PREDICTING COMPUTER TASK PERFORMANCE: PERSONAL GOAL AND SELF-EFFICACY

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ABSTRACT

Computer task performance is an essential driver of end user productivity. Recent research indicates that computer self-efficacy (CSE) is an important determinant of computer task performance. Contrary to the significant interest in understanding the role of CSE in predicting computer task performance, little attention has been given to understanding the role of personal goal (PG), which can be as powerful as or more powerful than CSE in predicting and determining computer task performance. Employing CSE and PG, the present research develops and validates a theoretical model that predicts individual computer task performance. The model was tested using PLS on data from an intensive software (Microsoft Excel) training program, in which forty-one MBA students participated. Results largely support the theorized relationships of the proposed model and provide important insights on how individual motivational beliefs influence computer skill acquisition and task performance. Implications are drawn for future research and practice.

Keywords: End-user training, computer self-efficacy, personal goal, computer task performance, PLS

INTRODUCTION

Computer task performance is a major contributor to end-user productivity. Most organizational activities are becoming increasingly dependent on computers and computer-based information systems (IS). The expected productivity gains from the use of IS cannot be realized unless people are equipped with the requisite computer skills. Many people experience substantial difficulty in learning to use computers (Carroll & Rosson, 1987; Landauer, 1995; Wildstrom, 1998), and often abandon or underuse multimillion-dollar computer-based systems due to their lack of ability to use the systems effectively (Ganzel, 1998; McCarroll, 1991). IS researchers have long recognized computer training as one of the critical factors responsible for ensuring the success of end-user computing (Bohlen & Ferratt, 1997; Cheney, Mann, & Amoroso, 1986; McLean, Kappelman, & Thompson, 1993; Nelson & Cheney, 1987). A recent industry survey shows that 99% of U.S. organizations teach their employees how to use computer applications (Industry Report, 2001). Understanding the key mechanisms that govern computer skill acquisition and task performance is a critical issue that has a significant impact on daily employee functions, return on IS investment, and ultimate organizational success.

Prior research examined a number of individual variables by which computer learning and task performance could be predicted. (e.g., Bostrom, Olfman, & Sein, 1990; Evans & Simkin, 1989; Marcolin, Munro, & Campbell, 1997; Martocchio & Judge, 1997; Webster & Martocchio, 1992). Of late, an increased focus on the variables related to computer learning and task performance has included a construct called computer self-efficacy (CSE), perception of one’s capability to use a computer. In addition to being an important variable that influences individual’s decision to accept or use information technology (Compeau & Higgins, 1995b; Hill, Smith, & Mann, 1987; Taylor & Todd, 1995; Venkatesh 2000), CSE has been found to significantly influence task performance in various training settings (e.g., Compeau & Higgins, 1995a; Gist, Schwoerer, & Rosen, 1989; Johnson & Marakas, 2000; Martocchio & Dulebohn, 1994).

Contrary to the significant interest in understanding the role of CSE in predicting computer learning and task performance, little attention has been given to understanding the role of personal goal (PG), which is defined as the performance standard an individual is trying to accomplish on a given task (Locke & Latham, 1990). Goal setting theory (Locke & Latham, 1984, 1990) views the constructs of both PG and self-efficacy as key determinants of task performance that have powerful direct and independent effects. In various studies conducted outside of the computer training domain, PG has been found as powerful as, and in many cases, more powerful than self-efficacy in predicting task performance (Bandura & Cervone, 1986; Earley & Lituchy, 1991; Locke & Latham, 1990; Mitchell, Hopper, Daniels, George-Falvy, & James, 1994; Wood & Locke, 1987). The joint effects of self-efficacy and PG on performance indicates that performance is determined not only by how confident one is of being able to do the task at hand but by how much one is trying to achieve. Goal setting theory also theorizes that self-efficacy can indirectly influence task performance through its effect on PG. Within the computer training domain, it is unknown how powerful PG is in predicting trainee performance or how significantly CSE is linked to PG. Very few studies, if any, have examined either the relative predictive power of CSE and PG with regard to computer task performance or the relationship between CSE and PG.

