Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition

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Computer skills are key to organizational performance, and past research indicates that behavior modeling is a highly effective form of computer skill training. The present research develops and tests a new theoretical model of the underlying *observational learning processes* by which modeling-based training interventions influence computer task performance. Observational learning processes are represented as a second-order construct with four dimensions (attention, retention, production, and motivation). New measures for these dimensions were developed and shown to have strong psychometric properties. The proposed model controls for two pretraining individual differences (motivation to learn and self-efficacy) and specifies the relationships among three training outcomes (declarative knowledge, post-training self-efficacy, and task performance). The model was tested using PLS on data from an experiment ($N = 95$) on computer spreadsheet training. As hypothesized, observational learning processes significantly influenced training outcomes. A representative modeling-based training intervention (retention enhancement) significantly improved task performance through its specific effects on the retention processes dimension of observational learning. The new model provides a more complete theoretical account of the mechanisms by which modeling-based interventions affect training outcomes, which should enable future research to systematically evaluate the effectiveness of a wide range of modeling-based training interventions. Further, the new instruments can be used by practitioners to refine ongoing training programs.
(*Observational Learning; Modeling-Based Training; Retention Enhancement; Behavior Modeling; Computer Training; Skill Aquisition*)

1. Introduction

Effective computer training is a major contributor to organizational performance. Motorola estimated that every dollar they spend on training produces thirty dollars in productivity gains within three years (Kirkpatrick 1993). Of the nearly 57 billion dollars spent annually on formal training activities by organizations in the United States, computer skill training is the most frequent type of training provided (Industry Report 2001). Various training methods are currently used to teach computer skills (Gattiker 1992, Industry Report 2001), but the strengths and weaknesses of alternative methods, and the reasons underlying their relative effectiveness, are not well understood (Compeau and Higgins 1995a, Davis and Bostrom 1993, Lim et al. 1997, Martocchio

Information Systems Research © 2003 INFORMS
Vol. 14, No. 2, June 2003, pp. 146–169
1047-7047/03/1402/0146$05.00
1526-5536 electronic ISSN

and Webster 1992, Olfman and Mandviwalla 1994, Santhanam and Sein 1994).

One consistent finding is that behavior modeling yields better training outcomes than other methods such as lecture-based instruction (Bolt et al. 2001, Compeau and Higgins 1995a, Johnson and Marakas 2000, Simon et al. 1996, Simon and Werner 1996), computer-aided instruction (Gist et al. 1988, 1989), and self-study from a manual (Simon et al. 1996, Simon and Werner 1996). In modeling-based training, trainees watch someone else perform a target behavior and then attempt to reenact it. Before behavior modeling was established as an effective approach for computer skill training, its effectiveness for supervisory skill training was well established (for metaanalysis, see Burke and Day 1986). Given the nonsignificant results obtained in comparisons of many other training methods (e.g., Bostrom et al. 1990, Davis and Bostrom 1993, Olfman and Bostrom 1991, Olfman and Mandviwalla 1994, Santhanam and Sein 1994, Sein and Santhanam 1999), the convergence of findings by different researchers showing the effectiveness of modeling-based training for computer skills warrants continued research on how this category of training might be further improved.

Several specific techniques from other contexts may potentially extend and improve the performance of modeling-based training for computer skills (for recent discussions of training techniques, see Donovan and Radosevich 1999, Kozlowski et al. 2001, May and Kahnweiler 2000, Salas and Cannon-Bowers 2001, Venkatesh 1999). However, the opportunity for Information Systems (IS) researchers to identify, prioritize, and verify the effectiveness of such techniques has been constrained by limited existing knowledge about the psychological mechanisms underlying modeling-based training for computer skills. IS researchers have emphasized the need to tap into the explanatory processes linking experimental manipulations with dependent variables in order to improve our theoretical understanding (Benbasat 1989, Lim et al. 1997, Olfman and Bostrom 1991, Todd and Benbasat 1987).

The underlying rationale for behavior modeling in general comes from social cognitive theory (Bandura 1986), which posits that modeling-based training interventions affect training outcomes through their influence on one or more of four observational learning processes:

(1) Attention: People cannot learn from modeled actions unless they are attentive when observing them.

(2) Retention: Actions must be cognitively registered as symbolic representations in memory in order to regulate future behavior.

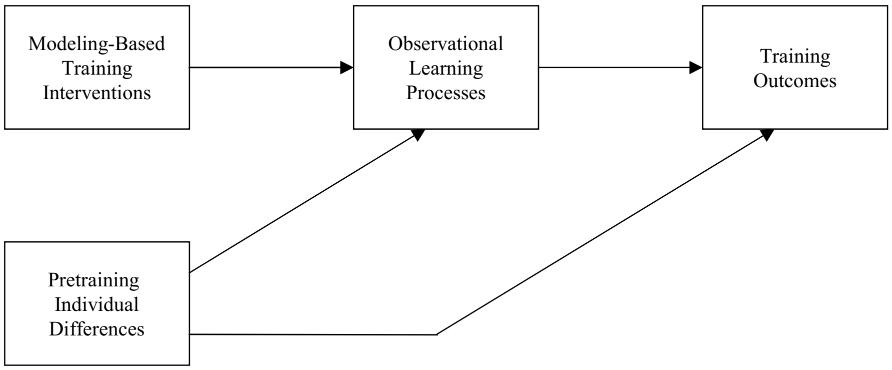
(3) Production: The retained symbolic memory of actions must be reconverted into overt actions to generate desired responses.

(4) Motivation: The symbolic memory of actions will weaken unless the perceived consequences of performing the actions are sufficiently favorable to cause repeated performance.

Although these four observational learning processes have served as the theoretical rationale for much research concerning the effects of modeling-based interventions, they have not previously been operationalized or empirically tested (Bandura 2001).

The objective of this research is to develop and perform an initial test of a new model designed to trace the influence of modeling-based interventions on training outcomes through their effects on observational learning processes. Although many IS studies have examined the effects of different training interventions on one or more training outcomes (for a recent review of prior research findings on computer training outcomes, see Yi and Davis 2001), the present model attempts to extend previous research by (1) specifying the mediating role of observational learning processes linking modeling-based training interventions to training outcomes, and (2) specifying the causal relationships among the three training outcomes of declarative knowledge, post-training self-efficacy, and task performance. Observational learning processes are modeled as an aggregate second-order construct (Edwards 2001) composed of four dimensions: Attention, retention, production, and motivation. If a theoretical model linking observational learning processes to training outcomes were to become established, it might provide the means to evaluate various modeling-based interventions. Such a model might be used to understand why a particular training intervention is more effective than others, and how the intervention can be further improved.

Figure 1 Conceptual Framework



2. Research Model and Hypotheses

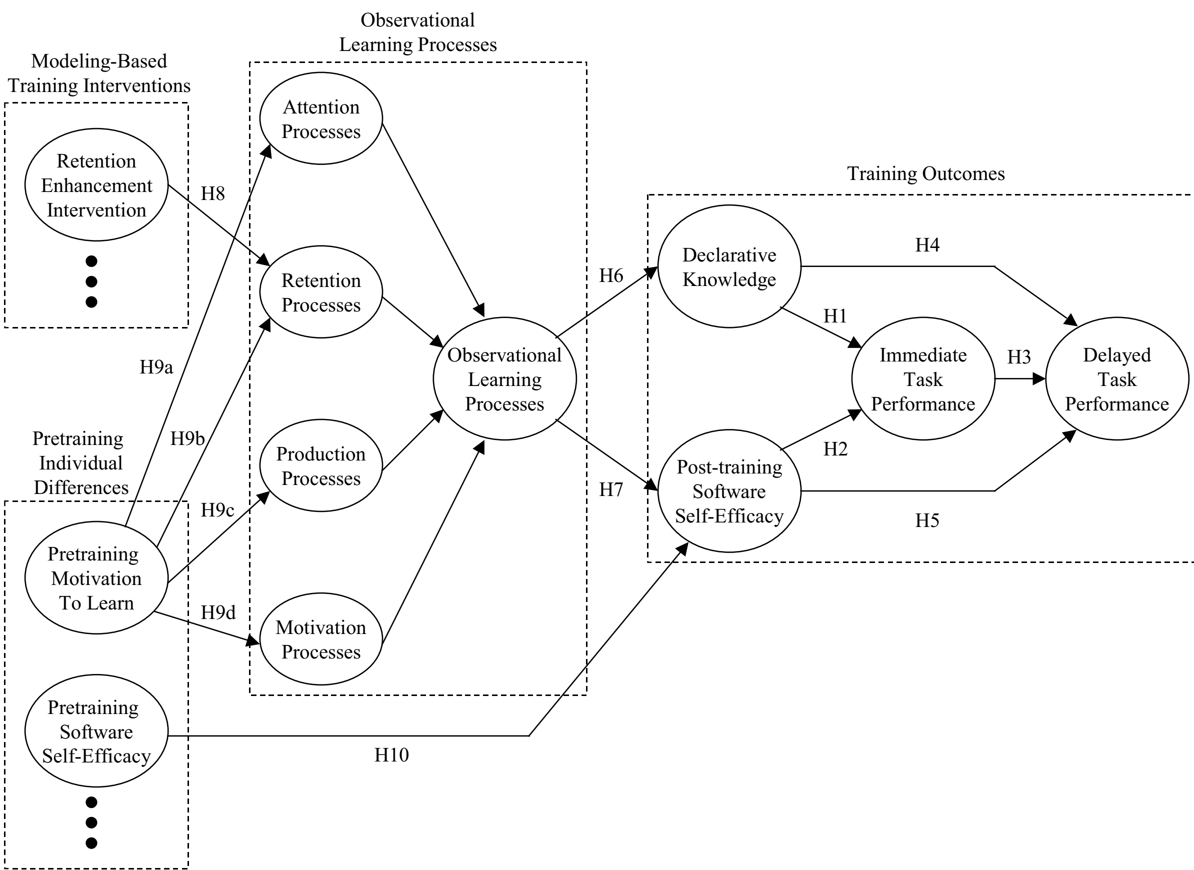
Figure 1 presents the conceptual framework within which the proposed model is formulated. Based on social cognitive theory (Bandura 1986), the framework argues that modeling-based training interventions will improve training outcomes through their effects on observational learning processes. Pretraining individual differences may affect training outcomes either directly or indirectly through observational learning processes. Observational learning processes are theorized to influence training outcomes, and to mediate the effects of modeling-based training interventions. The theoretical rationale for the model draws upon observational learning research from both within and beyond the computer skill domain. The model is specifically intended to apply within the domain of modeling-based approaches to computer skill training, and is not designed to generalize beyond these boundary conditions (e.g., to noncomputer training or to computer training that does not involve observational learning). Figure 2 further specifies each element of the proposed model examined in this study as well as hypotheses relating them.

