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A Longitudinal Examination of the Effects of Computer Self-efficacy Growth on Performance during Technology Training

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Abstract

Technology training in the classroom is critical in preparing students for upper level classes as well as professional careers, especially in fields such as technology. One of the key enablers to this process is computer self-efficacy (CSE), which has an extensive stream of empirical research. Despite this, one of the missing pieces is how CSE actually changes during training, and how such change is related to antecedents and performance outcomes. Measuring change requires repeated data gathering and the use of latent growth modeling, a relatively new statistical technique. This study examines CSE (specifically general CSE or GCSE) growth over time during training, and how this growth is influenced by anxiety and gender and influences performance, using a semester-long lab course covering three applications. The use of GCSE growth more accurately models how students actually learn in a technology classroom. It provides novel clarity in the interaction of gender, anxiety, GCSE, specific CSEs, and performance during training. The study finds that the relationship between anxiety and self-efficacy decreases over time during training, becoming non-significant; it clarifies the significant role gender plays in influencing GCSE at the start of and during training. It finds GCSE influences application performance only through specific CSEs.

Keywords: Computer self-efficacy, general computer self-efficacy, technology training, computer anxiety, gender, latent growth modeling

Introduction

As computing technology has become ubiquitous in the workplace, the ability of individuals to perform technology tasks takes on critical importance. Frequently the expectation exists that employees, and in particular recent college graduates, have embraced technology and so can adequately use or even excel in its use in the workplace. Yet recent studies have shown that this is simply not the case for many (Buche, Davis, & Vician, 2007; Powell, 2013). Learning to use technology can create apprehension, fear, and can reinforce a lack of confidence in one's ability to learn. This displays itself in the major a student

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chooses, which courses a student takes, and success or failure in learning technology in the college classroom and on the job. Indeed, the psychological effects of learning and using technology have been highlighted in a growing number of studies (Buche et al., 2007; Kase & Ritter, 2004; Powell, 2013).

Most universities require some basic level of computer literacy in the curriculum, either through skills-based course(s), self-paced tutorials or simply a test (or tests). The literacy requirements for some majors in colleges such as business or science are even more extensive, frequently including additional courses that require skills such as spreadsheets, databases, or statistical software. The purposes of such requirements are to prepare students for higher-level classes as well as professional careers. For some students, however, the influence of psychological effects impacts career choice, selection of college major, and impairs technology learning (Buche et al., 2007). It is critical, therefore, that educators better understand the psychological factors which influence learning in the classroom, and in particular for technology-intensive courses.

This study examines the influence of one of the key enablers of technology learning and performance in the classroom; computer self-efficacy (CSE). Self-efficacy has an extensive research stream that documents factors which influence it (antecedents) as well as its motivating influence on technology choices, learning and using technology, and attitudes and beliefs concerning technology. Yet despite this existing evidence, key gaps are still missing in our understanding about the effects of CSE on and during training. In particular, one missing piece is how CSE changes over time during training, and how this change is related to both antecedents and the critical outcome of performance. Almost all previous studies, even longitudinal ones, examine the relationship between self-efficacy and other constructs at a single point in time, or two points in time for longitudinal studies. One or two snapshots in time, while clearly illuminating, is not the same as examining an individual's *growth rate* in self-efficacy over time, and how this *growth* is influenced by antecedent factors or how it influences outcomes such as classroom performance. The significance of self-efficacy's relationships with outcomes (or antecedents) depends, to some extent, on when the snapshot in time is taken; growth rates, on the other hand, are immune to timing constraints since they factor in change over the entire training time. The addition of self-efficacy growth rates provides a powerful extension to previous literature and models *change* in self-efficacy as it actually occurs in individuals during training. Growth rates are established by taking multiple data measures during the entire training cycle and are tested using the relatively new statistical technique of latent growth modeling.

This study examines individual self-efficacy growth during a semester-long lab course encompassing three applications: spreadsheets, databases and web design (html). It includes the effect of gender as well as what may be the most important attitude that influences (or hinders) technology learning; computer anxiety. In addition, the study includes two common types of self-efficacy – general self-efficacy and application-specific self-efficacies (for the three different applications) – in clarifying what type of self-efficacy is better suited for educators or researchers to use in monitoring or predicting learning and performance. It examines issues not empirically studied before to our knowledge, including how the relationship between anxiety and self-efficacy actually changes over time, and how self-efficacy growth rates influence the critical outcome of performance in the classroom. This has important ramifications for the classroom teacher or trainer. An effective technology instructor is sensitive to individual differences that hinder or foster learning, promoting those factors that enhance learning while identifying as early as possible those individuals who may be at risk, such as those with high anxiety or low self-efficacy. Cognitive and behavioral intervention is then appropriate for those at-risk individuals; effective instructors use appropriate techniques to alleviate anxiety or build confidence (or self-efficacy). These efforts can include encouragement, verbal persuasion, modeling effective performance, providing appropriate feedback, and positive reinforcement strategies that allow each individual to experience successful outcomes.

This study extends previous research in two important ways. First, it clarifies the role general computer self-efficacy plays by including growth rates, which mirror how students actually learn over time during training. It examines the role gender and anxiety play as antecedents to self-efficacy and self-efficacy growth over time, as well as clarifying the role that both types of self-efficacy, general and specific, play in influencing performance. Conceptually, it clarifies how these two distinct types of self-efficacy work in unison to influence performance, while offering a recommendation on which may be more appropriate for educators to use in monitoring this important influence on learning. Secondly, and based on the first, this study has important implications for teachers and educators. Based on these findings, teachers will be better prepared in the classroom, especially for those introductory computer literacy courses. Such edification is important for teachers in order to maximize educational efforts in the classroom; to understand, for example, when and for how long intervention techniques make a difference in student learning. It is also important to our conceptual understanding of how self-efficacy operates over time during training, which permits both educators and researchers to make more effective decisions and recommendations to improve technology training. Given the importance of technology in today's business environment, the role colleges and technology teachers therein perform is critical in preparing students, all students, to be able to use such skills. Understanding the process by which self-efficacy grows and influences outcomes during training can enhance student learning and better prepare graduates for professional careers.

Literature Review

Self-efficacy (SE) is defined as an individual's perception of ability to accomplish a task, and is based on Bandura's Social Cognitive Theory (1986, 1997). According to Bandura (1997, p. 39), self-efficacy beliefs are not merely "passive foretellers" of future action, they stimulate a motivational component that mobilizes the effort and cognitive skills necessary in task accomplishment and learning. Self-efficacy regulates the level of motivation at several levels, including goal setting, influencing attentional processes, and influencing attitudes (Bandura & Jourden, 1991). A person with high SE tends to set higher goals, has a stronger commitment to them, figures out solutions when task learning or accomplishment is difficult, and has better attitudes toward the task, which enhances motivation to learn and accomplish the task (Bandura, 1997; Downey & Smith, 2011; Marakas, Yi, & Johnson, 1998). Computer self-efficacy (CSE) is "an individual's perceptions of his or her ability to use computers in the accomplishment of a task" (Compeau & Higgins, 1995a, p. 191). CSE has a long stream of existing research in which a compelling case has been made for its positive and significant influence on technology learning and performance. CSE is a strong predictor of a variety of computing attitudes, beliefs, behaviors, and performance. For example, those with higher CSE are less anxious about computing technology (Downey, Rainer, & Bartczak, 2008; Johnson & Marakas, 2000), have more liking or affect towards technology (Downey & McMurtrey, 2007), use technology more (Compeau & Higgins, 1995a; Compeau, Higgins, & Huff, 1999) and perform better in computing related tasks (Compeau & Higgins, 1995b; Downey & Rainer, 2009; Marakas et al, 1998; Mitchell, Hopper, Daniels, George-Falvy, & James, 1994). While this study examines CSE as a moderator in learning technology, it is also been identified as a key outcome of learning (Kraiger, Ford, & Salas, 1993). Indeed, in recent education and organizational literature, it has been modeled as a vital consequence (outcome) in higher education settings (DeSantis, 2013; Lester, Hannah, Harms, Vogelgesang, & Avolio, 2011; Nelson, Poms, & Wolf, 2012; Smith & Woodworth, 2012).