In an overview of past research on computer training, Gattiker (1992) pointed out that many reports were based on studies of very short duration (less than four hours), while literature suggested more extended hours of training and skill practice for relatively complex tasks (Ackerman, 1992). In fact, most IS training studies have focused on understanding the underlying mechanisms behind only an initial skill set of a computer application. In sum, employing CSE and PG, the present research develops a theoretical model that predicts individual computer task performance, and empirically validates the model in an intensive computer software training program that lasted more than a month.

The rest of the paper is organized as follows. Section 2 develops the proposed theoretical model. Section 3 describes the study method employed for this research. Section 4 presents the test of the proposed model using PLS. Finally, section 5 discusses findings and concludes the paper by suggesting future research directions and practical implications.

CONCEPTUAL BACKGROUND AND RESEARCH MODEL

Figure 1 presents the research model. On the basis of social cognitive theory (Bandura, 1977, 1986) and goal setting theory (Locke & Latham, 1984, 1990), the model theorizes CSE and PG as the key determinants of computer task performance. CSE is also hypothesized to influence computer task performance through its effects on PG. The model includes two potentially relevant pre-training variables, prior experience and age, to isolate and control for pre-training individual differences, thereby more precisely evaluating the theorized effects of CSE and PG on computer task performance. Each element of the proposed model and the specific hypotheses relating them are further described below.

Insert Figure 1 about here

Computer Self-Efficacy

Social cognitive theory (Bandura, 1977, 1986) posits that people are driven neither only by inner forces, nor simply by external stimuli. Instead, human behavior is explained via a model of triadic reciprocality in which behavior, cognitive and personal factors, and environmental events all operate interactively as determinants of each other. A key regulatory mechanism in this dynamic relationship that affects human behavior is self-efficacy, people's judgments of their capabilities to perform certain activities. The theory postulates that psychological procedures, whatever their form, serve as a means of creating and strengthening expectations of personal efficacy (Bandura, 1997), which in turn determines what actions to take, how much effort to invest, how long to persevere, and what strategies to use in the face of challenging situations.

According to Bandura (1986, 1997), self-efficacy is a situation specific belief regarding a specific task accomplishment. Bandura opposes the idea of measuring global efficacy belief without specifying the activities or conditions under which they must be performed, but he also acknowledges that it is a multi-level construct. It is important to draw a distinction between general CSE, which operates at the general computing level across multiple application domains, and software-specific CSE, which operates at the application-specific software level (Marakas, Yi, & Johnson, 1998). The present model focuses on software-specific CSE because it more closely corresponds in specificity to the task performance criterion of the current context (Bandura, 1997). Self-efficacy formulated at the general computing level is more appropriate in estimating one's ability to use a computer across diverse application domains (Marakas et al., 1998).

Computer software training provides an opportunity for an end-user to obtain the component skills and the confidence required for effective use of the target software application. Social cognitive theory (Bandura, 1986, 1997) posits individual self-perception of efficacy as a key determinant of skill acquisition and task performance. A substantial body of research has reported significant empirical relationships between self-efficacy and performance (e.g., Colquitt, LePine, & Noe, 2000; Kraiger, Ford, & Salas, 1993; Salas & Cannon-Bowers, 2001). Previous research, specifically on computer training, has found post-training software-specific CSE to be a significant predictor of task performance (Compeau & Higgins, 1995a; Gist et al., 1989; Johnson & Marakas, 2000; Martocchio & Judge, 1997). However, our understanding of CSE in relation to task performance is limited because most studies examined the predictive validity of CSE with regard to a fairly simple task performance, focusing on the initial use of a software program or one specific feature within the program. Extending prior research, the present study examines the effect of post-training CSE on a complex task performance, which requires the use of a comprehensive set of software features, and hypothesizes that:

H1: Computer self-efficacy will positively influence computer task performance.

Personal Goal

The basic premise of goal setting theory (Locke & Latham, 1984, 1990) is that conscious human behavior is purposeful and it is regulated by the individual's goal. Focusing on the question of why some individuals perform better on work tasks than others even when they are similar in ability and knowledge, the theory seeks the answer from their differing levels of goals. Given that the person has requisite ability and knowledge, the theory asserts that there is a positive linear relationship between the level of goal and performance. That is, individuals with more challenging goals exert more effort in line with the demands of the higher performance standards (Bandura & Cervone, 1986; Terborg, 1976) and maintain effort over more extended time (Sales, 1970; Singer, Korienek, Jarvis, McCloskey, & Candeletti, 1981) than individuals with less challenging goals, thereby producing higher performance.

