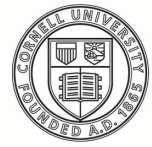
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A Multilevel Analysis of the Effects of Technical Interruptions on Learning and Attrition From Web-Based Instruction

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Abstract

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Keywords

interruptions, technical difficulties, self-regulation, attrition, web-based training

Comments

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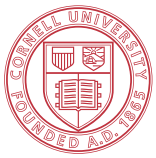

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Working Paper 08 – 11

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This paper has not undergone formal review or approval of the faculty of the ILR School. It is intended to make results of Center research available to others interested in preliminary form to encourage discussion and suggestions.

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Abstract

As training is increasingly integrated in the workplace and embedded in work technology, trainees are confronted by a variety of workplace and technological interruptions. This article presents a conceptual framework characterizing different types of interruptions and the extent to which they disrupt learning. A longitudinal design was then used to examine the effects of one form of interruption—technical difficulties—on trainees' (N = 530) self-regulatory processes, learning, and attrition from Web-based instruction. Test scores were 1.33 points lower (out of 20) in modules where trainees encountered technical difficulties. Technical difficulties also had differential effects on attrition rates over time with attrition from the first module being 10 percentage points higher for trainees who encountered these interruptions. Technical difficulties increased negative thoughts and impaired learning more for trainees who dropped out than those who completed the course. Finally, the negative effects of technical difficulties on self-regulatory processes were less for trainees with high technology self-efficacy, but self-efficacy did not mitigate the negative effects of technical difficulties on learning. The implications of these findings for future research and practice are discussed.

Keywords

Interruptions; Technical difficulties; Self-regulation; Attrition; Web-based training

A Multilevel Analysis of the Effects of Technical Interruptions on Learning and Attrition from Web-Based Instruction

Across a wide range of occupations, employees are interrupted repeatedly throughout the workday. An interruption occurs when an individual encounters an "externally generated, randomly occurring, discrete event that breaks continuity of cognitive focus on a primary task" (Corragio, 1990, p. 19). Some common workplace interruptions include e-mails, telephone calls, and colleagues dropping by to chat or ask a work-related question. In fact, 38% of employees reported experiencing six or more interruptions per hour and 32% reported being distracted by interruptions in the average work day (Pitney Bowes, 2000). Additionally, O'Conaill and Frolich (1995) suggested that over 40% of the time, managers do not return to their original task after being interrupted.

Interruptions break attention from a primary task—redirecting an individual's attention towards the interruption. The result is cognitive interference and increased information processing demands, which can lead to the processing of fewer information cues, memory loss, and confusion among information cues residing in memory (Speier, Vessey, & Valacich, 2003). Indeed, research examining the effects of interruptions on performance suggests that interruptions decrease task efficiency by increasing processing time and errors (Cellier & Eyrolle, 1992; Gillie & Broadbent, 1989; Monk, Boehm-Davis, & Trafton, 2004; Zijlstra, Roe, Leonora, & Krediet, 1999).

Despite a growing body of research on interruptions and performance, few studies have examined the effects of interruptions during training (Langan-Fox, Armstrong, Balvin, & Anglim, 2002). Yet, as the move towards technology-delivered instruction takes training out of the formal classroom environment—allowing for instruction anytime and anywhere—the potential for interruptions greatly increases. For example, a recent study conducted by Skillsoft of over 200 employees across 16 organizations and 14 countries found that 77% of those surveyed reported

being unable to complete Web-based courses in one attempt (Baldwin-Evans, 2004). These individuals cited time constraints and workplace interruptions as the most common reasons for failing to complete a course in one attempt. This is not surprising given that 68% of the respondents indicated they participate in online learning at their desk as opposed to in a special learning area or at home.

In Web-based training environments, trainees may encounter a unique type of interruption, technical difficulties, which results from the nature of technology-delivered instruction. Technical difficulties refer to interruptions that individuals encounter when interfacing with technology, such as not being able to access the training content due to a dropped Internet connection. Previous research has found technical difficulties tend to result in trainees experiencing increased frustration (North, Strain, & Abbott, 2000) and have a negative effect on satisfaction with the instructional experience (Wentling, Park, & Pieper, 2007), which may be one reason why attrition rates are often higher in Web-based than in traditional classroom instruction (Welsh, Wanberg, Brown, & Simmering, 2003). The goal of the current study was to extend research on workplace interruptions to understand how technical difficulties influence self-regulation, learning, and attrition in Web-based instruction.

The current research makes several contributions to the interruptions and training literatures. First, we review and synthesize research on interruptions to delineate dimensions that characterize different types of interruptions and their potential effects on performance. This typology is used to understand the nature of the technical difficulties examined in the current study and to provide a theoretical foundation for hypothesizing the effects of technical difficulties on learning processes and training outcomes. Second, we use a longitudinal, experimental design to test our hypotheses and clarify how technical difficulties influence self-regulatory processes, learning, and attrition. Our methodological approach is consistent with recent research that suggests modeling change over time is a critical element of understanding the

learning process (Smillie, Yeo, Furnham, & Jackson, 2006; Yeo & Neal, 2008). Third, numerous observers have noted that attrition may be problematic in Web-based courses (e.g., Rosset & Schafer, 2003; Welsh et al., 2003), but our understanding of the factors that drive attrition in technology-delivered instruction remains limited. In the present study, we focus attention on this issue by examining whether technical difficulties increase attrition and whether the effects of technical difficulties on self-regulatory processes and learning differ for trainees who drop out of training relative to trainees who complete the course. Finally, a growing body of research suggests individual differences influence trainees' self-regulatory processes and learning over time (e.g., Donovan & Williams, 2003; Yeo & Neal, 2004). The current study contributes to this research stream by examining whether trainees' technology self-efficacy moderates the effects of technical difficulties on self-regulation and learning. In the following section, we present a typology of interruptions and then use this typology to explore the potential effects of technical difficulties, as one specific form of interruption, on training outcomes.

A Typology of Interruptions

Interruptions can take many different forms, and the degree to which an interruption influences task performance varies based on the nature of the interruption (Kahneman, 1973). Prior research suggests that interruptions vary across three main dimensions: temporal factors, content of the interruption, and urgency (Gillie & Broadbent, 1989; Speier et al., 2003; Zijlstra et al., 1999; see Table 1). Temporal factors include the frequency, duration, and timing of the interruption. Each time individuals are interrupted, they require a period of recovery to reprocess some of the primary task information (Kahneman). Therefore, more frequent interruptions, such as receiving e-mail alerts whenever there is a new message rather than a digest of all messages once a day, lead to higher levels of cognitive load and a greater chance of errors (Speier, Valacich, & Vessey, 1999). Duration refers to the length of time that the interruption draws attention away from the primary task. As the length of interruptions increase, it becomes

more likely that an individual will forget some of the information needed to perform the primary task and have difficulty resuming performance routines. Additionally, interruptions can occur at any point during a task, with research suggesting that interruptions during the middle of a task require a longer time to resume the primary task than interruptions occurring at the beginning of the task or between subtasks (Monk et al., 2004). Taken together, interruptions that are more frequent, last longer, and occur in the middle of tasks are more disruptive to performance.

Table 1
Dimensions of Interruptions and the Extent to which they Disrupt Performance

	Magnitude of Disruption	
Dimension	***Low*** ⟷	***High***
Temporal factors – Frequency – Duration – Timing	Infrequent, short duration, beginning of task or between subtasks	Frequent, long duration, in the middle of task
Content – Relevance – Complexity	Relevant to primary task, low complexity	Irrelevant to primary task, high complexity
Urgency – Synchronicity – Source – Consequence	Asynchronous, low status source, inconsequential	Synchronous, high status source, significant impact

A second important dimension is information content, which includes both the relevance and complexity of the interruption. When the interruption is irrelevant to the primary task, the required cognitive processing resources and information load increases (Biggs, Bedard, Gaber, & Unsmeier, 1985; Evaristo, Adams, & Corley, 1995). Interruptions that introduce irrelevant content require an individual to process more information cues and may require different types of information processing (e.g., symbolic vs. spatial; Iselin, 1988). Cognitive load theory refers to these additional cognitive demands as extraneous load, because they are unnecessary and extrinsic to the primary task (Sweller, van Merrienboer, & Paas, 1998). A high level of extraneous load increases the likelihood that an individual's cognitive capacity will be exceeded

(Sweller, 1988). Research also suggests that the complexity of attending to the interruption is important for determining how disruptive the interruption is to performance (Gillie & Broadbent, 1989). If an interruption is complex and requires a high level of cognitive focus, less resources can be devoted to the primary task. Thus, interruptions that are irrelevant to the primary task content and are cognitively complex are likely to produce higher levels of cognitive load and be more detrimental to performance.

The third dimension, urgency, refers to whether or not the interruption requires an immediate response or action. This is determined by the interruption's synchronicity, source, and the consequence of nonresponse. Workplace interruptions can be categorized as either synchronous or asynchronous. Synchronous interruptions occur in real time and include face-to-face chats, telephone calls, and instant messaging. Asynchronous interruptions do not require an immediate response and include e-mails and text messages. Given that an immediate response is expected in the case of synchronous interruptions, employees frequently allow these types of interruptions to take priority over other workplace activities (Watson, Raineier, & Koh, 1991). The source of the interruption refers to the status of the individual who generated the message and his/her importance to one's professional or personal life. Interruptions generated by individuals with more status (e.g., supervisors vs. peers) are generally more disruptive because employees are more likely to shift attention to responding to the interruption. Consequence refers to whether or not failing to respond to the interruption potentially has negative consequences on some aspect of one's life, including being able to complete the primary task. When interruptions are perceived as potentially having negative consequences, employees are more likely to attend to them and respond promptly.

