is avoided (Figure 1). We will explain when and why planned time and dates should affect the learning process in the sections that follow.

Following through on time. Time on task reflects the amount of effort that trainees devote to learning (Fisher & Ford, 1998; Sitzmann & Ely, in press). Vancouver and Kendall (2006) found that trainees’ planned study time had a positive effect on time on task at the within-subjects level of 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 would need to devote to reviewing in order to achieve their training goals (Winne, 1996). However, family and work constraints may severely restrict the amount of time that trainees have available to devote to learner controlled 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 should have deleterious effects on the learning process. Specifically, trainees may be insufficiently prepared for the upcoming exam, impairing their learning performance. Thus, planning to devote substantial time to training should only have a positive effect on learning performance when trainees’ 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,
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2005). Consistent with Schmidt and Dolis’s (2009) work, the cumulative demands placed by
different goals may exceed an individual’s available time. At this point, they 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 training in a given module,
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 the goal of learning the course material when trainees have insufficient time to
achieve that goal, they may abandon the 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.

\[ H3: \text{Trainees’ planned time on task will have a positive effect on their actual time on task.} \]

\[ H4: \text{Time on task will moderate the effect of the amount of time that trainees planned to devote to training on learning. Trainees’ planned time on task will only have a positive effect on learning performance when their actual time on task is high.} \]

\[ H5: \text{Time on task will moderate the effect of the amount of time that trainees planned to devote to training on attrition from the subsequent module. Trainees’ planned time on task will only have a negative effect on attrition when their actual time on task is high.} \]

\[ \text{Following through on dates.} \] We also examined the extent to which trainees reviewed the
material on the dates specified in their training plans. We expect that a match between trainees’
planned and actual dates will reduce procrastination and interact with procrastination when
predicting learning and attrition. Procrastination refers to a deliberate delay of a voluntary course
of action, despite expecting to be worse off due to the delay (Steel, 2007). 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
day because it is part of their schedule (Gollwitzer, 1999). As a result, following through on one’s planned dates should reduce procrastination, given that it will effectuate behavior without relying on conscious intent (Steel, 2007). This is consistent with recent meta-analytic findings indicating that the corrected correlation between planning and procrastination is -0.72 (Sitzmann & Ely, in press).

Although not following through on one’s plan can cause procrastination, it is also possible that one could plan to procrastinate. In such cases, the plan itself could be detrimental to learning and attrition, even when one follows through on the plan. Indeed, poor quality planning can have a detrimental effect on performance (Smith et al., 1990; Weingart, 1992). Planning to procrastinate may also be an indicator of low conscientiousness, and last-minute efforts tend to be less effective than work that is completed in advance (Steel, 2007). Indeed, Steel reported a meta-analytic corrected correlation of -0.19 between procrastination and performance and the credibility interval revealed that “procrastination is usually harmful, sometimes harmless, but never helpful” (p. 80). As a result, we expect that learning will be highest and attrition lowest when trainees both follow through on their planned training dates and procrastination is avoided.

H6: The degree of similarity between trainees’ planned and actual dates for participating in the course will have a negative effect on procrastination.

H7: Procrastination will moderate the effect of a match between trainees’ planned and actual training dates on learning. A strong match between trainees’ planned and actual dates will only have a positive effect on learning performance if procrastination is low.

H8: Procrastination will moderate the effect of a match between trainees’ planned and actual training dates on attrition from the subsequent module. A strong match between trainees’ planned and actual dates will only have a negative effect on attrition if procrastination is low.

Negative Feedback Loop
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. Based on control theory (Carver & Scheier, 1998), we expect feedback to influence one’s planned time on task in the subsequent module. However, there is no theoretical reason to expect feedback will influence the extent to which trainees follow through on their planned dates for training.