Although it is unknown specifically how PG is related to task performance in the context of computer training, there is empirical evidence that PG affects task performance over and above self-efficacy in a training or education context. For example, Wood and Locke (1987) examined the relationship between PG and performance in college courses. They found that grade goals were significantly related to academic course performance over and above the effects of self-efficacy in three studies. In a meta-analysis based on the results of thirteen studies, which measured each of the relationships between PG, self-efficacy, and performance, Locke and Latham (1990) found the mean of the relationship between PG and performance (r = .42) to be slightly higher than that of the relationship between self-efficacy and performance (r = .39). These findings suggest that PG can be a significant determinant of task performance in a computer-training program. Thus, we hypothesize that:

H2. Personal goal will positively influence computer task performance.

In addition to the direct effects of PG and self-efficacy on individual performance, goal setting theory (Locke & Latham, 1984, 1990) posits that self-efficacy affects performance through PG. That is, other things being equal, individuals with higher self-efficacy perceptions tend to set higher goals and subsequently achieve superior performance. In a meta-analysis, Locke and Latham (1990) found the link between self-efficacy and PG (*r* = .39) to be as strong as the link between self-efficacy and performance (*r* = .39). Earley and Lituchy (1991) compared three motivational models that described the relationships among self-efficacy, PG, and performance in alternative ways, and found the study results to consistently support the mediating role of PG in the relation of self-efficacy and performance as proposed by Locke and Latham (1990). Based on these findings, we hypothesize the following:

H3. Computer self-efficacy will positively influence personal goal.

Individual Differences: Prior Experience and Age

Even when trainees have the same levels of goals and self-efficacy, they may not perform at the same level due to their pre-training individual differences. Studies on goal setting theory and self-efficacy have found that prior experience (sometimes called past performance) with the task was a significant predictor of performance over and above PG and self-efficacy (Mitchell et al., 1994; Wood & Bandura, 1989; Wood & Locke, 1987). Colquitt et al. (2000) conducted a meta-analytic review of training literature for the past 20 years and showed that the effect of age on training outcomes was only partially mediated by self-efficacy and other motivational variables. In the context of end-user training, several researchers have confirmed the significant role of prior experience (Bolt, Killough, & Koh, 2001; Compeau & Higgins, 1995a; Johnson & Marakas, 2000; Martocchio & Dulebohn, 1994; Olfman & Bostrom, 1991; Webster & Martocchio, 1993) and age (Martocchio, 1994; Martocchio & Webster, 1992; Webster & Martocchio, 1995) in determining training outcomes. In those studies, training outcomes were positively related to prior experience, but negatively to age. By controlling for potentially relevant pre-training individual difference variables, and accounting for variance in task performance that is unrelated to CSE and PG, which would otherwise increase error variance, the present research model seeks to provide a more precise evaluation of the CSE and PG effects on task performance. Thus, we hypothesize that:

H4. Prior experience will positively influence computer task performance.

H5. Age will negatively influence computer task performance.

METHOD

Procedure

A training program over a period of four weeks on an electronic spreadsheet program (Microsoft Excel for Windows) was set up at a large university in the eastern United States. Participants were 41 MBA students (41.5% female and 58.5% male). The participant ages ranged from 24 to 48, with the average of 29.4. Most participants (90.2%) reported using a spreadsheet program not more than 10 hours a week. All the participants had work experience, with an average of three to five years.

The training program started with the basic features of Excel and progressively covered more advanced features such as business modeling, charting and graphing, financial and statistical analysis, database structuring and querying, and development of complete business applications with macro programming and interface design. The trainees met on four consecutive Saturdays, and two half-days – one half-day on Friday just before the first Saturday and the other half-day on Monday after the last Saturday. During the first half-day session, trainees filled out a questionnaire that included demographic information, took a hands-on test designed to assess prior experience with Excel (25 minutes), and received a brief introductory lecture about basic spreadsheet features. On the last Saturday, trainees again filled out a questionnaire that included post-training software-specific CSE and PG measures. Two days later, which was the last half-day, trainees took a comprehensive hands-on test for computer task performance (150 minutes).