2.1. Training Outcomes

Colquitt et al.'s (2000) metaanalysis of 106 training studies spanning 20 years found that the three most commonly examined outcomes in training research are declarative knowledge, task performance, and post-training self-efficacy. The proposed model includes all three of these training outcomes. Although Kraiger et al. (1993) and Colquitt et al. (2000) treat these three constructs as alternate measures of training outcomes, without specifying a causal structure among them, we posit that declarative knowledge and post-training self-efficacy function as two distinct causal mechanisms by which training interventions may influence task performance.

2.1.1. Declarative Knowledge and Task Performance. Much contemporary theorizing about how individuals learn cognitive skills suggests that knowledge evolves from an initial declarative or propositional form, through knowledge compilation, toward an automatic, proceduralized form (Anderson 1982, 1985; Glaser 1990; Kanfer and Ackerman 1989; Kozlowski et al. 2001; Kraiger et al. 1993; Martocchio 1994; May and Kahnweiler 2000; Olfman and Mandviwalla 1994). Declarative knowledge is defined by Anderson (1985, p. 199) as "knowledge about facts and things." Information content is obtained in the declarative phase either by verbal specifications of task objectives and instructions, or trainees "may observe demonstrations of the task, may encode and store task rules, and may derive strategies for the task" (Kanfer and Ackerman 1989, p. 660). The declarative knowledge phase thereby establishes an initial cognitive representation of the task. During the subsequent knowledge compilation stage, "persons integrate the sequences of cognitive and motor processes required to perform the task" (Kanfer and Ackerman 1989, p. 660). As learners advance toward procedural knowledge about how to perform a cognitive activity, they develop and refine knowledge

Figure 2 Proposed Research Model



structures for organizing and accessing knowledge (Anderson 1985, Kraiger et al. 1993). Colquitt et al. (2000) found a corrected metaanalytic correlation of 0.55 between declarative knowledge and task performance. In a software training context, Martocchio and Dulebohn (1994) found a correlation of 0.24 ($p < 0.05$) between declarative knowledge and hands-on performance. Because substantial theory and evidence support the idea that declarative knowledge is generally a necessary precursor to skilled task performance, we hypothesize:

Hypothesis 1. *Declarative knowledge will positively influence immediate task performance.*

2.1.2. Self-Efficacy and Task Performance. According to Kraiger et al. (1993, p. 320), "self-efficacy refers to one's perceived performance capabilities for a specific activity." According to social cognitive theory, self-efficacy is a major determinant of an individual's task performance (Bandura 1986, 1997). Self-efficacy is theoretically and empirically distinct from declarative knowledge (Kraiger et al. 1993, Marcolin et al. 2000, Martocchio 1994), and is theorized to perform self-regulatory and motivational roles in controlling behavioral performance of acquired skills (Ackerman et al. 1995, Kanfer and Ackerman 1989, Mitchell et al. 1994). Numerous studies have reported significant empirical relationships between self-efficacy and performance (e.g., Ackerman et al. 1995, Kraiger et al. 1993, Mitchell et al. 1994, Salas and Cannon-Bowers 2001). For example, in three recent metaanalyses of the relationship between self-efficacy and performance across a wide range of behavioral domains, Colquitt et al. (2000), Locke and Latham (1990), and Stajkovic and Luthans (1998) found metaanalytic correlations between self-efficacy and performance of 0.40, 0.39, and 0.38, respectively.

Previous research specifically on computer training has found post-training software self-efficacy to be a significant predictor of task performance (Compeau and Higgins 1995a, Gist et al. 1989, Johnson and Marakas 2000, Martocchio 1994, Martocchio and Dulebohn 1994, Martocchio and Judge 1997, Martocchio and Webster 1992). In the computer training context, Marcolin et al. (2000, p. 46) confirmed that "self-efficacy and knowledge do indeed differ," using a multitrait-multimethod analysis, wherein both declarative knowledge and self-efficacy were measured with both multiple-choice tests and questionnaire-based self-reports. It is important to distinguish between an individual's general computer self-efficacy, which conceptually spans a range of computer applications, and his or her self-efficacy regarding a specific software application (Gist et al. 1989, Marakas et al. 1998, Marcolin et al. 2000). The present model focuses on software-specific self-efficacy, because it more closely corresponds in specificity to the task performance criterion of the current context (Bandura 1997). Given the well-established theoretical rationale and empirical support for an effect of self-efficacy on task performance, we hypothesize:

Hypothesis 2. *Post-training software self-efficacy will positively influence immediate task performance.*

2.1.3. Immediate Versus Delayed Task Performance. The proposed model includes task performance measured both immediately following training and again after an intervening period of time (i.e., 10 days). Since we examine the early phases of skill acquisition, we do not expect trainees' skill levels to approach full automaticity (Ackerman 1987, Glaser 1990), at which time the ongoing influence of both declarative knowledge and self-efficacy would be theorized to diminish or even disappear (Ackerman et al. 1995, Bandura 1986, Colquitt et al. 2000, Willingham 1998). If the skill acquisition process has not reached full automaticity ten days after training, we would expect post-training declarative knowledge and self-efficacy to continue exerting influence on delayed task performance above and beyond the effects of immediate task performance. Empirical evidence supports a predictive relationship between immediate and subsequent task performance (Ackerman et al. 1995, Alliger et al. 1997, Compeau and Higgins 1995a, Mitchell et al. 1994). Although we were unable to find previous empirical support for the effect of declarative knowledge on delayed task performance beyond immediate task performance, there is empirical evidence that post-training self-efficacy affects subsequent task performance beyond immediate task performance (Ackerman et al. 1995, Colquitt et al. 2000, Johnson and Marakas 2000, Mathieu et al. 1993, Stajkovic and Luthans 1998). Following this rationale, we hypothesize:

Hypothesis 3. *Immediate task performance will positively influence delayed task performance.*

Hypothesis 4. *Declarative knowledge will positively influence delayed task performance.*

Hypothesis 5. *Post-training software self-efficacy will positively influence delayed task performance.*

2.2. Observational Learning Processes

Social cognitive theory (Bandura 1986) posits four observational learning processes responsible for the effects of modeling-based training: "*Attentional processes* regulate exploration and perception of modeled activities; through *retention processes*, transitory experiences are converted for memory representation into symbolic conceptions that serve as internal models for response production and standards for response correction; *production processes* govern the organization of constituent subskills into new response patterns; and *motivation processes* determine whether or not observationally acquired competencies will be put to use" (Bandura 1986, p. 51). The effectiveness of observational learning is theorized to depend on the extent to which these component processes are affected (Bandura 1986). The model proposed in the current research views these component processes as distinct dimensions of observational learning processes, which are represented as a multidimensional second-order construct. Because we theorize that an increase in any one of the dimensions in isolation will increase the total overall magnitude of the observational learning processes (OLP) construct without necessarily affecting the other three dimensions, we specify OLP as a formative or aggregate (as opposed to reflective) second-order factor (Chin 1998, Edwards 2001).

Consistent with Hypotheses 1 and 2, we theorize that observational learning processes can influence task performance via two fundamental and distinct mechanisms: Declarative knowledge and post-training software self-efficacy. Individuals differ in their attentional and cognitive capabilities. To the extent that an individual pays closer attention, engages oneself more actively in symbolic coding and cognitive rehearsal, reproduces the demonstrated skills more frequently and accurately, and becomes more motivated to learn and use the system, it would be reasonable to expect them to develop higher declarative knowledge and higher self-efficacy.[1] Compeau and Higgins (1995a) found that the effect of behavior modeling on performance was not fully mediated by computer self-efficacy, which suggests other mediating mechanisms such as declarative knowledge. Given that declarative knowledge and post-training self-efficacy are theorized as distinct proximal determinants of task performance, they are hypothesized to mediate the effect of observational learning processes on task performance:

Hypothesis 6. *Observational learning processes will positively influence declarative knowledge.*

Hypothesis 7. *Observational learning processes will positively influence post-training software self-efficacy.*

2.3. Modeling-Based Training Interventions

Many specific training interventions studied, both within and beyond the computer training domain, hold promise for improving training outcomes when used in conjunction with observational learning. These include reciprocal peer training and codiscovery (Glaser 1990, Lim et al. 1997, May and Kahnweiler 2000), conceptual (vs. procedural) training (Olfman and Mandviwalla 1994, Santhanam and Sein 1994), exploration (Davis and Bostrom 1993, Lim et al. 1997), mastery (vs. performance) orientation (Kozlowski et al. 2001, Stevens and Gist 1997), goal-directed error recovery (Sein and Santhanam 1999), feedback (Cannon-Bowers et al. 1998, Martocchio and Webster 1992, May and Kahnweiler 2000), alternative practice schedules (Cannon-Bowers et al. 1998), overlearning (Driskell et al. 1992, May and Kahnweiler 2000), simulation-based games (Cannon-Bowers et al. 1998, Salas and Cannon-Bowers 2001, Venkatesh 1999), and various attentional and metacognitive prepractice interventions (Cannon-Bowers et al. 1998). The role of observational learning processes in mediating the effects of these training interventions on training outcomes has not before been examined. For the initial test of the proposed model, we specifically examined the effect of adding a retention enhancement intervention to a modeling-based training protocol.