Specifically, we expect that receiving positive feedback on their learning performance should cause trainees to plan to decrease subsequent efforts, whereas receiving negative feedback should cause them 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. Carver and Scheier (1998) argue that under certain conditions, high levels of performance cause one to coast or allocate less effort to that task (Schmidt & DeShon, 2010; Vancouver, Thompson, Tischner, & Putka, 2002). Indeed, receiving positive feedback can result in a decrease in effort and motivation on that task (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).

**H9:** Learning performance will have a negative effect on the amount of time that trainees 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. Participants who responded to an advertisement were sent a username, password, and link to a website with information on navigating the course as well as the course login page. The training consisted of a four-hour online course that was divided into four modules and 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 in training.

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. 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. Trainees’ goals were the same across experimental conditions—to improve their knowledge and skills related to Microsoft Excel.

Before beginning the course, trainees were randomly assigned to one of six conditions for a 2 (planning intervention, no planning intervention) x 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 a message indicating that, “Research evidence suggests that creating a plan enhances learning and assists people in completing training. The primary reason people drop out is that 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, on average, each module takes about one hour to complete, but the amount of time that they spend reviewing is 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 material. The final component of the planning worksheet informed trainees that they need 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 the plan that they created 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 then asked three self-regulation prompts 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, 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 that it is possible that the periodic breaks during training while trainees responded to the prompt questions, rather than the having trainees reflect on their self-regulatory processes, may _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 are going to focus exclusively on trainees’ planned and actual study time and dates in the analyses examining the effects of following through on one’s plans on learning and attrition._
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 prompts questions, and asked trainees about their satisfaction with the course overall, the course format, and the training platform, as well as the utility of training. For example, *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 periodic questions during training, other than the measures that all trainees completed at the end of each of the modules.

*Measures*

After finishing each module, trainees completed a test to assess their learning performance. Time on task, the dates for completing the modules, procrastination, 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 course when 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 were designed to measure trainees’ capacity to recall factual information presented during
training whereas others measured trainees’ capacity to recall sequences of actions for executing Excel functions or how such actions affect the appearance of an Excel spreadsheet. The average learning scores across the four modules ranged from 60% to 68% correct.

Attrition. Data from the learning management system was used to assess attrition. Of the 488 trainees who enrolled in the course, 155 (31.8%) dropped out in module 1, 99 (20.3%) dropped out in module 2, 64 (13.1%) dropped out in module 3, and 23 (4.7%) dropped out in module 4. Thus, 147 (30.1%) trainees who signed up for voluntary online Microsoft Excel training also completed the course.

Planned and actual time on task. Trainees’ planned time on task reflects the total 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 hours 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 such that time spent responding to surveys did not contaminate the data. The actual amount of time that trainees dedicated to training ranged from an average of 0.85 to 1.07 hours per module.

Match between planned and actual 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 day they had planned; mismatches indicate either there was a date included in trainees plans when they failed to log in or trainees logged in on a date that was not included in their plans. For example, if trainees planned to complete module one on December 2 and 3, but actually completed the module on December 1, 2, and 3, their match score would be 0.67. The average date match across the four modules ranged from 0.52 to 0.73.
**Procrastination.** Procrastination reflects the number of days that passed between completing the training modules. For module one, this reflects the number of days between completing the pretraining survey and finishing reviewing the first module. For modules two through four, procrastination reflects the number of days that passed between reviewing the exam feedback from the previous module and finishing reviewing the material for the next module. For example, the procrastination score for module four would be five days if a trainee reviewed the feedback for module three on Monday and finished reviewing module four on Saturday. The average procrastination score across the four modules ranged from 1.18 to 2.12.

**Control variables.** Age and self-reported familiarity with the topic of training were included as control variables in each of the analyses because prior research has found that these factors are related to learning in online training (Sitzmann et al., 2006; Sitzmann, Ely, Bell, & Bauer, 2010). Familiarity with the topic was measured with a single item asking trainees to rate on a 5-point Likert scale (1 = not at all to 5 = very), *How knowledgeable are you about Microsoft Excel?* The average level of pretraining familiarity with Excel was 2.57 (*SD* = 0.91).