On each of the four Saturdays, trainees met from 9:00 a.m. to 5:00 p.m. attending two lectures and two workshop sessions. Each lecture (one in the morning and the other in the afternoon) lasted for 90 minutes and introduced key concepts, examples, and applications at a conceptual level to provide a frame of reference within which the more detailed hands-on material could be assimilated. The class was co-taught by two instructors, including one of the authors. The instructors took turns covering different topics.

The hands-on workshop session lasted 90 minutes in the morning and 120 minutes in the afternoon. Trainees were asked to solve assigned problems proceeding from highly guided and detailed step-by-step instruction, to increasingly integrative case examples that required the trainees to apply the newly acquired expertise in novel ways. Correct answers were provided to allow trainees to self-check their own progress. To further reinforce the training material, trainees were asked to solve a number of problems outside of the training workshop. Table 1 summarizes the training procedures and elements.

Insert Table 1 about here

Measures

Computer Task Performance

The dependent variable of the study, computer task performance, was measured by a comprehensive set of problems designed to evaluate trainees' overall competencies gained during the training. Each problem typically started with a description of a business problem, which was followed by a list of computer tasks to be completed. The tasks required the use of software functions such as present value analysis, two-input data table construction, charting, database filtering, pivot table analysis, interface design, and macro programming. Upon completion of the test, each trainee submitted their results on a provided diskette. Two graders independently graded the answers using a scoring key on a scale from 0 to 100. The correlation between the grader scores was high at .89 ($p < .001$). Each grader's scores were used as indicators of the task performance construct.

Computer Self-Efficacy

CSE was measured at the spreadsheet application level by five items adopted from Johnson and Marakas (2000). Trainees were asked to indicate the extent to which they agreed or disagreed with the following statements: "I believe I have the ability to manipulate the way a number appears in a spreadsheet," "I believe I have the ability to use a spreadsheet to communicate numeric information to others," "I believe I have the ability to summarize numeric information using a spreadsheet," "I believe I have the ability to use a spreadsheet to share numeric information with others," and "I believe I have the ability to use a spreadsheet to assist me in making decisions." The self-efficacy measure captured the magnitude (yes or no) and strength (on a scale from 1 to 10, where 1 = "quite uncertain" and 10 = "quite certain") of each individual's self-efficacy. For further analysis, the magnitude scale was converted to 0 (no) or 1 (yes), and then multiplied by the strength items per Lee and Bobko (1994).

Personal Goal

The measure consisted of two items adopted from prior research (Locke & Bryan, 1968; Wood & Locke, 1987). The items were (1) the grade the trainee hoped to make in the course, and (2) the personal goal the trainee has for the course grade.

Prior Experience

Each subject's prior experience with the target computer program was measured using a hands-on skill test designed to assess basic spreadsheet skills with 12 computer tasks (Johnson & Marakas, 2000; Yi & Davis, 2001). The test includes entering a formula in multiple cells, using functions to calculate total and average amounts, computing year-to-date sales and % change of sales, copying the format of a cell, and changing the formats of numbers. Each trainee saved the test result in a diskette and submitted the diskette at the end of the test. The grading of the answers was handled by the spreadsheet program module developed through several stages of programming and accuracy verification. Each task was scored with 1 point for totally correct answers, .5 point for partially correct answers, and 0 for incorrect or missing answers. The percentage of correct answers was calculated from the total scores and used as the prior experience measure.

Demographics

Age, sex, the length and frequency of computer use and spreadsheet program use, and work experience were measured by the pre-training questionnaire. Only age was a significant predictor of the task performance among these demographic variables.

