The Relationship of Learning Style and Training Method to End-User Computer Satisfaction and Computer Use: A Structural Equation Model

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Motivated by the desire to support the installation of a new computer system, to determine the optimum method of training novice computer users, and to assess learning style's role in computing system training, this study used structural equation modeling to examine and understand the results of a field experiment. Four hundred and fifty members of the U.S. Navy were studied using three training methods: (1) instruction, (2) exploration, and (3) behavior modeling. Trainees' learning style was determined using Kolb's Learning Styles Inventory. The results of the analysis indicate that trainees whose learning style matched training methodology were more successful in training outcomes, had higher computing satisfaction, and had higher levels of computer use. The results showed that behavior modeling trainees were not influenced by learning style and these trainees had the highest levels of satisfaction and computer use.

Forty percent of the respondents to a National Association of Manufacturers survey reported having serious problems upgrading their company's technology because of a lack of employee skills (National Association of Manufacturers, 1993). Another survey estimated that 55% of Americans have some degree of "technophobia," or resistance to using technology in their daily lives (Filipczak, 1994). These figures are especially troublesome, given the increasing number of jobs, even at lower levels of organizations, where technical skills are essential for successful job performance ("Tackling the Information Technology Skills Gap," 1993). The computer literacy problem is compounded by the wide range of training options available to industry and the lack of reliable indicators that predict trainee success.

The IS literature has identified training as a critical factor in the success of decision support systems (Fuerst et al., 1982; Sanders & Courtney, 1985), strategic innovation (Kotter & Schlesinger, 1979), and implementation (Alavi & Joachimsthaler, 1992; Bronsema & Keen, 1983; Lucas et al., 1988; Nelson & Cheney, 1987). Further, Grover and Teng (1994) identified training as a critical factor in the implementation of customer-based interorganizational systems and Cronan and Douglas (1990) found training critical in the implementation of end-user computing (EUC). Gist et al. (1989) examined training methods including behavior modeling, a non-traditional training method, in a study of self-efficacy and mastery of a computer software program and found that participants in the behavior modeling treatment reported more effective cognitive working styles, more ease with the task, less frustration with the task, and higher satisfaction with the training than did participants of other treatment groups. In examination of various forms of computer-related training in a classroom setting, the degree to which student or group participation varied with regard to training method and the change in instructor style (Feather, 1999; Leidner and Jarvenpaa, 1993). Their research did not include the behavior modeling technique and was restricted to the classroom environment. Compeau and Higgins (1995) also used the behavior modeling technique in their study of self-efficacy.

Several studies in the information systems area have investigated learning style (Bostrom et al., 1990; Burke, 2000; Davis & Davis, 1990; Harrision & Rainer, 1992; Palvia, 1991; Vessey &

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Galletta, 1991). The current investigation builds upon and expands the work reported in Simon et al. (1996) and Simon and Werner (1996). The goal of the initial study was to identify the optimum training method for novice computer users using 200 members of the U.S. Navy. Results indicated that the behavior modeling training treatment produced optimum training outcomes. A review of the findings uncovered a desire by the Navy to identify indicators that might help predict successful training outcomes before training took place. This interest led to the investigation that is reported in this work. To conduct the follow-up study, the original training material and test instruments were modified to focus more on the proprietary computer system and less on basic computer knowledge. The Kolb Learning Style Inventory was selected to measure trainee style, a potential predictor of training success, in part due to the Navy's familiarity with it and its fit into the existing theoretical framework.