2.3.1. Retention Enhancement Intervention. A *retention enhancement* intervention consists of inducing trainees to engage in two information processing activities: (1) Symbolic coding, the process by which trainees "organize and reduce the diverse elements of a modeled performance into a pattern of verbal symbols that can be easily stored, retained intact over time, quickly retrieved, and used to guide performance" (Decker 1980, p. 628), and (2) cognitive rehearsal, "the process in which individuals visualize or imagine themselves performing behaviors that previously were seen performed by another individual" (Decker 1980, p. 628). A recent study of modeling-based computer training found that trainees who performed retention enhancement activities in addition to hands-on practice achieved higher cognitive learning than those who performed hands-on practice only (Yi and Davis 2001). However, that study did not examine the mediating role of observational learning processes. According to Bandura (1986, p. 56), retention enhancement works by causing trainees to "transform what they observe into succinct symbols to capture the essential features and structures of the modeled activities." Such symbols serve as guides for action, and "play an especially influential role in the early phases of response acquisition" (Bandura 1986, p. 56). Social cognitive theory (Bandura 1986) suggests that such retention enhancement interventions influence training outcomes specifically by improving the

[1] The authors thank an anonymous reviewer for insightful comments on this aspect of the model.

retention processes dimension of observational learning. Consistent with this view, we hypothesize:

Hypothesis 8. *The retention enhancement intervention will positively influence the retention processes, but not the attention, production, or motivation processes, of observational learning.*

2.4. Pretraining Individual Differences

Figure 1 depicts the general principle of controlling for potentially relevant pretraining individual difference variables when examining the effects of training interventions (Bostrom et al. 1990, Olfman and Bostrom 1991, Venkatesh and Morris 2000). This approach seeks to provide a more precise evaluation of training effects by accounting for variance in observational learning processes and training outcomes that is unrelated to training interventions, which would otherwise increase error variance. Although there are several individual difference variables that IS researchers may want to control for when testing the effects of modeling-based training interventions (e.g., Ackerman et al. 1995, Colquitt et al. 2000, Noe 1986, Salas and Cannon-Bowers 2001), the initial model developed here includes two having particular relevance: Pretraining motivation to learn and self-efficacy.

2.4.1. Pretraining Motivation to Learn. Pretraining motivation to learn is defined as a trainee's desire to master the content of the training program (Noe 1986, Noe and Schmitt 1986). Several studies have shown that motivation to learn is useful for predicting training effectiveness. For example, Baldwin et al. (1991) found that pretraining motivation was significantly related to learning in a managerial training program on performance appraisal and feedback. Colquitt et al. (2000) found modest metaanalytic correlations between pretraining motivation to learn and declarative knowledge (0.27), post-training self-efficacy (0.18), and task performance (0.16). However, Colquitt et al.'s (2000) metaanalysis did not include observational learning processes. Social cognitive theory (Bandura 1986) argues that motivation to learn modeled skills increases trainees' active engagement in all four observational learning processes. Following this line of reasoning, we hypothesize that pretraining motivation to learn will influence training outcomes via observational learning processes:

Hypothesis 9. *Pretraining motivation to learn will positively influence the attention, retention, production, and motivation processes of observational learning.*

2.4.2. Pretraining Self-Efficacy. Self-efficacy has been conceptualized both as an antecedent to and an outcome of training (Gist 1987, Tannenbaum et al. 1991). The proposed model posits that pretraining self-efficacy and observational learning processes jointly influence post-training self-efficacy. Colquitt et al. (2000) reported a metaanalytic correlation of 0.59 between pretraining and post-training self-efficacy. Previous research on computer training found pretraining software self-efficacy to be a significant predictor of post-training software self-efficacy (Martocchio 1994, Martocchio and Webster 1992). The proposed model therefore hypothesizes pretraining self-efficacy as a determinant of postraining self-efficacy to account for individual differences in pretraining self-efficacy:

Hypothesis 10. *Pretraining software self-efficacy will positively influence post-training software self-efficacy.*

3. Method

3.1. Participants

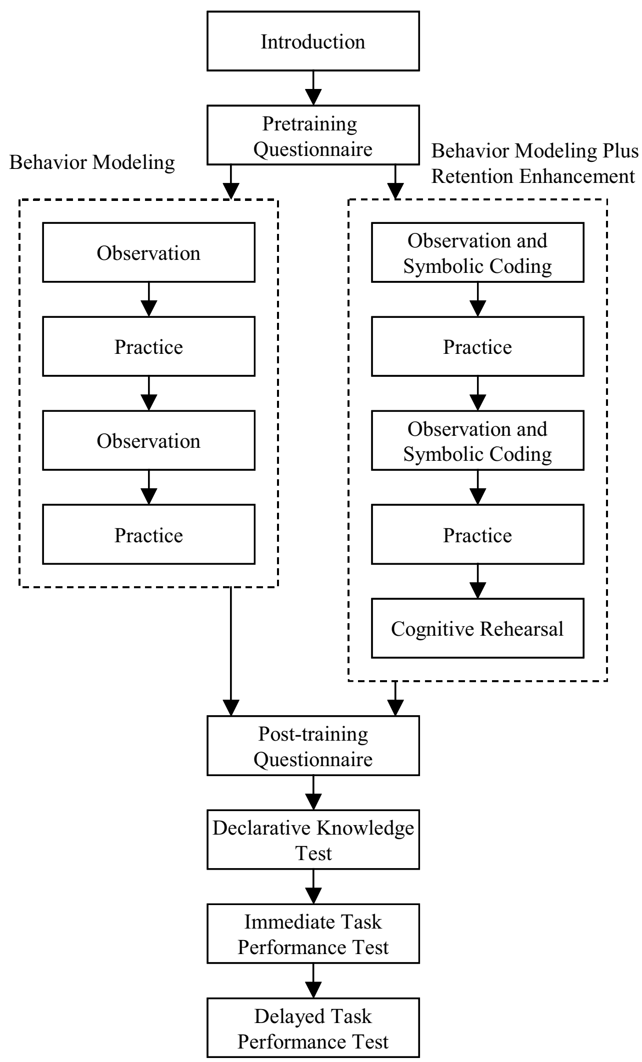
A training program on a popular type of software, the electronic spreadsheet Microsoft Excel for Windows, was set up at a large university in the eastern United States. Participants were undergraduate (freshman) business majors voluntarily recruited from an introductory computer course. Each subject received a fixed number of extra credit points toward the course grade and a $10 subject fee for participating in the study. To encourage subjects to focus on skill mastery, they were provided confidential feedback regarding their performance (Colquitt and Simmering 1998, Martocchio and Dulebohn 1994, Martocchio and Webster 1992, May and Kahnweiler 2000). A total of 95 students (58% female and 42% male) ranging in age from 18 to 26 completed the training. Most participants had limited prior experience using Excel. Specifically, 45 participants (47.4%) indicated that they had never used any spreadsheet program, 43 (45.3%) used one less than one hour in a typical week, and seven (7.4%) used one between one and three hours per week. Most participants (95.8%) reported having used computers more than a year.

3.2. Procedure

Two facilitators, a hired professional instructor and one of the authors, led trainees through the training procedures using scripts[2] developed and pretested in a pilot study. In each computer lab, a facilitator welcomed participants and directed them to an available computer. Once all participants were seated, the facilitator closed the door and started the workshop. Following the prepared script, facilitators first introduced themselves, distributed and collected pretraining questionnaires, and then implemented the training procedure. Participants were not informed that different training conditions were being tested. Except for a one-paragraph introduction of the software interface, included in the script and presented by facilitators, conceptual explanations and behavior modeling demonstrations were delivered entirely by videotape. The same videotapes were used in all training conditions. The facilitators provided limited assistance when trainees requested it, which was restricted to guiding trainees through the steps of the training script without providing additional conceptual or procedural instruction directly. Fewer than 10% of trainees requested assistance. The facilitators used stopwatches to control the time allowed for each step in the training procedures according to timing guidelines specified in the training script. After training procedures were completed, each trainee completed a post-training questionnaire, the timed declarative knowledge test (seven minutes), and the timed hands-on task performance test (15 minutes), and was thanked and dismissed. A measure of trainees' reactions to their facilitator collected in the post-training questionnaire showed no differences between facilitators. The task performance test was administered a second time ten days later during regular class time. The same performance test was used to measure both immediate and delayed task performance in order to control for instrumentation effects (Cook and Campbell 1979). To deter any intentional efforts to memorize answers to specific questions, trainees were not informed beforehand that they would be tested again later. Figure 3 shows the sequence of steps of the experimental procedures.

The videotape used was a commercial product acquired by the authors from a third-party vendor specializing in computer training materials. The tape consisted of five segments: Formulas (11 minutes), advanced formulas (15 minutes), functions (10 minutes), advanced functions (11 minutes), and

Figure 3 Experiment Procedure



[2] The training scripts are available from the first author upon request.

formatting (13 minutes). In each section, the same middle-aged male model explained major concepts and then demonstrated the specific steps needed to carry out example operations. At the end of the segment, the model summarized key learning points of the demonstration. Each trainee had access to a computer during the workshop except when the video was playing. Installed on each computer in advance was a copy of the spreadsheet exercise file containing the same rows and columns of initial numbers as presented in the video, which trainees used to start their hands-on practice.

3.3. Design

The two training conditions, (1) behavior modeling, and (2) behavior modeling plus retention enhancement, were identical except for including the retention enhancement intervention in the latter condition. The experiment was conducted on two consecutive days (Friday and Saturday). There were two three-hour training sessions each day, and in each session there were two training workshops conducted simultaneously in separate labs, each implementing a different training condition with a different facilitator. As shown in Table 1, facilitators, labs, days, and sessions were counterbalanced across training conditions to control for any potential confounding effects. There were no significant effects of facilitator, lab, day, or session on any of the study variables in the sample described below. Participant characteristics did not differ significantly across training conditions in pretest questionnaire measures of age, gender, computer experience, spreadsheet experience, English as native language, pretraining motivation to learn, or pretraining software self-efficacy.