Technical Difficulties in Web-Based Instruction

In the early years of classroom-based distance education, technological issues were a persistent cause of concern. Technology was often unreliable, resulting in dropped connections

and degraded images, and the novelty of the medium led to usability problems among both instructors and students (Cavanaugh, Milkovich, & Tang, 2000; Collis, 1995; Webster & Hackley, 1997). Research found that these technological issues typically had a negative effect on important training outcomes (Cavanaugh et al., 2000; Webster & Hackley, 1997). Although technological advances solved many of these early issues with distance education, new technological issues have emerged as organizations adopt new delivery media (e.g., the Web) and technology-delivered instruction moves out of the classroom (Tai, 2007). Today, self-paced online learning is the most frequently utilized form of Web-based instruction, and instructor-led distance education accounts for less than a third of all online learning in the average organization (Paradise, 2007).

Two of the most common technical difficulties in Web-based instruction are low bandwidth and incorrect configurations (i.e., browser or computer settings; Munzer, 2002). The effects of these technical difficulties during Web-based instruction depends on the nature of the interruption relative to the three dimensions identified earlier—temporal factors, content, and urgency. For example, low bandwidth issues, which result in a delay as content is loaded, occurs throughout training (frequent; middle of task), are irrelevant to the training content, and occur in real time as employees participate in training (synchronous). Yet, the length of the interruption is limited (short duration), is resolved without action by the trainee (low complexity), and does not prevent the trainee from completing training (low impact). Thus, low bandwidth issues are likely to create a moderate level of disruption. Technical difficulties stemming from incorrect configurations are also likely to create a moderate level of disruption because they are irrelevant to the training content, require action by the trainee to resolve, occur in real time, and can have a significant impact on the trainees' ability to view content if not resolved. Yet, configuration issues typically occur at the beginning of the program, interrupt less frequently during training, and have a short duration (e.g., an error message or warning). The typology

highlights the fact that these two types of technical difficulties differ on a number of dimensions (e.g., frequency, timing) but also share several similarities (e.g., unrelated to training content, occur in real time) and, overall, should create a similar level of disruption. In the following sections, we use the typology of interruptions as well as theories of cognitive load and self-regulation to develop hypotheses surrounding the effects of technical difficulties on attrition, learning, and self-regulation during Web-based instruction.

Technical Difficulties and Attrition

Although there are several existing models of the student attrition process (e.g., Bean, 1980; Spady, 1970; Tinto, 1975), most were developed to explain attrition of non-traditional students from college settings. Further, these models include commitment to the academic institution and social integration factors, which may not be relevant in asynchronous, organizational training courses. Outside of the education literature, Mobley, Hand, Baker, and Meglino (1979) used expectancy theory (Vroom, 1964) to examine attrition from military training. They found that trainees' expectancies of success in their Marine enlistment predicted attrition. Expectancy theory is also likely to provide a basis for understanding attrition in voluntary organizational training. Expectancy theory proposes the belief that increased effort will result in improvements in training performance is a key determinant of motivation. If trainees perceive that technical difficulties limit the amount that they will learn in training, encountering technical difficulties may have a negative effect on trainees' expectancies, decreasing motivation to complete the course. In addition, after a trainee attends to a technical interruption, he or she must be motivated to return to the training (Zijlstra et al., 1999). If trainees become frustrated or overwhelmed when they encounter technical difficulties, they may withdraw from the situation by dropping the course.

H1: Attrition will be higher when trainees encounter technical difficulties than when they do not encounter technical difficulties during training.

Technical Difficulties and Learning

Technical difficulties interrupt trainees' learning processes. Cohen's (1978; 1980) cognitive fatigue model suggests that interruptions are uncontrollable and unpredictable stressors that produce information overload, leading to cognitive fatigue. Technical difficulties can produce appreciable mental strain as well as increase employees' heart rate, blood pressure, and the extent to which they are irritated, tired, and unable to relax (Johansson & Aronsson, 1984). Technical difficulties during training increase the cognitive load imposed on trainees—leaving trainees with fewer resources to devote towards learning the course content (Sweller et al., 1998).When cognitive overload occurs, it may result in trainees forgetting some of the information they were processing, such that information is lost or not entered into long-term memory, leading to decrements in learning (Speier et al., 1999).

H2: Trainees will learn less in modules where they encounter technical difficulties than in modules where they do not encounter technical difficulties.

Self-Regulatory Processes and Learning

Self-regulation may be employees' most essential asset (Porath & Bateman, 2006), and the extent to which trainees continue to maintain affective and cognitive control should predict learning. Failing to regulate one's emotions impairs learning and performance because negative emotions direct attention away from training towards oneself (Kanfer, Ackerman, & Heggestad, 1996; Kozlowski & Bell, 2006). Emotion control enables trainees to harness and use emotions to facilitate decision making and problem solving (Salovey, Hsee, & Mayer, 1993), which should ultimately improve performance. Research also suggests cognitive regulation has a positive effect on learning and academic achievement (e.g., Lee, Sheldon, & Turban, 2003; Pintrich & De Groot, 1990; Schunk & Zimmerman, 1994). Recently, Kozlowski and Bell (2006) found self-regulatory processes explained between 6% and 21% of the variance in trainees' knowledge and performance, after controlling for individual differences and training manipulations. Self-

efficacy and self-evaluation activity had a positive effect on knowledge and performance while negative affect and off-task thoughts had a negative effect.

> *H3: Self-regulatory processes will have a positive effect on learning such that trainees will learn more when they experience fewer negative thoughts, exhibit higher levels of mental focus, and engage in more metacognitive activity.*

Technical Difficulties and Self-Regulatory Processes

Action regulation theory (Greiner, Ragland, & Fisher, 1997; Hacker, 1978, 1992) can be used to understand the psychological process by which trainees respond to stressful situations, such as encountering technical difficulties during training. This theory suggests that during goal-directed activities, individuals engage in strategies to facilitate goal attainment, continually monitor their goal progress, and revise their strategies if they detect that goal progress is not being made. When things go wrong and people fear they are not going to reach the standard they set for successful performance, panic sets in (Davis, 1948; van der Linden, Sonnentag, Frese, & van Dyck, 2001). This results in disorganization in subsequent behavior and impairs self-regulation. Loss of control can result in an emergency reaction in which trainees act rapidly in ways that do not enable goal attainment (Dörner & Wearing, 1995; van der Linden et al.).

In the current study, we examined the extent to which technical difficulties influenced three self-regulatory processes—negative thoughts, mental focus, and metacognition. Johansson and Aronsson (1984) found technical breakdowns resulted in trainees feeling irritated and unable to relax. Similarly, Zijlstra et al. (1999) found that workers who had been interrupted reported significantly less positive emotional states than workers who had not been interrupted. This suggests trainees should have difficulty controlling their emotions when they encounter technical difficulties and, thus, negative thoughts should increase. When trainees devote attentional resources towards negative thoughts, fewer resources are available for thinking about the training material and developing strategies for learning (Kanfer & Ackerman,

1989; Mikulincer, 1989). This suggests interruptions should decrease mental focus on the training material. Also, in the current study metacognition focused on the extent to which trainees monitored their learning and engaged in strategies for mastering the course content, rather than developing strategies to overcome the interruptions. When trainees encounter technical difficulties, they are likely to engage in less metacognitive activity pertinent to the training material.

> *H4: Technical difficulties will have a negative effect on self-regulatory processes such that trainees will experience more negative thoughts, focus less of their mental resources on the training material, and engage in less metacognitive activity in modules where they encounter technical difficulties than in modules where they do not encounter technical difficulties.*

Comparison of Learning and Self-Regulatory Processes for Completers versus Dropouts

Training research often ignores the extent to which attrition influences the relationships between antecedents of learning processes and learning and, via list-wise deletion, those who drop out of training are removed from all analyses (e.g., Barker, 2002; Fordis et al. 2005; Johnson, Aragon, Shaik, & Palma-Rivas, 2000; O'Neil & Poirier, 2000). Research that excludes dropouts may suffer from nonrandom mortality, which threatens the internal validity of the results (Cook & Campbell, 1979). Although it is intuitive that there are critical differences between trainees who drop out and trainees who complete a course, no studies to date have explicitly compared these groups.

We believe the effects of technical difficulties on self-regulatory processes and learning differ for completers and dropouts. Trainees who drop out are likely to have lower levels of goal commitment for completing the course (Bean & Metzner, 1985) and, when they encounter interruptions, may be more easily disrupted from learning the training material. Relative to trainees who complete the course, trainees who drop out should have difficulty maintaining their affective and cognitive self-regulatory processes and learn less when faced with technical

difficulties. This is consistent with research by Kanfer, Ackerman, Murtha, Dugdale, and Nelson (1994) that suggests trainees who are unable to control their emotions or manage their motivation are more likely to withdraw from training. This suggests that for trainees who drop out of training, technical difficulties contribute to an overall failure of the learning process—impairing self-regulatory processes and learning.

> *H5: The effect of technical difficulties on self-regulatory processes and learning will be more negative for trainees who drop the course than for trainees who complete the course.*

Technology Self-Efficacy

A growing body of research has shown that individual differences influence trainees' learning and self-regulatory processes over time (e.g., Donovan & Williams, 2003; Yeo & Neal, 2004, 2008). This research suggests that although technical difficulties may impede self-regulation and learning among all trainees, the magnitude of these effects may vary across individuals. In Web-based instruction, technology self-efficacy reflects an important trait that may moderate the effects of technical difficulties. Technology self-efficacy refers to trainees' confidence in both their computer skills and their ability to overcome technical difficulties. Judgments of efficacy have been shown to predict effort, persistence, and resilience when faced with obstacles (Bandura, 1986, 1997). Self-efficacy also influences affect, as the range of emotions that trainees experience in difficult situations depends on their efficacy for coping with the situation (Bandura, 1997). Within an online training environment, trainees' technology self-efficacy should be an important moderator of the effect of technical difficulties on self-regulatory processes and learning. When confronted with technical difficulties, trainees with high efficacy should continue to persist and direct their effort towards learning the training material, while remaining calm and not allowing technical difficulties to influence their learning.

H6: Technology self-efficacy will moderate the relationships between technical difficulties and both self-regulatory processes and learning, such that the effects of technical difficulties will be less negative for trainees with high rather than low technology self-efficacy.