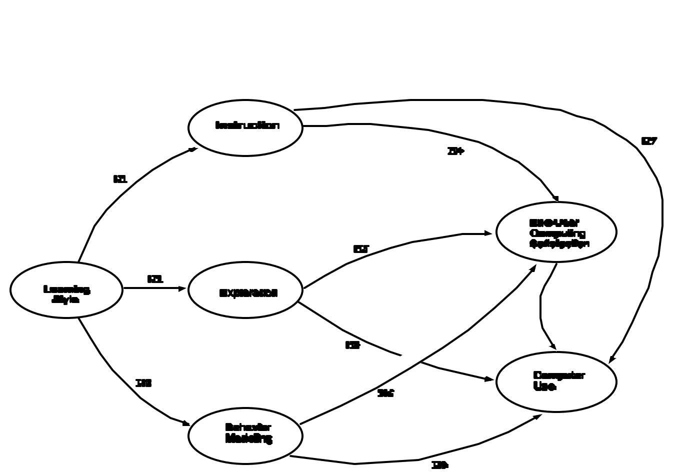
The current study uses structural equation modeling to link learning style with training technique in a computer-training environment and to determine the effect of learning style and training treatment on end-user satisfaction and computer use. The theoretical basis for this work is the same as in earlier works having been derived from the training and education psychology literature. A unique aspect of this study is the inclusion of the Kolb learning style inventory and its link with training treatment to ascertain the optimum combination and its effect on training outcomes, end-user satisfaction, and computer use. This study also employs a field experiment conducted with a new sample of 450 active duty U.S. Navy personnel, with the elimination of the control treatment found in earlier works. The setting for this experiment was the implementation of Micro-SNAP, a computerized logistics system that resulted in new methods of ordering and tracking material, inventorying, and maintaining records keeping.

Descriptive Model

This section presents the research model and the hypotheses tested in this research, as well as the theoretical basis for the propositions. The model (see Figure 1) focuses on learning styles and training techniques and how they relate to end-user computing satisfaction (EUCS) and computer use. Rather than attempt to define the domain of variables related to EUCS or computer use, this model explains the relationship of specific variables, learning style and training type. Although previous studies (Amoroso & Cheney, 1991) have investigated *past computer training* as it relates to EUCS, this micro examination of training-related variables provides detailed insight into a specific area of EUCS, extending the earlier work (Simon et al., 1996; Simon & Werner, 1996).

The relationships tested in this model were derived from the training and EUCS literature described in the following sections. Relevant literature for each set of variables is presented followed by the propositions that were tested. The structural equation model is the vehicle used to test the hypotheses. The paths of the model are used to assess the strengths of the relationship between the variables. The oval found on the extreme left side of the model represents the learner's cognitive learning style. As suggested by the literature, the learning styles of the trainees/learners should directly influence their performance (transfer of knowledge) based on which of the three training treatments (the second set of ovals) they receive. Trainees/learners whose training treatment most matches their learning styles can also be expected to perform best. The fit between a training

Figure 1: Complete (Overidentified) Path Model



treatment and the type of information comprising training can also be expected to affect trainee performance. Consequently, trainees/learners who perform best in the training treatment can be expected to have the highest levels of end-user satisfaction and will be prone to use the system to a greater extent.

The following sections provide a review of the Kolb model and training methods from the management and education psychology literature. Next a discussion of the literature, the variables, and the hypotheses that will be tested in this study are presented, followed by a review of the data analysis. Finally, implications for research and practice are discussed.

Kolb Learning Model

The Kolb Learning Model (1976, 1984) has its base in Lewin's Experimental Learning Model (1951). The Lewin model views the learning process as a continuous loop. Two aspects of this learning model are particularly noteworthy. The first is the emphasis on *here-and-now concrete experience* to validate and test abstract concepts. The focal point for learning is immediate personal experience that contributes real-life meanings and texture to abstract concepts while at the same time providing concrete, publicly shared reference points for testing the implications and ideas created during the learning process. The second emphasis, action research and laboratory training are based on *feedback processes*. This information feedback provides the basis for the continuous process of goal-directed action and evaluation of consequences of that action. It is that feedback loop that Lewin believed could eliminate ineffectiveness in the organization, the training process in this study.