3.3.1. Behavior Modeling Condition. This condition consisted of observation and hands-on practice

Table 1 **Experimental Design**

		Lab 1	Lab 2
Day 1	Session 1	Non-RE, Facilitator 1	RE, Facilitator 2
	Session 2	RE, Facilitator 1	Non-RE, Facilitator 2
Day 2	Session 1	Non-RE, Facilitator 2	RE, Facilitator 1
	Session 2	RE, Facilitator 2	Non-RE, Facilitator 1

Note. RE refers to retention enhancement treatment.

only (with no retention enhancement intervention). Trainees in this condition watched the first two video segments for 26 minutes, practiced for 15 minutes, watched the remaining video segments for 34 minutes, and practiced for another 15 minutes. The duration of about 30 minutes of observation for one lesson is consistent with previous studies (Compeau and Higgins 1995a, Gist et al. 1989). The video segments included explanation of concepts and demonstration of procedural steps. A pretest confirmed that the 15-minute practice time was adequate for most subjects to reenact the behaviors presented.

After the second practice period, facilitators administered a questionnaire measuring post-training self-efficacy, a multiple-choice test of declarative knowledge, and a hands-on task performance test. Total time for this condition was 150 minutes, including 30 minutes of hands-on practice. As is true of the other condition, the remaining 120 minutes were used for introduction, pre- and post-training questionnaire administration, video observation, and testing of declarative knowledge and task performance.

3.3.2. Behavior Modeling Plus Retention Enhancement Condition. In addition to the observation and hands-on practice elements of the behavior modeling condition, this condition included the retention enhancement intervention. After completing the pretraining questionnaire, trainees in this condition received blank papers labeled with section headings for summary activities. Then, for the first two segments of the video, the tape was played and paused at the end of each segment. As instructed, during each pause trainees summarized the computer operations that had been presented by the video by writing down key points of the demonstration under the appropriate section heading. Two minutes were allotted for this symbolic coding process after each segment. After the summary of the second segment, trainees practiced the demonstrated skills on the computer for 15 minutes. After the hands-on practice, trainees continued with the remaining three segments of video instruction and demonstration. The tape was paused at the end of each of the three segments, and trainees performed symbolic coding for two minutes during each pause. After the final symbolic coding activity, trainees again had 15 minutes of hands-on practice. After hands-on practice, trainees cognitively rehearsed their own summary for five minutes. Consistent with Decker (1980), trainees were instructed to relax and mentally picture themselves performing the computer operations while reviewing the summaries for all five video segments. Trainees were instructed to repeat the mental rehearsal as many times as possible until asked to stop.

After cognitive rehearsal, facilitators administered the same measures of post-training self-efficacy, declarative knowledge, and task performance as used in the behavior modeling condition without retention enhancement. In total, the retention enhancement intervention added 15 minutes of training time—two minutes for each of the five symbolic coding tasks performed after viewing a video segment, plus five minutes for cognitive rehearsal. Pretesting indicated that this time allocation was sufficient for trainees to complete the assigned activities, and that additional time tended to result in apparent participant boredom. Total time for this condition was 165 minutes, including 15 minutes of retention enhancement and 30 minutes of hands-on practice.

Because the retention enhancement intervention required an additional 15 minutes, a potential rival explanation might be that any significant effects observed in this study are due to the extended training time itself, rather than to the fact that the additional training time was devoted to the retention enhancement intervention. However, a recent study by Yi and Davis (2001) showed a significant effect of a retention enhancement intervention on learning even when the total training procedure time was held constant across training conditions (by increasing the hands-on training time by an amount equal to the time required to administer the retention enhancement intervention). Therefore, training effects could not be attributed to increased total training time in that study. In the present study, the retention enhancement intervention is theorized to have a specific effect on the retention processes dimension of observational learning, but not on the other three processes. Such a finding would further cast doubt on the possibility that the effect of the retention enhancement intervention was merely due to additional training time. Therefore, to make the treatment and control conditions as equivalent as possible on all characteristics (including hands-on training time) with the exception of the retention enhancement manipulation, we chose not to equalize total training procedure time in the present study.

3.4. Measures

3.4.1. Task Performance and Declarative Knowledge. A hands-on performance measure that contained 11 computer tasks was used to assess trainee task performance on the target computer program. Each task was scored with one point for each totally correct answer, a half point for each partially correct answer, and zero points for incorrect or missing answers. Answers were graded using a program developed by the authors for this purpose through several stages of program coding and accuracy verification. Pilot testing of this grading program showed over 98% consistency with the average scores of two human graders. The declarative knowledge measure consisted of 13 multiple-choice questions designed to assess trainee understanding of the concepts and features needed to use the software program appropriately. Multiple-choice tests such as this are the most frequent method used in the training literature to measure declarative knowledge (Kraiger et al. 1993). In the computer training context, Marcolin et al. (2000) showed that a paper-and-pencil multiple-choice test similar to the one employed here successfully differentiated between declarative knowledge and self-efficacy. The items of task performance and declarative knowledge (see Appendix A for sample items) were composed in an effort to cover the content domain of topics presented by the training materials thoroughly and evenly (Boudreau et al. 2001, Nunnally and Bernstein 1994). These items are modeled as formative (also called aggregate or composite) indicators of their construct because each of the task performance and declarative knowledge constructs is viewed as the aggregation of component knowledge (Bollen and Lennox 1991, Chin 1998, Edwards and Bagozzi 2000, Law et al. 1998), and each item captures a different facet of the construct (Marcolin et al. 2000).

3.4.2. Software Self-Efficacy. Software self-efficacy was measured at the spreadsheet application level by seven items from the instrument developed by

Johnson and Marakas (2000). Consistent with prior research (Compeau and Higgins 1995b, Marakas et al. 1998), the self-efficacy measure captured the magnitude ("can you perform the specified behavior?" yes or no) and strength (on a scale from 1 to 10, where 1 = "quite uncertain" and 10 = "quite certain") of each individual's software self-efficacy. The magnitude scale was converted to 0 (no) or 1 (yes), and then multiplied by the strength items per Lee and Bobko (1994).

3.4.3. Observational Learning Processes. There are no validated instruments to directly measure observational learning processes (Bandura 2001). Prior studies on observational learning have either assumed the existence of observational learning processes, ignored them, or inferred their existence by developing various interventions to influence the purported processes and observing that the interventions significantly affected training outcomes (Bandura 1986, 1997). However, no attempt has been made to explicitly measure observational learning processes directly. To test the proposed model and trace the hypothesized effects on the observational learning processes, we developed an instrument that measures observational learning processes tailored to the current subject matter.

Following standard measure development procedures (e.g., Boudreau et al. 2001, Churchhill 1979, Davis 1989, Moore and Benbasat 1991, Nunnally and Bernstein 1994, Straub 1989), scales to measure observational learning processes were developed through several iterative steps including specifying the domain of the construct, generating a sample of items, pilot-testing and purifying items, collecting additional data, and assessing the reliability and validity of the measure. Based on social cognitive theory (Bandura 1986), conceptual definitions of attention, retention, reproduction, and motivation processes were used as a guide to compose an initial sample of items covering the four component processes. Ten items for each process dimension (40 items total) were composed, which were then pretested by a group of expert judges consisting of three university professors and one doctoral student. Based on the feedback from the judges, some of the items were revised to better fit the theoretical domain of the construct and improve readability. Two pilot tests were then undertaken to further purify the items using samples of 67 and 85, respectively. Results of each pilot test were used for item analyses, which led to further refinement of the measure to enhance convergent and discriminant validity. Items were selected for inclusion or elimination based on their ability to discriminate among the four observational learning dimensions, their tendency to load together consistently, and their even coverage of the target content domains. The final instrument used for the present study consisted of sixteen items, four items for each dimension of observational learning processes. An 11-point Likert-type scale (0 = "completely disagree," 5 = "neither agree nor disagree," 10 = "completely agree") was used for all items. Throughout the scale development processes, considerable efforts were made to carefully distinguish among the four dimensions of the observational learning construct, and to isolate observational learning processes from software self-efficacy, pretraining motivation to learn, declarative knowledge, and task performance. Table 2 presents the sixteen items used in the main study.

3.4.4. Pretraining Motivation to Learn. A four-item scale adapted from prior research (Baldwin et al. 1991, Hicks and Klimoski 1987, Martocchio and Dulebohn 1994, Noe and Schmitt 1986) was used to assess trainees' pretraining motivation to learn the spreadsheet skills. Trainees were asked to indicate on an 11-point Likert-type scale (0 = "completely disagree," 5 = "neither agree nor disagree," 10 = "completely agree") the extent to which they agreed or disagreed with the following statements: "I am very much interested in taking this training class," "I am excited about learning the spreadsheet skills that will be covered in this training class," "I will try to learn as much as I can from this training class," and "I am motivated to learn the training material in this class."

