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The Effects of Technical Difficulties on Learning and Attrition during Online Training

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Abstract

Although online instruction has many potential benefits, technical difficulties are one drawback to the increased use of this medium. A repeated measures design was used to examine the effect that technical difficulties have on learning and attrition from voluntary online training. Adult learners ($N = 530$) were recruited online and volunteered to participate in a four-hour training program on using computer spreadsheets. Technical difficulties were inserted in some of the training modules in the form of error messages. Using multilevel modeling, the results indicated that the presence of these technical difficulties impaired learning, such that test scores were lower in modules where trainees encountered technical difficulties than in modules where they did not encounter technical difficulties. Furthermore, the effect on learning was greater among trainees who eventually withdrew from the course than among trainees who completed the course. With regards to attrition, pretraining motivation provided a buffer against dropping out, especially when trainees encountered technical difficulties. Learning also predicted attrition from the subsequent module, such that attrition was higher among trainees with low test scores in the previous module. The current study disentangles some of the implications of technical difficulties and suggests that organizations should provide trainees with the technical support required to overcome technical difficulties in training. Furthermore, the findings contribute to our theoretical understanding of the implications of interruptions on performance in online training.

Keywords: Technical difficulties; Attrition; Interruptions; Motivation; Online training

The Effects of Technical Difficulties on Learning and Attrition during Online Training

Technology...is a queer thing. It brings you great gifts with one hand, and it stabs you in the back with the other.

-C.P. Snow, 1971

Technology has had a large impact on the modern work environment, including the move towards technology-delivered instruction. Currently, 33% of learning hours in organizational training courses are delivered with technology (Paradise, 2008). Organizations are drawn to online training in an attempt to cut costs and create material that can be delivered anytime, anywhere, and tailored to meet individual needs (DeRouin, Fritzsche, & Salas, 2004; Wisher, 2006). Although the benefits of online training are numerous (see Sitzmann, Kraiger, Stewart, & Wisher, 2006; Welsh, Wanberg, Brown, & Simmering, 2003), researchers have also suggested that technical difficulties, which inevitably arise during online training, have the potential to disrupt the learning process (Webster & Hackley, 1997).

Technical difficulties refer to interruptions that individuals encounter when interfacing with technology, such as error messages that result from incorrect configurations (i.e., browser or computer settings; Munzer, 2002). 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 media that led to usability problems for instructors and students (Cavanaugh, Milkovich, & Tang, 2000; Collis, 1995; Webster & Hackley, 1997). Although technological advances solved many of these early issues with distance education, additional 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).

Research has found that technological issues can have a negative effect on important training outcomes (Cavanaugh et al., 2000; Webster & Hackley, 1997). Specifically, technical difficulties increase trainees' frustration (North, Strain, & Abbott, 2000) and have a negative effect on their satisfaction with the instructional experience (Wentling, Park, & Pieper, 2007). This may explain why attrition rates are often higher in online than traditional classroom instruction (Welsh et al., 2003).

Although prior research has examined the effect of technical difficulties on trainee affect, we know relatively little about the impact of these interruptions on other important training outcomes. The goal of the current research is to address this gap in the literature by examining the effects of technical difficulties on trainees' cognition and behavior. Using a field sample of adult learners and a repeated measures, experimental design, we tested the effects of technical difficulties on learning and attrition during training. Our methodological approach is consistent with recent research that suggests modeling change over time is critical for understanding the learning process (e.g., Yeo & Neal, 2008). Moreover, numerous observers have noted that attrition may be problematic in online courses (e.g., Rossett & Schafer, 2003; Welsh et al., 2003), but our understanding of the factors that influence attrition in online instruction remains limited. We focus attention on this issue by examining the effects of technical difficulties and learning on attrition. Finally, a growing body of research suggests that individual differences influence training outcomes (e.g., Kanfer & Ackerman, 1989; Sitzmann, Bell, Kraiger, & Kanar, 2009; Yeo & Neal, 2004). The current study contributes to this research stream by examining whether trainees' pretraining motivation moderates the effects of technical difficulties on learning and attrition. In the following section, we present an overview of technical difficulties

and use an interruptions framework as a conceptual lens for considering the effects of technical difficulties in a training environment.