This study used the Kolb Learning Style Inventory to measure the degree to which a learner was aligned along the said dimensions. A complete review of the Kolb model is found in Simon et al. (1996). The learning style inventory employs a series of nine four-item scales where the learners rank the items that best represent their own styles of learning (see Figure 2). Since its development in the mid-seventies, the scale has been widely used and has a reliability coefficient in excess of .80.

Figure 2: Kolb Learning Style Inventory Items

Learning ability	X-axis	Y-axis
Concrete Experience (CE)	receptive feeling present-oriented	accepting intuitive experience
Reflective Observation (RO)	observing reflecting reserved	observation tentative watching
Abstract Conceptualization (AC)	analytical conceptualization rational	evaluative thinking logical
Active Experiment (AE)	active experimentation practical	responsible doing pragmatic
AC-CE	AC_x-CE_x	AC_y-CE_y
AE-RO	AE_x-RO_x	AE_y-RO_y

Training Methods

The primary independent variable in this study is training method. This study operationalizes three training methods: (1) instruction, (2) exploratory, and (3) behavior modeling. *Instruction-based learning* has been characterized as the situation when "the entire content of what is to be learned is presented to the learner in final form" (Ausubel, 1963, p.16). This method offers a traditional approach that is widely accepted and understood. It is appropriate for almost all training needs and can be very dynamic, since the instructor is present to deal with any questions or problems that may arise and give individual attention as needed (Wehr, 1988). *Exploration learning* has been characterized as "a matter of rearranging or transforming evidence in such a way that one is enabled to go beyond the evidence so reassembled to additional new insights" (Bruner, 1966, p. 72). Glaser (1966) describes exploration learning as a process by which individuals are granted the freedom to impose their own structures on learning. Exploration may also involve an inductive process through which an individual learns general concepts by starting with specific tasks or examples (Taba, 1963) and has been credited as the best way to learn personal computing (Brynda, 1992). Exploration based training in this study is operationalized as an independent study format utilizing self-paced manuals. The *behavior modeling* method—developed in the 1970s for building an individual's skills—is a combination of the exploration and instruction methods that concentrates on the idea of observing and doing while following a role model. The theoretical constructs of behavior modeling are sound and well established (Bandura, 1969; Goldstein & Sorcher, 1974). Trainees then imitate the role model's behavior in practice. The technique emphasizes learning points in the instruction mode and modeling, practice, and feedback in the exploration or hands-on mode. Learning points are simply guidelines to lead an individual to a desired objective. A complete review of the training methods used in this study is found in Simon et al., 1996.

Comprehensive Training Model

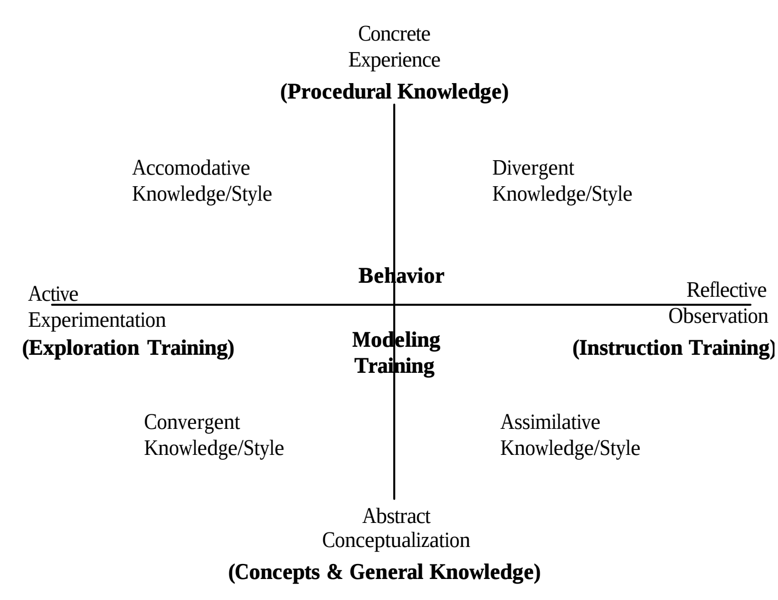
The comprehensive training model (Figure 3) overlays the training techniques and information types used in this study over the Kolb Training Model. This expanded model illustrates the anticipated "fit" of cognitive styles of learners explained by Kolb and the three training techniques prescribed by the literature on the horizontal axis. The instruction technique overlays the reflective observation end of the axis, while the exploration technique is matched with active experimentation. Consequently, trainees whose learning styles match a particular training technique are expected to achieve superior performance. Since the behavior modeling technique is composed of elements of both instruction-based and exploration training, it has been placed in the center of the comprehensive training model. This placement and the nature of the technique suggest that all learners, regardless of learning style, should excel.