Computer self-efficacy is multileveled; that is, it operates on individuals at a domain or application level (e.g., spreadsheet self-efficacy or accounting software self-efficacy), which is labeled specific CSE, as well as at a general level, or "across multiple computer application domains" (Marakas et al., 1998, p. 129) or the "entire computing domain" (Downey et al., 2008, p. 23), referred to as general CSE or GCSE. Self-efficacy could also legitimately be measured for domains in between, such as software or networking self-efficacy. Specific self-efficacy is a perception of ability for specific domains, while general self-efficacy is a judgment across all computing domains, and is more trait-like, changing more slowly (Eden & Kinnar, 1991). These distinctions make GCSE and CSEs different but related constructs, and each has been used in multiple studies, sometimes interchangeably. In empirical studies, both GCSE and specific CSEs have demonstrated a significant relationship with computer performance. GCSE, for example, demonstrated a significant relationship with spreadsheets and text editors such as Microsoft Word (Compeau & Higgins, 1995b; Downey & Zeltmann, 2009). Application-specific CSEs have influenced performance in a wide variety of applications (Downey & Rainer, 2009; Downey et al., 2008; Johnson & Marakas, 2000).

The two issues central to this study include differences between general and specific CSEs and how the growth of self-efficacy over time during training influences performance and is influenced by two important antecedents, anxiety and gender. The first issue centers on the question of which type of individual judgment (GCSE or CSEs) is better or more appropriate at monitoring learning and performance in technology courses. For a university course on spreadsheets, for example, an instructor who wishes to monitor self-efficacy to enhance learning can choose a specific spreadsheet CSE measure or a general CSE (GCSE) measure. For courses that include multiple applications, the instructor could choose multiple CSEs or the single GCSE. The advantage of a single GCSE instrument is obvious; it could be used for a course with any number of applications and indeed for any number of technology courses in the curriculum, saving time and energy for both teachers and students. However the literature includes some serious conceptual concerns about using GCSE in place of application-specific CSEs. These concerns revolve around the levels inherent in measuring self-efficacy and its related outcomes. According to some leading theorists, specific self-efficacy measures most strongly relate to specific performance (Bandura, 1997; Gist & Mitchell, 1992; Marakas et al., 1998). This thinking suggests that the further one goes from specific to general in terms of self-efficacy, the less accurately the self-efficacy measure predicts specific performance. This conceptual view relies in part on the notion that the level of self-efficacy (specific to general) should match the level of the outcome to which it is compared (Ajzen, 1991; Pajares, 1996). Labeled "specificity matching", it is the assumption that matching levels is crucial for predictive power (Chen, Gully, & Eden, 2001, p. 64). Accordingly, a spreadsheet CSE should be a better predictor of spreadsheet performance than is a general CSE instrument (GCSE) (and a GCSE should be a better predictor of general computer constructs). This notion, however, has been empirically challenged in at least one study, which found solid evidence that specificity matching did not always hold true, and depended in part on which outcome was used (Downey et al., 2008).

While a plethora of empirical results support the strong relationship between specific CSEs and specific performance, few have done a comparison between GCSE and specific CSEs. In those few that have, the results have been mixed. Johnson and Marakas (2000) found that both GCSE and CSE-spreadsheets (a specific measure) significantly predicted spreadsheet performance, though the strength of the specific measure was somewhat stronger. Agarwal, Sambamurthy, and Stair (2000) found that GCSE significantly predicted CSE-Windows 95 and Windows 95 ease of use, but did not predict CSE-Lotus or Lotus ease of use; at the same time, both specific CSEs (Lotus and Windows 95) did predict ease of use for both. In a direct non-longitudinal comparison of GCSE and six different CSEs, Downey et al. (2008) found that GCSE was better at predicting computer anxiety and affect (general computing attitudes) than specific CSEs, but both GCSE and the appropriate specific CSE significantly predicted competence in the six applications plus actual performance in two of the domains (word processing and spreadsheets). In that study, the authors found that specific CSEs were significantly better at predicting competencies in some applications (spreadsheets, databases, graphic programs, and web design), even though GCSE was also significant, but there was no significant difference between GCSE and specific CSEs in predicting word processing (competence or performance test), email competence, or spreadsheet performance.

These mixed findings suggest that further research is appropriate to ascertain whether GCSE may be appropriately used to monitor self-efficacy change during training, or if indeed instructors or researchers should use specific CSEs. It also points to a gap in our conceptual understanding of how the different forms of self-efficacy interact with each other in an individual to motivate and influence performance. Both GCSE and CSEs seem to work in concert to influence performance. While GCSE changes more slowly than specific CSEs, both are distinct perceptions of computer ability in an individual and both should influence outcomes. How this occurs, however, has received little empirical attention and lacks clarity.

The different levels of self-efficacy also influence each other. The relationship between GCSE and application-specific CSEs has been labeled the "generality effect" and is defined as the process by which "general CSE influences SE judgments of component subdomains" (Downey et al., 2008, p. 25); it has also been called the "carryover effect" (Agarwal et al., 2000, p. 423). Conceptually, GCSE generalizes to or influences specific CSEs over time. This relationship has been examined statically and longitudinally. Pre-training GCSE has been found to significantly influence post-training specific CSEs (Mone, 1994), including specific software self-efficacy (Gist, Schwoerer, & Rosen, 1989) and CSE-Windows 95 (Agarwal et al., 2000). In a meta-analytic study, there was a correlation of 0.59 between pre-training and post-training self-efficacy (Colquitt, LePine, & Noe, 2000). The complex interplay between general and/or specific self-efficacies and application performance during training is complicated by two issues. One issue is the existence of antecedent factors which may influence self-efficacy beliefs at the start of training as well as self-efficacy growth during training. The other issue is that of self-efficacy growth itself. We cover the growth issue first.

