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The Physiological Influence of Self-Efficacy During Monitored Web-Based Training

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This study examined the role of self-efficacy during monitored, online training. Ninety-five e-learners completed a challenging Web-based software training program. As hypothesized, lower pre-training learning self-efficacy predicted higher levels of in-training mental workload (measured via heart-rate variability) as well as lower levels of post-training performance on knowledge and skill tests.

Training has long been essential to the health and wellbeing of work organizations. However, not everyone reacts the same way to learning opportunities and events. Understanding how different people function during training can contribute to improvements in training design and delivery. As such, there is theoretical and practical interest in identifying individual differences that matter during training. For example, researchers have spend time studying the influences of agreeableness on reactions to training (e.g., Sitzmann, Brown, Casper, Ely, & Zimmerman, 2008), the impact of goal orientation on persistence, procrastination, and the use of metacognitive learning strategies (Wolters, 2004), and the effect of conscientiousness on motivation to learn (Colquitt & Simmering, 1998). Although it is not a stable disposition, self-efficacy is a particularly important individual difference known to affect critical training processes and outcomes (e.g., Brown, 2001; Colquitt, LePine, & Noe, 2000; Martocchio & Judge, 1997; Saks, 1994; Warr & Bunce, 1995).

This study is designed to replicate and extend what is known about self-efficacy's influence. The purpose of this research is twofold. First, this study examines whether the known link between pre-training self-efficacy and post-training performance generalizes to a self-directed, web-based training environment in which e-learners believe their activities are being electronically monitored. Though commonplace in practice, this comparatively new learner-controlled training environment is understudied relative to more traditional settings such as classroom training and non-monitored web-based instruction. Second, this study tests whether low pre-training self-efficacy elevates the mental workload learners experience during training. To examine this phenomenon, we use a physiological index of in-training mental workload – heart-rate variability. As this is the first known study to test the physiological influence of self-efficacy during training, this research provides an important contribution and extension to the literature.

Monitoring Web-based Training

Whereas years of research have concentrated on trainees learning in traditional classroom environments, studies focusing on learners operating in emerging technology-mediated training environments are not as common. Monitored, web-based training is one such environment that has grown increasingly prevalent. Typically, web-based training gives learners the latitude to control the sequence of material that is provided as well as the number of topics and total amount of material covered (Clark & Mayer, 2008; DeRouin, Fritsche, & Salas, 2005; Kraiger & Jerden, 2007). Because it is difficult if not impossible to physically observe the degree to which trainees engage with the material during this form of instruction, e-learning packages can be designed to allow employers to track activities such as which training modules the learners have tried, how long trainees work on each module, the number of practice exercises attempted/completed, etc. (Thompson, Sebastianelli, & Murray, in press). The mounting capacity to monitor e-learners accords with a more general trend toward electronic surveillance in the workplace. According to a survey conducted by the American Management Association in 2005, 36% of U.S. companies report recording computer activity such as keystrokes, and 76% reported tracking the online activity of employees.

Even if web-based training is not monitored, learners may erroneously believe that it is. With today's workforce facing increasingly invasive information collection and dissemination demands from their employers (Alge, Ballinger, Tangirala, & Oakley, 2006), employees' sensitivity to the possibility of monitoring might also be on the rise. Research by Thompson et al. (in press) supports this claim, suggesting that non-monitored e-learners may assume their training is monitored even in the absence of any indication that their activities are being tracked. Perceptions are arguably more important than reality when it comes to the influence of electronic monitoring on workers in general and trainees in particular. This underscores the importance of research on learners who perceive that their training is monitored, regardless of whether their employers have made use of monitoring technology.

While studies pinpointing the effects of web-based media and electronic monitoring perceptions on trainees are beneficial, these are not the only research requirements prompted by today's ever-changing training landscape. Monitored, web-based training has presumably become a fact of life for the many employees who have already moved to this form of instruction. As such, there is a need to better understand learning as it occurs during monitored, web-based training irrespective of any cross-media comparisons between monitored and non-monitored learners. In other words, research is needed to shed light on learning as it occurs in these newer environments in and of themselves. As described next, a particularly fruitful research avenue concerns the influence of self-efficacy on how people experience this form of training.