An Overview of Technical Difficulties and Workplace Interruptions

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. An interruption occurs when an individual encounters an externally generated event that breaks continuity of cognitive focus and impedes progress on a primary task (Corragio, 1990; Jett & George, 2003). A recent study of more than 200 employees across 16 organizations and 14 countries found that 77% of those surveyed reported being unable to complete online 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 that they participate in online training at their desk as opposed to a special learning area or at home.

Action regulation theory can be used to understand the role of interruptions on training outcomes (Frese & Zapf, 1994; Hacker 1982). Interruptions serve as a regulation obstacle—they make it more difficult to pursue a goal and regulate goal progress. 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, an increase in stress, and confusion among information cues residing in memory (Jett & George, 2003; Speier, Vessey, & Valacich, 2003). When an activity is interrupted, the individual must exert more effort in order to overcome the obstacle (Zohar, 1999). This depletes resources that could have been devoted to the primary task, and the effect is exacerbated when the interruption is unexpected (Rogelberg, Leach, Warr, &

Burnfield, 2006). 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).

This interruptions framework can be used to understand the effect of technical difficulties during training. Technical difficulties are unpredictable and disrupt trainees' attentional focus from the training material. As a result, the cognitive load of learning the training material increases and trainees may experience an increase in stress (Frese & Zapf, 1994; Jett & George, 2003; Rogelberg et al., 2006). Ultimately, technical difficulties may decrease learning and increase attrition from training. However, research suggests that there is variability in how people respond to interruptions and some people are more sensitive to interruptions than others (Jett & George, 2003; Kirmeyer, 1988; Oldham, Kulik, & Stepina, 1991). We contribute to this research stream by examining whether pretraining motivation moderates the effects of technical difficulties on learning and attrition. In the following section, we propose hypotheses for the interrelationships among technical difficulties, learning, and attrition and propose that pretraining motivation may provide a buffer against the deleterious effects of technical difficulties.

Effects of Technical Difficulties and Pretraining Motivation on Learning and Attrition

Technical difficulties should impair learning. Interruptions are a regulation obstacle—they make it harder to concentrate on the training material and pursue learning goals (Frese & Zapf, 1994). When trainees are interrupted, they have to modify their action plan to accommodate the interruption. Cohen's (1978; 1980) cognitive fatigue model suggests that interruptions are uncontrollable and unpredictable stressors that produce information overload, leading to cognitive fatigue. Given that working memory has a limited capacity (Miller, 1956),

cognitive load theory proposes that optimal learning occurs when the load placed on working memory is minimal in order to facilitate changes in long term memory (Sweller, 1988).

Technical difficulties during training increase the cognitive load imposed on trainees—leaving them with fewer resources to devote towards learning the course content (Sweller, van Merriënboer, & Paas, 1998).

H1: Trainees will have lower knowledge levels in modules where they encounter technical difficulties than in modules where they do not encounter technical difficulties.

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 from traditional classroom instruction. More recently, researchers have expanded these models to better understand attrition from online courses (Berge & Huang, 2004; Boyles, 2000). Berge and Huang (2004) identified three categories of variables that influence attrition from online training: circumstantial (e.g., instructional design), personal (e.g., trainees' individual differences), and institutional (e.g., organizational values). Survey results generally support this model, with the majority of reasons provided for dropping out falling into the circumstantial or personal categories (Frankola, 2001; Muilenberg & Berge, 2005; Wang, Foucar-Szocki, Griffen, O'Connor, & Sceiford, 2003). The current study examined the effect of one circumstantial (i.e., technical difficulties) and one personal (i.e., pretraining motivation) factor on attrition.

With regards to circumstantial variables, a recent survey found technical difficulties were rated as one of the strongest predictors of attrition (Muilenberg & Berge, 2005). As Tannenbaum, Mathieu, Salas, and Cannon-Bowers (1991) noted, "When training fails to meet trainees' expectations and desires, or training fulfillment is low, we hypothesize some dysfunctional outcomes, such as negative attitude change, poor training reactions, and failure to

complete the training” (p. 760). When trainees encounter technical difficulties they perceive that their learning progress is impeded (Lan et al., 2003), which may result in trainees withdrawing from the course.

H2: Attrition will be higher when trainees encounter technical difficulties than when they do not encounter technical difficulties during training.