**Data Analysis**

Mixed-effects modeling with full maximum likelihood estimates was used to analyze the within-subject results for the continuous outcomes—time on task, procrastination, 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 fixed 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 (Vancouver & Kendall, 2006). 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 to 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 to the control condition (coded 0). All of 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.

We followed the model building procedure specified by Bliese and Ployhart (2002). First, we ran the unconditional means (null) model to examine the variance in the outcomes before accounting for any predictors, which allows for the calculation of an intraclass correlation coefficient (ICC). In the next step, module was added as a covariate and we determined the variability in the growth parameters. Then, we specified alternative error structures while testing for improvements in model fit to account for potential autocorrelation and non-independence among observations. The error structure of the baseline model was compared against first-order autoregressive, autoregressive and heterogeneous, and unstructured error structures. We used the change in deviance statistics to decide which error structure provided the best fit for the data and chose autoregressive and heterogeneous for each continuous outcome.

Consistent with 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 in order 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 non-hypothesized effects.

Results

The ICCs, descriptive statistics, and correlations among study variables are presented in Table 1. Noteworthy is that, on average, trainees planned to devote 1.90 hours (SD = 1.33) to reviewing the material per module, but the mean of their actual time on task was 0.95 hours (SD = 0.81). Thus, on average, trainees devoted nearly an hour less time per module than they 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). But, trainees who planned to devote more time to training performed worse on the exams (r = -.17, p < .05).

Next, we examined the effects of the training interventions on learning and attrition from training (see Table 2). Test scores were on average 7 percentage points higher when trainees were familiar with Microsoft Excel before starting the course (γ = 0.04, p < .05), when comparing trainees one standard deviation above and below the mean in terms of their familiarity with Excel. Hypothesis 1 predicted that prompting self-regulation will moderate the effect of the planning intervention on learning, such that the planning intervention will only enhance learning if it is implemented in conjunction with prompting self-regulation. In support of Hypothesis 1, the two-way interaction between the planning and prompts interventions was significant (γ = 0.10; see Figure 2). When trainees received both interventions, their learning performance was
between 5 and 8 percentage points greater than when they received a single or neither intervention.

Next, we used hierarchical generalized linear modeling to predict attrition from training. 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. Pretraining familiarity with the topic of training also had a significant effect on attrition (logit = -0.30), such that the probability of dropping out was 10 percentage points greater for trainees who were low in terms of their familiarity with Microsoft Excel at the beginning of the course. Hypothesis 2 predicted an interaction between the planning and prompts interventions when predicting attrition, such that the planning intervention will only reduce attrition if it is implemented in conjunction with prompting self-regulation. Supporting the hypothesis, the interaction was significant (logit = -0.39) and attrition was lowest among trainees who received both the planning and prompts interventions (see Figure 3). The probability of dropping out was between 5 and 6 percentage points lower in the condition that received both the planning and prompts interventions than in the conditions that receive only one or neither interventions.

It is interesting to note that across both of these analyses the group that was asked interrupting questions (a control condition that provided trainees with a mental break from training as they responded to survey questions, but the questions were not designed to increase self-regulatory activity) did not differ significantly from the no prompts control in their learning or attrition. Also, this condition never interacted with the planning intervention when predicting learning or attrition. This adds support to research conclusions (Sitzmann et al., 2009; Sitzmann & Ely, 2010) indicating that the beneficial effects of prompting self-regulation are driven by changes in self-regulatory activity rather than periodic breaks from training.
The next sets 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). Supporting Hypothesis 3, the amount of time that trainees planned to devote to training had a positive effect on time on task ($\gamma = 0.05, p < .05$), such that time on task was 13 minutes 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 9 percentage points greater when they spent a longer rather than a shorter amount of time reviewing the course material.