Training Self-Efficacy and Performance

Derived from social cognitive theory, self-efficacy is defined as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Self-efficacy is said to influence individuals' thought patterns, emotional reactions, and feelings of stress and anxiety (Bandura, 1986 as cited in Saks, 1994), especially in unfamiliar and aversive situations (Bandura, 1982). Training or learning self-efficacy is a domain-specific form of self-efficacy, typically assessed prior to training. This has been included in past research (e.g., Brown, 2001; Warr & Bunce, 1995) to capture perceptions of the confidence trainees have in their ability to learn the content of an upcoming course.

Training self-efficacy influences how individuals approach their training, and the outcomes of training as well (Brown, 2001). Overall, self-efficacy has been found to positively predict pre-training motivation (Machin & Fogarty, 2004) as well as training proficiency (e.g., Martocchio & Judge, 1997). In their meta-analytic review of 20 years of training research, Colquitt et al. (2000) found self-efficacy to be a significant predictor of both training motivation and outcomes (e.g., declarative knowledge, skill acquisition, and transfer). Citing numerous examples from the literature (e.g., Gist, Stevens, & Bavetta, 1991; Mathieu, Tannenbaum, & Salas, 1992; Quiñones, 1995), Colquitt et al. (2000) note that "research has consistently shown positive relationships between self-efficacy, motivation to learn, and learning" (p. 680). Mitchell, Hopper, Daniels, George-Falvy, and James (1994) demonstrated that self-efficacy is a better predictor of performance than goals set during the early phases of skill acquisition. Meanwhile, Gist, Schwoerer, and Rosen (1989) found support for their hypothesis that personnel scoring high in an initial measure of computer self-efficacy would outperform participants with low computer self-efficacy on a skills test administered at the end of a 3-hour software training course. This finding is consistent with other studies (e.g., Barling & Beattie, 1983; Stumpf, Brief, & Hartman, 1987; Taylor, Locke, Lee, & Gist, 1984) demonstrating a positive relationship between initial self-efficacy and performance. Finally, although they did not look at computer-based training, Warr and Bunce (1995) studied trainees engaged in a self-paced training program, which, like much of web-based training, is a learner-controlled environment. Their results indicated a positive association between pre-training learning self-efficacy and performance on assignments and exercises submitted by trainees at the conclusion of the course.

Given the aforementioned need to study training phenomena in the context of today's emerging learning environments, the present study seeks to replicate the link between pre-training self-efficacy and post training performance to determine whether this relationship occurs in a monitored, web-based setting.

Training Self-Efficacy and Mental Workload

Mental workload has been defined as the mental and/or perceptual cost incurred by a person to achieve a given performance level (Hart & Staveland, 1988) or simply the effort invested in task performance (Braarud, 2001). Despite the increases in motivation and performance that are expected to result from high pre-training self-efficacy, we posit that it is actually *low* self-efficacy e-learners who will experience the greatest mental workload during training.

Although this proposition remains untested, past research and theory support it. There are three related issues that may contribute to the mental workload experienced by low self-efficacy e-learners – task difficulty, task-related worries, and evaluation anxiety. First, mental workload varies with task difficulty, with harder tasks requiring more mental effort. For instance, solving a complex algebra problem will typically generate a higher mental workload than solving a simple addition problem such as 12 + 23 (Croizet et al., 2004). To the extent that trainees' low self-efficacy beliefs are somewhat rooted in reality (i.e., to the extent that low confidence stems from comparatively low aptitude), the training at hand will be relatively difficult for low self-efficacy learners, prompting a heightened mental workload.

Self-related worries are expected to add to the difficulty of a training program. This is the second reason why low self-efficacy should raise mental workload during training. Bandura (1991) points out that individuals whose self-efficacy is low tend to dwell on their personal deficiencies. This line of reasoning is consistent with training research linking self-efficacy to anxiety (Martocchio, 1994; Saks, 1994; Warr & Bunce, 1995). For example, Martocchio (1994) found that helping trainees believe they can build on their present abilities (as opposed to telling them their efforts are constrained by their present ability level) is associated with a significant decline in anxiety. In their study of junior managers enrolled in a 4-month self-directed training program, Warr and Bunce (1995) found a negative relationship between pre-training self-efficacy and learning task anxiety. Saks (1994) has stated that training which requires learners to work on their own (as is the case with most web-based training programs) can be "debilitating" for individuals with low self-efficacy. This is supported by his research, which suggests that independent, self-structured forms of training are particularly stressful for low self-efficacy learners (Saks, 1994).