Summary

In summary, we propose technical difficulties increase attrition from Web-based training (H1) and decrease learning (H2), such that trainees will be more likely to drop out and will learn less in modules where they encounter technical difficulties. Self-regulatory processes will also predict learning such that trainees will learn more when they experience fewer negative thoughts, exhibit higher levels of mental focus, and engage in more metacognitive activity (H3), but technical difficulties will impair trainees' self-regulatory processes (H4). In addition, the effect of technical difficulties on self-regulatory processes and learning will differ for trainees who complete the course and trainees who drop out (H5), highlighting the value of modeling the effects of attrition in training. Finally, technology self-efficacy will moderate the effect of technical difficulties on both self-regulatory processes and learning (H6).

Method

Participants

Five-hundred thirty adults were recruited online and received free training in exchange for research participation. The majority of participants were employed full- or part-time (75%) and 51% held a bachelor's or more advanced degree. The average age of participants was 41 years and 69% were female.

Experimental Design and Procedure

Advertisements for free Microsoft Excel training were posted on Internet community sites and noted the benefits of Excel skills for advancing one's career. After responding to the online

posting, all interested participants were sent a username, password, and a link to the learning management system where the course was hosted. The training consisted of a five-hour Web-based course, which was divided into four modules that covered a variety of Excel functions including formatting cells, formulas, graphing, and pivot tables. The instruction was text-based and included screen shots demonstrating how to perform various functions in Excel. The data used in the examples was available for trainees, and they were encouraged to open Excel and practice the functions as they were demonstrated.

Trainees were given a high level of control over the pace of instruction; they could choose the amount of time spent on each module and complete the course in a single day or spread it out over several weeks.[1] However, trainees were required to review all of the modules 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.

In the current study, interruptions were operationalized as error messages embedded in the training to simulate technical difficulties. Technical difficulties were selected to meet the definitional requirement of an interruption as "an externally generated, randomly occurring, discrete event that breaks continuity of cognitive focus on a primary task" (Corragio, 1990, p. 19). As it is inevitable that technical difficulties occasionally occur in Web-based instruction (Waterhouse & Rogers, 2004), embedding error messages in the course content created plausible interruptions. As discussed earlier, low bandwidth and incorrect configurations are two of the most common technical difficulties in Web-based instruction (Munzer, 2002). Because we could not manipulate participants' bandwidth or computer configurations, we were unable to replicate these specific technical difficulties. But, the interruptions introduced in the current study possessed many of the same underlying characteristics and were designed to create a similar

[1] We examined days required to complete the course as a moderator variable and found the effect of technical difficulties on learning over time did not differ according to completion times.

(moderate) level of disruption. With regards to temporal factors, the error messages appeared with moderate frequency, lasted a short duration, and were embedded throughout the course content. The content of the error messages was unrelated to the training material and was of moderate complexity. The urgency of the error messages was moderate, given that they occurred in real time and required an immediate response, but the consequence was low because the error messages had no bearing on trainees' ability to access the course content.

Before beginning the course, trainees were randomly assigned to one of eight experimental conditions. The conditions differed based on both the number of modules with technical difficulties (zero to four) and the pattern of which of the four modules contained error messages embedded in the course content. For example, one condition received error messages in modules one and three, a second condition received error messages in modules three and four, and a third condition received error messages in all four modules. In the modules with technical difficulties, six error messages were inserted in the training slides such that when trainees attempted to access the slide an error message would appear. Examples of error messages included in the course are "Browser alert: The current file system is not optimized for your browser. You may experience technical difficulties," and "Invalid Request: The request you have made cannot be processed at this time. Please make a new request." When trainees clicked the next button they progressed to a new slide and the error message disappeared. No error messages were inserted in the modules that did not include technical difficulties. Trainees received the same course content regardless of whether they were assigned to a condition with error messages.

Measures

The measures used in this study were administered at five points in time. Demographics and technology self-efficacy were collected before participants began the training program. Self-regulatory processes and learning were measured at the end of each of the four training

modules. Trainees responded to the technology self-efficacy and self-regulatory process measures on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Technology self-efficacy. Technology self-efficacy was measured with five items developed for the purpose of the current study. Sample items include, "I have the computer skills necessary to succeed in most situations," and "I am confident I can overcome technical difficulties during training." Coefficient alpha was .83.

Negative thoughts. Negative thoughts during training were assessed using five items adapted from Kanfer et al. (1994). Sample items include, "I got mad at myself during training," and "I became frustrated with my inability to improve my performance." Reliabilities across the four modules ranged from .80 to .84.

Mental focus. Mental focus was assessed using six items from Lee et al. (2003). Sample items include, "During the training, I had good concentration," and "During the training, I became easily absorbed in the training material." Reliabilities across the four modules ranged from .84 to .92.

Metacognition. Metacognition was assessed using six items adapted from Pintrich, Smith, Garcia, and McKeachie (1993). This measure was designed to assess metacognition for learning and includes items related to trainees' knowledge of and control over their learning activities. Sample items include, "While going through the training, I asked myself questions to make sure I understood the material that I had been reading," and "When going through the training material I ensured that I understood all of the key points presented." Reliabilities across the four points in time ranged from .76 to .88.

Learning. At the end of each module, trainees completed a 20-item multiple-choice assessment of declarative and procedural knowledge. Test questions assessed trainees' ability to remember factual information presented during training (e.g., "What do you call a group of defined cells? a) span, b) range, c) series, d) array"), while others contained screen shots and

assessed trainees' ability to remember the steps for performing Excel functions or how their actions will affect the appearance of an Excel spreadsheet (e.g., "Using track changes, your colleague changed the retail price of the Japanese Toothpick Holder in cell C11 from $100 to $200. If you reject the change in C11, what will be in cell C11? a) $100 with a comment that the change has been rejected, b) $200 with a comment that the change has been rejected, c) $100 with no comment, d) $200 with no comment"). Average test scores for the four modules ranged from 12.73 to 15.89 on a 20-point scale.

Manipulation Check

At the end of each module, participants answered two questions designed to examine the effect of the technical difficulties manipulation: "How often during the module you just completed did you experience technical difficulties?" and "While reviewing the training slides in this module, how often did you encounter computer errors?" Both items were rated on a five-point Likert scale (1 = never to 5 = very often). Coefficient alpha ranged from .85 to .94 across the four modules.

Data Analysis

Hierarchical linear modeling (HLM) with full maximum likelihood estimates was used to analyze the within-person results. We ran a series of analyses to analyze changes in learning and self-regulatory processes across the four training modules and used the model building procedure specified by Bliese and Ployhart (2002). For each outcome variable (i.e., learning and self-regulatory processes), we first ran the unconditional means (null) model to examine the variance in the outcome before accounting for any predictors. This model allowed for the calculation of an intraclass correlation coefficient, which partitions the variance into within- and between-person components. This permitted us to examine whether significant within- and between-person variance exists in test scores and each of the self-regulatory processes before running additional HLM models. Next, we added module as a covariate in all of the analyses

because time dependent analyses can be sensitive to order effects (Vancouver & Kendall, 2006). Module was centered such that the intercept represents scores at module one.

The next step of the initial model building sequence involved identifying the appropriate error structure of the random effects portion of the model. We followed Bliese and Ployhart's (2002) recommendation and 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, and we used the change in deviance statistics to decide which error structure provided the best fit for the data (Bliese & Ployhart).

After establishing the baseline model, we ran a series of analyses adding one fixed or random effect to the model at a time. All of the predictors, except for module, were grand mean centered. We used .05 as the criterion for significance for main effects. Consistent with previous research (Yeo & Neal, 2004, 2006), we interpreted cross-level interactions at the .10 level because of lowered parameter reliability (Snijders & Bosker, 1999).

One of the advantages of using HLM with a longitudinal design is the robustness of calculating parameters with all available data, despite missing data points (Bryk & Raudenbush, 1992; Ployhart, Holtz, & Bliese, 2002). Missing data can be ignored if it meets Rubin's (1976) missing at random assumption, meaning dropout is random. However, in the current study, we hypothesized that dropping out of training would be related to whether trainees encountered technical difficulties, self-regulatory processes, and learning. Thus, we used a pattern-mixture model for missing data, following the procedure outlined by Hedeker and Gibbons (1997). Pattern-mixture models divide subjects into groups depending on their missing data pattern and the grouping variable is used as a model covariate. In the current study, we created a completion status variable which indicates whether or not trainees completed the course (coded

1) or dropped out, meaning they completed at least one module but not the entire course (coded 0).[2] All analyses were then run three times. First, we ran analyses for all subjects who provided self-regulation and learning data to test the study hypotheses (*N* = 245). Second, we ran the exact same analyses including only completers in the dataset (i.e., the 101 participants who completed the course). Third, we created a pattern-mixture model. In this model, completion status was added as a predictor of the intercept, and we tested the interaction between completion status and each of the fixed effects in order to examine if the main effects differed for trainees who completed the course and those who dropped out. It is not conceptually sound to suggest that future attrition causes prior learning or self-regulatory processes, and testing this model does not imply causality (Sturman & Trevor, 2001). Rather, this model compares the learning and self-regulation slopes and provides a statistical test of whether the effects of technical difficulties on learning and self-regulatory processes differ for completers and dropouts.

HLM is appropriate for longitudinal data where the random effects are normally distributed (Raudenbush, Bryk, Cheong, & Congdon, 2004). However, the assumption of normality is not realistic with binary outcomes (e.g., attrition). Thus, we examined the effect of technical difficulties on attrition using hierarchical generalized linear modeling (HGLM) with the procedure specified by Raudenbush and colleagues. Completion status was coded 1 for modules where trainees remained in the course and 0 for modules when trainees were no longer in the course. Three predictors were included in the model—module, technical difficulties, and the interaction between technical difficulties and module—in order to examine if the probability of completing the course was predicted by whether trainees experienced technical difficulties and whether the effect of technical difficulties on attrition differed over time.

[2] Trainees who dropped out in the first module were not included in the pattern-mixture analyses because they did not provide self-regulation and learning data.