Hypothesis 4 predicted that time on task would moderate the effect of the amount of time that trainees planned 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. The interaction between time on task and planned amount of time for training was significant ($\gamma = 0.02$). In support of Hypothesis 4, planning to spend additional 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 5 suggested that planning to devote additional time to training will only reduce attrition when trainees’ actual time on task is high. In support of 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 = -0.40, $p < .05$; see Figure 5). When trainees planned to devote a lot of time to reviewing, the probability of dropping out was 29 percentage points greater when their time on task was lower rather than higher.

In support of Hypothesis 6, the match between trainees’ planned and actual dates had a
negative effect on procrastination ($\gamma = -3.90, p < .05$). Trainees procrastinated an average of 2.95 fewer days when they had a strong rather than a weak match between their planned and actual training dates.

Next, we tested Hypothesis 7—a strong match between trainees’ planned and actual dates will only improve learning if trainees also avoid procrastinating. In support of the hypothesis, trainees’ learning performance was highest when they both had a strong date match and procrastination was low ($\gamma = -0.02, p < .05$; see Figure 6). Specifically, when trainees had a strong date match, their learning performance was 9 percentage points higher when their procrastination was lower rather than higher.

Hypothesis 8 predicted a strong match between trainees’ planned and actual dates will only reduce attrition if trainees also avoid procrastinating. The interaction between the degree of similarity between trainees’ planned and actual dates with procrastination was not significant (logit = 0.06), failing to support the hypothesis. Rather, the match between trainees planned and actual dates had a main effect on attrition (logit = 1.01, $p < .05$). The probability of dropping out of the subsequent module was 12 percentage points greater when trainees had a strong rather than a weak match.

Finally, we tested Hypothesis 9—trainees’ learning performance will have a negative effect on the amount of time that they plan to devote to training in the subsequent module. The results supported this hypothesis ($\gamma = -0.92, p < .05$). The amount of time that trainees planned to devote to reviewing was 21 minutes less following higher 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, in press). Specifically, using a sample of working adults, 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 each of four online modules. The repeated nature of the intervention is imperative due to evidence that trainees do not plan too far into the future and trainees’ plans evolve as they carry out the task (Anderson, 1990; Carver & Scheier, 2000; Frese & Zapf, 1994). Furthermore, the intervention required trainees to create a learning plan, whereas past research has taught trainees about the value of engaging in planning activities or provided them with tools to encourage planning activities (e.g., Azevedo & Cromley, 2004; Corliss, 2005). This lends tremendous insight as to the implications 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, we found that one of two conditions must be present for trainees to benefit from a planning intervention. First of all, the planning intervention was advantageous for enhancing learning and reducing attrition when trainees were also periodically 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 are instrumental for learning and occur subsequent to planning (Golwitzer & 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 and avoid
procrastination, whereas the prompts intervention should remind trainees to concentrate during
training, monitor their learning progress, and utilize effective learning strategies. Thus, in
concert, these two interventions should provide trainees with the repertoire of self-regulated
learning strategies that they need to enhance their understanding of the course topic and ensure
that they complete online courses.

Trainees also benefited from the planning intervention when they followed through on
the plans that they established, relative to when they did not follow through on their plans. 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 et al., 2010). Indeed, following through on one’s plans improved training outcomes.
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
spent reviewing course material. 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. Following through on the decision to
devote substantial time to training may be an indicator 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.

A high level of fit between trainees’ planned and actual dates for training proved
advantageous for reducing procrastination. Corroborating our prediction, a match between
trainees’ planned and actual dates for training also interacted with procrastination when predicting learning; trainees’ maximized their learning performance when they trained on the planned days and avoided procrastinating. Planning to procrastinate is a poor quality plan because last-minute efforts tend to be less effective than work that is completed in advance (Steel, 2007). Indeed, the current results confirmed previous research indicating that poor quality planning can have a detrimental effect on performance (Smith et al., 1990; Weingart, 1992) in that planning to procrastinate was detrimental to performance. This finding may also explain why previous research has not found a consistent effect of planning on learning (Ely & Sitzmann, 2009; Sitzmann & Ely, in press); plans are only advantageous if they are high quality and followed through upon.