3.4.5. Manipulation Checks for Retention Enhancement. The manipulation of the symbolic coding component of retention enhancement was verified

Table 2 Measure of Observational Learning Processses

Processes	Scale Items
Attention	I paid close attention to the video demonstration.
	I was able to concentrate on the video demonstration.
	The video demonstration held my attention.
	During the video demonstration, I was absorbed by the demonstrated activities.
Retention	I had the opportunity to summarize the key aspects of demonstrated computer operations.
	I had the opportunity to symbolically process the presented information.
	I had the opportunity to mentally visualize the demonstrated computer operations.
	I had the opportunity to mentally practice the demonstrated computer operations.
Production	I had the opportunity to accurately reproduce the demonstrated computer operations.
	I had enough practice of the demonstrated computer skills.
	The training provided me with the opportunity to produce the procedural steps demonstrated through the video.
	The training helped me practice the key component skills required to produce the demonstrated computer operations.
Motivation	The training provided information that motivated me to use Excel.
	The training helped me see the usefulness of Excel.
	The training increased my intention to master Excel.
	The training showed me the value of using Excel in solving problems.

by comparing across treatment conditions the number of trainees who actually made written summaries during their training workshops. Specifically, all the papers either distributed by the facilitators for symbolic coding or self-supplied by trainees for note taking were collected and examined to see how many trainees actually created any sort of summary. Although there were varying degrees of completeness, all trainees ($n = 48$) in the retention-enhancement condition performed symbolic coding, whereas only one of 47 trainees (2%) in the non-retention-enhancement condition created any written summary ($\chi^2(1) = 23.77, p < 0.001$). The manipulation of the cognitive rehearsal component of retention enhancement was verified by examining the number of times trainees performed the rehearsal activity. After cognitive rehearsal, trainees in the retention enhancement condition recorded the number of times they were able to mentally rehearse the key learning points in the five minutes allotted. Trainees in the retention-enhancement condition reported having cognitively rehearsed the presented skills 4.08 times on average, suggesting that the retention enhancement intervention was successfully manipulated. We sought to conceal the nature of the treatment condition from members of the control condition in order to deter possible hypothesis-guessing, compensatory rivalry, and resentful demoralization (Cook and Campbell 1979). Therefore, we did not ask trainees in the non-retention-enhancement condition how many times they performed the rehearsal activity (because they were not requested to perform the rehearsal activity and they were not given time to cognitively rehearse the skills).

4. Results

Measure validation and model testing were conducted using Partial Least Squares (PLS) Graph Version 2.91.03.04 (Chin and Frye 1998), a structural equation modeling tool that utilizes a component-based approach to estimation. Whereas covariance-based SEM tools such as LISREL and EQS use a maximum likelihood function to obtain parameter estimates, the component-based PLS uses a least squares estimation procedure, allowing the flexibility to represent both formative and reflective latent constructs, while placing minimal demands on measurement scales, sample size, and distributional assumptions (Chin 1998, Falk and Miller 1992, Fornell and Bookstein 1982, Wold 1982).

4.1. Psychometric Properties of Measures

Before testing the hypothesized structural model, psychometric properties of the measures for the seven latent constructs measured by self-report questionnaires were evaluated through confirmatory factor analysis using a measurement model in which the first-order latent constructs were specified as correlated variables with no causal paths. The measurement model was assessed by using PLS to examine internal consistency reliability and convergent and discriminant validity (Barclay et al. 1995, Chin 1998, Compeau et al. 1999). Internal consistency reliability (also known as composite reliability) was computed from the normal PLS output using the following formula: ICR $= (\sum \lambda_i)^2/[(\sum \lambda_i)^2 + \sum(1 - \lambda_i^2)]$ where λ_i

is the standardized component loading of a manifest indicator on a latent construct (Chin 1998). Internal consistencies (similar to Cronbach's alpha) of 0.70 or higher are considered adequate (Agarwal and Karahanna 2000, Barclay et al. 1995, Compeau et al. 1999). Convergent and discriminant validity was assessed by applying two criteria: (1) The square root of the average variance extracted (AVE) by a construct from its indicators should be at least 0.707 (i.e., AVE > 0.50) and should exceed that construct's correlation with other constructs (Barclay et al. 1995, Chin 1998, Fornell and Larcker 1981) and (2) standardized item loadings (similar to loadings in principal components) should be at least 0.707, and items should load more highly on constructs they are intended to measure than on other constructs (Agarwal and Karahanna 2000, Compeau et al. 1999). The square root of the AVE was computed from normal PLS output by taking the square root of the following formula: $\text{AVE} = \sum \lambda_i^2 / [\sum \lambda_i^2 + \sum (1 - \lambda_i^2)]$ (Chin 1998). Cross-loadings were computed by calculating the correlations between latent variable component scores and the manifest indicators of other latent constructs (Chin 1998). These criteria for reliability and convergent and discriminant validity should be applied only for latent constructs with reflective indicators, and are not appropriate for formative indicators (Chin 1998, Gefen et al. 2000).

Table 3 shows internal consistency reliabilities, convergent and discriminant validities, and correlations among latent constructs. The correlations in Table 3 were generated by PLS, and the remaining indices were computed using Excel and SPSS on the PLS output (since this version of PLS does not perform these calculations). Specifically, from the output of the PLS measurement model run, the rescaled data matrix and the matrix of latent variable scores (the eta matrix) were read by Excel and edited to reorganize the data into 96 rows (label line plus 95 records corresponding to respondents) by 42 columns (respondent ID, 34 columns of rescaled item scores, and seven columns of factor scores). Pearson correlations were computed between the seven factor scores and 34 rescaled item scores in this matrix using SPSS to obtain the factor structure matrix of loadings and cross-loadings shown in Table 4.

Table 3 **Reliabilities, Convergent and Discriminant Validities, and Correlations Among Latent Constructs—Measurement Model**

Latent Construct	ICR	1	2	3	4	5	6	7
(1) OLP: Attention	0.94	**0.90**						
(2) OLP: Retention	0.95	0.73	**0.91**					
(3) OLP: Production	0.95	0.70	0.84	**0.91**				
(4) OLP: Motivation	0.94	0.62	0.63	0.61	**0.89**			
(5) Pretraining Motivation	0.90	0.41	0.38	0.33	0.48	**0.83**		
(6) Pretraining SSE	0.95	0.17	0.24	0.31	0.22	0.13	**0.86**	
(7) Post-training SSE	0.96	0.46	0.50	0.52	0.46	0.14	0.45	**0.88**

Note. OLP = Observational Learning Processes Dimensions; SSE = Software Self-Efficacy; ICR = Internal Consistency Reliability, which should be 0.70 or greater. All self-report constructs range from 0 (strongly disagree) to 10 (strongly agree). Diagonal elements (bold) are the square roots of average variance extracted (AVE) by latent constructs from their indicators. Off-diagonal elements are correlations between latent constructs. For convergent and discriminant validity, diagonal elements should be at least 0.707 (i.e., AVE > 0.50) and larger than off-diagonal elements in the same row and column.

The internal consistency reliabilities were all at least 0.90, exceeding minimal reliability criteria (Table 3). As strong evidence of convergent and discriminant validity: (1) The square root of the average variance extracted for each construct (Table 3 diagonal elements) was greater than 0.707 (i.e., AVE > 0.50) and greater than the correlation between that construct and other constructs (without exception) (2) the factor structure matrix (Table 4) shows that all items exhibited high loadings (>0.707) on their respective constructs (with only one of the 34 items showing a loading below 0.80) and no items loaded higher on constructs they were not intended to measure. Overall, the self-report measurement instruments exhibited sufficiently strong psychometric properties to support valid testing of the proposed structural model.

4.2. Test of Model and Hypotheses

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. The proposed model conceptualized the four first-order OLP dimensions as formative indicators of the second-order OLP construct. Because PLS Graph (Version 2.91.03.04) does not directly permit the representation of second-order latent constructs, it is necessary to test such