Results

Manipulation Check

Our first analysis used HLM to assess whether trainees reported experiencing more technical difficulties in modules where error messages were embedded in training than in modules without error messages. Technical difficulties (a repeated measure, dichotomous variable indicating whether error messages were present [coded 1] or absent [coded 0] in each module) was a significant predictor of perceptions of technical difficulties ($\gamma = 0.74$, $p < .05$). Trainees reported experiencing more technical difficulties in modules where error messages were embedded than in modules without error messages.

Within- and Between-Persons Correlations

Table 1 presents descriptive statistics and within- and between-persons correlations for study measures. At the between-persons level, learning was significantly correlated with technology self-efficacy ($r = .20$), negative thoughts ($r = -.33$), and mental focus ($r = .17$). At the within-person level, learning was significantly correlated with negative thoughts ($r = -.25$) and mental focus ($r = .25$). Learning was not significantly correlated with metacognition at the between-persons level ($r = -.01$), but was significantly related to metacognition at the within-person level ($r = .13$). Negative thoughts, mental focus, and metacognition were moderately to strongly related at the within- and between-persons levels of analysis (strength of the correlations ranged from .34 to .54 at the within-person level and .28 to .62 at the between-persons level).

Table 2
Descriptive Statistics and Correlations among Study Variables at the Between- and Within-Person Levels of Analysis

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Technology self-efficacy	3.83	0.68	-						
2. Negative thoughts	2.15	0.63	-.34*	-	-.54*	-.38*	-.25*	-.04	.01
3. Mental focus	3.62	0.61	.12	-.62*	-	.34*	.25*	.08	-.03
4. Metacognition	3.52	0.53	.02	-.28*	.35*	-	.13*	.04	-.08
5. Learning	14.45	3.22	.20*	-.33*	.17*	-.01	-	.00	-.01
6. Attrition	0.19	0.39	.01	-.04	-.03	.06	.11	-	-.01
7. Technical difficulties	0.48	0.50	-	-	-	-	-	-	-

Note. Between-persons correlations are below the diagonal while within-person correlations are above the diagonal. For the between-persons correlations, attrition is coded such that 1 indicates trainees completed the course and 0 indicates trainees dropped the course. For the within-person correlations, attrition is coded such that 1 indicates trainees completed the module and 0 indicates trainees did not complete the module. Technical difficulties are coded such that 1 indicates trainees received error messages in the module and 0 indicates trainees did not receive error messages in the module.
* $p < .05$

Attrition

In the current study, trainees were classified into three categories: early dropouts (entered the training course but withdrew before completing the first module), dropouts (completed at least one module, but withdrew before completing the final module), and completers. Within our sample, there were 275 early dropouts, 154 dropouts, and 101 completers.

The first set of analyses tested Hypothesis 1, which states that attrition is greater when trainees encounter technical difficulties than when trainees do not encounter technical difficulties. Thus, we used HGLM to examine if attrition rates for the four modules were related to whether technical difficulties were embedded in the training material. The results suggest technical difficulties did not have a significant main effect on attrition. However, module ($\gamma = -1.01$; $p < .01$) and the module by technical difficulties interaction ($\gamma = 0.21$; $p < .10$) predicted attrition, indicating technical difficulties had a greater effect on attrition at the beginning than towards the end of training. Five-hundred thirty trainees completed the pretraining survey and began the first module (see Table 3). Forty-seven percent of trainees who were assigned to a condition without error messages in module one dropped the course while 57% of trainees who

were assigned to a condition with error messages in module one dropped the course. Thus, technical difficulties resulted in a 10-percentage point increase in the attrition rate in the first training module.[3] In addition, the overall completion rate was 21%, with only 18% of trainees completing the course when they were assigned to conditions with technical difficulties in at least one of the modules. Overall, these results partially support Hypothesis 1 and indicate technical difficulties increased attrition more towards the beginning than the end of training.

Table 3
Attrition Rates for the Four Modules Based on whether Trainees were Assigned to a Condition with Technical Difficulties Embedded in the Module

Module	Number of Trainees who Entered the Training Module	Attrition Rates	
		No Technical Difficulties During Module	Technical Difficulties During Module
1	530	47.1% (*N* = 128)	57.0% (*N* = 147)
2	255	34.5% (*N* = 51)	29.0% (*N* = 31)
3	177	29.2% (*N* = 26)	26.2% (*N* = 22)
4	125	19.6% (*N* = 10)	18.9% (*N* = 14)

Note. Percentage is based on the proportion of trainees assigned to a condition who dropped the course during the module.

In the current study, we were able to examine the effect of technical difficulties on attrition for all three types of learners. However, early dropouts are not included in the HLM pattern-mixture analyses, given that trainees needed to complete at least one module for us to assess their self-regulatory processes and learning.

Predicting Learning

As mentioned earlier, the procedure outlined by Hedeker and Gibbons (1997) was followed when running the HLM analyses. Thus, we ran three sets of analyses to test each hypothesis: 1) analyses with the entire dataset (*N* = 245) without accounting for completion status, 2) analyses with data from the 101 trainees who completed the entire course, and 3) pattern-mixture analyses, which models the effects of completion status (*N* = 245). When

[3] In a post hoc analysis we examined whether technical difficulties were more likely to increase attrition the first time they were encountered (regardless of which module trainees were completing) or if trainees were more susceptible to the effect of technical difficulties in module one. The results indicate the probability of dropping out during modules two through four was not influenced by whether trainees were assigned to a condition with technical difficulties in a previous module.

describing our results, we will focus primarily on the pattern-mixture analyses and note when there are substantial differences across the three sets of analyses.

The first step in building the growth model for learning involved estimating the ICC. The ICC value was .28, indicating that 28% of the variance in learning was attributable to between-person differences and 72% was explained by within-person variability over time. Next, we added module to the analyses to control for order effects. Then predictors were added to the model in order of theoretical importance as specified by Bliese and Ployhart (2002). Instead of reporting changes in parameters as each fixed and random effect was added to the model, the results presented are based on the final model.

The results of the final model predicting learning are presented in Table 4. Hypothesis 2 predicts that trainees learn less in modules where they encounter technical difficulties than in modules where they do not encounter technical difficulties. In support of our hypothesis, technical difficulties had a significant negative effect on learning, γ = -1.33. This suggests that in modules where trainees encountered technical difficulties, their test scores were 1.33 points lower (out of 20) than in modules where they did not encounter technical difficulties.

Hypothesis 3 predicts that negative thoughts have a negative effect on learning, while mental focus and metacognition have positive effects on learning. Negative thoughts impaired learning (γ = -1.57), such that for every one-point increase in negative thoughts, test scores decreased by 1.57 points. Mental focus did not have a significant main effect on learning while metacognition had a negative effect on learning, γ = -1.72. For every one-point increase in trainees' metacognition, test scores decreased by 1.72 points, which is opposite the hypothesized direction. Taken together these results partially support Hypothesis 3.

Table 4

HLM Results Examining the Effects of Technical Difficulties, Self-Regulatory Processes, Technology Self-Efficacy, and Completion Status on Test Scores

	All Subjects (*N* = 245)	Completers (*N* = 101)	Pattern-mixture (*N* = 245)
Intercept	15.84*	16.84*	15.76*
	(0.22)	(.26)	(0.30)
Module[a]	-0.71*	-0.86*	-1.35*
	(0.12)	(0.13)	(0.29)
Technical difficulties[a]	-0.55*	-0.24	-1.33*
	(0.27)	(0.31)	(0.41)
Negative thoughts[a]	-1.06*	-0.35	-1.57*
	(0.26)	(0.31)	(0.35)
Mental focus[a]	0.49†	0.26	0.60
	(0.25)	(0.27)	(0.40)
Metacognition[a]	-0.53*	0.24	-1.72*
	(0.27)	(0.30)	(0.37)
Technology self-efficacy[b]	0.26	-0.17	0.14
	(0.31)	(0.35)	(0.29)
Technical difficulties x Technology self-efficacy	0.65†	0.48	0.78*
	(0.39)	(0.47)	(0.38)
Completion status[b]			0.89†
			(0.43)
Module x Completion status			0.60†
			(0.32)
Technical difficulties x Completion status			1.13*
			(0.53)
Negative thoughts x Completion status			1.28*
			(0.48)
Mental focus x Completion status			-0.28
			(0.49)
Metacognition x Completion status			2.10*
			(0.51)

Note: The top number is the fixed effect coefficient while the number in parentheses is the standard error. Completion status was coded such that 1 indicates trainees completed the course and 0 indicates trainees dropped the course.
[a]Within-person predictor; [b]Between-persons predictor
* $p < .05$; † $p < .10$

Next, we tested Hypothesis 5, which predicts the effect of technical difficulties on learning is more negative for trainees who drop the course than for trainees who complete the course. The technical difficulties by completion status interaction was positive ($\gamma = 1.13$), supporting the hypothesis. As shown in Figure 1, technical difficulties impaired learning for trainees who dropped the course but not trainees who completed the course. The results also suggest negative thoughts interacted with completion status, $\gamma = 1.28$. As shown in Figure 2,

experiencing negative thoughts had a more detrimental effect on test scores for trainees who dropped the course than for trainees who completed the course. The metacognition by completion status interaction was also significant (γ = 2.10), although the direction of the effect was counter to our expectation. As shown in Figure 3, for trainees who completed the course, metacognition did not influence test scores. Among trainees who dropped the course, trainees performed better in modules where they engaged in less rather than more metacognitive activity.

Figure 1
Graph of the two-way interaction between technical difficulties and completion status when predicting test scores.