Changes in CSE over Time

During technology training, students or employees usually experience changes in their self-efficacy beliefs regarding technology. Usually such change is positive in nature; that is, one's CSE increases due to the training. Occasionally training decreases CSE as a result of factors such as negative feedback or poor training methodology (Marakas et al., 1998). However, almost all studies examine CSE at a single point in time (cross-sectional) or at two points in time, the classic longitudinal methodology. There are several longitudinal studies, for example, that use a pre- and post-method (Gist & Mitchell, 1992; Compeau et al. 1999; Agarwal et al. 2000; Yi & Davis, 2003). Only in such longitudinal studies can growth in CSE be examined, but even in these important works, the findings are completely dependent on which two times were selected for measurement. Thus one critical factor is when in the training cycle the two longitudinal snapshots were taken. Another factor is that one's self-efficacy judgments may be influenced by momentary feelings such as alertness, desire and comfort (Mitchell et al., 1994), as well as a mix of other short-term constraints such as environment and goals (Gist & Mitchell, 1992). Therefore, it is likely that at times a particular measure of one's judgment of technology ability is influenced by factors other than perceived ability. In this case, the measure of one's self-efficacy would be somewhat different than a duplicate measure taken at a slightly different time. Perhaps even more importantly, the resulting potentially erroneous measure of self-efficacy is then used to draw conclusions about its relationships with other constructs, including antecedents and any measured outcomes. This does not in any way diminish the value of previous longitudinal studies of CSE; they added immensely to our understanding of self-efficacy and its relationships with other constructs. However, measurement error exists in all measures (and momentary feelings are such an example for CSE); a more accurate solution is a measure that relies not on a particular time, but encompasses the growth in self-efficacy over time during training. This is not a measure taken at a particular time, but rather the accumulation of several measures over time during training.

The only way to measure change during training is by taking repeated measures. In fact Bandura and Jourden state that the "temporal dynamics of triadic reciprocality require the *sequential measurement* of interacting factors to isolate the effects of the constituent influences" (Bandura & Jourden, 1991, p. 941, italics added). In addition to repeated measures, different statistical tools are required. The researcher must collect at least three waves of longitudinal data. To analyze such data, the statistical technique of latent growth modeling (LGM) has become increasingly popular. Still relatively new in the IT research field, LGM is a structural equation modeling (SEM) technique that uses two latent variables to describe the construct undergoing change. These latent variables, called *intercept* and *slope*, represent the construct's initial value at time 1 (labeled intercept) for each respondent and the shape of each respondent's change (labeled slope) over all time waves. In this study, we examine general CSE (GCSE), which we measured at four equally spaced time intervals approximately one month apart. The latent variable intercept is a constant, and represents respondents' initial level of GCSE (measured at time 1, the beginning of the semester). The latent variable slope represents the shape of the change across the four time periods for each respondent. Both the measurement and structural models are fitted and tested using conventional SEM statistics (e.g., confirmatory factor analysis and fit statistics such as χ^2, CFI, RMSEA, etc.). A fuller description of the process of testing LGM models is beyond the scope of this study; interested readers are directed to references (Bollen & Curran, 2006; Kher & Serva, 2014; Serva, Kher, & Laurenceau, 2011).

The addition of a slope variable, which encompasses a respondent's growth in GCSE over time during training, represents a significant advancement in our ability to understand how self-efficacy actually changes and how this growth is related to other variables. For relationships, it is no longer a snapshot in time (or two snapshots), but rather the relationship between a latent *growth* construct and other variables. It is not exact, of course, for the actual growth measured is limited by the number of measures taken, but the magnitude of potential measurement error is much less. A self-efficacy growth measure instead of a measure of self-efficacy at a particular time in the training cycle allows a researcher to examine self-efficacy influences in a way that more accurately mirrors how individuals actually learn. This is conceptually different than previous research in which the relationship between self-efficacy and a particular outcome is examined at one or two points in time.

As mentioned, one's self-efficacy may be influenced by a number of factors. In this study we examined two key ones, anxiety and gender.

Computer Anxiety

Computer anxiety may be defined as a fear of computers or computer use (Loyd & Gressard, 1984). It is a domain-specific fear (specific to the computing domain) and is influenced by a variety of emotional and environmental factors (Marakas et al., 1998). Like CSE, computer anxiety has a large stream of research extending back to the early 1980s (for excellent summaries, see Kase & Ritter, 2004; Powell, 2013). Anxiety is an important issue in both educational institutions and business organizations because of its influence on choice of behavior, motivation to learn, effort or persistence in learning and performance. Students with computer anxiety tend to avoid classes and majors that emphasize computer use, learn computing tasks more slowly (or not at all), and exhibit poor attitudes toward computing (Havelka, Beasley, & Broome, 2004). In the Havelka et al. (2004) study, there were significant differences in anxiety levels among business majors, with management information systems (MIS) students reporting less anxiety, while general business, management and marketing majors reported significantly higher anxiety levels. This suggests that anxiety may play an important role in choosing a major. In organizations, anxiety can lead to employee dissatisfaction and turnover, as well as poor job performance. Computer anxiety has a deleterious effect on learning computer related tasks. Anxiety is an aversive emotional state that affects attentional control and is based in part on the working memory model of Baddeley (1976). Anxious individuals allocate cognitive processing (attention) to threat-related stimuli and to deciding how to respond to these stimuli (Eysenck, Derakshan, Santos, & Calvo, 2007). This reduces attention available to learning and/or task accomplishment and impairs cognitive processing efficiency.

Most theorists and studies maintain that anxiety is a cognitive state rather than a trait, and therefore one's anxiety levels with respect to any domain can change (Buche et al., 2007). For computing anxiety, studies have produced mixed results in terms of anxiety change over time. Using introductory computing applications courses, for example, one study found a significant decrease in anxiety levels during the course (Kernan & Howard, 1990); another study found a significant increase (Carlson & Wright, 1993). A third study found both: some students experienced decreases in anxiety while others experienced increases (Buche et al., 2007). These studies reinforce the proposition that, for some students, mere participation in introductory computing courses is not enough to reduce anxiety levels, and in fact can do the opposite. The mixed findings indicate further study is appropriate.

The relationship between anxiety and performance has also found mixed results. In the meta-analysis of anxiety studies between 1990 and 2010, half of the empirical studies found no relationship between anxiety and performance and half found a negative relationship (Powell, 2013). Thus, anxiety either had no effect, or higher anxiety levels correlated with lower performance. Many potential reasons for these contradictory findings exist. Computing experience may be one factor; in some studies, respondents were novice users while in others they were not. The task complexity of the performance measure differed in studies, which may have influenced findings. It is also possible that while anxious individuals devote attention to non-task efforts, reducing their working memory system, they take longer completing tasks but do not necessarily make more errors (Buche et al., 2007). Therefore, for anxious individuals, there is no effect on performance (assuming sufficient time to perform).

Another explanation is that anxiety's effects on performance are indirect, through its effect on self-efficacy (Hauser, Paul, & Bradley, 2012). Bandura (1997) characterized self-efficacy change as emanating from enactive mastery, vicarious experience, verbal persuasion, and affective beliefs. Affective beliefs can be positive or negative. Individuals make judgments of how well they will perform based in part on how positively aroused (enthusiastic or excited) or negatively aroused (fearful or anxious) they feel (Gist & Mitchell, 1992). Thus a highly anxious person will not have much confidence in their ability to carry out computing tasks. According to Bandura, this relationship is reciprocal in nature. Marakas and colleagues (1998) concur, and describe how estimations of self-efficacy contribute to higher (or lower) emotional arousal (including anxiety), potentially creating a spiralling effect.