The third reason we expect low self-efficacy to raise e-learners' mental workload has to do with evaluation anxiety. As mentioned earlier, much e-learning today is electronically monitored, and e-learners may believe their activities are being tracked even when they are not (Thompson et al., in press). As such, evaluation anxiety is expected to contribute to the mental workload experienced by low self-efficacy learners during training. This contention is supported by the testing literature, where low self-efficacy is commonly shown to produce heightened levels of test anxiety (McIlroy, Bunting, & Adamson, 2000; Muris, 2002; Pintrich & DeGroot, 1990). For example, Muris (2002) found academic self-efficacy to be related to school phobia in a large sample of normal adolescents. Pintrich and DeGroot (1990) showed that self-efficacy is negatively related to a test anxiety scale consisting of items such as “When I take a test I think about how poorly I am doing.” Meanwhile, among all of the individual difference variables examined by McIlroy et al. (2000), self-efficacy was the clearest and most consistent predictor of all four types of test anxiety studied – worry, tension, bodily symptoms, and task-irrelevant thoughts.

The preceding literature focuses on self-efficacy’s relationship to anxiety, not mental workload. However, it is considered relevant because negative emotions such as anxiety can divert attentional resources away from the task at hand (Bell & Kozlowski, 2008). As stated by Kanfer and Ackerman (1989), “attentional focus on emotional states disrupts the mapping of distal resource allocations (i.e., intended effort) to actual allocations of on-task effort” (p. 662). In short, heightened mental workload can result from cognitive interference produced by extra peripheral activity such as self-related worries (Croizet et al., 2004).

Measuring In-training Mental Workload

Testing the influence of self-efficacy on mental workload requires a meaningful assessment of in-training cognitive load. Unfortunately, how learners function *during* training can be something of a “black box” that is difficult to measure. While some studies have used time on task to gauge learner effort, this is believed by training researchers to be a contaminated measure (Fisher & Ford, 1998). Other studies have attempted to assess mental effort or workload by asking learners to self report either the degree to which they expect to exert effort (measured prior to training), or the degree to which they recall exerting effort (measured after training). For example, in their study of the effects of goal orientation on mental focus during learning, Lee, Sheldon, and Turban (2003) asked undergraduate students to self-report their anticipated levels of mental focus by rating their responses to questions such as, “When preparing for this test I expect that I will have good concentration.” Another example is provided by the work of Steele-Johnson, Beauregard, Hoover, and Schmidt (2000) who asked undergraduates participating in a computerized class scheduling training program to rate responses to items such as “I put a lot of effort into this task.”

Although these types of self-reports avoid the contamination associated with time on task, they are not without problems. Three types of error seem likely. First, there is the potential for error associated with the inability to accurately forecast one’s future effort or recall one’s past effort. Intentional response distortion presents a second possible source of error, as some people may report exerting more mental effort than they actually experienced in order to avoid the costs of a socially undesirable response. Third, there is the issue of mono-method bias stemming from exclusively self-report data (e.g., Sitzmann et al., 2008) when attempting to examine the relationship between mental effort and other measures such as self-efficacy.

Physiological indices such as heart-rate variability (HRV) circumvent many of the concerns associated with self-report measures of mental effort because they do not ask learners to self-reflect. A number of authors (e.g., Croizet et al., 2004; Rowe, Sibert, & Irwin, 1998) have discussed the advantages of employing such indices to determine mental effort. Physiologically, heart-rate variability is a measure of cardiac autonomic function that reflects both sympathetic and parasympathetic nervous system activity including balances and imbalances (De Vito, Galloway, Nimmo, Maas, & McMurray, 2002; Mussalo et al., 2001). It is determined by mediated beat to beat variability and reflects this continuous oscillation around its mean value, thus providing non-invasive data about control of heart-rate in real-life conditions (Routledge, Chowdhary, & Townend, 2002). Most heart-rate variability measures produce several different indices of physiological functioning. The index of interest in this study is the High Frequency score, which is found to decrease as mental workload increases (e.g., Croizet et al., 2004).