With regards to personal variables, the decision to withdraw from training activities should be influenced by trainees’ pretraining motivation (Berge & Huang, 2004; Noe & Wilk, 1993). Pretraining motivation refers to trainees’ desire to learn the content of a training program (Noe, 1986). Trainees who exhibit high pretraining motivation are more committed to their goals (Colquitt & Simmering, 1998) and enthusiastic about learning (Noe & Schmitt, 1986). Drawing on expectancy theory (Vroom, 1964), Mobley, Hand, Baker, and Meglino (1979) found that trainees’ expectancies of their success in training significantly predicted attrition.

Researchers have also consistently demonstrated that motivation to learn has a positive effect on learning outcomes (e.g., Mathieu, Tannenbaum, & Salas, 1992; Randel, Main, Seymour, & Morris, 1992; Zazanis, Zaccaro, & Kilcullen, 2001). Colquitt, LePine, and Noe (2000) reported motivation to learn has a moderate effect on declarative knowledge ($\rho = .27$) and a small effect on skill acquisition ($\rho = .16$). Thus, trainees should learn more and be less likely to drop out of voluntary online training when they have high levels of pretraining motivation.

H3: Pretraining motivation will have a positive effect on learning.

H4: Pretraining motivation will have a negative effect on attrition.

High levels of pretraining motivation may also buffer trainees against the negative effects of technical difficulties on learning and attrition. Motivation is crucial for determining how trainees respond to environmental stimuli (Pintrich, Cross, Kozma, & McKeachie, 1986). When

trainees encounter technical difficulties, they perceive that their learning progress is impeded (Lan et al., 2003). Trainees with high pretraining motivation are more committed to their training goals (Colquitt & Simmering, 1998), thereby, enabling them to continue learning the course material, despite technical glitches. Moreover, trainees who enter the course with a strong desire to learn the course content exhibit higher levels of persistence during training (Warr & Downing, 2000), suggesting that trainees with high pretraining motivation may be less likely to withdraw from training when they encounter technical difficulties.

H5: Pretraining motivation interacts with technical difficulties when predicting learning such that technical difficulties will have less of a negative effect on knowledge levels when trainees have high levels of pretraining motivation.

H6: Pretraining motivation interacts with technical difficulties when predicting attrition such that trainees will be less likely to drop out when they encounter technical difficulties if they have high levels of pretraining motivation.

Attrition from the Subsequent Module

In addition to technical difficulties predicting attrition, trainees' performance in the course should influence attrition. Research in the field of education has consistently shown that poor school performance (e.g., low test scores, poor grades) serves as a powerful predictor of students' decisions to drop out of school (e.g., Barrington & Hendricks, 1989; Rumberger, 1995). Furthermore, rational choice theory assumes that the behavior of a group of people reflects the choices made by individuals as they strive to minimize costs and maximize benefits (Homans, 1961; Scott, 2000). When choosing to devote time and energy in voluntary activities, individuals should continue to devote resources towards an activity as long as they believe that they are receiving a return on their investment. Within the context of voluntary training, trainees

should be more likely to remain in a course if they are benefiting by learning the course content. When trainees perform poorly in a voluntary course, it may indicate that they are not benefiting from the course, leading them to withdraw from training.

H7: Learning predicts attrition from the subsequent module. Trainees will be more likely to drop out when their knowledge level was low in the previous module than when their knowledge level was high in the previous module.

Comparison of Learning for Completers and Dropouts

Training research often ignores the extent to which attrition influences the relationships examined in training evaluation studies. Nearly all training research conducted to date has focused on the performance of trainees who completed the course, and, via list-wise deletion, those who dropped out of training were removed from all analyses (e.g., Barker, 2002; Fordis et al., 2005; Johnson, Aragon, Shaik, & Palma-Rivas, 2000; O'Neil & Poirier, 2000). This approach is methodologically convenient, but may be problematic. Research that excludes dropouts may suffer from nonrandom mortality, which threatens the internal validity of the results (Cook & Campbell, 1979). If there are relationships among study variables that differ as a function of attrition (i.e., the strength or direction of the relationship is different for completers and dropouts), removing participants without complete data (i.e., dropouts) may bias tests of these relationships and interpretations of the findings.

In the current study, we focus on the factors that predict attrition from voluntary online training. However, we also believe that the effect of technical difficulties on learning is likely to be greater among trainees who ultimately drop out of training. It is important to examine how these processes differ for completers and dropouts, as it may provide insight into why some

trainees eventually withdraw from training. As such, we examined whether the effect of technical difficulties on learning differed across these two groups of trainees.