The relationship between computer self-efficacy and computer anxiety has been examined in multiple studies and there is consensus that the relationship is negative; that is, high self-efficacy is associated with low anxiety and low self-efficacy is associated with high anxiety. Because of its reciprocal nature, some studies have placed anxiety as a dependent variable (Downey & McMurtrey, 2007; Downey et al., 2008). Other studies have found that anxiety is a significant antecedent to self-efficacy (Hauser et al., 2012; Johnson & Marakas, 2000; MacCallum, Jeffrey, & Kinshuk, 2014). In this study we posit that anxiety influences self-efficacy (specifically GCSE).

Gender and Self-efficacy

The role of gender in technology use also has a long history of research. In general, the prevalent impression is that computing (and science, math, electronics, etc.) is a "male" domain and men therefore have more favorable attitudes toward technology, less anxiety, more experience, higher self-efficacy and more skills. These assumptions have empirical support in previous IT diffusion literature, which suggests that women exhibit different perceptual beliefs and usage patterns for technology (Kase & Ritter, 2004). Another study concluded that masculinity, rather than biological gender itself, was a significant factor in higher male technology self-efficacy (Huffman, Whetten, & Huffman, 2013). Using the technology acceptance model (TAM), gender was a significant factor in a longitudinal study, with usage behavior for men determined by usefulness, while usage for women determined by ease of use and subjective norm (Venkatesh & Morris, 2000).

Of interest in this study is the relationship between gender and self-efficacy. Previous studies typically fall into two categories: those that find males have higher computer self-efficacy and those that find no difference in self-efficacy between genders. In the former category, gender has been found to be related to one's self-efficacy beliefs, with males possessing significantly higher computer self-efficacy (Roach, McGaughey, & Downey, 2011; Saleem, Beadry, & Croteau, 2011). In a recent meta-analytic study, Huang (2013) examined 247 independent studies worldwide and found that males possessed significantly higher math and computer self-efficacy than females. Marakas et al. (1998) model gender as a moderator in the self-efficacy-performance relationship. But other studies suggest that gender plays no significant role. One longitudinal study involving business undergraduate students measured CSE before and after training, using four different CSE measures; the authors found that both males and females significantly increased their self-efficacy beliefs for all four measures and further there was no difference in mean levels of CSE (Torkzadeh, Pflughoeft, & Hall, 1999). Other studies have also found no relationship between gender and self-efficacy (e.g., Salanova, Grau, Cifre, & Llorens, 2000). One potential reason for these mixed findings is the timing of the data gathering. Most studies examine the relationship before or after training. What is missing from previous studies is if or how gender influences one's *change* in self-efficacy over time during training. By examining gender's relationship with change in self-efficacy, the constraint of data gathering timing is eliminated. If gender significantly predicts change in self-efficacy over time, this would suggest that gender has an influence regardless of when the relationship was measured.

Model and Hypotheses

In this study, we chose GCSE as the construct undergoing change in order to clarify whether it is an appropriate scale to monitor learning and performance in the classroom (rather than one or several individual CSEs). GCSE was measured at four times over the course of the semester, as was computer anxiety. The three application-specific CSEs (spreadsheets, databases and web design) and performance were measured at the end of training. While repeated measures and latent growth modeling is relatively new in the IS field, there have been a few recent studies that examined various models (Lee & Mirchandani, 2010; Serva et al., 2011). In another recent study of ours, we examined change in GCSE over time during training using LGM (Kher, Downey, & Monk, 2013). That study found that GCSE increased non-linearly during training, that it remained stable for the first two months of training, then increased significantly over the final two months of training. The study found that computer anxiety, measured only at the start of training, was a significant predictor of GCSE. In addition, both initial GCSE (intercept) and change in GCSE (slope) significantly influenced three specific CSEs, measured at the end of training.

This study extends the previous one by adding gender, including anxiety at all four time periods, and adding the critical dimension of performance (Figure 1). How does the relationship between anxiety and GCSE change over time? Controlling for anxiety and gender, what is the relationship between initial GCSE (intercept) and performance in three computer application domains, spreadsheets, databases, and web design (html)? What is the relationship between GCSE change over time (slope) and performance in the three domains? Further, how does the addition of specific CSEs in those domains change the GCSE-performance relationships?

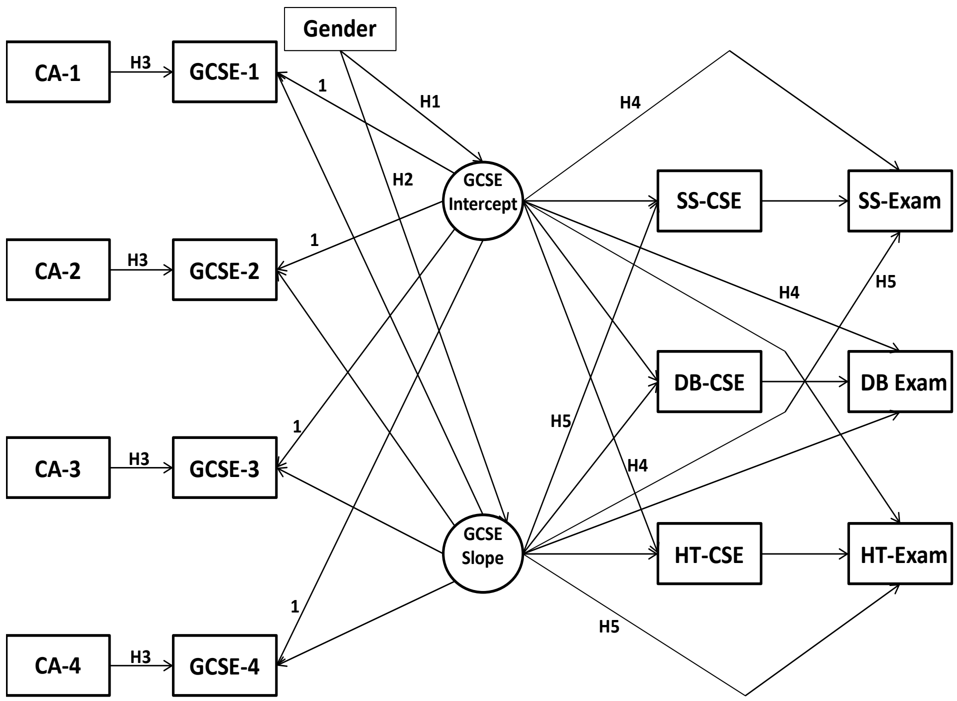

Figure 1: Base model

As shown in the study model (Figure 1) the study examines how technology performance is influenced by self-efficacy during training. In particular, it examines how *change in self-efficacy* (i.e., slope) influences performance. As an individual's perception of ability for using technology typically increases during training, how does this *change* influence performance? This adds a unique dimension to previous longitudinal studies that only looked at two snapshots in time and is more closely aligned with how individuals actually function in a training environment.

In the model, the paths representing hypotheses are labeled with a starting "H"; the paths from GCSE intercept/slope to the four GCSEs are labeled "1", indicating they were constrained to 1 and are a constant. The hypotheses are examined below.