Although HRV has not yet found its way into mainstream training research, numerous studies in other areas have used it to assess mental workload (e.g., De Vito et al., 2002; Kallio et al., 2000; McMillan, 2002; Mussalo et al., 2001; Routledge et al., 2002). HRV has been utilized in both laboratory and field settings and has been found to be sensitive to manipulations in task complexity (e.g., Rowe et al., 1998). For example, Aasman, Mulder, and Mulder (1987), showed that HRV levels were significantly altered when participants were asked to think about other things (e.g., keep a running mental count of memory set items) during a button-pressing exercise. Meanwhile, Croizet et al. (2004) used the High Frequency measure of HRV to demonstrate the disruptive, heightened mental workload that hinders performance in the presence of stereotype threat – a phenomenon involving an apprehension about being evaluated based on a negative stereotype (Myers, 2005). Thus, the literature supports the use of HRV as an index of mental workload.

Hypotheses

In summary, several research streams combine to suggest the following: (a) monitored web-based training is a common but understudied learning environment in need of research attention; (b) low self-efficacy prior to training suppresses learning and skill development; (c) low pre-training self-efficacy should heighten mental workload during training due to increases in training difficulty as well as extra peripheral activity such as self-related worries and evaluation anxiety; and (d) high mental load during training should manifest itself in HRV reductions. In accordance with this reasoning, the following predictions will be tested.

> *Hypothesis 1*: Lower levels of pre-training self-efficacy will predict lower levels of performance on a post-training declarative knowledge test.

> *Hypothesis 2*: Lower levels of pre-training self-efficacy will predict lower levels of performance on a post-training skills test.

> *Hypothesis 3*: Lower levels of pre-training self-efficacy will predict higher levels of mental workload (i.e., lower levels of HRV) during training.

Method

Participants

Trainees were students at a large Southeastern university who volunteered to participate for course credit. We included only trainees from whom we obtained complete data, which reduced our original sample of N=110 to a final sample of N=95, 51% of whom were men. The mean age of the sample was 20.32 (SD=5.00). With regard to ethnicity, 76% of the sample was Caucasian, 13% was African-American, 4% was Asian, 3% was Hispanic, and approximately 4% reported another ethnicity.

Materials

All participants completed a Web-based training program created to develop skills in Microsoft Excel spreadsheet building and database management. A basic working knowledge of Microsoft Excel was a prerequisite for participation. Designed to be challenging, this program exposed e-learners to content and examples corresponding to eight advanced Microsoft Excel program functions. Pilot testing suggested it was highly unlikely that learners would know how to perform these functions prior to training; data collected from our sample, presented later, support this assumption. Trainees were free to complete the modules in any order. The program included optional practice exercises, which were presented after the instructional material for each module.

Procedure

This study was part of a larger data collection effort. It took place in an office-like laboratory with four desktop computers separated by dividers into cubicles. Each trainee participated in the study individually. Upon arrival, participants were seated at a computer reserved for questionnaire completion and given an informed consent form which indicated that the study would entail completing a Web-based training program designed to teach Microsoft Excel knowledge and skills. Next, they were asked to complete an online, pre-training questionnaire. Participants were then moved to the training computer. At this time, a small, lightweight HRV monitor was cleaned and comfortably clipped to the participant's right earlobe. The participant's age (obtained from the informed consent form) and gender were entered into the HRV program to ensure accurate readings. Participants were asked to remain still and quiet while a five-minute baseline HRV measurement was collected. The HRV monitor included a cord that ran from the participant's ear clip to a computer to the right of the participant's training workstation. A large divider visually separated the participant's workstation/training computer from the computer running the HRV hardware and software.