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. The course website indicated that trainees were expected to complete all four modules within two weeks of the day that they enrolled. It is possible that some trainees assumed that this was a firm deadline and they had a strong date match toward the end of their two-weeks as they were completing multiple consecutive modules but also dropped out when they ran out of time for training. Moreover, the interaction between date match and procrastination did not reach statistical significance when predicting attrition from the subsequent module. It is possible that trainees who procrastinated for an extended period of time eventually dropped out in the current (rather than the subsequent) module, attenuating this effect. 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 self-regulation in subsequent sections of the course (Carver & Scheier, 2000; Kanfer & Ackerman, 1989; Vancouver & Kendall, 2006; Sitzmann & Ely, 2010). This study established that trainees planned to allocate less time to the subsequent module following higher rather than lower learning performance. On one hand, this is a functional aspect of regulating multiple competing goals; by planning to allocate less time to training, 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, and devoting less time to training resulted in lower learning performance. Thus, future research should investigate whether certain trainees are capable of devoting the bare minimum amount of time to training while still ensuring course mastery and the individual differences which 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, fail to devote enough time to training, become distracted while learning, fail to accurately assess their knowledge levels, and utilize ineffective learning strategies, which prevent them from achieving their full learning potential (Brown, 2001; DeRouin, Fritzsche, & Salas, 2005; Kanfer & Ackerman, 1989; Sitzmann, Ely, Bell et al., 2010; Sitzmann, Ely, Brown, & Bauer, 2010; Steel, 2007). Training practitioners owe it to the people who are participating in their learner controlled online courses to provide them with the support that they need to successfully complete training. Trainees’ learning performance and the likelihood that they will complete a course will be maximized when two interventions are implemented in concert during training. First, trainees should be asked to fill out a planning
Planning Intervention

worksheet at the beginning of each of the training modules so that they think through how much time they need and when they will find time to complete the course. Second, trainees should be asked self-regulation prompts questions periodically throughout training so that they remember to monitor their learning performance, concentrate on learning, and utilize effective learning strategies. Implementing these two interventions will enhance trainees’ learning performance and increase the probability that they complete the course.

The amount of time that trainees plan to devote to training also holds tremendous potential for diagnosing whether trainees are setting aside sufficient time to learn the material. 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 relative to other trainees. 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. Failure to follow through on the dates that one sets aside for training is also a warning sign that trainees may end up procrastinating in completing the course. Thus, along with encouraging planning, organizations must ensure that trainees follow through on both the dates and amount of time that they set aside for training.

*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. Additional research is needed to investigate why trainees sign up for online training and drop out before they can benefit from the
instructional experience. Future research should also continuously measure learning as trainees progress through the course in order 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, suggesting that the results should be replicated in a laboratory setting.

The current study failed to find a main effect of prompting self-regulation on learning and attrition. Three previous studies have found a significant effect of prompting self-regulation on learning at the within-subjects 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 prompting self-regulation reduced attrition by 17 percentage points, relative to a no prompts control condition. Thus, it seems reasonable that random error may have hidden real differences between the self-regulation prompts and control conditions and the lack of significant main effects on learning and attrition represent Type II errors. Indeed, the main effects on learning and attrition are in the hypothesized direction (albeit not statistically significant). Additional research is needed to determine the conditions under which prompting self-regulation is beneficial for enhancing the learning process.