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%), whereas 20% were unemployed, and 5% were students. There was also variability in participants' educational backgrounds: 15% had a high school diploma or GED, 7% had an associates or technical degree, 27% had completed some college, 22% had a bachelor's degree, 9% had completed some graduate school, and 20% had a graduate or professional degree. The average age of participants was 41 years ($SD = 11.6$; ages ranged from 19 to 72) 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 online course, which lasted approximately four-hours, was divided into four modules. The modules covered a variety of Excel functions including formatting cells, formulas, graphing, and pivot tables. 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. 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, technical difficulties were operationalized as error messages embedded in training. Before beginning the course, trainees were randomly assigned to 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 “Web Browser: The web browser you are using is incompatible with this training,” 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. Trainees received the same course content regardless of whether they were assigned to a condition with error messages.

Measures

Pretraining motivation. Pretraining motivation was assessed before participants began the training program in order to obtain information on trainees’ desire to learn the content of the

training program. The scale consisted of eight items adapted from Noe and Schmitt (1986). Sample items include, “I will try to learn as much as I can from this Excel course,” “I would like to improve my Excel skills,” and “I am motivated to learn the skills emphasized in the training program.” Trainees responded to the items on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Coefficient alpha was .81 and the average level of pretraining motivation was 4.33 ($SD = 0.44$; range = 2.00 to 5.00).

Learning. At the end of each module, trainees completed a 20-item multiple-choice assessment of declarative and procedural knowledge. Some 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”). Other questions contained screen shots and assessed trainees’ ability to remember the steps for performing Excel functions or how their actions 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”). Test scores were converted to the percent correct to aid interpretation. The average test score was 79% correct for module 1 ($SD = 0.15$; range = 25 to 100% correct); average of 73% correct for module 2 ($SD = 0.16$; range = 20 to 100% correct); average of 64% correct for module 3 ($SD = 0.18$; range = 20 to 100% correct); and average of 73% correct for module 4 ($SD = 0.20$; range = 15 to 100% correct). Thus, there was tremendous variability across participants in their performance in the course.

Attrition. Data from the learning management system was used to assess which modules trainees completed. Trainees received a 0 in modules that they completed and a 1 in the module where they dropped out.

Manipulation Check and Control Variable

At the end of each module, we administered a manipulation check and a measure of participants' familiarity with the training content. Participants answered two questions in order 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 5-point Likert scale (1 = never to 5 = very often). Coefficient alphas ranged from .85 to .94 across the four modules.

Content familiarity was included as a control variable in the analyses predicting learning because it should influence the cognitive load of learning the training material and, thus, the amount that trainees learn (Paas, Renkl, & Sweller, 2003; Sweller, 1999). At the end of each module, trainees were asked "What percentage of the material presented in this training module were you already familiar with?" Trainees responded on a scale ranging from 0 to 10 indicating the percent of material they were familiar with before training (0 = 0%...10 = 100%). The average level of content familiarity was 4.70 ($SD = 2.67$; range = 0 to 10).

We also calculated one-way ANOVAs and chi-square tests to examine whether there were differences across experimental conditions in pretraining motivation, age, sex, education, and occupational status. None of the analyses were significant, indicating that random assignment was effective for ensuring the conditions were similar at the beginning of the experiment.

Data Analysis

Using the model building procedure specified by Bliese and Ployhart (2002), hierarchical linear modeling (HLM) with full maximum likelihood estimates was used to analyze changes in learning across the four training modules. First, we tested 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 (ICC), which partitions the variance into within- and between-person components. This permitted us to examine whether significant within- and between-person variance exists in learning 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. We used the change in deviance statistics to decide which error structure provided the best fit for the data. After establishing the baseline model, we performed a series of analyses to test the study hypotheses. All of the predictors, except for module, were grand mean centered. Due to the directional nature of the hypotheses, we used one-tailed tests of significance.

One of the advantages of using HLM with a repeated measures 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, dropping out of training may be related to whether trainees encountered technical difficulties and the amount that they had learned. 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 indicating whether trainees completed the course (coded 1) or dropped out (coded 0), meaning they completed at least one module but not the entire course. Completion status was then 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. However, trainees who dropped out in the first module were not included in the pattern-mixture analyses because they did not provide learning data. It is not conceptually sound to suggest that future attrition causes prior learning, and testing this model does not imply causality (Sturman & Trevor, 2001). Rather, this model accounts for the non-randomness of the missing data by comparing the learning slopes for completers and dropouts.