At the completion of the baseline HRV measurement, participants filled out a paper and pencil measure which asked them to rate their familiarity with the Excel functions to be covered during training. Next, they were shown a screen that appeared to control a monitoring program. They were informed that the software would enable the experimenters to track activities such as "keystrokes, how long you spend reading each training topic, how many practice exercises you attempt, how long you spend on each practice exercise, any errors you make while working on the training program, your efficiency, and all other Internet activity, such as checking e-mail and visiting extraneous web sites" either in real time or asynchronously. At this time participants also received a fictitious paper report detailing the information that was supposedly captured by the monitoring program. Participants were asked to click on an icon to initiate the monitoring software, which took them to the introductory page of the training program. Next, they were given an envelope containing a demographics questionnaire and asked to remove the HRV clip, complete the demographics questionnaire, and notify the experimenter in a predetermined room once they were finished training. To enhance motivation and effort, participants were told that the five individuals demonstrating greatest mastery of the material on a post-test administered at the conclusion of training would be entered into a drawing for $75. At this point, the HRV monitoring software was initiated to collect a 20 minute segment of data and the experimenter left the room.

The experimenter waited in a separate office and returned to the laboratory once participants indicated they were through training. The experimenter then visibly "turned off" the monitoring program by selecting an on-screen "off" icon, moved participants to the computer where they had previously completed their pre-training questionnaire, and informed them that all activities on this separate computer were not monitored. Participants were then asked to complete an online post training questionnaire, a multiple choice Excel knowledge test, and an Excel skills test on this non-monitored computer. Finally, they were given a debriefing form and dismissed.

Measured Variables

Baseline mental workload. Mental workload was measured via the High Frequency component of HRV, which is found to decrease as mental workload increases (e.g., Croizet et al., 2004). A 5-minute baseline assessment was taken, as indicated above.

Prior familiarity with training content (8 items). Prior to training, participants were shown example spreadsheets that were similar to the materials to be presented during training. They were then asked to rate the degree to which they felt they could already perform training-related functions on the spreadsheet. Each of the eight items corresponded to one of the eight training modules. An example item stem reads, "Please consider the following table, which displays estimated budgets for two locations catered by a catering company." After reading this stem and viewing the corresponding table, participants were asked to use a 1 (*strongly disagree*) to 5 (*strongly agree*) scale to rate their agreement with the following statement: "I already know how to insert an array formula in cell C15 that will return the average of the 'Food,' 'Beverages,' and 'Party Favors' budgets for 'Location B' in 2004."

Pre-training learning self-efficacy (7 items, alpha=.93). The degree to which participants felt confident in their ability to do well in training was assessed with scales adapted from Brown (2001), Guthrie and Schwoerer (1994), and Warr and Bunce (1995). An example item is, "I am confident that I can succeed in training." Items were accompanied by a 1 (*strongly disagree*) to

5 (*strongly agree*) response scale and averaged prior to analysis. Therefore, scores could range from 1 to 5, with higher scores representing higher levels of training self-efficacy.

In-training mental workload. As described above, a recording of each learner's High Frequency HRV was gathered during the first 20 minutes of training to assess in-training mental workload.

Electronic monitoring awareness (4 items, alpha=.83). Four items measuring perceptions of monitoring required participants to fill in a percentage that represented their level of certainty related to the presence of electronic monitoring. An example item is, "In between 0 and 100 percent, what do you think the probability is that the experimenters can check the computer later to get a record of how long it took you to complete each training module?" Items were averaged with a possible range of 0-100; the higher the values, the more confident participants were that their training activities had been monitored.

Post-training declarative knowledge (10 items). A 10-item multiple choice test was designed to assess declarative knowledge based on principles taught during the Excel training. Each item contained 2-4 choices from which one was correct. An example item is, "A reference in Excel refers to a _____," with response options "A: sign or symbol specifying a calculation to perform," "B: a value that always stays the same," "C: the cell or cells where data to be used is located," and "D: blank cell." Test items were scored as either incorrect (0) or correct (1) and summed prior to analysis. Scores could therefore range between 0 (no items correct) and 10 (all items correct), with greater values reflecting greater knowledge levels.