Table 4 Factor Structure Matrix of Loadings and Cross-Loadings—Measurement Model

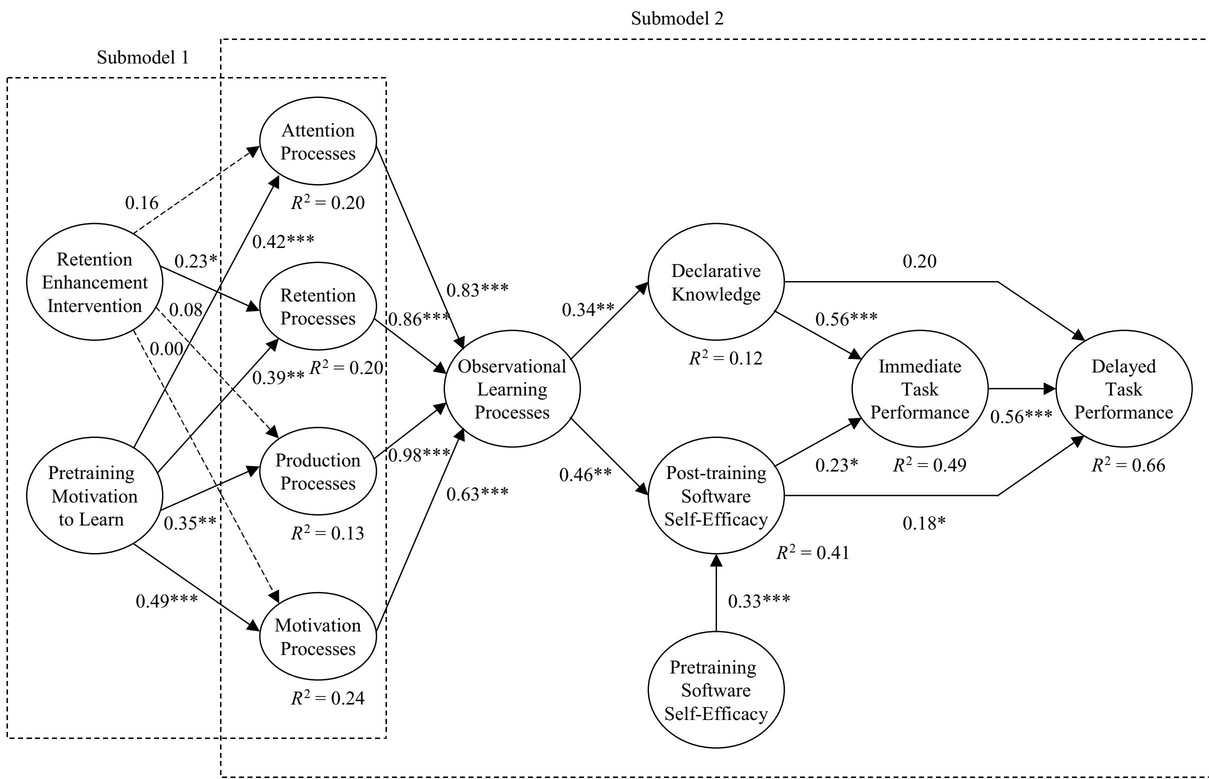
Scale Items	1	2	3	4	5	6	7
(1) OLP: Attention							
a. paid close attention	**0.90**	0.67	0.62	0.62	0.34	0.15	0.44
b. able to concentrate	**0.92**	0.72	0.68	0.61	0.38	0.21	0.47
c. held my attention	**0.92**	0.65	0.67	0.52	0.35	0.13	0.44
d. I was absorbed	**0.85**	0.57	0.55	0.48	0.42	0.12	0.27
(2) OLP: Retention							
a. summarize the key aspects	0.65	**0.90**	0.73	0.56	0.31	0.17	0.43
b. symbolically process	0.71	**0.90**	0.76	0.61	0.32	0.23	0.46
c. mentally visualize	0.63	**0.93**	0.75	0.58	0.41	0.24	0.46
d. mentally practice	0.66	**0.91**	0.81	0.56	0.33	0.25	0.46
(3) OLP: Production							
a. accurately reproduce	0.66	0.85	**0.92**	0.62	0.34	0.30	0.57
b. had enough practice	0.62	0.68	**0.86**	0.44	0.16	0.34	0.43
c. produce the procedural steps	0.61	0.78	**0.94**	0.55	0.34	0.23	0.39
d. helped me practice	0.65	0.73	**0.92**	0.61	0.36	0.27	0.49
(4) OLP: Motivation							
a. motivated me	0.57	0.59	0.66	**0.82**	0.32	0.17	0.42
b. helped me see the usefulness	0.53	0.61	0.55	**0.90**	0.49	0.23	0.41
c. increased my intention	0.56	0.53	0.48	**0.90**	0.44	0.17	0.36
d. showed me the value	0.55	0.53	0.49	**0.92**	0.43	0.22	0.44
(5) Pretraining Motivation							
a. very much interested	0.37	0.25	0.29	0.36	**0.87**	0.19	0.18
b. excited about the learning	0.40	0.33	0.31	0.47	**0.87**	0.16	0.23
c. will try to learn	0.27	0.38	0.26	0.36	**0.77**	−0.04	−0.03
d. motivated to learn	0.33	0.30	0.24	0.39	**0.82**	0.10	0.08
(6) Pretraining SSE							
a. manipulate the way	0.19	0.20	0.30	0.22	0.10	**0.83**	0.41
b. understand the cell references	0.07	0.13	0.19	0.14	0.09	**0.88**	0.32
c. enter numbers	0.16	0.21	0.31	0.23	0.13	**0.81**	0.38
d. use a spreadsheet	0.15	0.22	0.27	0.18	0.09	**0.89**	0.42
e. write a simple formula	0.10	0.14	0.19	0.15	0.09	**0.84**	0.37
f. summarize numeric information	0.16	0.26	0.29	0.22	0.10	**0.89**	0.44
g. share numeric information	0.21	0.30	0.31	0.22	0.17	**0.89**	0.40
(7) Post-training SSE							
a. manipulate the way	0.35	0.45	0.44	0.44	0.11	0.36	**0.88**
b. understand the cell references	0.34	0.40	0.39	0.34	0.14	0.41	**0.86**
c. enter numbers	0.37	0.45	0.43	0.43	0.10	0.25	**0.87**
d. use a spreadsheet	0.44	0.44	0.47	0.39	0.08	0.52	**0.90**
e. write a simple formula	0.43	0.40	0.43	0.44	0.22	0.42	**0.87**
f. summarize numeric information	0.43	0.49	0.53	0.40	0.10	0.45	**0.93**
g. share numeric information	0.44	0.45	0.49	0.40	0.13	0.39	**0.87**

Note. OLP = Observational Learning Processes Dimensions; SSE = Software Self-Efficacy. For convergent and discriminant validity, items should load high (>0.707) on their respective constructs (bold) and no item should load higher on constructs other than the one it was intended to measure.

models indirectly by separately testing the first-order constructs comprising a second-order construct in a submodel, and then treating the computed first-order factor scores as manifest indicators of the second-order construct in a separate model (e.g., Agarwal and Karahanna 2000). Therefore, we separately tested two submodels (Figure 4): Submodel 1 relating the first-order OLP constructs to their indicators and determinants, and Submodel 2 relating the second-order OLP construct to the remaining constructs.

Submodel 1 (Figure 4) containing the retention enhancement intervention, pretraining motivation,

Figure 4 **PLS Test of Proposed Model**



Note. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

and the four first-order OLP dimensions (attention processes, retention processes, production processes, and motivation processes) was tested (see Appendix B for construct correlations and indicator weights and loadings of Submodel 1), and factor scores for each OLP dimension were obtained from PLS for subsequent use as inputs to Submodel 2. Because OLP is modeled as a formative second-order construct, we needed to avoid unstable estimates of weights resulting from multicollinearity among first-order factors when running Submodel 2 (Chin 1998). Following Fornell and Bookstein (1982), Submodel 2 (Figure 4) was therefore tested using loadings rather than weights to relate the first-order OLP dimensions to the second-order OLP construct[3] (see Appendix C for construct correlations and indicator weights and loadings of Submodel 2). Following Chin (1998), bootstrapping (with 500 resamples) was performed on both submodels to obtain estimates of standard errors for testing the statistical significance of path coefficients using t-tests.

[3] Because PLS Graph Version 2.91.03.04 does not support the option of using loadings (as opposed to weights) to link formative indicators to constructs, as recommended by Fornell and Bookstein (1982), this required a preliminary run of Submodel 2 to get loading estimates, followed by an intermediate step using Excel of using the loadings to compute scores for the OLP second-order formative latent construct. In the preliminary run of Submodel 2, the factor scores for each OLP dimension were represented as formative indicators of the second-order OLP construct and loadings relating each first-order dimension to the second-order construct were estimated ($\lambda_1 = 0.83$ for attention, $\lambda_2 = 0.86$ for retention, $\lambda_3 = 0.98$ for production, and $\lambda_4 = 0.63$ for motivation). The first-order factor scores were then multiplied by their loadings and summed to derive a composite second-order OLP score for each respondent ($\text{OLP} = \sum \lambda_j F_j$ where F_j = first-order factor scores from Submodel 1 for OLP dimensions $j = 1, 4$). In the main run of Submodel 2; this composite OLP score was specified as a manifest indicator of the second-order OLP construct. Collectively, these steps are equivalent to running Submodel 2 with the loadings shown in Figure 4.

Figure 4 summarizes model-testing results. Supporting Hypothesis 1, declarative knowledge had a significant effect on immediate task performance ($\beta = 0.56, p < 0.001$). Supporting Hypothesis 2, post-training self-efficacy had a significant effect on immediate task performance ($\beta = 0.23, p < 0.05$). Supporting Hypothesis 3, immediate task performance had a significant effect on delayed task performance ($\beta = 0.56, p < 0.001$). Inconsistent with Hypothesis 4, declarative knowledge had no significant effect on delayed performance over and above immediate task performance and post-training self-efficacy ($\beta = 0.20$, n.s.). Supporting Hypothesis 5, post-training self-efficacy had a significant effect on delayed task performance over and above immediate task performance and post-training self-efficacy ($\beta = 0.18$, $p < 0.05$). The model explained substantial variance in both immediate ($R^2 = 0.49$) and delayed ($R^2 = 0.66$) task performance.

Supporting Hypotheses 6 and 7, OLP had a significant effect on declarative knowledge ($\beta = 0.34$, $p < 0.01$) and post-training self-efficacy ($\beta = 0.46$, $p < 0.01$). Supporting Hypothesis 8, the retention enhancement intervention significantly affected the retention processes of observational learning ($\beta = 0.23$, $p < 0.05$), but did not affect the attention ($\beta = 0.16$, n.s.), production ($\beta = 0.08$, n.s.), or motivation ($\beta = 0.00$, n.s.) processes. Supporting Hypothesis 9, pretraining motivation to learn had significant effects on all four processes of observational learning: attention ($\beta = 0.42, p < 0.001$), retention ($\beta = 0.39$, $p < 0.01$), production ($\beta = 0.35, p < 0.01$), and motivation ($\beta = 0.49, p < 0.001$). Supporting Hypothesis 10, pretraining self-efficacy had a significant effect on post-training self-efficacy ($\beta = 0.33, p < 0.001$). The model accounted for substantial variance in post-training self-efficacy ($R^2 = 0.41$), and modest variances in declarative knowledge ($R^2 = 0.12$), attention processes ($R^2 = 0.20$), retention processes ($R^2 = 0.20$), production processes ($R^2 = 0.13$), and motivation processes ($R^2 = 0.24$). In sum, the model test supported all hypotheses except Hypothesis 4.

Following Edwards (2001), we acknowledge the need to consider alternative specifications of a multidimensional construct such as OLP. One alternative to the formative second-order model addressed above is to operationalize the four observational learning processes as distinct first-order constructs simultaneously influencing declarative knowledge and post-training self-efficacy. A key limitation of this approach is that multicollinearity among the OLP dimensions resulted in instability and serious distortion of the estimated path coefficients between the second-order OLP construct and the two immediate downstream variables (declarative knowledge and post-training self-efficacy). Except for these links, the test of this specification produced nearly identical path coefficients as shown in Figure 4.

A second approach is to treat OLP as a second-order factor with the four process dimensions as first-order factors, as in the model in Figure 4, but to model the effects of the retention enhancement intervention and pretraining motivation directly on the second-order OLP construct. A serious drawback to this approach is that representing the effect of the retention enhancement intervention directly on the second-order OLP construct masks its theorized specific effect on the retention processes dimension of OLP. Testing this model showed a significant effect of pretraining motivation on OLP ($\beta = 0.46, p < 0.001$), but no significant effect of the retention enhancement intervention ($\beta = 0.14$, n.s.), although the paths of the remaining part of the model were nearly identical to the model shown in Figure 4.