RESULTS

Cronbach alpha measures of internal consistency reliability were all high and acceptable at .92 for CSE, and .80 for PG. Further measure validation and model testing were conducted using PLS (Partial Least Squares) Graph Version 2.91.03.04 (Chin & Frye, 1998), a structural equation modeling tool that utilizes a component-based approach to estimation. The PLS approach (Agarwal & Karahanna, 2000; Barclay, Higgins, & Thomson, 1995; Chin, 1998; Compeau, Higgins, & Huff, 1999; Falk & Miller, 1992; Wold, 1982), like other structural equation modeling (SEM) techniques such as LISREL (Jöreskog and Sörbom, 1993) and EQS (Bentler, 1985), allows researchers to simultaneously assess measurement model parameters and structural path coefficients. Whereas covariance-based SEM techniques such as LISREL and EQS use a maximum likelihood function to obtain estimators in models, the component-based PLS uses a least squares estimation procedure.

PLS avoids many of the restrictive assumptions underlying covariance-based structural equation modeling (SEM) techniques such as multivariate normality and large sample size (Barclay et al., 1995; Chin, 1998; Fornell & Bookstein, 1982; Wold, 1982). Chin (1998, p. 311) advises that "if one were to use a regression heuristic of 10 cases per indicator," the sample size requirement would be 10 times (1) the largest number of formative indicators or (2) the largest number of independent variables impacting a dependent variable, whichever is the greater. In our model, all items are modeled as reflective indicators because they are viewed as effects (not causes) of latent variables (Bollen & Lennox, 1991), and the largest number of independent variables estimated for a dependent variable is four. Thus, our sample size of 41 meets the requirement for the PLS estimation procedures.

PLS Measurement Model

The measurement model in PLS is assessed by examining internal consistency and convergent and discriminant validity (Barclay et al., 1995; Chin, 1998; Compeau et al., 1999). Internal consistency reliability (similar to Cronbach's alpha) of .7 or higher are considered adequate (Agarwal & Karahanna, 2000; Barclay et al., 1995; Compeau et al., 1999). Convergent and discriminant validity is assessed in two ways: (1) the square root of the average variance extracted (AVE) by a construct from its indicators should be at least .707 (i.e., AVE > .50) and should exceed that construct's correlation with other constructs (Barclay et al., 1995; Chin, 1998; Fornell & Larcker, 1981), and (2) item loadings (similar to item loadings in principal components) should be at least .707, and items should load more highly on constructs they are intended to measure than on other constructs (Agarwal & Karahanna, 2000; Compeau et al., 1999).

Table 2 shows internal consistency reliabilities, convergent and discriminant validities, and correlations among constructs. The internal consistency reliabilities were all higher than .90, exceeding the reliability criteria of .70. As strong evidence of convergent and discriminant validity, the square root of the AVE for each construct was greater than .707 (i.e., AVE > .50) and greater than the correlation between that construct and other constructs, without exception.

Insert Table 2 about here

Table 3 provides the factor structure matrix of loadings and cross-loadings. The factor matrix shows that all items without exception exhibited high loadings (> .707) on their respective constructs and no items without exception loaded higher on the other constructs. Overall, the measured scales show excellent psychometric properties with high reliability and appropriate convergent and discriminant validity.

Insert Table 3 about here

PLS Structural Model

The PLS structural model and hypotheses were assessed by examining path coefficients (similar to standardized beta weights in a regression analysis) and their significance levels. As recommended (Chin, 1998), bootstrapping (with 120 subsamples) was performed to test the statistical significance of each path coefficient using t-tests. Inconsistent with H1, CSE had no significant effect on task performance ($\beta = .16$, *ns*). Supporting H2, PG had a significant effect on task performance ($\beta = .32$, $p < .05$). Supporting H3, CSE had a significant effect on PG (β = .39, $p < .05$). Supporting H4, prior experience had a significant effect on task performance (β = .43, $p < .05$). Supporting H5, age had a significant effect on task performance in the expected direction (β = -.29, $p < .05$). The model explained substantial variance in computer task performance (R^2 = .38). Figure 2 summarizes the results of model testing.

Insert Figure 2 about here

Although the earlier discussion of PLS with sample size requirements justifies the use of PLS in our study, we also tested the research model using ordinary least-squares regression method (Cohen & Cohen, 1983) to cross-examine the PLS testing results. Results from this analysis were almost identical to the results from the PLS analysis. All the significant paths in the PLS model remained significant and the path coefficients were very similar - the difference between the two corresponding paths between the PLS model and the regression model was always less than .01.