Information type, shown on the vertical axis, is accounted for during the evaluations that were conducted to derive trainee outcomes in three areas: transfer of knowledge, end-user computing satisfaction, and computer use. Two information types were tested: (1) procedural knowledge and (2) concepts & general knowledge. Those two measures were aggregated to produce a third overall information type. The three information types represent the three models under investigation: aggregated (A), skills-based (S) (procedural knowledge), and comprehension (C) (concepts & general knowledge). To account for the three information types and the expected outcomes under the different types, three sets of hypotheses were developed. The hypotheses are differentiated by the letters representing each information type or model as discussed here.

Hypotheses Associated with Learning Style and Training Technique

Hall and Freda (1982) argue that the instruction-based approach is often most effective.

Figure 3: Comprehensive Training Model



Friedlander (1965) suggests that there is actually a demotivating effect associated with incorrect solutions in exploratory training and that this effect can outweigh the motivating effect of reaching a correct solution on one's own. Further, the enhancements to learning, retention, and transferability of exploration learning may not justify the increased time it requires (Ausubel, 1963). Instruction-based training leads to quick reinforcement for the instructor and the student. Exploration training may require more effort on the part of the student and the results may be far in the future (Glaser, 1966). Additionally, instruction based training has the effect of minimizing incorrect responses and allowing learners to apply rules more quickly. Hall and Freda (1982) found that instruction-based training was more effective than exploratory training in courses that primarily teach rules or general tasks.

With regard to the instruction training technique, Kolb suggests that reflective observation (RO) learners should outperform their active experimentation (AE) counterparts. Extending Kolb's logic, one would expect a learning style/training technique match with information type. The hypotheses H1(A) and H1(C) listed below suggest that learning style will positively influence instruction trainees especially when the information consists of general concepts. H1(S) suggests that there will be no influence of learning style during skills-based evaluation. It is not expected that instruction trainees will excel during this evaluation since there is no learning skills/information type match and trainees have no opportunity during training to practice those skills.

H1(A) Learning style will positively influence the outcomes of instruction trainees; specifically, reflective observation (RO) trainees will achieve superior results.

H1(S) Learning style will have no influence on the outcomes of instruction trainees.

H1(C) Learning style will positively influence the outcomes of instruction trainees; specifically, reflective observation (RO) trainees will achieve superior results.

Bruner (1966) argues that exploration training helps learners organize information, making it more readily available for later application or problem solving. He also suggests that this method motivates the individual. The conclusion is that the individual becomes more self-motivated to solve problems in an independent fashion. It has also been suggested that the information learned using exploration is more readily transferable, because exploration allows the individual to easily accommodate new information, with that information being learned in terms of information already acquired (Taba, 1963). This theory has been extended by Carrol and Mack (1985). Their theory of active learning suggests that individuals modify their internal representations of a system by actually working with it. The traits of exploration trainees, listed above, are very similar to Kolb's characteristics of active exploration (AE) learners. The learning style of AE trainees indicates that these learners should be particularly adept at assimilating procedural information, whether independently or in a group situation, leading to hypotheses H2(A) & (S) below. Hypothesis H2(C) is suggested since the technique is "hands-on" in orientation; thus it is not anticipated that the exploration trainees would excel in the comprehension evaluation.