Gollwitzer and colleagues have conducted a plethora of studies that demonstrate a main effect of planning on task outcomes, which is inconsistent with the lack of a significant main effect of the planning intervention on learning and attrition in the current study. Consistent with research by Buehler et al. (2010), we suggest that differences in research results may be driven by the length of time and number of activities necessary to carry out one’s plans. The tasks in Gollwitzer’s research tended to require 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 minute negotiation) that required a single, continuous action (e.g., Brandstatter, Lengfelder, & Gollwitzer 2001; Gollwitzer & Brandstatter, 1997; Trötschel & Gollwitzer, 2007).

In the current study, trainees had to review about four hours of material and complete four exams to establish an effect of the planning intervention. Indeed, Buehler et al. found the effects of planning on behavior are strongest when task completion occurs in a single, continuous session. However, when repeated efforts are needed to accomplish a task, planning does not have a significant effect on performance because many individuals fail to follow through on their plans over time. Additional research is needed to examine whether a planning intervention has a greater effect on training outcomes in shorter than longer courses and how the impact of the intervention can be maximized in lengthy training programs.

Research is also needed to examine how trainees’ goal orientations and goal commitment influence the planning process. In the current study, the goal was implied—to improve their knowledge and skills related to Microsoft Excel. However, some trainees may have had a goal of performing well on the exams while others were focusing on learning the training material. Learning and performance goals have different relations with self-regulation constructs and learning (Payne, Youngcourt, & Beaubien, 2007). Goal commitment, defined as one’s dedication to achieving a goal (Locke & Latham, 1990), may also play a role in explaining why some trainees did not follow through on the plans that they established. It is likely that trainees who are committed to their training goals are prone to follow through on both the dates and time set aside for training. Thus, future research should measure whether trainees are striving for learning or performance goals as well as goal commitment and examine their implications for planning and following through on the plans that are established.
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 against 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 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 potential benefits of completing the course. Via targeting trainees when they are most at risk of dropping out, an adaptive intervention may provide all trainees with the support that they need to succeed in online training.

Conclusions

Planning is one of the least frequently researched components of the self-regulated learning process (Sitzmann & Ely, in press), despite the fact that some of the most prominent self-regulation theories—goal setting, control, action regulation—advocate for the instrumental role of planning in understanding how people regulate goal-directed behavior. We addressed this gap in the literature by utilizing 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 follow through on the plans that they
establish. There was also a cyclical relationship between planned study time, time on task, and learning performance. 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. Via implementing self-regulated learning interventions and examining how trainees carry out their plans over time, we can provide the external support that trainees need to succeed in learner controlled online training.
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Table 1

_Intraclass Correlation Coefficients, Descriptive Statistics, and Correlations among Study Variables at the Within- and Between-Subjects Levels of Analysis_

| Variable | ICC | Mean  | SD   | 1   | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|----------|-----|-------|------|-----|------|------|------|------|------|------|------|------|------|------|
| 1. Age   | –   | 46.51 | 11.54| –   | –    | –    | –    | –    | –    | –    | –    | –    | –    | –    |
| 2. Pretraining familiarity with topic of training | –   | 2.57  | 0.91 | .05 | –    | –    | –    | –    | –    | –    | –    | –    | –    | –    |
| 3. Planned amount of time for training | .48 | 1.90  | 1.33 | .04 | .03  | –    | .02  | .18  | .04  | –    | –    | –    | –    | -.05 |
| 4. Time on task | .36 | 0.95  | 0.81 | .14 | .02  | .13  | –    | .01  | .13  | –    | –    | –    | –    | .16  |
| 5. Match planned & actual dates | –   | 0.65  | 0.38 | .02 | -.03 | -.23 | .00  | -.37 | –    | –    | –    | –    | –    | -.02 |
| 6. Procrastination | .29 | 1.61  | 3.50 | .05 | -.05 | .02  | .05  | -.42 | –    | –    | –    | –    | –    | -.03 |
| 7. Planning intervention | –   | 0.47  | 0.50 | .08 | .05  | –    | –    | –    | –    | –    | –    | –    | –    | –    |
| 9. Prompting self-regulation condition | –   | 0.32  | 0.47 | .00 | .04  | .03  | .04  | -.03 | .04  | .04  | –    | –    | –    | –    |
| 9. Interrupting questions condition | –   | 0.34  | 0.47 | -.03| -.02 | -.07 | -.09 | .03  | .10  | -.01 | -.49 | –    | –    | –    |
| 10. Learning | .35 | 0.63  | 0.21 | -.05| .19  | -.17 | .25  | .10  | .04  | .04  | .04  | -.03 | –    | –    |
| 11. Attrition | .20 | 0.70  | 0.46 | -.16| -.18 | -.10 | -.28 | .08  | .02  | -.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 to 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 prompts questions, trainees who were asked questions designed to interrupt learning but not stimulate self-regulatory activity, and a control condition that was 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 to 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, match planned and actual dates, and procrastination were calculated for the 231 trainees in the planning condition; due to missing data, Ns ranged from 171-231. The remaining between-subjects correlations utilized data from all 488 trainees; due to missing data, Ns ranged from 329-488. Ns for the within-subjects correlations ranged from 377-461.*