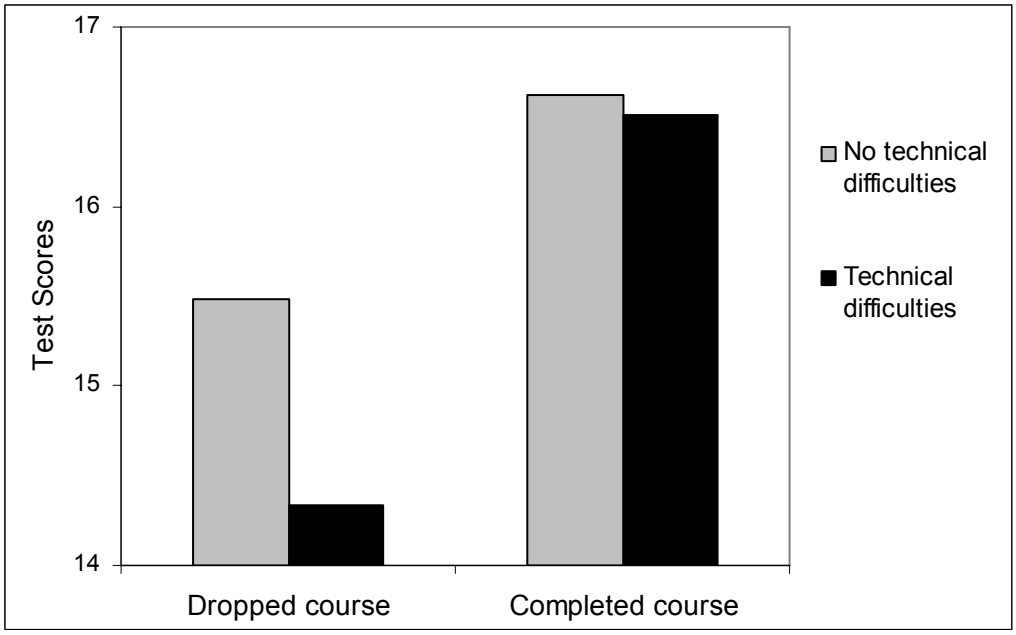


Figure 2
Graph of the two-way interaction between negative thoughts and completion status when predicting test scores

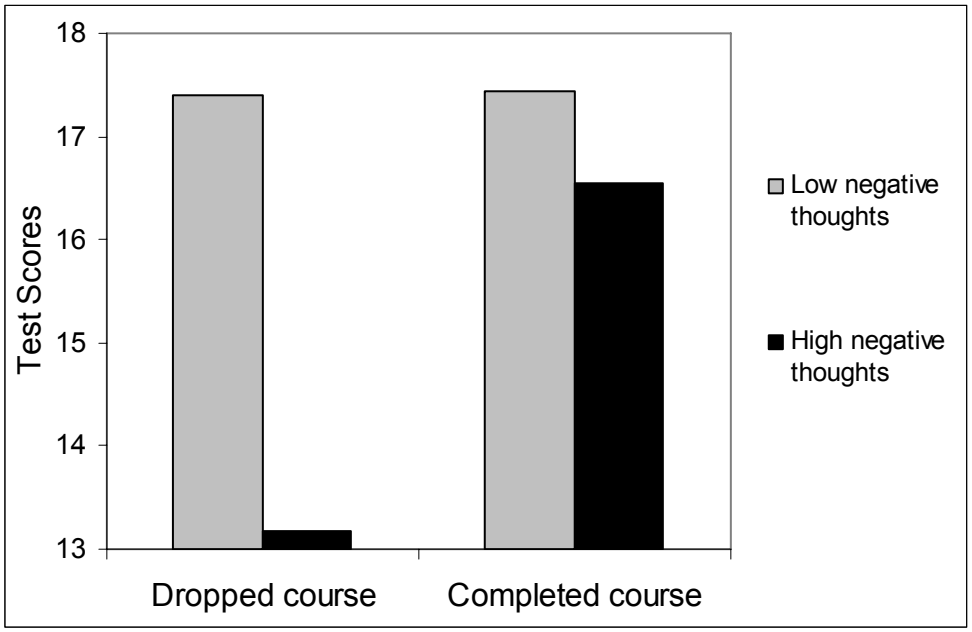
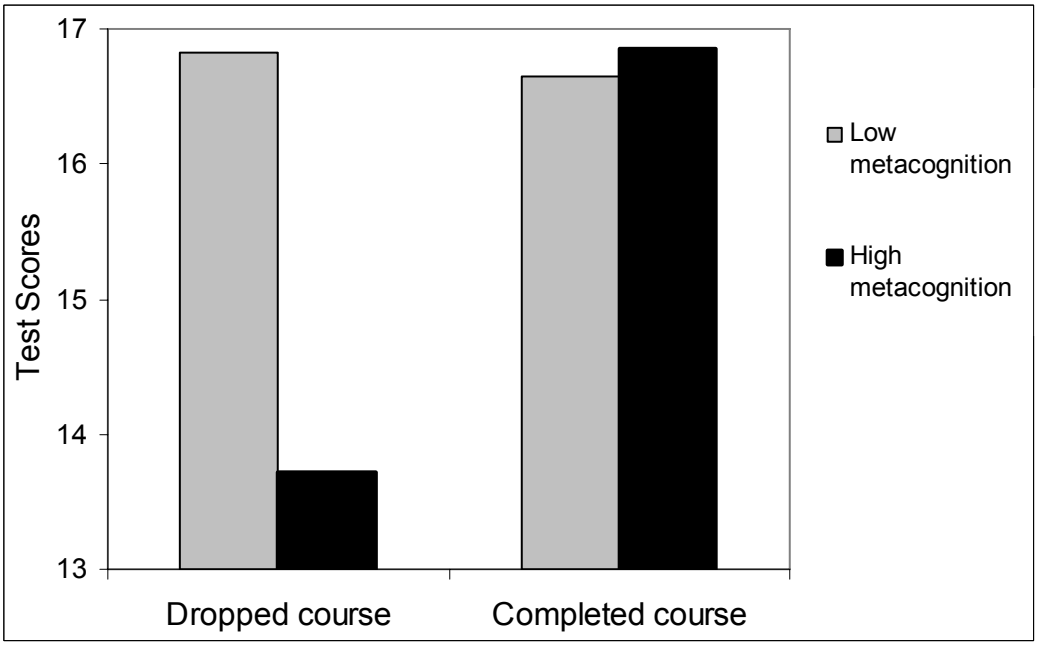
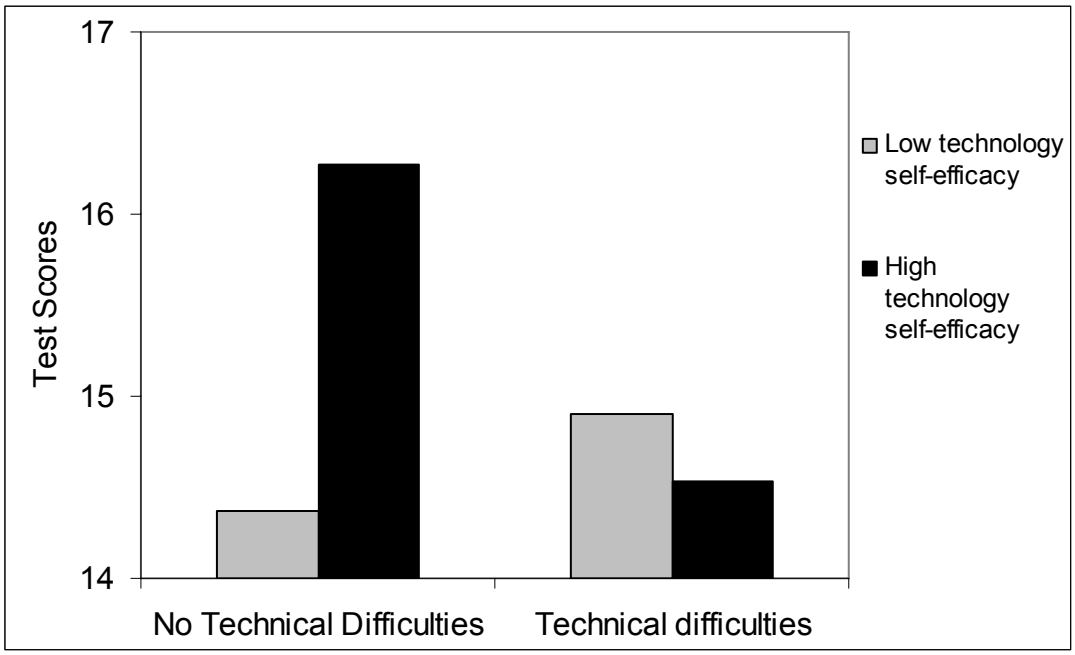


Figure 3
Graph of the two-way interaction between metacognition and completion status when predicting test scores



Hypothesis 6 predicts that the effect of technical difficulties on learning is less negative for trainees with high rather than low technology self-efficacy. Technology self-efficacy significantly interacted with technical difficulties when predicting learning (γ = 0.78). As shown in Figure 4, when trainees did not encounter technical difficulties, trainees with high technology self-efficacy learned more than trainees with low technology self-efficacy. However, when trainees encountered technical difficulties, trainees with high technology self-efficacy performed slightly worse than trainees with low technology self-efficacy. Thus, the interaction is in the opposite direction of Hypothesis 6. This may be due to the fact that error messages appeared at random during training, and trainees were unable to overcome the technical difficulties, despite their confidence in their technical expertise.

Figure 4
Graph of the two-way interaction between technology self-efficacy and technical difficulties when predicting test scores.



HLM Analyses Predicting Self-Regulatory Processes

The first step in building the growth model for self-regulation required estimation of the ICC for the dependent variables: negative thoughts, mental focus, and metacognition. The ICC values were .42, .37, and .49, respectively. This indicates that 42% of the variance in negative thoughts was attributable to between-person differences and 58% was attributable to within-person variability over time; 37% was between-persons and 63% was within-person for mental focus; 49% was between-persons and 51% was within-person for metacognition.

First, we tested Hypothesis 4 that technical difficulties have a negative effect on self-regulatory processes such that trainees experience more negative thoughts, focus less of their mental resources on the training material, and engage in less metacognitive activity in modules where they encounter technical difficulties than in modules where they do not encounter technical difficulties (see Table 5). Technical difficulties did not have a significant effect on negative thoughts or mental focus, but they had a negative effect on metacognition (γ = -0.23) in the pattern-mixture analyses. Metacognition was 0.23 points lower in modules where trainees experienced technical difficulties than in modules where trainees did not experience technical difficulties. Thus, the results partially support Hypothesis 4.