H2(A) Learning style will positively influence the outcomes of exploration trainees; specifically, active experimentation (AE) trainees will achieve superior results.

H2(S) Learning style will positively influence the outcomes of exploration trainees; specifically, active experimentation (AE) trainees will achieve superior results.

H2(C) Learning style will have no influence on the outcomes of exploration trainees.

No one method has been found to be universally more effective in all training of the different types of tasks to different ability students. Hall and Freda's (1982) research suggests that a combination of methods, used within a given course for conveying different instructional content, would most likely be more effective than the use of a single method for an entire course. While each person can learn a limited number of transactions easily, training and practice are required to extend the range of situations that can be managed with facility. According to Sorcher and Spence (1982), behavior modeling works because people develop individual ways of extending their abilities. They suggest a variation of the usual procedure of presenting concrete behavioral guidelines for training skills. They propose that training should emphasize general principles, and trainees should be encouraged to devise alternative ways to apply the principles in various situations.

Since behavior modeling extends the elements of both instruction and exploration, it is assumed that a technique of this type should prove highly effective for all trainees regardless of learning style. Additionally, since behavior modeling uses a combination of general examples plus hands-on practice and experimentation, the technique should be highly successful for both information types. Gist et al. (1989) conducted a comparison of alternative training methods in a non-industrial setting. They studied self-efficacy and mastery of a computer software program, and found that participants in the behavior modeling treatment reported more effective cognitive working styles, more ease with the task, less frustration with the task, and higher satisfaction with the training than did participants of other treatment groups.

Given the attributes of the behavior modeling technique and its applicability to various learning styles and information types, the three hypotheses listed below were derived.

H3(A) Learning style will have no influence on the outcomes of behavior modeling trainees.

H3(S) Learning style will have no influence on the outcomes of behavior modeling trainees.

H3(C) Learning style will have no influence on the outcomes of behavior modeling trainees.

End-User Computing Satisfaction

End-user satisfaction has been widely researched in the IS literature as a measurement which provides a summary evaluation for researchers and a formative evaluation for practitioners. The measure has been used to predict outcomes, to uncover user perceptions of IS systems, or to measure training effectiveness, as in this study. In other words, user (information) satisfaction is a perceptual or subjective measure of system success; it serves as a substitute for objective determinants of information system effectiveness (Ives, Olson, & Baroudi, 1983). In this study, the Doll and Torkzadeh (1988) instrument was used to gather trainees' perceptions of EUCS. The EUCS instrument was administered six weeks following the training after the trainees had the opportunity to work with the system. The hypotheses listed below intuitively assume that the higher the trainee scores on training evaluation the more satisfied they will be with the system. The hypotheses decompose training into three specific treatments that, it is assumed, will demonstrate varying strengths of relationships with user satisfaction.

As was hypothesized in the previous section, the match between learning style and training technique should significantly impact the performance and thus the level of satisfaction of the end user. Additionally, if the training technique does not match the information type then the expected outcome should result in reduced performance and as a result, lower levels of EUCS. Again, the hypotheses support the contention that a multi-approach technique such as behavior modeling will result in higher levels of EUCS. Hellman (1992) found that a program using the techniques included in behavior modeling leads to the success of end-user computing.

H4(A) Instruction training will positively influence end-user computing satisfaction.

H4(S) Instruction training will have no influence on end-user computing satisfaction.

H4(C) Instruction training will positively influence end-user computing satisfaction.

H5(A) Exploration training will positively influence end-user computing satisfaction.

H5(S) Exploration training will positively influence end-user computing satisfaction.

H5(C) Exploration training will have no influence on end-user computing satisfaction.

H6(A) Behavior modeling training will positively influence end-user computing satisfaction.