*p < .05 (two-tailed).
Table 2

Results Examining the Effects of the Planning and Prompts Interventions on Learning and Attrition

<table>
<thead>
<tr>
<th></th>
<th>Hyp. 1 Learning</th>
<th>Hyp. 1 Learning</th>
<th>Hyp. 1 Attrition</th>
<th>Hyp. 1 Attrition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>0.67†</td>
<td>-0.68†</td>
<td>-0.70†</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.15)</td>
<td>(0.17)</td>
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<tr>
<td>Module(^a)</td>
<td>-0.03†</td>
<td>-0.03†</td>
<td>-0.20†</td>
<td>-0.20†</td>
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<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Age(^b)</td>
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<td>0.00</td>
<td>-0.02†</td>
<td>-0.02†</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Pretraining familiarity with topic of training(^b)</td>
<td>0.04†</td>
<td>0.04†</td>
<td>-0.30†</td>
<td>-0.30†</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Planning intervention(^b)</td>
<td>0.02</td>
<td>-0.03</td>
<td>-0.05</td>
<td>-0.01</td>
</tr>
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<td></td>
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<td>(0.03)</td>
<td>(0.14)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Prompting self-regulation condition vs. control(^b)</td>
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<td>-0.12</td>
<td>0.06</td>
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<td>(0.03)</td>
<td>(0.17)</td>
<td>(0.23)</td>
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<tr>
<td>Interrupting questions condition vs. control(^b)</td>
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<td>-0.03</td>
<td>-0.15</td>
</tr>
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<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.16)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Planning intervention x Prompting self-regulation condition</td>
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<td>-0.39*</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.34)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planning intervention x Interrupting questions condition</td>
<td>0.05</td>
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<tr>
<td></td>
<td>(0.05)</td>
<td>(0.33)</td>
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</tbody>
</table>

Note: Hyp. indicates hypothesis. Mixed-effects modeling was used to predict learning and hierarchical generalized linear modeling was used to predict attrition. In the analyses predicting learning, the top number is the fixed effect and the bottom number is the standard error. In the analyses predicting attrition, the top number is the logit and the bottom number is the standard error. Attrition was coded such that 0 indicates that trainees completed the module and 1 indicates that trainees dropped out in the module. The planning intervention was dummy coded such that trainees who received the intervention (coded 1) were compared to 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 prompts questions, trainees who were asked questions designed to interrupt learning but not stimulate self-regulatory activity, and a control condition that was 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 to the control condition (coded 0). 

\(^{1}\)Analyses with main effects.

\(^{2}\)Analyses with main effects and interactions.

\(^{a}\)Within-subject predictor.

\(^{b}\)Between-subjects predictor.

†p < .05 (two-tailed for non-hypothesized effects).