DISCUSSION

Summary of Findings

Overall, there was significant empirical support for the proposed model. As expected, PG was a significant predictor of computer task performance. Past experience and age were also significant predictors of computer task performance. CSE was significantly related to PG. Four of five hypotheses were supported. Contrary to expectation, the hypothesized effect of post-training CSE on task performance (H1) was not supported, indicating a weaker contribution of CSE for the given set of task skills than was expected. As trainees build their confidence in using the software application in an extended training period, the predictive strength of software-specific CSE seems to diminish rapidly. Mitchell et al. (1994) found that, PG and past performance were better predictors of performance than self-efficacy as experience with an air traffic control task increased. Our findings are consistent with their results.

The specific contributions of the present research can be articulated by comparing it with other similar studies. In the computer training context, a number of studies showed a significant effect of software-specific CSE on learning or task performance (Compeau & Higgins, 1995; Johnson & Marakas, 2000; Martocchio & Dulebohn, 1994), but did not examine the effect of PG as a determinant of task performance. The current study shows that PG is a more powerful determinant of computer task performance than CSE. Evans & Simkin (1989) examined 34 independent variables to find that those individual difference variables, while the number was considerable, could explain only 23 percent of the variance in computer proficiency. The results, which were similar to the results of other studies, show that the task of finding effective predictors of computer proficiency and task performance is elusive. Using only four variables, the current research model explained considerable variance in post-training hands-on task performance (R^2 = .38), designed to measure trainee competencies gained over a 1-month period of computer software training in a field study setting. Outside of the computer-training domain, Wood and Locke (1987) examined self-efficacy, PG, and ability, explaining 25 percent to 28 percent variation in academic performance. The current study model outperforms those models in accounting for individual task performance.

The present study introduces a new variable, PG, which has been shown to be an important determinant of task performance in other domains, into the computer-training domain. The findings show that PG affects computer task performance over and above self-efficacy, prior experience, and age. The study results support the applicability of goal-setting theory (Locke & Latham, 1990) to an end-user training program, and identify an important underlying mechanism that governs an individual’s computer task performance. Despite the significant amount of interest on self-efficacy, most computer training studies have demonstrated the predictive validity of CSE in relation to performance for fairly simple tasks. Our findings suggest that PG plays a more important role in acquiring complex computer skills. Also, it should be noted that the present study was conducted in a longitudinal field study setting that lasted more than a month, covering a full range of skills required for the effective use of a sophisticated software program. Most previous studies on computer training were conducted in a relatively short period of time (typically less than a day or two), focusing on an initial skill set of a computer application. Consequently, our understanding of the mechanisms that govern the process of computer skill acquisition, in particular beyond the initial phase, has been limited. The current study demonstrated that, for complex computer skill acquisition, PG is a more powerful predictor of task performance, and that self-efficacy has no significant effect on task performance over and above PG. Instead, a self-efficacy belief with regard to a specific software program is a significant determinant of PG, influencing task performance indirectly via PG. Although future research should further compare the relative effects of these two constructs under varying training conditions, the current study extends prior work by empirically demonstrating the predictive validity of PG in a computer training context and testing the theorized causal chains among CSE, PG, and task performance.

Limitations and Future Research Implications

Several limitations of the present study should be noted. One of the trainers was the principal investigator, who was aware of the study hypotheses. However, this study did not involve any treatments or manipulations. In addition, trainees were fully informed that the content of their questionnaire responses would not affect their grade in any way. The post-training variables were not available during training, and the performance assessments were handled either by a computer program or human graders who were not aware of the hypotheses. Thus, the possible threats of hypothesis–guessing, evaluation apprehension, and experimenter expectations to internal validity (Cook & Campbell, 1979) were avoided or minimized for this study.