Post-training skills (14 items). Participants' post-training skill level was measured with a test containing Excel spreadsheets that were similar to the training materials. Instructions on the spreadsheets directed participants to perform specific functions. An example test item is, "Insert a formula in cell D12 using the IF function that will sum cells C3 through C10 (also written as C3:C10) only if the average of (B3:B10) is greater than 1000. Otherwise, have the formula return a 0." Test items were scored as either incorrect (0) or correct (1), with no partial credit awarded. A randomly selected subset of 15 of the tests was scored independently by four raters. Interrater reliability statistics revealed that the scoring instructions for one item needed to be revised for clarity. The revised scoring method had uniformly high reliability (ICC=.85-1.00 for the 14 items). As values greater than or equal to.70 are believed to represent satisfactory levels of interrater reliability (Fleiss, Levin, & Paik, 2003; LeBreton, Burgess, Kaiser, Atchley, & James, 2003), reliability was deemed acceptable and the remaining tests were scored by one rater using the revised method. We summed the points earned by each individual prior to analysis. Scores could therefore range between 0 and 14, with greater values reflecting greater skill levels.

Results

Preliminary Analyses

First, data were checked for violations of normality assumptions. Specifically, skewness and kurtosis levels were examined. Four variables demonstrated unacceptable skewness and kurtosis values exceeding an absolute value of one. These variables were transformed as follows. Pre-training self-efficacy and post-training skills test scores were negatively skewed and therefore needed to be reflected prior to transformation. After reflecting both variables by subtracting every score from a constant one greater than the highest score, we conducted a square root transformation and then re-examined the transformed scores for normality. Skewness values were reduced to acceptable levels below an absolute value of .8. Both square-root transformed variables were then un-reflected prior to subsequent analyses to restore the original order of the variable, as recommended when transforming negatively skewed variables (Osborne, 2002). While this had no effect on the nature of the score (i.e., reflected and un-reflected transformed variables correlated -1.00) it eases interpretability by ensuring that higher self-efficacy and skills test scores represented greater levels of efficacy and skills respectively.[1] Both the initial and the in-training HRV variables were positively skewed, which is consistent with trends suggested by other studies applying logarithmic transformations to HRV data prior to analysis (e.g., Croizet et al., 2004; Thompson et al., in press). Square root transformations on both HRV variables were conducted but failed to reduce skewness values below absolute values of one. Logarithmic transformations were then conducted on the original variables, yielding acceptable skewness values below an absolute value of .3. These log transformed scores were used in subsequent analyses.

Next, the data were examined to confirm that the training content was unfamiliar to learners prior to this study. As noted earlier, participants used a 5-point scale to rate the degree to which they believed they could already perform training-related functions on example spreadsheets. There were eight such items in all, with one item corresponding to each training module and higher ratings representing greater familiarity. The average response across the eight items (*M*=2.21; *SD*=0.77) was below the scale midpoint. The modal response to six of the eight items was 1, and the median response was either 1 or 2 for seven of the eight items, suggesting that most trainees did not enter the program with the skills taught during training.

As we intended this to be an examination of e-learners who believe their training is monitored, we also looked at the degree to which the sample held this perception. Across the four items tapping electronic monitoring awareness, the average certainty rating was 80%, suggesting a reasonable level of confidence among trainees that electronic monitoring had taken place during training.

Hypothesis Tests

Table 1 provides descriptive statistics and shows the partial correlations (controlling for baseline HRV) among pre-training self-efficacy, in-training mental workload (i.e., HRV), post-training declarative knowledge, and post-training skills. As shown by the significant correlations in Table 1, the data supported all three hypotheses. Lower levels of pre-training self-efficacy predicted lower levels of performance on a post-training declarative knowledge test (Hypothesis 1), lower levels of performance on a post-training skills test (Hypothesis 2), yet higher levels of mental workload (i.e., lower levels of HRV) during training (Hypothesis 3).

Discussion

This study shows that the link between pre-training self-efficacy and post-training performance generalizes to today's self-directed, web-based environment in which e-learners hold the belief (whether accurate or mistaken) that their activities are electronically monitored. This is also the first study to demonstrate the physiological influence of pre-training learning self-efficacy in any training context. Learners who entered training with a relatively low level of self-efficacy experienced a heightened mental workload, which manifested itself in HRV reductions during training. Interestingly, this heightened mental workload appeared to neither contribute to nor inhibit performance, as suggested by the lack of correlation between HRV and the two post-training performance measures. This pattern is reminiscent of Martocchio's (1994) findings which showed that an intervention raising trainees' self-efficacy produced a significant decline in self-reported anxiety; however, the effects of the intervention on the acquisition of declarative knowledge were not mediated by computer anxiety.