*p < .05 (one-tailed for hypothesized effects).
### Table 3

**Results Examining the Relationships between Trainees’ Plans, Time on Task, Procrastination, Learning, and Attrition**

<table>
<thead>
<tr>
<th></th>
<th>Hyp. 3</th>
<th>Hyp. 6</th>
<th>Hyp. 4 &amp; 7</th>
<th>Hyp. 5 &amp; 8</th>
<th>Hyp. 9</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time on Task</td>
<td>Procrastination</td>
<td>Learning</td>
<td>Learning</td>
<td>Attrition (in subsequent module)</td>
</tr>
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<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.30)</td>
</tr>
<tr>
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<td>-0.03†</td>
<td>-0.04†</td>
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</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.14)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Age&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.03†</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Pretraining familiarity with</td>
<td>-0.06</td>
<td>-0.15</td>
<td>0.04†</td>
<td>0.04†</td>
<td>-0.32</td>
</tr>
<tr>
<td>topic of training&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(0.05)</td>
<td>(0.17)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Prompting self-regulation</td>
<td>0.07</td>
<td>0.25</td>
<td>0.08†</td>
<td>0.07†</td>
<td>-0.44</td>
</tr>
<tr>
<td>condition vs. control&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(0.11)</td>
<td>(0.39)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.38)</td>
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<tr>
<td>Interrupting questions condition vs. control&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.17</td>
<td>0.51</td>
<td>0.04</td>
<td>0.04</td>
<td>-0.33</td>
</tr>
<tr>
<td>Planned amount of time for training&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.05*</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
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<tr>
<td></td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Time on task&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.05†</td>
<td>0.05†</td>
<td>-0.42</td>
<td>-0.47†</td>
<td>0.04</td>
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<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Match planned &amp; actual dates&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-3.90*</td>
<td>0.02</td>
<td>0.01</td>
<td>1.01†</td>
<td>1.02†</td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.48)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>Procrastination&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.04)</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>Learning&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td>-0.92*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.46)</td>
<td></td>
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<tr>
<td>Planned amount of time for training x Time on task</td>
<td>0.02*</td>
<td>-0.40*</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.25)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date match x Procrastination</td>
<td>-0.02*</td>
<td>0.06</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.12)</td>
<td></td>
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Note: Hyp. indicates hypothesis. Mixed-effects modeling was used to predict time on task, procrastination, learning, and planned amount of time in the subsequent module. In these analyses, the top number is the fixed effect and the bottom number is the standard error. Hierarchical generalized linear modeling was used to predict attrition; the top number is the logit and the bottom number is the standard error. Attrition was coded such that 0 indicates that trainees completed the module and 1 indicates that trainees dropped out in the module. There were three conditions in the prompting self-regulation manipulation: trainees who were asked self-regulation prompts questions, trainees who were asked questions designed to interrupt learning but not stimulate self-regulatory activity, and a control condition that was 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 to the control condition (coded 0). \( N \) ranged from 149 for the analyses predicting outcomes in the subsequent module to 203 for the analyses predicting outcomes in the current module.

1. Analyses with main effects.
2. Analyses with main effects and interactions.
   a. Within-subject predictor.
   b. Between-subjects predictor.
   † \( p < .05 \) (two-tailed for non-hypothesized effects).
   * \( p < .05 \) (one-tailed for hypothesized effects).
Figure 1. Model of the effect of following through on trainees’ plans on the learning process.
Figure 2. Graph of the interaction between the planning and prompts interventions when predicting learning.
Figure 3. Graph of the interaction between the planning and prompts interventions when predicting attrition.
Figure 4. Graph of the interaction between trainees’ planned and actual time on task when predicting learning.
Figure 5. Graph of the interaction between trainees’ planned and actual time on task when predicting attrition from the subsequent module.
Figure 6. Graph of the interaction between the degree of similarity among trainees’ planned and actual training dates and procrastination when predicting learning.