HLM is appropriate for repeated measures 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 and learning on attrition using hierarchical generalized linear modeling (HGLM) with the procedure specified by Raudenbush and colleagues. Attrition was coded 0 for

modules where trainees remained in the course and 1 for the module where trainees dropped out of the course.

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, $\gamma = 0.67$. Trainees reported experiencing more technical difficulties in modules with error messages than in modules without error messages.

Learning

Trainees were classified into three categories: early dropouts (started the 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 265 early dropouts, 162 dropouts, and 103 completers (see Table 1). In the first module, attrition was eight percentage points higher for trainees in the technical difficulties condition than trainees in the control condition. Across modules two through four, the attrition rates tended to be similar across the two conditions. Additionally, attrition rates decreased across the modules for trainees in both conditions—the overall attrition rate in the first module was 50%, but by the fourth module it had decreased to 20%. Thus, 19% of trainees who started Excel training completed the course. We were able to examine the effect of technical difficulties on attrition for all three types of trainees (early dropouts, dropouts, and completers). However, early dropouts are not included

in the HLM analyses predicting learning given that trainees needed to complete at least one module for us to assess their learning.

The first step in building the growth model for learning involved estimating the ICC. The ICC value for learning was .28. This indicates 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 models predicting learning are presented in Table 2. These analyses demonstrate that test scores decreased over time ($\gamma = -0.05$; $p < .05$). In addition, content familiarity and pretraining motivation had positive effects on learning ($\gamma = 0.01$ and 0.04 , respectively, $p < .05$). Hypothesis 1 predicted that trainees would have lower knowledge levels in modules where they encountered technical difficulties than in modules where they did not encounter technical difficulties. In support of the hypothesis, technical difficulties had a significant negative effect on test scores, $\gamma = -0.03$. In modules where trainees encountered technical difficulties, their test scores were 3 percentage points lower than in modules where they did not encounter technical difficulties.

Hypothesis 3 predicted a main effect of pretraining motivation on learning, whereas Hypothesis 5 predicted a two-way interaction between pretraining motivation and technical difficulties on learning. For every one-point increase in pretraining motivation, knowledge levels increased by 4 percentage points ($\gamma = 0.04$; $p < .05$), supporting Hypothesis 3. However, the

interaction between pretraining motivation and technical difficulties was not significant ($\gamma = 0.02$), failing to support Hypothesis 5.

Finally, the pattern-mixture results suggested that the effect of technical difficulties on learning was more negative for trainees who dropped the course than for trainees who completed the course ($\gamma = 0.06$; $p < .05$). For trainees who completed the course, technical difficulties did not have an effect on learning (see Figure 1). However for trainees who dropped the course, technical difficulties impaired learning.

Attrition

We used HGLM to examine if attrition rates for the four modules were related to trainees' pretraining motivation and the technical difficulties manipulation (see Table 3). The main effect for module indicates that the probability of dropping out of training decreased over time (logit = -0.45 ; $p < .05$). Hypotheses 2 and 4 predicted attrition would be higher when trainees encountered technical difficulties during training (H2) and for trainees with lower pretraining motivation (H4). Technical difficulties did not have a significant main effect on attrition (logit = 0.15), failing to support Hypothesis 2. In support of Hypothesis 4, attrition was 6 percentage points lower for trainees with higher rather than lower pretraining motivation (logit = -0.28 , $p < .05$). Hypothesis 6 predicted pretraining motivation would interact with technical difficulties such that trainees would be less likely to drop out when they encountered technical difficulties if they had high levels of pretraining motivation. The pretraining motivation by technical difficulties interaction was significant (logit = -0.83). In support of Hypothesis 6 (see Figure 2), high levels of pretraining motivation provided a buffer against dropping out when trainees encountered technical difficulties.

Finally, we tested Hypothesis 7, which suggested that learning would predict attrition from

the subsequent module. In support of Hypothesis 7, learning significantly predicted attrition in the subsequent module, $\text{logit} = -4.07$. Attrition was 18 percentage points lower for trainees with higher rather than lower knowledge levels in the previous module.