A third specification is a restricted or reduced model that includes just the retention processes dimension of OLP linking the retention enhancement intervention to declarative knowledge and post-training self-efficacy (eliminating attention, production, and motivation processes from the model). A drawback of this approach is that it provides an incomplete view of the observational learning processes, omitting three of the four OLP dimensions, which may introduce distortions in parameter estimates because of omitted variables. When each OLP dimension was separately included in the model, we observed a pattern of results that was highly consistent with the model in Figure 4. Each dimension had a significant effect on post-training self-efficacy ($\beta = 0.40, p < 0.001$ for attention; $\beta = 0.41, p < 0.01$ for retention; $\beta = 0.42, p < 0.01$ for production; $\beta = 0.38, p < 0.01$ for motivation), and three of the four significantly affected declarative knowledge ($\beta = 0.35, p < 0.01$ for attention; $\beta = 0.31, p < 0.01$ for retention; $\beta = 0.41, p < 0.001$ for production; $\beta = 0.12$, n.s. for motivation). Retention processes was the only dimension that was significantly affected by the retention enhancement intervention ($\beta = 0.23, p < 0.05$). Thus, while these alternative first- and second-order models provide complementary views into the underlying phenomena, and are all fairly consistent, the model presented in Figure 4 has the greatest theoretical justification, and provides the best insight into the dynamics linking modeling-based training interventions to training outcomes via observational learning processes.[4]

In order to confirm the mediational roles played by retention processes, declarative knowledge, and post-training self-efficacy in linking the retention enhancement intervention to task performance, a series of hierarchical model tests were performed using PLS. First, the retention enhancement intervention had a significant direct effect on both immediate ($\beta = 0.39, p < 0.001$) and delayed ($\beta = 0.38, p < 0.001$) task performance. This significant direct effect became nonsignificant when declarative knowledge and post-training self-efficacy were added to the model ($t = 0.70$, n.s. for immediate task performance; $t = 0.84$, n.s. for delayed task performance), showing that declarative knowledge and post-training self-efficacy mediated the retention enhancement-performance relationship. Similarly, the significant direct effect of the OLP construct on task performance ($\beta = 0.40, p < 0.001$ for immediate task performance; $\beta = 0.45, p < 0.001$ for delayed task performance) became nonsignificant when declarative knowledge and post-training self-efficacy were added to the model ($t = 0.02$, n.s. for immediate task performance; $t = -0.32$, n.s. for delayed task performance). This supports the theoretical proposition that declarative knowledge and post-training self-efficacy mediate the significant effect of OLP on task performance. Finally, the significant direct effect of the retention enhancement intervention on declarative knowledge ($\beta = 0.42, p < 0.001$) and post-training self-efficacy ($\beta = 0.20, p < 0.05$) became nonsignificant when the OLP construct was added to the model ($t = 1.26$, n.s. for declarative knowledge; $t = 1.28$, n.s. for post-training self-efficacy). Taken together, these analyses add support for the proposed model's position that the effect of the retention enhancement intervention on task performance is accounted for by its indirect effect through OLP, declarative knowledge, and post-training self-efficacy.

A *post hoc* analysis conducted to eliminate any confounding of results based on trainees' differing levels of prior experience with spreadsheet programs showed no significant effects of spreadsheet experience on any of the endogenous model constructs over and above the other proposed determinants of that construct. In addition, consistent with the research model, there was no direct effect of OLP on task performance ($\beta = 0.06$, n.s.) over and above the effects mediated by declarative knowledge and post-training self-efficacy.

5. Discussion

5.1. Summary of Findings

The objectives of the present research were to develop and perform an initial test of a new theoretical model of the observational learning processes that link modeling-based training interventions to computer training outcomes. The new model was successful in explaining the mechanisms through which a modeling-based intervention (retention enhancement) influences computer task performance. As theorized, the retention enhancement intervention specifically influenced the retention processes, but not the attention, production, or motivation processes, of observational learning. All four dimensions of observational learning processes were significantly influenced by pretraining motivation. The four dimensions were found to be significant formative indicators of the second-order construct of observational learning processes. In turn, observational learning processes significantly influenced both declarative knowledge and post-training software self-efficacy, which represent two fundamental and distinct causal pathways by which modeling-based computer training interventions are theorized by the new model to influence task

[4] The authors are grateful for the helpful suggestions of an anonymous reviewer that led to this final model specification.

performance. Immediate task performance was significantly influenced by both declarative knowledge and post-training self-efficacy. Task performance measured ten days later was significantly influenced by both immediate task performance and post-training self-efficacy, but not by declarative knowledge. Nine of ten hypotheses were supported. These findings significantly extend prior research on observational learning by establishing the mediating processes that link training interventions to outcomes. Further, the findings clarify the distinct and important roles that observational learning processes, declarative knowledge, and self-efficacy play as mediational mechanisms linking training interventions to task performance.

5.2. Limitations

Several limitations of the present study should be noted when interpreting its findings. This is an initial test of a newly formulated model that should be subjected to further testing and refinement. Support for the new model should be tested in different contexts to establish external validity. It is currently unknown how well the model and its findings will generalize beyond the specific conditions of this study such as software application type, subject characteristics, and training period. Though the software application examined in this study (spreadsheet) was selected to be consistent with several previous behavior modeling studies (Compeau and Higgins 1995a; Gist et al. 1988, 1989), and to be representative of software programs widely used in current business organizations, our results may or may not generalize to other types of software. Most participants in the present study had substantial computer experience, but limited experience with the target software program. Further work is needed to understand how well the new model generalizes to trainees with very little prior general computer experience, or to those with extensive prior experience with the target software application. The training program was approximately three hours long in the present study. In practice, training programs vary in length from less than an hour to several weeks or more. However, even in cases where training is conducted over multiple consecutive days, it is common for material to be covered in sessions lasting up to three hours, as in the present study. Overall, the sample of training phenomena captured in the present study may be reasonably representative of what would be obtained with differing training durations.

Two of the relationships examined in the proposed model were found nonsignificant, but might have been found significant had the sample size been larger. Statistical significance of any tested hypothesis is influenced by various factors such as sample size, number of indicators, and the variance of indicators (e.g., Chin 1998). The sample size of 95 should be adequate following the guidelines of Falk and Miller (1992) who suggest that a 5:1 ratio of cases to the maximum number of manifest indicators in any single block of the model is reasonable. By their guideline, our sample size requirement would be 80 (16 indicators for the observational learning processes block times 5). Our sample size of 95 exceeds this guideline. The sample size was adequate to detect significance for 9 of the 10 hypotheses tested in this study. However, Hypothesis 4 was not supported, despite a sizable path coefficient of 0.20. Similarly, the effect of the retention enhancement intervention on the attention dimension of observational learning was not significant (as hypothesized) despite being relatively large (0.16). For both of these cases, it should be kept in mind that a true relationship may actually exist despite a nonsignificant result, and that a study with different sample size, number of indicators, and amount of variance in measures might find these nonsignificant relationships to be significant.

5.3. Implications for Future Research

As true with virtually all models of complex behavioral phenomena, the current model is almost certainly incomplete, and ongoing investigation is needed to improve the degree to which it approximates the modeling-based computer skill acquisition process. The possible omission of some individual differences, mediational processes, training outcomes, and contextual factors could distort findings and alter their interpretations. For example, the present model does not include a potentially important construct from social cognitive theory (Bandura 1986): Performance outcome expectations. However, prior studies found mixed results regarding the significance of outcome expectations (Ackerman et al. 1995, Compeau and Higgins 1995a, Johnson and Marakas 2000, Mitchell et al. 1994, Stajkovic and Luthans 1998, Vancouver et al. 2001). We next recommend additional constructs for future investigation.

5.3.1. Observational Learning Processes and Training Interventions. The present study appears to be the first to explicate and trace the observational learning processes linking modeling-based training interventions to training outcomes. There has been consistent progress recently toward understanding the interrelationships of key constructs governing the computer skill acquisition process. The current model and findings are consistent with this accumulating base of knowledge, and contributes a more complete explanation of the psychological mechanisms linking training interventions to task performance, which adds to the base of knowledge from which future research can continue making progress toward a better understanding of how modeling-based training works.

Further research is needed not only to further refine and extend the observational learning model and its newly developed measures, but also to specifically examine the role of other modeling-based training interventions within the observational learning model. For example, the effects of variations in motor and mental practice structure (i.e., randomized, blocked, guided, simulated, spaced, massed, etc.) (Cannon-Bowers et al. 1998, Donovan and Radosevich 1999) and in positive and negative model display combination (Baldwin 1992) deserve further investigation. Interventions that induce an affectively positive or cognitively playful mood are also promising (Martocchio and Webster 1992, Venkatesh 1999, Venkatesh and Speier 2000, Webster and Martocchio 1993). The effectiveness of various prepractice training interventions such as attentional advice, metacognitive strategies, advance organizers, preparatory information, and prepractice briefs should also be examined as possible enhancers of training effectiveness (Cannon-Bowers et al. 1998). In each of these cases, the observational learning processes of attention, retention, production, and motivation could be evaluated as potential mediators of the effects of these training interventions on training outcomes.