Gender is a predictor of starting GCSE (i.e., intercept) and change in GCSE (slope). As discussed, the relationship between gender and GCSE measured at one point in time has had mixed results, though most studies seem to find that females have lower self-efficacy than males. This leads to our first hypothesis:

> *H1: Gender will be significantly related to GCSE, measured at the start of training (GCSE intercept).*

While H1 has been examined in many previous studies, the next hypothesis is novel in that it examines the relationship between gender and *change* in GCSE over time. Given the mixed findings with respect to gender and self-efficacy, findings that may be influenced by the point in time in which the relationship was examined, this tests a relationship which is not time-dependent. Given that GCSE change over time (slope) is based on individual change in GCSE over the course of training, the result will establish if gender is significant not just at the start or end, but across the spectrum of training. We frame this hypothesis as if the relationship will be significant, though *a priori* it is unclear:

> *H2: Gender will be significantly related to change in GCSE over time (GCSE slope).*

For most individuals, anxiety decreases over time during training and has a negative relationship with self-efficacy. Given that most studies include one or possibly two snapshots in time, they assume that the relationship between the two is relatively constant, and is reported as such. What is different about this study, however, is that we examine the relationship between anxiety and GCSE repeatedly over the course of training (specifically four different times). Therefore we examine if or how the relationship changes over time. This has important implications for educators. If the relationship is strong and steady, as is assumed in most existing studies, then trainers should continue with efforts to not only improve performance but also to decrease anxiety. However, if the strength of the relationship changes, then trainers should alter training tactics. For example, if the relationship becomes non-significant at some point in training, efforts to specifically decrease anxiety become much less important at that time. Given that this has not been examined before, we make no *a priori* guess at how the relationship between anxiety and GCSE change over time. Hence, we again merely frame this as if there will be a change in the relationship:

> *H3: The relationship between computer anxiety and GCSE will change over time during training, both measured four times during training.*

We posit that GCSE influences both performance and specific CSEs. In our previous study, both starting GCSE (intercept) and change in GCSE (slope) significantly influenced all three specific CSEs, spreadsheets, databases and web design (Kher et al., 2013). We expect no difference in this study, though the model has changed and now includes gender and anxiety (see Figure 1). But this study also includes the critical outcome of performance. Given previous study findings that support the influence of GCSE on performance, we propose the following:

> *H4: GCSE (intercept) will have a positive relationship with spreadsheet, database, and web design performance.*

H4 has been examined in multiple studies (GCSE intercept, after all, is GCSE measured at the start of training); change in GCSE over time (slope), however, has not. To our knowledge, it has never been empirically examined. Change in GCSE has been shown to influence specific CSEs of spreadsheets, databases, and web design (Kher et al., 2013), but as noted, this study includes performance in those applications. Change in GCSE (slope) over time is a measure of an individual's rate of change for general self-efficacy. As such, one would expect it to positively influence performance. As an individual's self-efficacy during training increases, at each time increment one would expect it to have a positive influence on performance. Given that change in GCSE (or slope) includes the spectrum of change in self-efficacy, it avoids the timing problem in previous longitudinal studies of when the relationship is measured. Like previous hypotheses, though, we make no *a priori* prediction of the strength of the relationship:

> *H5: GCSE over time (slope) will be significantly related to spreadsheet, database and web design performance.*

Methodology

Participants

The participants for this study consisted of students enrolled in an introductory MIS course at a large northern U.S. university. The course included hands-on lab instruction for spreadsheets (Microsoft Excel), databases (Microsoft Access), and basic web design (html). A total of 230 students participated in the study. Demographic data was collected at the start of the class (in the first wave). On average, responders were 18.8 years of age (sd = 0.77), 127 were female (55%) and 103 male (45%). Because this was an introductory course, most of the respondents were in their early college career (usually freshmen or sophomores). Data on anxiety and general computer self-efficacy (GCSE) was collected in four waves which were equally spaced throughout the semester (specifically, data was collected in weeks one, five, nine, and thirteen). Thus a month of training occurred between successive data collection waves. The same measure of both GCSE and anxiety was used in all four data collection waves. Data on specific CSEs for spreadsheets, databases and web (html) were collected in the last wave. The performance tests were administered at the end of training.

Study Measures

Most of the scales in this study utilized previously reported and validated instruments. See the Appendix for the scale items. Computer anxiety was measured using four items from the Computer Anxiety Rating Scale (Heinssen, Glass, & Knight, 1987). Each item ranged from 1 to 7, with anchors of "Strongly Disagree" and "Strongly Agree". There were four self-efficacy measures, one general CSE and three application-specific CSEs. The GCSE scale came from Marakas, Johnson, & Clay (2007) and consisted of six items, and exhibited excellent reliability and validity (convergent and discriminant) in their original study. The three CSE scales were modeled after Marakas et al. (2007) and Downey and McMurtrey (2007). The CSE-spreadsheet scale included six task-based items, the CSE-database scale included five task-based items, and the CSE-web (html) scale included five task-based items. All self-efficacy scales measured confidence on a scale of 0 (no confidence) to 10, as recommended (Bandura, 1997; Marakas et al., 1998). The three domain tests were all performance-driven. Students opened up spreadsheets, databases and an html editor and carried out tasks. These three tests provided a majority of the grade for the class.

Results

The model was tested statistically using LGM, which estimates within a SEM framework. Descriptive statistics (means, standard deviations, reliability and correlations) for the variables used are presented in Table 1. GCSE scores at each of the four time periods (GCSE1-GCSE4) were calculated by taking the average of each individual's responses to the six GCSE items. The averages for GCSE remained about the same during the first two time periods (68.8 and 69.0), then increased during the last two time periods (74.7 and 80.3). Anxiety was also measured at all four times. On a scale of 0-7 (with 7 indicating maximum anxiety), the scores decreased each time period in an approximately linear fashion, from 2.64 to 2.28. Average CSEs for spreadsheets (SS: 87.2), databases (DB: 86) and web design (html: 88.6), measured at the end of the semester, were relatively high on a scale of 0-100. The performance tests, standardized to 100, measured at the end of training, indicate students scored above average in both databases and spreadsheets, and extremely high in web design (html). All scales had adequate internal reliability (alpha).

Table 1: Descriptive statistics with correlations

	α	mean	SD	1	2	3	4	5	6	7	8	9	10
1 Anx1	.72	2.6	1.1	1									
2 Anx2	.74	2.5	1.1	.79**	1								
3 Anx3	.75	2.4	1.1	.71**	.82**	1							
4 Anx4	.79	2.3	1.1	.66**	.77**	.78**	1						
5 SE-1	.81	68	19.9	-.53**	-.45**	-.39**	-.37**	1					
6 SE-2	.82	69	20.6	-.51**	-.53**	-.46**	-.38**	.76**	1				
7 SE-3	.85	75	19.2	-.50**	-.49**	-.46**	-.40**	.74**	.75**	1			
8 SE-4	.85	80	17.8	-.40**	-.50**	-.42**	-.39**	.67**	.74**	.80**	1		
9 SS	.87	87	13.3	-.21**	-.26**	-.29**	-.23**	.30**	.26**	.44**	.44**	1	
10 DB	.89	86	13.3	-.19**	-.31**	-.32**	-.25**	.26**	.28**	.44**	.44**	.77**	1
11 Web	.65	89	13.2	-.11	-.18**	-.20**	-.19**	.15*	.17**	.36**	.36**	.60**	.51**
SS test	na	86	15	correlation between CSE-SS and SS test: 0.42**									
DB test	na	86	22	correlation between CSE-DB and DB test: 0.47**									
Web test	na	97	4.6	correlation between CSE-web and web test: 0.16*									

* p < 0.05; ** p < 0.01

The first step in analyzing a model using LGM is to establish the growth pattern of the variable undergoing change (GCSE). As previously reported, a non-linear growth pattern emerged (Kher et al., 2013). The data fit the non-linear model well (χ^2 = 78.2, df = 63, p < 0.09, CFI = 0.98, RMSEA = 0.03), and resulted in significant path loadings for the four time periods of 0, 0, 1, and 2. During the semester, students' judgment of self-efficacy was slow to change initially, but in the last half of training, increased significantly. Figure 2 provides the model results.