Discussion

A solid research base has established that interruptions are detrimental to performance on complex tasks (e.g., Baron, 1986; Speier, Valacich, & Vessey 1999; Speier et al., 2003). The current study extended this research by focusing on knowledge acquisition during online 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). Based on an interruptions framework, we provided theoretical explanations for the effects of technical difficulties on learning and attrition. We then used data from a repeated measures field study to empirically examine the extent to which technical difficulties predicted these outcomes.

Learning

Technical difficulties influenced the amount that trainees learned during training, such that test scores were lower in modules where trainees encountered technical difficulties. Furthermore, comparing differences in the effects of technical difficulties on learning among completers and dropouts demonstrated the importance of accounting for attrition in training research. Our results provide strong evidence that technical difficulties have differential effects on learning among trainees who completed the course and trainees who dropped out. Specifically, completers seem to have a buffer against the deleterious effects of technical difficulties, such that their knowledge levels were not affected by these interruptions. Training research has rarely considered the potential implications of attrition in models of learning (e.g.,

Barker, 2002; Fordis et al., 2005; Johnson et al., 2000; O'Neil & Poirier, 2000), but research that excludes dropouts may suffer from nonrandom mortality, threatening internal validity (Cook & Campbell, 1979). Thus, training researchers are encouraged to model the effects of attrition in their data and compare completers and dropouts when appropriate.

Trainees also learned more when their pretraining motivation was high. However, contrary to expectations, pretraining motivation did not provide a buffer against the effects of technical difficulties on learning. As suggested by action regulation theory, interruptions have a harmful effect on cognitive activity (Zijlstra et al., 1999). Encountering technical difficulties may have disrupted trainees' cognitive processes, such that they were no longer devoting sufficient cognitive resources to learning the training material. Although pretraining motivation had a positive main effect on knowledge levels, it may not have been sufficient for counteracting the detriments to learning incurred by technical difficulties. Additional research is needed to investigate the role of pretraining motivation in overcoming the deleterious effects of interruptions on learning.

Attrition

The results revealed that pretraining motivation predicted attrition from training and interacted with technical difficulties, such that trainees were less likely to drop out when they encountered technical difficulties if they were highly motivated to learn the training content. Trainees who enter a course with a strong desire to learn the course content exhibit higher levels of persistence during training (Warr & Downing, 2000), resulting in pretraining motivation providing a buffer against attrition from training. Motivation is also crucial for determining how trainees respond to environmental stimuli (Pintrich et al., 1986). When trainees encounter technical difficulties they perceive that their learning progress is impeded (Lan et al., 2003).

However, trainees with high pretraining motivation are more committed to their training goals (Colquitt & Simmering, 1998), thereby, enabling them to remain in the course, despite technical difficulties.

Learning was also a strong predictor of attrition from training—attrition was 18 percentage points higher following low rather than high test scores during training. Rational choice theory assumes that the behavior of a group of people reflects the choices made by individuals as they strive to minimize costs and maximize benefits (Homans, 1961; Scott, 2000). That is, people make decisions by comparing the costs and benefits of different courses of action. Low test scores are a sign that the benefits of training are reduced for trainees and their time may be better spent pursuing other goals. Thus, trainees may choose to leave training before investing additional time in a course when they are unlikely to reap great benefits.

In the current study, only 19% of trainees who started the voluntary online training also completed the course. This is consistent with previous research suggesting attrition is often problematic in online training (Levy, 2007; Rossett & Schafer, 2003; Welsh et al., 2003). In fact, evidence suggests that attrition rates for online courses are often double those found in traditional, on-site courses (Levy, 2007). 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 classmates may dissuade trainees who are considering dropping out. In contrast, during online instruction, trainees are often given control over their instructional experience (DeRouin et al., 2004; Sitzmann et al., 2006) and dropping out may be as simple as closing the program. Thus,

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

Recommendations for Practitioners

Although even the best-designed courses are not immune to technical difficulties (Lan et al. 2003), the current study suggests that there are steps practitioners can take to mitigate the effects of technical difficulties on learning. Previous research has recommended that organizations provide trainees with computer and Internet skills courses to assist them in navigating online training environments and to facilitate technology acceptance (Marler, Liang, & Dulebohn, 2006; 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 the skills 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 needed to resolve issues quickly. Finally, cognitive load theory suggests that simultaneously learning the instructional content and how to navigate the instructional environment imposes cognitive load that can interfere with learning (Clarke, Ayres, & Sweller, 2005; Sweller et al., 1998). Thus, it may be beneficial to have trainees view a brief video on navigating the training environment and utilizing the training software before they access the course content. This may limit the cognitive load as well as the number of technical glitches that trainees encounter during training.