Common method bias (i.e., constructs that are self-reported at the same point in time) is one criticism that has been levied against past studies examining the relationship between self-efficacy and reactions to training (Sitzmann et al., 2008). At a minimum, Sitzmann et al. (2008) suggest separating the administration of measures to at least reduce shared transient error. One strength of the current study is the reliance on four distinct types of measurement (a subjective self-assessment, a physiological measure, a multiple choice test of declarative knowledge, and a hands-on skills test) taken at three different points in time (before, during, and after training).

[1] It is perhaps worth noting that failing to correct for this negative skewness would have yielded stronger support (i.e., larger correlations, smaller *p* values) for the study hypotheses.

Limitations and Future Research

The preceding strengths notwithstanding, several study limitations need to be acknowledged. As our primary interest is employees in the workplace, this study's reliance on a student sample is a potential threat to external validity. Given the questions driving this research and the difficulty of connecting a sample of "real world" employees to an HRV monitor during training, we felt the benefits of a laboratory setting outweighed the costs in this particular instance. Nevertheless, the degree to which our findings generalize to other types of trainees and settings remains undetermined.

There are also unknowns regarding whether low pre-training self-efficacy raises the mental workload experienced by people using other methods and modalities to train. Independent, self-structured forms of training have been shown to be particularly stressful for low self-efficacy learners (Saks, 1994). Future research examining the degree to which the findings uncovered in this study generalize to classroom training and web-based training that is not monitored would be informative.

Finally, research pinpointing the exact reasons for the heightened mental workload experienced by low self-efficacy e-learners is an important next step in this line of inquiry. Possible reasons include increases in training difficulty as well as extra peripheral activity such as self-related worries and evaluation anxiety. At present, the extent to which each of these factors contributes to the linkage between self-efficacy and HRV remains unknown.

Practical Implications

The current study's findings may have implications for e-learners' reactions to training as well as their health and wellbeing. As suggested above, self-related worries and evaluation anxieties may help account for the elevated levels of mental workload experienced by low self-efficacy e-learners. This is noteworthy because recent meta-analytic evidence clearly demonstrates an association between learners' anxiety and their reactions to training (Sitzmann et al., 2008). The health-related implications of HRV reductions during training are also important to consider. HRV, which is viewed as a prognostic measure in individuals with hypertension, coronary heart disease, and heart failure, also has predictive value for morbidity and mortality among healthy adults (De Vito et al., 2002; Mussalo et al., 2001; Stein & Kleiger, 1999).

As Gist (1987) points out, "many training sessions focus more on lectures and verbal persuasion, imparting relevant knowledge but doing little to relieve debilitating low self-efficacy" (p. 479). E-learners with low self-efficacy may benefit from training designed to increase self-efficacy as well as knowledge and skill (Gist et al., 1989). Sitzmann et al. (2008) recommend techniques classroom instructors might use to reduce trainee anxiety (e.g., having trainees engage in brief relaxation exercises during breaks). The work of Bell and Kozlowski (2008) provides an additional example of emotional control strategies in the classroom. Determining a way to adapt emotion control training to a monitored, web-based learning environment would be useful. The advantage of administering such strategies over the Internet is that their frequency and/or duration can be readily tailored and dynamically adapted to the needs (e.g., self-efficacy levels) of individual trainees.

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Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	*M*	*SD*	1	2	3	4
1. Pre-training self-efficacy	1.90	0.19	–			
2. In-training mental workload (HRV)	2.38	0.41	.20*	–		
3. Post-training declarative knowledge	6.74	1.56	.20*	.00	–	
4. Post-training skills	2.45	0.57	.21*	.00	.51**	–

Notes. *N*=95. The correlations shown above were computed after controlling for pre-training baseline HRV scores. A logarithmic transformation was conducted on the HRV measures and square root transformations were conducted on pre-training self-efficacy and post-training skills scores prior to analysis to reduce skewness. Values above reflect the transformed scores. Mental workload values represent the High Frequency component of HRV, which decreases as mental workload increases.

*$p < .05$ (1-tailed)

**$p < .01$ (1-tailed)