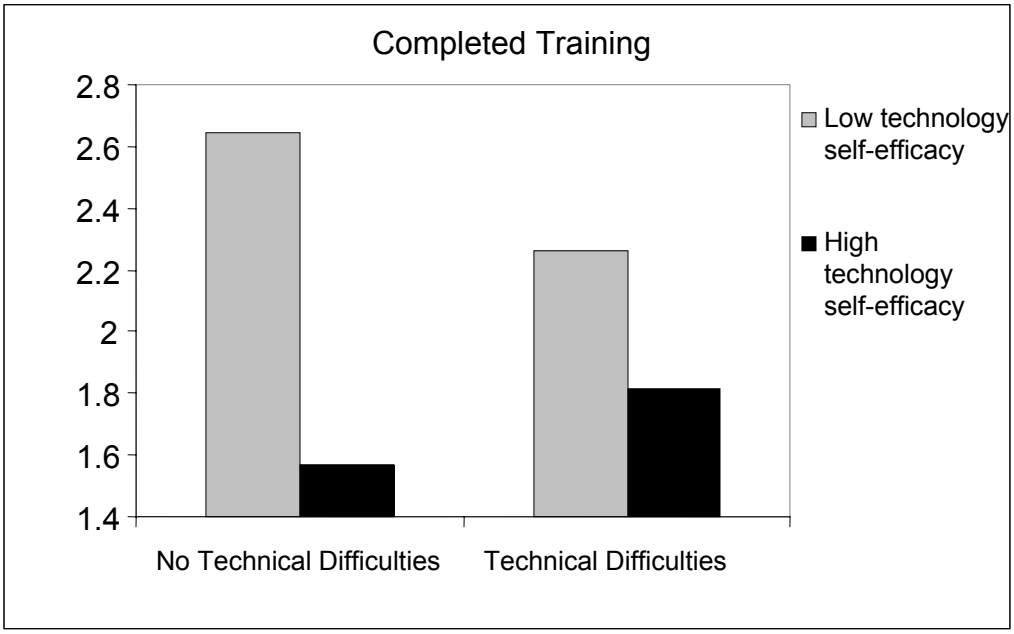
Next Hypothesis 5—the effects of technical difficulties on self-regulatory processes are more negative for trainees who drop the course than for trainees who complete the course—was tested. In support of the hypothesis, the technical difficulties by completion status interaction terms indicated that trainees who completed the course had fewer negative thoughts (γ = -0.19) and higher levels of mental focus (γ = 0.21) and metacognition (γ = 0.25) when they encountered technical difficulties than trainees who dropped the course.

Hypothesis 6 predicts the effects of technical difficulties on self-regulatory processes are less negative for trainees with high rather than low technology self-efficacy. In support of the hypothesis, technical difficulties impaired mental focus (γ = 0.33) and metacognition (γ = 0.27)

more for trainees with low rather than high technology self-efficacy. The technology self-efficacy by technical difficulties interaction was significant when predicting negative thoughts for trainees who completed the course ($\gamma = 0.22$), but not in the pattern-mixture model. The results also supported a three-way interaction between technical difficulties, technology self-efficacy, and completion status for all three self-regulatory processes.

As shown in Figure 5, for both trainees who completed the course and trainees who dropped out, trainees with low technology self-efficacy experienced more negative thoughts than trainees with high technology efficacy. However, the effect of technical difficulties on negative thoughts was strongest for trainees with low technology self-efficacy who withdrew from the course. Among trainees who completed the course, the discrepancy between trainees with high and low technology efficacy was greater when trainees did not experience technical difficulties; among trainees who withdrew from the course, the discrepancy was greater when trainees experienced technical difficulties. Thus, trainees who completed the course may be better at using their technology self-efficacy as a buffer against the negative thoughts that can result from technical glitches than trainees who dropped the course.

Figure 5
Graph of the three-way interaction between technical difficulties, technology self-efficacy, and completion status when predicting negative thoughts



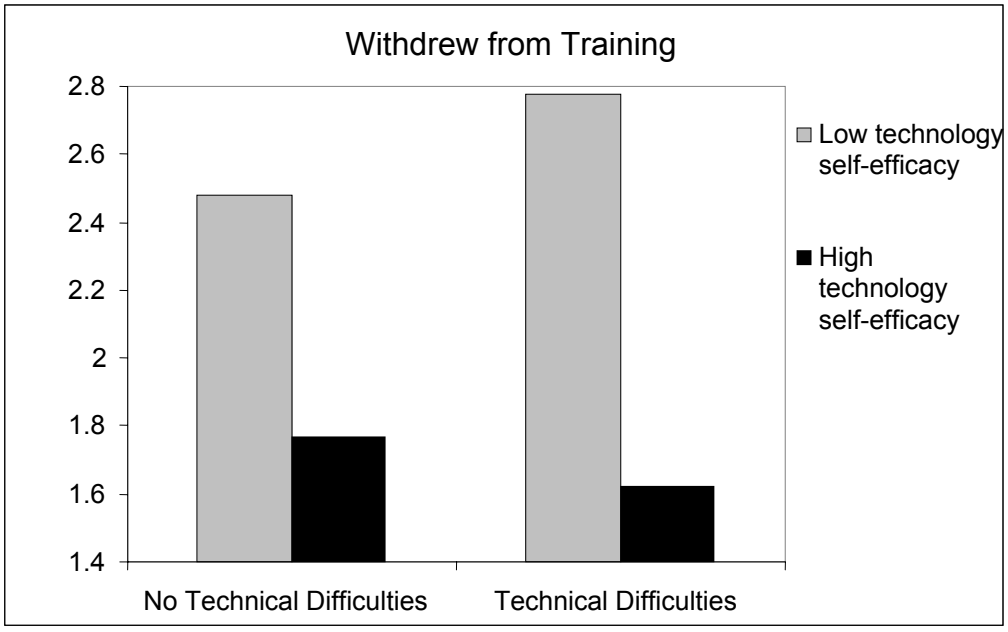


Table 5
HLM Results Examining the Effects of Technical Difficulties, Technology Self-Efficacy, and Completion Status on Self-Regulatory Processes

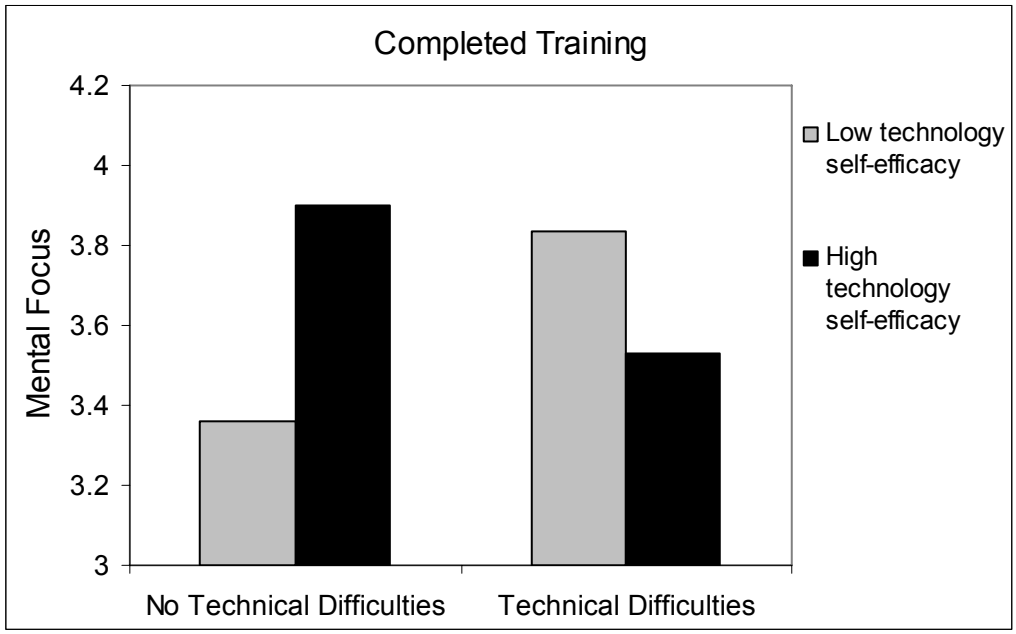
	Negative Thoughts			Mental Focus			Metacognition		
	All Subjects (*N* = 245)	Completers (*N* = 101)	Pattern-mixture (*N* = 245)	All Subjects (*N* = 245)	Completers (*N* = 101)	Pattern-mixture (*N* = 245)	All Subjects (*N* = 245)	Completers (*N* = 101)	Pattern-mixture (*N* = 245)
Intercept	2.02*	1.90*	2.01*	3.75*	3.70*	3.82*	3.64*	3.70*	3.65*
	(0.05)	(0.06)	(0.07)	(.05)	(.07)	(0.06)	(0.04)	(0.06)	(0.06)
Module[a]	0.13*	0.15*	0.24*	-0.15*	-0.11*	-0.27*	-0.05*	-0.07*	-0.04*
	(0.02)	(0.02)	(0.06)	(.03)	(.03)	(0.06)	(0.02)	(0.02)	(0.04)
Technical difficulties[a]	-0.04	-0.12†	0.08	-0.01	0.09	-0.12	-0.09†	0.01	-0.23*
	(0.06)	(0.07)	(0.09)	(.06)	(.08)	(0.09)	(0.05)	(0.05)	(0.08)
Technology self-efficacy[b]	-0.34*	-0.38*	-0.25*	0.13*	0.18†	0.05	-0.03	0.01	-0.11
	(0.06)	(0.08)	(0.08)	(.06)	(.09)	(0.08)	(0.06)	(0.09)	(0.07)
Technical difficulties x Technology self-efficacy	0.06	0.22*	-0.18	0.01	-0.28*	0.33*	0.08	-0.08	0.27*
	(0.08)	(0.10)	(0.12)	(.09)	(.11)	(0.13)	(0.07)	(0.08)	(0.10)
Completion status[b]			-0.09			-0.11			0.05
			(0.10)			(0.09)			(0.09)
Module x Completion status			-0.10			.15*			-0.02
			(0.06)			(0.07)			(0.05)
Technical difficulties x Completion status			-0.19†			0.21†			0.25*
			(0.11)			(0.12)			(0.10)
Technology self-efficacy x Completion status			-0.13			0.13			0.13
			(0.13)			(0.13)			(0.11)
Technical difficulties x Technology self-efficacy x Completion status			0.40*			-0.61*			-0.35*
			(0.16)			(0.17)			(0.13)