Pretraining motivation increased learning, reduced attrition, and buffered trainees from the negative effects of technical difficulties on attrition. As such, practitioners may want to

explore ways to increase trainees' motivation to learn. By communicating to employees the benefits of participating in development experiences, organizations can have a positive influence on trainees' learning attitudes and increase their motivation to engage in training (Leibowitz, Farren, & Kaye, 1986; Noe & Wilk, 1993).

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, Armstrong, Balvin, & Anglim, 2002). Although the current study examined technical difficulties as a specific type of interruption, theory suggests that these results should generalize to other workplace interruptions. Thus, 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 complete 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 Limitations and Directions for Future Research

Half of trainees ($N = 265$) dropped the course before completing the first exam. This precluded an assessment of the extent to which these trainees had learned the course material. It is possible that the high attrition rate in the first module occurred due to a mismatch between some learners' current knowledge of Excel and the difficulty of the material presented in the first module. Future research should continuously measure learning to better understand the implications of technical difficulties and individual differences across all stages of training. In addition, the attrition rate is likely higher in the current research than in other online courses because trainees were not paying for the course and there were no penalties for withdrawing.

Future research should examine organizational and situational factors that influence attrition rates.

Technical difficulties are just one of the many factors that influence attrition from online instruction (Muilenberg & Berge, 2005; Wang et al., 2003). For example, in a large sample survey, conflict between study, work, and family was one reason trainees provided for withdrawing from online training (Wang et al., 2003). Particularly when trainees are pursuing training as self-development, adding training to their work and family routines may upset work-family balances. Wang et al. also noted that in voluntary training, individuals may not want to learn an entire course—leading them to withdraw after they learn the portion that is of interest to them. Although these variables were not assessed in the current study, through random assignment, these factors should be equivalent across experimental conditions. Examining additional predictors of attrition from online training is an important avenue for future research.

Each module in the current study lasted approximately 60 minutes and learning was only measured once at the end of each module. As such, learning was tested as an antecedent of attrition in the subsequent module. However, it is possible that loss of interest in training preceded a decline in learning within the module. For example, trainees may have reviewed information about formulas in module two and realized that they were not learning the material, leading them to withdraw from module two. Future research needs to continuously measure learning to clarify the relationship between learning and attrition over time in voluntary online training.

We examined pretraining motivation as one individual difference that predicts learning and attrition. However, future research is needed to examine other individual differences that may both influence these important training outcomes and provide buffers against technical

difficulties. For example, researchers have suggested that self-regulation is important for adapting to changing situations (Smith, Ford, & Kozlowski, 1997). As such, trainees with high self-regulation or learning skills may be better able to overcome the obstacles associated with encountering technical difficulties, leading to higher levels of learning and lower levels of attrition. Similarly, trainees with higher levels of cognitive ability may be better able to compensate for the increase in cognitive load that theory suggests is imposed by technical difficulties (Speier et al., 2003). Exploring these research questions will provide a better understanding of the effects of technical difficulties on learning and attrition in online training.

It is important to note that we examined one form of interruption—technical difficulties—that occurred unpredictably throughout training, but allowed for a fairly quick resumption of the primary task. Research is needed to examine whether the current results apply to other forms of interruptions that differ in their timing, complexity, length, and predictability. For example, research suggests that the timing of interruptions can influence 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 also examine whether infrequent, complex interruptions are less disruptive than frequent, less complex interruptions. Moreover, if interruptions occur on a regular schedule, can trainees become habituated to them? This research stream should also directly measure why trainees dropout of online training in order to strengthen the causal link between interruptions and attrition.

It is also important to note that the disruption to trainees' cognitive focus is thought to be one of the mechanisms driving the effects of technical difficulties on learning and attrition. However, reduced access to the training material, loss of faith in the learning technology,

decreased motivation, and increased frustration are also plausible mediating mechanisms for the effects of technical glitches. Thus, future research should directly measure the mediating pathways by which technical difficulties affect training outcomes.