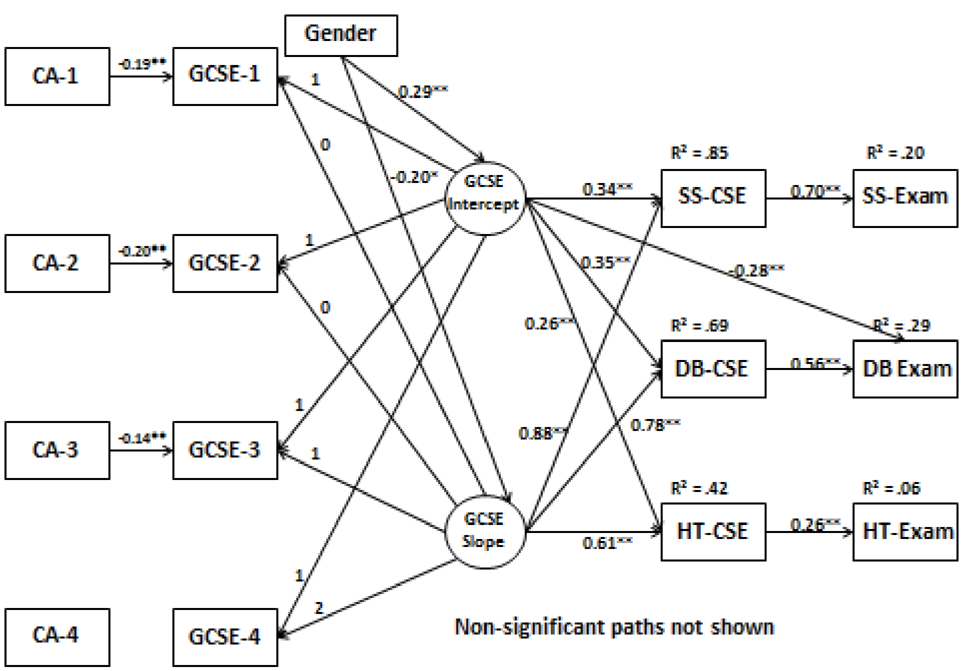

Figure 2: Model with (significant) paths from GCSE intercept/slope to exams

The mean intercept for the entire group was about 69 (p < 0.01), indicating that respondents started out with a score significantly greater than zero. The mean slope for the class was 5.7 (p < 0.01), indicating respondents' GCSE grew (mean was positive) significantly over the course of the training. The latent variables intercept and slope both had significant variance (17.6 and 4.5 respectfully; p < 0.01). The intercept variance indicates that respondents reported a significantly wide range of initial GCSE scores, while the slope variance indicates that respondents experienced significantly different growth rates for GCSE. There was a significant negative covariance between intercept and slope (-28.4, $p < 0.01$), which indicates that those who started with low GCSE (intercept) experienced more rapid growth (a higher magnitude slope), while those who started with higher GCSE experienced a slower growth rate.

The next step in LGM analyses is to include predictors and outcomes. There were two predictor variables: gender and anxiety. Gender displayed a significant relationship with one's starting GCSE (intercept) and one's change in GCSE over time (slope). Hypotheses 1 and 2 were thus supported. The standardized path between gender and intercept was 0.29 ($p < 0.01$), which means that at the start of the semester there was a significant gender difference in GCSE beliefs. As some studies have found, males had significantly higher levels of starting GCSE. The path between gender and slope was -0.20 ($p < 0.01$), which indicates that females had a greater change in GCSE over the course of the semester. Thus one's rate of change for GCSE depended in part on gender; males exhibited a significantly slower growth rate in GCSE during the semester. Anxiety was measured at all four time periods and for the first three periods had a significant negative relationship with GCSE (-0.19, -0.20, -0.14, all $p < 0.01$). The last time period, with anxiety and GCSE-4 measured at the end of the semester, the relationship was not significant (-0.07, $p = 0.21$). Early in training, students' anxiety levels significantly and negatively influenced their judgment of self-efficacy. But as training progressed, as students gained experience and skill, anxiety's influence weakened until it became not significant. Hypothesis 3 was therefore partially supported.

There were two outcomes of CGSE in the model: performance and three CSEs. After controlling for the effects of anxiety and gender, both intercept and slope influenced all three CSEs and all three CSEs influenced their respective performance test. However the paths from intercept and slope did not significantly influence the three performance tests, except intercept to the DB test (-0.28, $p < 0.01$; examined in the Discussion section). For the intercept, the path to the spreadsheet test was -0.11 ($p = 0.47$) and to the web test was -0.11 ($p = 0.17$). For slope, the path to the spreadsheet test was -0.28 ($p = 0.38$), to the database test -0.01 ($p = 0.95$), and to the web test -0.04 ($p = 0.74$). Hypotheses 4 and 5 were therefore not supported. One's initial judgment of ability for computers (GCSE-intercept) did not significantly influence end of training exams; nor did one change in GCSE over the course of the semester (slope). While the fit statistics were satisfactory, given that neither intercept nor slope influenced the performance test (save the one mentioned), the model was revised, removing the paths from intercept and slope to the three performance tests. The revised model, presented in Figure 3, also demonstrated a good fit for the data ($\chi^2 = 98.28$, df = 69, $p < 0.02$, CFI = 0.97, RMSEA = 0.04). Anxiety and gender influenced GCSE as before, with only very slight changes (and like before, anxiety did not influence GCSE at the end of the semester). The paths from GCSE intercept to the three CSEs (SS, DB, and html) were positive and significant (0.33, 0.33, and 0.24, respectfully, all $p < 0.01$). The paths from GCSE slope to the CSEs were also positive and significant (0.87, 0.78, and 0.61, all $p < 0.01$). In turn, each CSE also significantly influenced each performance test (spreadsheet 0.45, database 0.45, and html 0.22, all $p < 0.01$). For both models, effect sizes were similar and substantial, especially for the self-efficacy measures (those that follow are for the revised model). The R^2 values for the three specific CSEs were 0.84 (CSE-SS), 0.70 (CSE-DB) and 0.41 (CSE-web). R^2 values for the three performance tests were less, 0.20 (spreadsheet test), 0.21 (database test), and 0.05 (web test), but still within the range of similar studies.