Note. The top number is the fixed effect coefficient while the number in parentheses is the standard error. Completion status was coded such that 1 indicates trainees completed the course and 0 indicates trainees dropped the course.
[a]Within-person predictor; [b]Between-persons predictor.
* $p < .05$; † $p < .10$

The graph of the three-way interaction between technical difficulties, technology self-efficacy, and completion status when predicting mental focus is presented in Figure 6. Among trainees who completed the course and encountered technical difficulties, trainees with low technology efficacy increased their mental focus on the training material, while trainees with high technology efficacy decreased their mental focus. This may be adaptive given that trainees with high technology self-efficacy may feel they have the ability to overcome the technical problems and, as a result, may shift some of their cognitive resources from training towards the technical problems. However, trainees with low technology efficacy may doubt their ability to overcome technical difficulties and increase their concentration on the material in an attempt to continue learning the course content, despite the error messages. For trainees who dropped the course, technical difficulties greatly impaired the mental focus of trainees with low technology efficacy while trainees with high technology efficacy increased their mental focus when faced with technical difficulties. This drastic drop in mental focus for trainees with low technology self-efficacy may be one reason they dropped the course.

With regards to metacognition (see Figure 7), among trainees who completed the course, metacognition remained fairly high, despite trainees' technology efficacy and whether or not error messages were embedded in the course content. Among trainees who dropped the course, technical difficulties had a large negative effect on metacognition for trainees with low technology efficacy and a slight positive effect on metacognition for trainees with high technology efficacy. This drastic drop in metacognition for trainees with low technical efficacy may be another reason they dropped the course.

Figure 6
Graph of the three-way interaction between technical difficulties, technology self-efficacy, and completion status when predicting mental focus



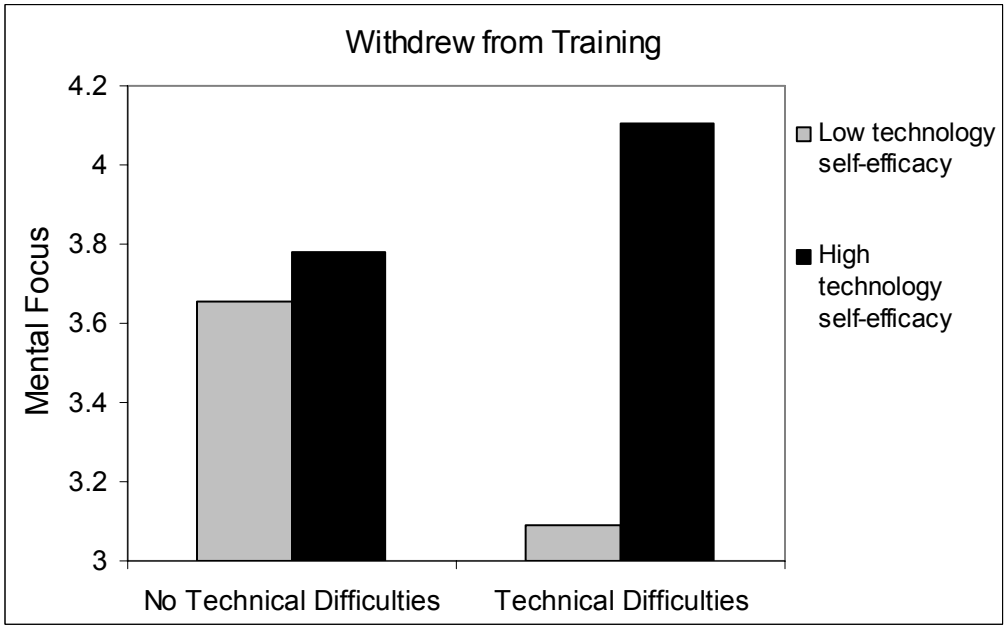
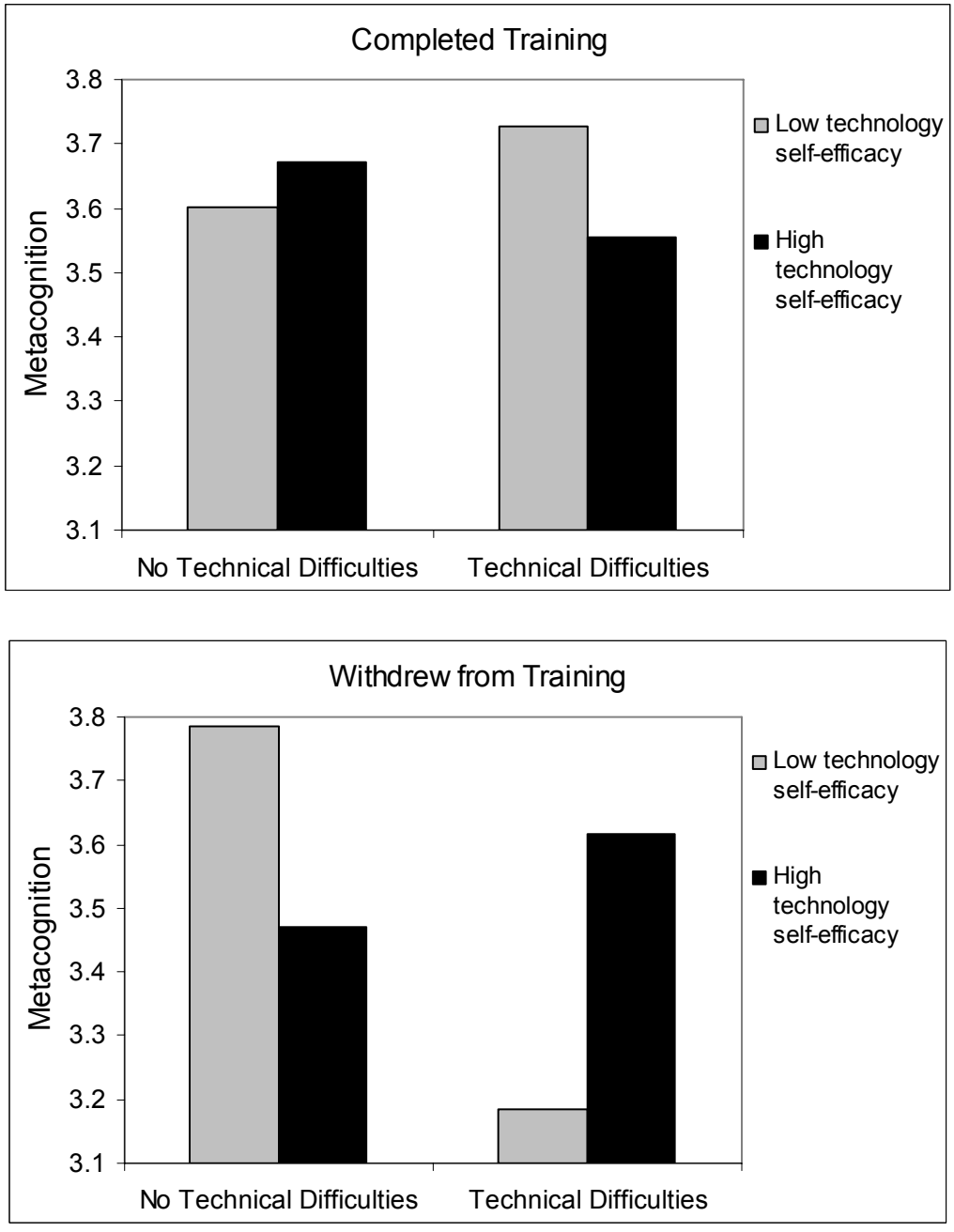


Figure 7
Graph of the three-way interaction between technical difficulties, technology self-efficacy, and completion status when predicting metacognition



Discussion

A solid research base has established that interruptions are detrimental to performance on complex tasks (e.g., Baron, 1986; Speier et al., 1999, 2003). The current study extends this research by focusing on knowledge acquisition during Web-based instruction, an arena where many have proposed interruptions such as technical difficulties may be problematic (Escaler, Valdez, & Hofileña, 2003; Lan et al., 2003; Munzer, 2002; Tallent-Runnels et al., 2005). Specifically, we provide a theoretical framework for categorizing interruptions and the extent to which they are likely to disrupt knowledge acquisition. Temporal factors, content, and urgency of interruptions are three criteria that can be used to distinguish among the plethora of interruptions that arise in training environments. We then empirically examined the extent to which one interruption—technical difficulties, which were designed to create a moderate level of disruption—predicted self-regulation, learning, and attrition.

Attrition

The model of action phases by Heckhausen and Gollwitzer (1987) may explain why more people dropped out of training when they encountered technical difficulties in the first module than towards the end of training. People progress through several stages when attempting to reach their goals (Brandstätter, Heimbeck, Malzacher, & Frese, 2003). Goal directed behavior is initiated when people develop broad goal intentions, such as "I intend to improve my knowledge of Microsoft Excel." Goal-directed behavior is then carried out and behavior is evaluated in terms of whether the goal was actually accomplished. When people initiate goal-oriented behavior they have a wide range of goals to choose from and impartially debate the feasibility and desirability of competing goals. Thus, obstacles to goal accomplishment may lead them to redirect their attention towards other goal pursuits. However, as they move towards completing their goals, people's mindsets become biased towards focusing on the favorable aspects of goal completion (Gollwitzer, 1990). Interruptions no longer

lead to withdrawal, but rather the recommencement of goal directed behavior (Lewin, 1926; Mahler, 1933). This suggests that trainees increase their motivation to reach their goals as they make progress towards goal accomplishment. In the current study, technical difficulties encountered in the first module may have preceded strong goal commitment and resulted in trainees directing their attention towards other pursuits. However, after trainees completed the first module, they may have increased their commitment to training, and technical difficulties were less likely to decrease their desire to master Excel. Future research should directly measure goal commitment to aid our understanding of predictors of attrition from Web-based training.