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 et al., 2009; Sitzmann & Ely, in press). Prompting self-regulation involves asking trainees self-reflective questions about their level of concentration, the effectiveness of their study strategies, and their training goals (e.g., “Am I concentrating on learning the training material?” and “Are the study tactics I have been using effective for learning the training material?”). Sitzmann and colleagues conducted three studies and found that trainees who were prompted to self-regulate learned more over time from technology-delivered instruction and prompting self-regulation resulted in a 17 percentage point reduction in attrition, relative to the control. 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 online instruction has many potential benefits, researchers have noted that technical difficulties and attrition are drawbacks to the increased use of this medium (Webster & Hackley, 1997; Welsh et al., 2003). The current results indicate pretraining motivation had a negative effect on attrition—attrition was 6 percentage points lower when trainees’ pretraining

motivation was high. Moreover, technical difficulties increased the probability of dropping out more for trainees with low pretraining motivation. Learning also predicted attrition from the subsequent module. For trainees with low test scores, attrition was 18 percentage points higher in the subsequent module than for trainees with high test scores. Furthermore, technical difficulties impaired 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 the effects of attrition in training research to better understand differences in predictors of learning for those who drop out relative to those who complete training. Using a repeated measures design and multilevel modeling, the current study provides a theoretical framework for understanding technical difficulties during training and disentangles some of their implications for online training.

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Table 1

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 Started the Module	Attrition Rates		
		No Technical Difficulties During Module	Technical Difficulties During Module	Total (across both conditions)
1	530	46% (<i>N</i> = 125)	54% (<i>N</i> = 140)	50% (<i>N</i> = 265)
2	265	33% (<i>N</i> = 51)	30% (<i>N</i> = 33)	32% (<i>N</i> = 84)
3	181	30% (<i>N</i> = 28)	27% (<i>N</i> = 24)	29% (<i>N</i> = 52)
4	129	21% (<i>N</i> = 11)	20% (<i>N</i> = 15)	20% (<i>N</i> = 26)

Note. Percentage is based on the proportion of trainees assigned to a condition who dropped the course during the module. Trainees differed in whether they were in the technical difficulties or no technical difficulties condition across the four modules.

Table 2

HLM Results Examining the Effects of Pretraining Motivation, Technical Difficulties, and Completion Status on Learning

	Main Effects	Main Effects & Interactions
Intercept	0.74* (0.01)	0.77* (0.02)
Module ^a	-0.05* (0.00)	-0.08* (0.02)
Content familiarity ^a	0.01* (0.00)	0.01* (0.00)
Pretraining motivation ^b	0.04* (0.02)	0.01 (0.03)
Technical difficulties ^a	-0.03* (0.01)	-0.07* (0.02)
Completion status ^b	0.10* (0.02)	0.06* (0.02)
Module x Completion status		0.04* (0.02)
Content familiarity x Completion status		-0.01 (0.01)
Pretraining motivation x Completion status		0.03 (0.04)
Technical difficulties x Completion status		0.06* (0.03)
Pretraining motivation x Technical difficulties		0.02 (0.03)

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. Content familiarity was included as a control variable because it should influence trainees' performance in the course.

^aWithin-person predictor; ^bBetween-persons predictor.

* $p < .05$ (one-tailed).

$N = 265$.

Table 3

HGLM Results Examining the Effects of Pretraining Motivation and Technical Difficulties on

Attrition

	Main Effects	Main Effects & Interaction
Intercept	-0.13 (0.10)	-0.13 (0.10)
Module ^a	-0.45* (0.07)	-0.46* (0.07)
Pretraining motivation ^b	-0.28* (0.16)	0.12 (0.21)
Technical difficulties ^a	0.15 (0.13)	0.16 (0.13)
Pretraining motivation x Technical difficulties		-0.83* (0.31)

Note: The top number is the logit while the number in parentheses is the standard error. Attrition was coded such that 0 indicates trainees completed the module and 1 indicates trainees dropped out during the module.

^aWithin-person predictor; ^bBetween-persons predictor.

* $p < .05$ (one-tailed).

$N = 265$.

Figure Captions

Figure 1. Comparison of the Effect of Technical Difficulties on Learning for Trainees who Dropped Out Versus Trainees who Completed Training

Figure 2. Two-Way Interaction between Pretraining Motivation and Technical Difficulties when Predicting Attrition