Recent motivation research has found that self-efficacy and PG are influenced by certain personal factors such as goal orientation (Ford, Smith, Weissbein, & Gully, 1998; Phillips & Gully, 1997; Steele-Johnson, Beauregard, Hoover, & Schmidt, 2000), locus of control (Phillips & Gully, 1997), self-esteem

(Pilegge & Holtz, 1997; Tang & Sarsfield-Baldwin, 1991), cognitive abilities (Kanfer & Ackerman, 1989; Kanfer, Ackerman, & Heggestad, 1996), and achievement motivation (Mathieu, Martineau, & Tannenbaum, 1993; Phillips & Gully, 1997). Also, many studies have demonstrated that self-efficacy and PG affect the development and use of effective task strategies to solve problems (Chesney & Locke, 1991; Gilliland & Landis, 1992; Wood & Bandura, 1989). These antecedent and consequent variables have not been incorporated into our current research model. Given that the model received empirical support in the context of computer training, further relations between these variables and the study variables of PG and CSE should be examined by future research in order to properly extend the current model and develop more in-depth understanding of the processes governing computer skill acquisition.

With regard to external validity, support for the study model should be tested in different contexts. The present study was conducted with MBA students, all of whom had work experience. The chosen software was a popular spreadsheet program, highly useful in the workplace. The length of training program was more than a month, which is longer than most prior computer training studies. The assessed performance outcomes included skills that can be directly used in real work settings. Thus, the current study maintains many important characteristics similar to organizational training settings. However, the findings should be validated in other settings by future research beyond the specific conditions of this study to ensure generalizability of the study findings.

Implications for Practice

The present study demonstrates the important roles PG and self-efficacy play in the process of computer skill acquisition. Organizational or training interventions that positively influence these variables are likely to produce significant improvements in computer task performance, which is the main driver of end-user productivity in the workplace. Over the past decade, prior studies identified several interventions to enhance CSE such as behavior modeling (Compeau & Higgins, 1995a; Gist et al., 1989), positive performance feedback (Martocchio & Webster, 1992), induced conception of ability (Martocchio, 1994), and management support (Henry & Stone, 1994). Outside of the computer-training context, the goal-setting research has identified a number of interventions that can affect PG, including assigned goals (Meyer & Gellatly, 1988), group goals (Matsui, Kakuyama, & Onglatco, 1987), role modeling (Rakestraw & Weiss, 1981), and normative information (Earley & Erez, 1991). Although the specific effects of such an intervention on self-efficacy and PG, and subsequent task performance in the context of computer skill training still need to be examined by future research, these interventions have the potential to substantially improve end-user's computer task performance.

We have found that prior experience and age have positive and negative significant effects on the development of computer skill acquisition, respectively. People who enter a training program with relatively little or no prior exposure to the target software should be given extra attention in order to be successful in acquiring computer skills, and that older trainees should be supported with extra care than younger trainees. Given that the effects of prior experience and age on task performance were in the opposite directions, providing more hands on experience with the software before training should help older trainees become successful in acquiring computer skills.

Conclusion

In conclusion, this research has developed a theoretical model that predicts individual task performance in an end-user computer training context using the central constructs of goal setting theory (Locke & Latham, 1984, 1990) and social cognitive theory (Bandura, 1977, 1986), and empirically validated the proposed model in a longitudinal field setting. The model has received significant empirical support. The present study extends previous research on end-user training by introducing a new variable, PG, and empirically demonstrating its importance in mediating the effect of CSE and predicting computer task performance. Organizational or training interventions that make positive impacts on these motivational variables should contribute to end-user's improved computer task performance, leading to increased work productivity.

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Table 1: Training Procedures and Elements

Week	Day	Training Elements
1	Fri.	Pre-training Questionnaire Prior Experience Assessment (25 min.) Lecture & Workshop (1): Introduction to Excel
1	Sat.	Lecture & Workshop (2 & 3): Building & Using Business Models
2	Sat.	Lecture & Workshop (4 & 5): Analyzing & Managing Business Data
3	Sat.	Lecture & Workshop (6 & 7): Developing Business Applications
4	Sat.	Lecture & Workshop (8 & 9): Integrating with Other Applications Post-training Questionnaire
5	Mon.	Computer Task Performance Assessment (150 min.)