5.3.2. Training Outcomes. The present research examined the three training outcomes most frequently studied in training studies: Declarative knowledge, self-efficacy, and task performance (Colquitt et al. 2000, Gagne 1984, Kraiger et al. 1993, Marcolin et al. 2000). Agarwal et al. (2000) showed that general computer self-efficacy has an influence on software-specific self-efficacy, without addressing the relationship of either form of self-efficacy to task performance. Bostrom et al. (1990) presented a research model depicting an interplay between attitudinal training outcomes and task performance, but they did not address the influence of declarative knowledge or post-training self-efficacy (either jointly or separately) on task performance. Lim et al. (1997) empirically differentiated task performance from inference potential in their model of computer training outcomes, but they did not examine the effect of either declarative knowledge or self-efficacy as determinants of task performance. Going beyond prior research, the new model specifically theorizes that declarative knowledge and self-efficacy are distinct fundamental causal pathways by which training interventions influence task performance. As we continue to better understand how training influences skill attainment, additional training outcomes might be considered. Of particular interest would be attempts to measure more directly the accumulated knowledge in trainees' memory, referred to variously as knowledge structures (Snow, 1989), knowledge organization (Kraiger et al. 1993, Kraiger et al. 1995), cognitive representations (Willingham 1998), scripts (Cellar and Wade 1988), schemata (Glaser 1990), and mental models (Santhanam and Sein 1994). Such increasingly direct measures of knowledge should lead to more precise assessments of the specific cognitive impacts of training interventions.

Future research should also consider the possible role of additional mediators beyond declarative knowledge and self-efficacy linking observational learning processes to task performance. In the present study, there was no significant effect of observational learning processes directly on task performance after controlling for declarative knowledge and self-efficacy. Nevertheless, it would be premature to rule out additional mediational mechanisms. Kozlowski et al.'s (2001) study of a simulated decision making task found that transfer and generalization were significantly influenced by knowledge structure coherence, a fourth training outcome, above and beyond significant effects of self-efficacy, task performance, and declarative knowledge. This suggests the possibility that knowledge structure characteristics (such as coherence and similarity to expert knowledge), beyond their role as additional training outcomes, may represent additional mediating constructs that should be added to the present model as theory progresses.

5.3.3. Individual Differences. The two individual difference constructs included in the new model are pretraining self-efficacy and motivation to learn. Given that pretraining motivation was shown to positively influence all four processes of observational learning, it would be fruitful to identify organizational interventions designed to increase trainees' pretraining motivation to learn. It would also be worthwhile for future research to examine the role of other individual difference constructs such as personality dimensions (Barrick and Mount 1991), intellectual ability (Ackerman 1987, Ackerman et al. 1995), conceptions of ability as acquirable skill versus innate talent (Martocchio 1994), general computer self-efficacy (Marakas et al. 1998), learning styles (Bostrom et al. 1990), and personal innovativeness (Agarwal and Prasad 1998). As with pretraining self-efficacy and motivation to learn, we would generally expect such individual difference constructs to function as distal determinants of task performance, achieving their influence indirectly through mediators such as declarative knowledge, self-efficacy, and observational learning processes (Bandura 1986, Colquitt et al. 2000, Stajkovic and Luthans 1998).

5.4. Conclusion

In conclusion, recent research establishing the effectiveness of behavior modeling and observational learning for computer skill acquisition has quickly advanced the theory and practice of software skill training. The present research contributes to this progress by formulating and performing an initial test of a model that explicitly measures the underlying observational learning processes linking such training interventions to task performance. The observational learning model introduced here may open the door to discovering many new modeling-based training innovations that build upon and improve the effectiveness of behavior modeling. A rich array of research issues surrounding computer training effectiveness should be investigated. Although the focus of the current research is predominantly theoretical, seeking to establish new theory that can be used by future researchers to cultivate training interventions, one fairly direct practical application of the current research would be to explore utilizing the new OLP measures as a diagnostic tool for assessing the strengths and weaknesses of existing modeling-based training practices. Given that most jobs worldwide increasingly rely on computer skills, and most organizations provide their employees with computer skill training, findings of this study have the potential to significantly enhance the job performance of organizational workers.

Acknowledgments

The authors thank the editor, associate editor, and reviewers for their valuable comments on earlier versions of this paper.

Appendix A. Sample Items for Declarative Knowledge and Task Performance

Task Performance Test

(1) Enter a formula to compute profits (=sales − expenses) for each season in cells B8:E8.

(2) Using an appropriate function, compute the total amounts of sales, expenses, and profits of year 2000. The computed amounts should be located in cells F6:F8.

(3) Using an appropriate function, compute the average amounts of sales, expenses, and profits of year 2000. The computed amounts should be located in cells G6:G8.

(4) Compute YTD (year-to-date) profits. The computed amounts should be located in cells B9:E9.

(5) Calculate % change of sales from the previous season. The computed amounts should be located in cells C11:E11.

Declarative Knowledge Test

(1) Cell F6 contains the formula =F3 − D3. What will be the contents of cell F7 if the entry in cell F6 is copied to cell F7?

a. = F3 − D3
b. = G3 − E3
c. = F4 − D4
d. = G4 − E4

(2) To copy the contents of a cell to adjacent cells using the fill handle, you need to move your mouse to the ______ and drag it over the target range.

a. lower right-hand corner of the cell
b. upper right-hand corner of the cell

c. right-side vertical border of the cell
d. center of the cell

(3) The Σ button on the tool bar represents:
a. autosum
b. sigma
c. integral
d. function wizard

(4) In Excel, which of the following has the lowest order of precedence?
a. addition and subtraction
b. parentheses
c. exponential
d. division and multiplication

(5) Which of the following operators do we use to compute a square root of a number?
a. *
b. /
c. ^
d. ++

Appendix B. Latent Construct Correlations, Indicator Weights, and Loadings—Submodel 1

Construct Correlations

Latent Construct	1	2	3	4	5	6
(1) Pretraining Motivation	—					
(2) OLP: Attention	0.42	—				
(3) OLP: Retention	0.38	0.72	—			
(4) OLP: Production	0.35	0.69	0.84	—		
(5) OLP: Motivation	0.49	0.62	0.63	0.61	—	
(6) Retention Enhancement	−0.01	0.16	0.22	0.07	−0.01	—

Indicator Weights and Loadings

Indicator	Weight	Loading	Indicator	Weight	Loading
PTM1	0.28	**0.86**	R4	0.27	**0.91**
PTM2	0.34	**0.88**	P1	0.30	**0.92**
PTM3	0.29	**0.78**	P2	0.15	**0.82**
PTM4	0.29	**0.82**	P3	0.31	**0.95**
A1	0.26	**0.89**	P4	0.32	**0.94**
A2	0.30	**0.92**	M1	0.21	**0.80**
A3	0.26	**0.92**	M2	0.33	**0.91**
A4	0.30	**0.86**	M3	0.29	**0.90**
R1	0.27	**0.90**	M4	0.29	**0.92**
R2	0.24	**0.89**	RE	1.00	**1.00**
R3	0.33	**0.94**			

Note. OLP: Observational Learning Processes Dimensions; PTM = Pretraining Motivation; A = Attention Processes; R = Retention Processes; P = Production Processes; M = Motivation Processes; RE = Retention Enhancement Intervention. All the indicators were specified as reflective. Thus, the loading scores (bold) were applied in the model run.

Appendix C. Latent Construct Correlations, Indicator Weights, and Loadings—Submodel 2

Construct Correlations

Latent Construct	1	2	3	4	5	6
(1) OLP	—					
(2) Pretraining SSE	0.27	—				
(3) Posttraining SSE	0.55	0.46	—			
(4) Declarative Knowledge	0.34	0.25	0.49	—		
(5) Immediate Task Performance	0.36	0.22	0.50	0.67	—	
(6) Delayed Task Performance	0.34	0.25	0.56	0.66	0.78	—

Indicator Weights and Loadings

Indicator	Weight	Loading	Indicator	Weight	Loading	Indicator	Weight	Loading
OLP1	0.31	**0.83**	DK1	**−0.09**	0.18	ITP6	**0.04**	0.68
OLP2	0.01	**0.86**	DK2	**0.21**	0.31	ITP7	**0.01**	0.46
OLP3	0.79	**0.98**	DK3	**0.10**	0.23	ITP8	**0.10**	0.63
OLP4	−0.04	**0.63**	DK4	**0.33**	0.52	ITP9	**0.09**	0.57
Pr_SSE1	0.17	**0.83**	DK5	**0.19**	0.31	ITP10	**0.19**	0.77
Pr_SSE2	0.14	**0.87**	DK6	**0.04**	0.32	ITP11	**0.24**	0.67
Pr_SSE3	0.16	**0.81**	DK7	**0.10**	0.33	DTP1	**−0.03**	0.33
Pr_SSE4	0.18	**0.89**	DK8	**0.25**	0.47	DTP2	**0.10**	0.42
Pr_SSE5	0.16	**0.84**	DK9	**0.22**	0.45	DTP3	**0.15**	0.56
Pr_SSE6	0.18	**0.90**	DK10	**0.19**	0.36	DTP4	**0.39**	0.84
Pr_SSE7	0.17	**0.89**	DK11	**0.54**	0.66	DTP5	**0.28**	0.78
Po_SSE1	0.16	**0.88**	DK12	**0.04**	0.46	DTP6	**−0.13**	0.71
Po_SSE2	0.15	**0.86**	DK13	**−0.04**	0.25	DTP7	**0.02**	0.49
Po_SSE3	0.15	**0.87**	ITP1	**−0.08**	0.22	DTP8	**0.11**	0.65
Po_SSE4	0.17	**0.90**	ITP2	**0.23**	0.41	DTP9	**0.17**	0.63
Po_SSE5	0.17	**0.88**	ITP3	**0.13**	0.62	DTP10	**0.27**	0.85
Po_SSE6	0.18	**0.93**	ITP4	**0.27**	0.76	DTP11	**0.01**	0.52
Po_SSE7	0.15	**0.87**	ITP5	**0.25**	0.76			

Note. OLP = Observational Learning Processes; Pr_SSE = Pretraining Software Self-Efficacy; Po_SSE = Post-training Software Self-Efficacy; DK = Declarative Knowledge; ITP = Immediate Task Performance; DTP = Delayed Task Performance. OLP, pretraining software self-efficacy, and post-training software self-efficacy used loading scores (bold); declarative knowledge, immediate task performance, and delayed task performance used weights (bold).

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Chris Higgins, Associate Editor. This paper was received on June 25, 1998, and was with the authors 26 months for 4 revisions.