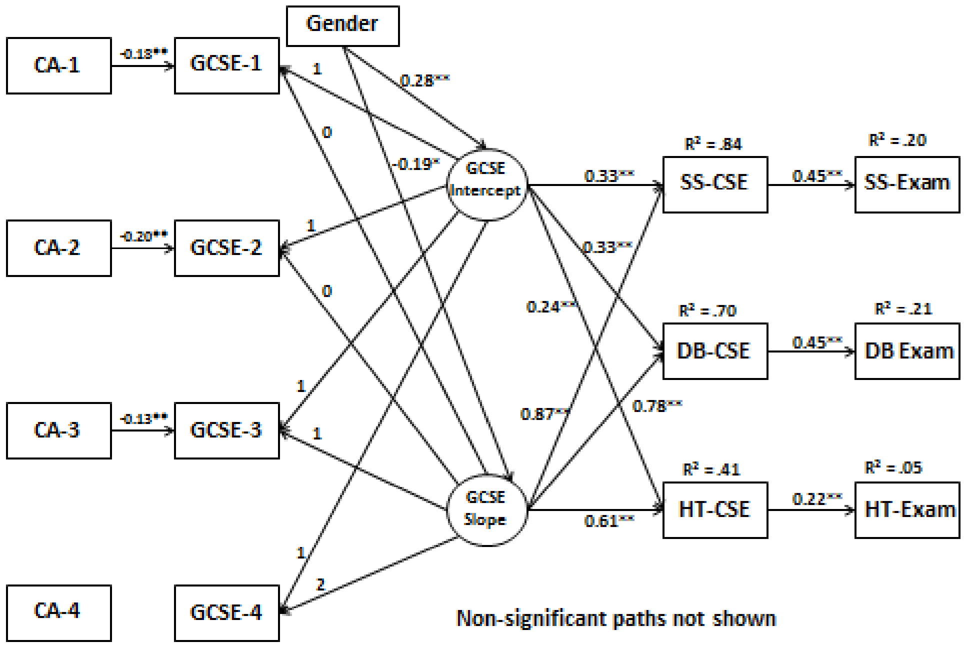

Figure 3: Final model with paths from GCSE intercept/slope to exams removed

Discussion

This study examined the influence of GCSE on application performance in spreadsheets, databases and web design over time during training. The study posited that both computer anxiety and gender would influence GCSE, while GCSE itself would influence performance. The study adds to the literature by examining both GCSE and anxiety over time during training, using repeated measures collection and the statistical technique of latent growth modeling. The methodology and findings in the study provide enhanced clarity on several critical factors involved in technology training. These findings are discussed below, along with the implications regarding training.

Computer Anxiety

While anxiety has been established in the literature as a significant influence on self-efficacy, how the relationship changes over time during training has rarely been explored. While some studies note change in anxiety over time, many assume that its relationship with self-efficacy during training is constant and report the relationship as if it were static. But these findings clarify the process. Anxiety decreased over the semester in a linear fashion (2.6, 2.5, 2.4 and 2.3). It was a strong and significant predictor of GCSE initially but, as training progressed, particularly after the first month, the relationship weakened. By the end of training, anxiety's influence on GCSE was not significant. The ramification for trainers is that less time needs to be spent on anxiety-relieving mechanisms as training progresses. Early in training, instructors should be sensitive to individual needs and constraints, identify early those with potential anxiety issues, and implement appropriate interventions if necessary (Buche et al., 2007). Identification of overly anxious students (and students with low self-efficacy levels, for that matter) can be done easily enough through simple testing or even observation. Interventions include building upon prior success by introducing simple and basic tasks, increasing difficulty level slowly (if possible) with personalized attention (Weil & Rosen, 1997). For these students and for these applications, the point at which anxiety no longer influences self-efficacy is at some point late in the semester. As a point for further study, it would be interesting to examine the relationship between the two over time for more advanced students. Are students in advanced courses, with presumably more advanced technical skills, immune from the effects of anxiety on self-efficacy? Testing more skilled IT personnel could answer this.

Gender

There have been mixed findings concerning gender and technology and self-efficacy. In support of some studies, here gender exhibited a significant influence on one's GCSE at the beginning of training; women in this study had significantly lower judgments of ability for their computing skills. Thus despite some studies suggesting the technology gender gap has decreased (Torkzadeh et al., 1999), we find it not so in this study. Instructors should keep this in mind in technology classrooms; efforts directed at women to enhance self-efficacy should be examined. Such activities could include verbal support and encouragement as well as focused training interventions. Over time, however, women experienced more growth during training in their self-efficacy beliefs than did men. Women's self-efficacy beliefs increased at a greater rate during the training than did men's. One reason for this finding is starting judgments of ability; men started with higher GCSE levels and thus had less room for growth. But this finding seems a win-win proposition: both genders experience the benefits of enhanced self-efficacy during training. Those who start with higher GCSE are already there; those with lower self-efficacy beliefs see it grow more rapidly during training.

General Computer Self-efficacy

GCSE is an important construct for educators/trainers because it is a judgment of overall computing skill, and can conceivably be used in place of multiple specific-domain CSEs. This study included two aspects of GCSE: GCSE at the start of training (intercept) and change over time of GCSE during training (slope), a relatively new way of examining GCSE. In this study, neither intercept nor slope was significantly related to the three application performances (with one exception). Thus GCSE did not directly influence performance. The one exception was the database exam in which there was a significant *negative* relationship with intercept. This finding is the opposite of what was hypothesized. The database portion of the class was the last of the three topics, so we suspect that the time elapsed from when GCSE (intercept) was first measured at the start of class to the database test at the end had some influence. It may be that database applications are somewhat different than the other two. However, despite this lone exception, the results suggest that GCSE's influence on application performance is not significant and supports previous theoretical positions (Bandura, 1997; Marakas et al., 1998). While GCSE did not influence performance, both starting GCSE (intercept) and its change over time (slope) did significantly influence the three application-specific CSEs of spreadsheets, databases, and html. And, unlike GCSE, the three application specific CSEs exerted a strong, significant influence on the performance exams.

This study clarifies the complex cognitive interactions present in students during learning and has repercussions for trainers and educators. As students begin technology training, they typically exhibit some anxiety about technology. Their confidence in general computing ability, GCSE, is also somewhat low, but significantly lower for women. As training progresses, anxiety decreases linearly while general self-efficacy increases non-linearly (it stays about the same for the first two months, then increases significantly). Women experience a significantly higher rate of change in self-efficacy over the training period in self-efficacy than men. The influence of anxiety on student's self-efficacy (GCSE) is initially strong and significant, but weakens over time and at the end of training is no longer significant. Students' general computer self-efficacy, both initial GCSE and its change over time, does not influence directly student performance in technology. However it was a strong influence on the three specific CSEs; in particular, slope, or change in

GCSE over time during training, had a remarkably strong relationship with the CSEs. The inclusion of slope, or change over time, provides a distinction not studied before, and clarifies how one's judgment of ability for the computing domain as a whole, as it changes over time, interacts with performance and specific CSEs. That the CSEs influenced performance was not surprising and is a core finding in previous studies (Bandura, 1997; Marakas et al., 1998). The influence of GCSE on performance, therefore, is indirect; it goes through application-specific CSEs.