In the current study, only 21% of trainees who started the Web-based Microsoft Excel training completed all four modules. This is consistent with previous research that suggests attrition is often problematic in Web-based training. In fact, evidence suggests that attrition rates for online courses are often double those found in traditional, on-site courses (Levy, 2007). Fordis et al. (2005) taught cholesterol management online and in the classroom to physicians. They found that the attrition rate was eight percentage points higher in Web-based (10%) than in classroom (2%) instruction. Barker (2002) found attrition was 10 percentage points higher in Web-based (32%) than in classroom (22%) instruction in an infant and toddler care training program for working adults. In classroom instruction, there are many obstacles to success including time and budgetary constraints, an inconsistent message, and the inability to tailor the message to the needs of individual learners (Welsh et al., 2003). However, classroom instruction also presents strong cues about appropriate behavior, which reduces the influence of personal choice on behavior (Mischel, 1977). Thus, social pressure from the instructor and other trainees may dissuade trainees who are considering dropping out. In contrast, during Web-based instruction, trainees are often given control over their instructional experience (Sitzmann, Kraiger, Stewart, & Wisher, 2006) and dropping out may be as simple as trainees turning off

their computers. Thus, research needs to investigate interventions that may mitigate the likelihood that trainees will drop out when they encounter interruptions or are bored during Web-based instruction. We will return to this issue later in the discussion section.

Learning and Self-Regulatory Processes

Technical difficulties were instrumental in determining the amount that trainees learned during training, such that test scores were lower in modules where trainees encountered technical difficulties. However, the negative effects of technical difficulties are not inevitable. After controlling for the effect of technical difficulties, test scores improved when trainees were able to keep their negative thoughts at bay during training. This is consistent with research by Chen, Gully, and Eden (2004) that found negative affectivity had a detrimental effect on learning. Resource allocation theory (Kanfer & Ackerman, 1989) provides a sound theoretical basis for understanding these results. Individuals have a limited pool of attentional resources, which can be directed towards on-task thoughts, off-task thoughts, or regulatory functions (Kanfer & Ackerman). These attentional foci all draw from the same resource pool. Thus, as more resources are directed towards off-task thoughts (e.g., negative thoughts), there are fewer remaining resources to be directed towards on-task thoughts (i.e., learning the training material).

The metacognition results support a mediated moderation model (Muller, Judd, & Yzerbyt, 2005) for understanding the metacognition-learning relationship, such that this effect is better understood by considering the moderating effect of completion status. The results suggest that among trainees who dropped the course, performance was greater in modules where trainees engaged in little metacognitive activity. Among trainees who completed the course, performance was similar in modules with high and low levels of metacognitive activity. At the within-subjects level of analysis, trainees' levels of metacognitive activity may be fairly low throughout the majority of the training but spike at the point when trainees are presented

with a concept they do not understand or after they are interrupted. Among trainees who drop out, metacognitive activity may not have enabled them to overcome the deleterious effects of technical difficulties. Thus, test scores were lower in modules with high metacognitive activity, leading to eventual withdrawal from the course. Trainees who completed the course may have engaged in metacognitive activity only when necessary, aiding performance and enabling them to complete the course. Additional research is needed to measure the quality rather than the quantity of metacognitive activity and to directly assess the role of metacognition in the attrition process.

Comparing differences in the effects of technical difficulties on learning processes and outcomes provides strong evidence for the importance of accounting for attrition in training research. For trainees who eventually dropped the course, encountering technical difficulties led to increased negative thoughts and decreased learning. Conversely, for trainees who completed the course, technical difficulties had a smaller effect on negative thoughts and learning. This emphasizes the criticality of accounting for the effects of attrition in research evaluating organizational training courses. The vast majority of Web-based training research focuses exclusively on trainees who complete the course (e.g., Johnson et al., 2000; O'Neil & Poirier, 2000), which threatens the internal validity of study results (Cook & Campbell, 1979). We encourage training researchers to compare the learning processes of completers and dropouts whenever possible. When predicting test scores, none of the hypothesized predictors were significant using only the data from the 101 participants who completed the training. However, accounting for completion status in the pattern mixture model allowed for a better understanding of the effects under investigation.

In the current study, we examined the extent to which technology self-efficacy moderated the effects of technical difficulties on self-regulatory processes and learning. The results suggest a three-way interaction between technical difficulties, technology self-efficacy,

and completion status when predicting self-regulatory processes. Relative to trainees who completed the course, trainees with low technology self-efficacy were more likely to increase their negative thoughts and decrease their mental focus and metacognition when faced with technical difficulties during training. These trainees may not have had the resiliency required for persisting and remaining calm when they encountered obstacles to their success during training (Bandura, 1986, 1997). However, additional research is needed to understand reasons why trainees with high self-efficacy for technology withdrew from training, given that these trainees had a similar pattern of self-regulation to high self-efficacy trainees who completed the course.

We also found a significant interaction between trainees' technology self-efficacy and technical difficulties when predicting test scores such that technology self-efficacy had a more positive effect on test scores when trainees did not experience technical difficulties. This may be due to the fact that error messages appeared at random during training, and technical expertise would not enable trainees to prevent the error messages from appearing later in training. Thus, technology self-efficacy may have more of a positive effect on learning when technical difficulties have greater consequence on trainees' ability to proceed in the training course.

Recommendations for Practitioners

While even the best-designed courses are not immune to technical difficulties, the current study suggests there are steps practitioners can take to mitigate the effects of technical difficulties on self-regulation and learning. Technology self-efficacy is an important buffer against the effects of technical difficulties on self-regulatory processes. Previous research has recommended that organizations provide trainees with computer and Internet skills courses to assist them in navigating online training environments (Sitzmann, Ely, & Wisher, 2008). Organizations should also provide trainees with information regarding common technical difficulties and how to overcome them. This may provide trainees with both the technical skills and self-efficacy necessary to overcome technical difficulties during training. Additionally, not all

trainees have the requisite knowledge to overcome certain technical difficulties. Providing trainees with access to technical support can help limit the disruptiveness of interruptions because technology support specialists should have the expertise to resolve issues more quickly.

Given the prevalence of workplace interruptions (e.g., telephone calls and e-mails), it is likely that a variety of interruptions occur while employees are learning new skills (Langan-Fox et al., 2002). While the current study examined technical difficulties as a specific type of interruption, theory suggests these results should generalize to other workplace interruptions. Organizations should be cognizant of the effects of interruptions on learning and provide employees with opportunities to minimize office interruptions while completing training. For example, providing trainees with a dedicated computer lab to conduct training can help to limit the intrusion of e-mails or colleagues with questions. Similarly, organizations could advise trainees to forward telephone calls to voicemail while they are engaged in training activities.

Study Limitation and Directions for Future Research

Over half of trainees (*N* = 275) dropped the course before completing the first exam. This precluded an assessment of the extent to which these trainees had learned the course material. However, these trainees are likely to be those who were most affected by technical difficulties given that attrition was 10 percentage points higher among trainees who encountered error messages in module one than among trainees who did not encounter error messages in the first module. Additional research should continuously measure learning to better understand the implications of technical difficulties for learners across all stages of training. In addition, the attrition rate is likely higher in the current research than in other Web-based courses because trainees were not paying for the course. Future research should examine organizational and situational factors that influence attrition rates.

In the current study, the technical difficulties were randomly dispersed throughout the training material. However, research suggests that the timing of interruptions can influence the effects on task performance, with interruptions occurring in the middle of subtasks being more disruptive than interruptions at the beginning of subtasks (Monk, Boehm-Davis, & Trafton, 2002; 2004). Research should examine whether the specific dimensions of interruptions have differential effects on knowledge acquisition and whether the effects of the dimensions are additive. For example, are infrequent, complex interruptions less disruptive than frequent, less complex interruptions? In the current study, trainees only needed to click next to move past the error message and resume training. Thus, while the interruption manipulation was moderately disruptive, it allowed for a fairly quick resumption of the main task. However, the modern work environment includes a variety of potentially more disruptive interruptions such as answering telephone calls or responding to e-mails. As organizations move towards Web-based instruction—allowing employees to complete training courses from their home or office computers—research is needed to better understand how these more disruptive interruptions influence learning and attrition.

Finally, given that technical difficulties are inevitable in online training, research is needed to examine interventions that can be used to reduce the negative effects of these interruptions on learning and attrition. One possibility is prompting trainees to self-regulate (Schmidt & Ford, 2003; Sitzmann, Bell, Kraiger, & Kanar, 2008). Self-regulation prompts encourage trainees to self-monitor and self-evaluate as they are learning the course material. Sitzmann, Bell et al. conducted two studies and found that trainees who were prompted to self-regulate learned more across time from technology-delivered instruction than trainees who were not encouraged to self-regulate. In addition, trainees could benefit from emotion control strategy training, which Bell and Kozlowski (2008) demonstrated decreases state anxiety. It is possible that encouraging trainees to engage in cognitive self-regulation and control their emotions will

enable them to maintain favorable learning outcomes and complete the course, despite technical difficulties.

Conclusion

Although Web-based instruction has many potential benefits (Welsh et al., 2003), technical difficulties are one potential drawback to the increased use of this medium. The current results indicate attrition was 10 percentage points higher when trainees encountered technical difficulties in the first training module, and only 18% of trainees managed to complete a course plagued with technical difficulties. Technical difficulties also impaired trainees' learning, and this impairment was greater among trainees who eventually withdrew from the course than among trainees who completed the course. This finding illustrates the value of modeling attrition in training research to better understand differences in predictors of learning for those who drop out relative to those who complete training. Moreover, trainees' technology self-efficacy may buffer those who complete the course from the deleterious effects of technical difficulties on self-regulatory processes. Using a longitudinal design and multilevel modeling, the current study provides a theoretical framework for understanding interruptions during training and disentangles some of the implications of technical difficulties during Web-based training.

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