Table 2: Reliabilities, Convergent and Discriminant Validities, and Correlations Among Constructs

Construct	ICR	1	2	3	4	5
1. Computer Self-efficacy	.94	**.88**				
2. Personal Goal	.92	.39	**.92**			
3. Prior Experience	1.00	-.04	.07	**1.00**		
4. Age	1.00	-.02	.08	.25	**1.00**	
5. Computer Task Performance	.97	.28	.39	.38	-.16	**.97**

Note. ICR = Internal Consistency Reliability, which should be greater than .70. Diagonal elements (bold) are the square root of average variance extracted (AVE) between the constructs and their indicator(s). Off-diagonal elements are correlations between constructs. For convergent and discriminant validity, diagonal elements should be at least .707 (i.e., AVE > .50) and larger than off-diagonal elements in the same row and column.

Table 3: Factor Matrix

Scale Items	1	2	3	4	5
1. Computer Self-efficacy					
a. manipulate the way a number appears	.76	.25	-.02	-.01	.26
b. use a spreadsheet to communicate	.95	.35	-.09	-.01	.27
c. summarize numeric information	.95	.41	-.03	-.01	.24
d. share numeric information	.93	.37	.01	-.01	.23
e. use a spreadsheet to assist me in making decisions	.76	.28	-.02	-.04	.21
2. Personal Goal					
a. grade I hope to make	.36	.92	.10	.11	.34
b. personal goal for the course	.35	.92	.03	.04	.38
3. Prior Experience					
a. pre-training test score	-.03	.07	1.00	.24	.38
4. Age					
a. trainee self-reported age	-.02	.08	.24	1.00	-.16
5. Computer Task Performance					
a. grader 1 score	.21	.30	.40	-.18	.97
b. grader 2 score	.32	.45	.33	-.14	.97

Figure 1: Proposed Research Model

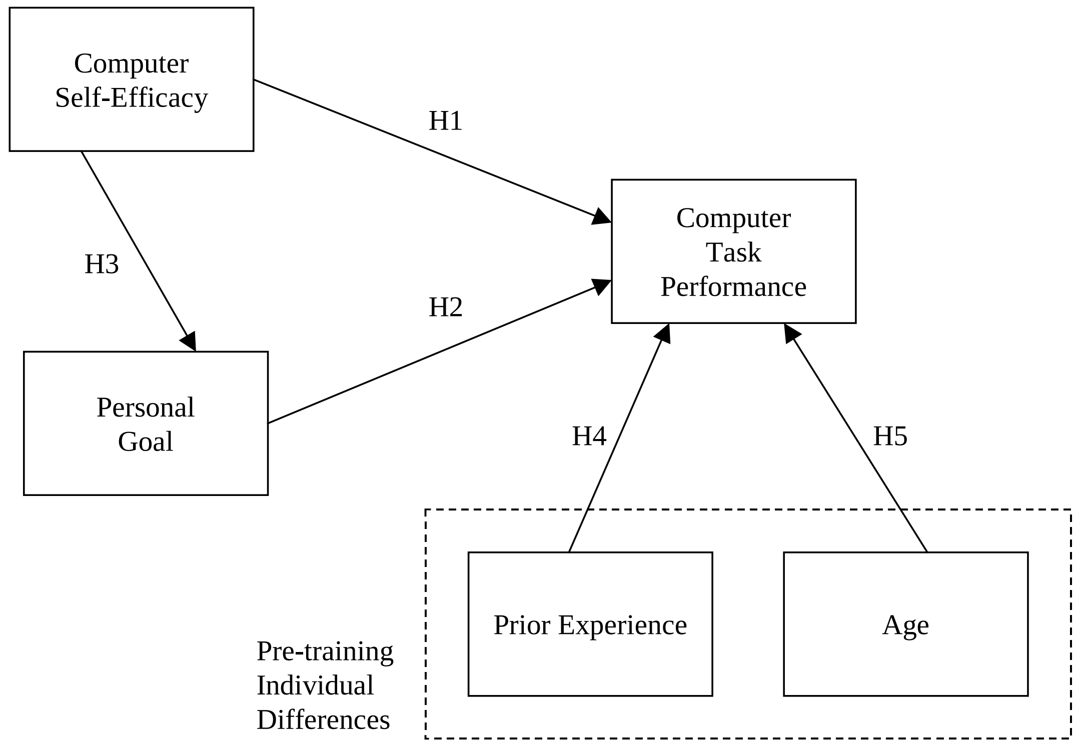

Figure 2: Model Testing Results