The implications for educators are substantial. First, it again confirms the importance of self-efficacy beliefs during the training process on actual performance. In particular, specific CSEs are strong predictors of performance, and general CSE a strong influence on specific CSEs. Therefore activities designed to enhance self-efficacy, whether general or specific, are important during training. These activities, explicated by Bandura (1997) and confirmed in multiple studies, include actual technology performance, watching others perform, verbal persuasion and encouragement, and methods to improve attitudes toward technology (and attitudes include anxiety). But this study also revealed that the role anxiety plays decreases during training. Efforts to alleviate anxiety, such as building on prior success and individualized attention, are important, at least early in training, but less so as students' skills are enhanced through training. Finally, instructors should be aware that women may have lower self-efficacy beliefs, and efforts to augment their beliefs, in ways just mentioned, could improve their learning.

These results also clarify one of the issues raised in this study: should teachers or researchers use general computer self-efficacy (GCSE) as a suitable measure of self-efficacy during training? It is clearly less laborious for students to use one GCSE instrument than for them to use multiple application-specific scales (depending on how many applications are in the course). While GCSE (intercept and slope) did not have a significant relationship with performance, it strongly influenced specific CSEs. Although clearly not conclusive, the clarity this study provides in how GCSE, CSEs, anxiety and performance interact over time during training does suggest that GCSE may be an appropriate surrogate for multiple application-specific CSEs. Of course, if a course includes only one (or perhaps two) applications, CSEs provide a more direct assessment of one's judgment of ability.

Conclusion

This study examined the influence of general computer self-efficacy over time during training on performance, controlling for anxiety and gender. It extends previous literature in several directions, in particular by including in the learning model the rate of change in self-efficacy over time during training. The addition of GCSE change, labeled slope in the statistical technique of latent growth modeling, allows both researchers and teachers to more clearly understand how learning occurs during technology training and the factors that influence it. Including rate of change provides a dimension not previously examined in a learning context, and clarifies the process of learning during technology courses.

This study found that general computer self-efficacy, both initial and as it changed over time, did not influence performance, but did influence downstream (in time) application-specific CSEs, which did in turn influence performance. It found that anxiety decreased linearly, while GCSE increased non-linearly, and their relationship was strong at the beginning but weakened to non-significance toward the end of training. The study found that women had significantly lower GCSE initially, but had a faster rate of increase over the semester than did their male counterparts. While the CSEs influenced performance, GCSE's influence on performance was found to be indirect. These findings clarify the complex process which occurs in students during technology training. It also has important ramifications for teachers. As has been found in other studies, anxiety influences self-efficacy, and self-efficacy influences performance, so interventions to assuage anxiety and enhance self-efficacy remain important. But this study found that while self-efficacy's influence on performance remains (in its application-specific form), anxiety's influence decreases to non-significance, and so as training progresses, teachers can reduce anxiety interventions. This study also found that gender intervention for technology classes is still appropriate.

There are a number of limitations in this study. This study examined a group of students taking an introductory lab-based technology course. This study examined three applications, but different ones may produce different results. While using students is appropriate in a didactic study such as this, how it may apply to technology employees is beyond the scope of this study. This study examined two antecedent factors, anxiety and gender, and one outcome, performance. Clearly there are a host of other influences on learning and performance. While anxiety and gender are important influences, other factors such as experience, attitudes, and other psychological beliefs or dispositions (e.g., self-esteem, personality) may exert an influence and should be studied for a clearer picture of learning. Collecting repeated measures on such influences can clarify how these constructs interact during training over time. The training methodology used in the classroom could also influence results, although for this study we attempted to limit this influence by using the same instructor (not one of the researchers) and the same lab for all study respondents. Some of these limitations lend themselves to further study. We examined change over time of general computer self-efficacy, but there are a host of other constructs that could be examined as influences over time during the learning process. These include application-specific CSEs, or any other psychological influence on learning (anxiety, affect, etc.). Using repeated measures and latent growth modeling opens up a new array of tools that allow researchers to examine more finely the factors that influence learning and, in particular, technology learning. While this study used freshmen/sophomore college students in a first technology class, other studies should examine other core groups, including of course employees.

The training and education of tomorrow's workforce, particularly with respect to technology, is a critical task in today's universities. Universities typically provide the primary final instruction on technology prior to entering the workplace. Therefore it is extremely pertinent for teachers and instructors to understand with greater clarity the cognitive process by which students learn. This study sheds some clarity on that process, and offers some suggestions for improving training in the classroom. Improving university technology training will produce more competent employees and hopefully induce more students to take technology courses by reducing the psychological barriers to learning technology. As employers require an ever greater number of tech-savvy employees, it is incumbent upon universities to help meet this demand by more effective and enhanced training.

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Appendix: Study Measures

Computer Anxiety

…I feel apprehensive about using computers
…It scares me to think I could cause the computer to destroy a large amount of information by hitting the wrong key
…I hesitate to use a computer for the fear of making mistakes that I cannot correct
…Computers are somewhat intimidating to me

General CSE

…I believe I have the ability to describe how a computer works.
…I believe I have the ability to install new software applications.
…I believe I have the ability to identify and correct common operational problems.
…I believe I have the ability to unpack and set up a new computer.
…I believe I have the ability to remove information that I no longer need from a computer.
…I believe I have the ability to use a computer to display or present information in a desired manner.

Spreadsheet CSE

...I believe I have the ability to properly use relative and absolute addressing.
...I believe I have the ability to use the spreadsheet's built-in mathematical and statistical functions.
...I believe I have the ability to use the spreadsheet's logical functions (e.g., IF and VLOOKUP).
...I believe I have the ability to create charts and graphs.
...I believe I have the ability to create a macro to automate a task.
...I believe I have the ability to create a pivot table to summarize business data.

Database CSE

...I believe I have the ability to create a Select query.
...I believe I have the ability to create a summation query that aggregates business data.
...I believe I have the ability to create a query with a calculated field.
...I believe I have the ability to create a database table.
...I believe I have the ability to create a report

Web Design (html) CSE

...I believe I have the ability to create different sized headings.
...I believe I have the ability to create a hypertext link to another webpage.
...I believe I have the ability to add an image to a webpage.
...I believe I have the ability to use FTP to transfer my webpage to a web server.
...I believe I have the ability to add a background image to my web page.

Biographies

James P. Downey is an associate professor in the MIS Department in the College of Business at the University of Central Arkansas. He received his Ph.D. in Management Information Systems from Auburn University. He spent 25 years as a Naval officer, including a tour in the Computer Science Department at the U.S. Naval Academy, before leaving the Navy in November 2004. His current research interests include project management, database management, and individual differences in behavior in human-computer interactions and end-user computing. He has been published in several journals, including *Journal of Information Systems Education*, *Journal of Organizational and End User Computing*, *Journal of Information Technology Education*, *Journal of Computer Information Systems*, *International Journal of Business Information Systems*, *Journal of Quantitative Analysis in Sports*, *International Journal of Training Development*, *Journal of Knowledge Management Practice*, and others.

Hemant V. Kher is an associate professor of operations management in the Department of Business Administration at the University of Delaware. He has a Ph.D. in Production & Operations Management from the University of South Carolina, a Masters in Industrial Administration from Lynchburg College, and a BSc in Physics from Bombay University. Before pursuing graduate studies, he worked in the Quality Control and Production Planning departments at Amforge Industries in India. He has consulted with small and multi-national firms on operations issues. He has published his research in *Decision Sciences, European Journal of Operational Research, International Journal of Production Research, Journal of Operations Management* and other journals.