H6(S) Behavior modeling training will positively influence end-user computing satisfaction.

H6(C) Behavior modeling training will positively influence end-user computing satisfaction.

Computer Use

Computer use has also been employed as a surrogate for information system success, usually in situations where use is voluntary. In an empirical study Schiffman et al. (1992) verified that user type had a significant impact on system usage and dependence. Fuerst and Cheney (1982) discovered a strong relationship between computer use and the experience of end-users. Amoroso and Cheney (1991) found that several determinants of end-user satisfaction were also determinants of computer use. This suggests that users who perform better during training evaluations will be more prone to use the system once training is complete. As discussed earlier, the factors that should help determine user performance are the match among user learning style, information type, and training treatment. The optimum fit should result in trainees with superior performance, higher levels of satisfaction, and consequently greater computer use. The computer use data were gathered as the trainees' self-reported weekly interaction with the computer system. The data were gathered during the follow-up evaluation (see below).

H7(A) Instruction training will positively influence computer use.

H7(S) Instruction training will not influence computer use.

H7(C) Instruction training will positively influence computer use.

H8(A) Exploration training will positively influence computer use.

H8(S) Exploration training will positively influence computer use.

H8(C) Exploration training will not influence computer use.

H9(A) Behavior modeling training will positively influence computer use.

H9(S) Behavior modeling training will positively influence computer use.

H9(C) Behavior modeling training will positively influence computer use.

Experiment

A field experiment was conducted using subjects who were serving in the U.S. Navy. Potential subjects filled out a background questionnaire rating their knowledge of general computing terms using a five-point Likert scale and reporting their ability to perform specific tasks such as saving, modifying, or writing a computer program (a copy of the questionnaire is available from the author). Because the study was interested in trainees with low computer literacy, only individuals who scored 30% or less on this pretest were included in the study. There is no widely accepted definition of computer literacy (Angel, 1994; Hannum, 1992), so the selection of this cutoff was arbitrary, but conservative, given the purposes of the study.

All subjects who were thus classified as "novice" computer users were then randomly assigned to one of the four conditions of the study. The sample was primarily (77.6%) male. The vast majority (94.7%) of subjects held enlisted rank. Seventy percent of the trainees had obtained a high school degree, 16% an associates degree, 13% an undergraduate degree, and one percent a graduate degree. Sixty five percent were under 25 years old, 24% were between 25-35 years of age, 10% were between 36 and 45 years old, and one percent was between 46 and 55 years old. There were no statistically significant differences between the three conditions on any of the demographic variables collected in this study.

Procedure

The impetus for training was the introduction of a new automated data processing system. This system, Micro-SNAP II, is a menu-driven application that was implemented to increase efficiency and reduce paperwork. Subjects were trained to use the new system on workstations similar to those found in their work areas. Training was important to subjects, insofar as computer skills could influence their future performance ratings and advancement opportunities. A recent survey of sailors found that computing skills were widely desired.

Three conditions were present in this study: 1) instruction, 2) exploration, and 3) behavior modeling. To ensure that the same basic content was available in each condition, scripts for the three training conditions were created using the same course outline. General computer information as well as specific Micro-SNAP II procedures and commands were presented in each condition. To ensure that trainees received the same amount of time in training, the length of training was held constant at two hours for all conditions. This length was based upon the amount of time it took a pilot group, in the initial study, to complete training in the exploration condition, which took the longest of the three conditions

This extended study included 150 trainees per condition. Five sessions were conducted per treatment, with 30 trainees per session. Times for the sessions were randomly selected, and trainees were excused from normal duties during their session. Data were collected at three points. Prior to training, background information and learning style were measured. Second, measures of cognitive and skill learning were collected immediately after training. Manipulation check and trainee reaction measures were also completed at this time. Third, as a test of retention and transfer, identical cognitive and skill measures were collected six weeks after training. Trainee satisfaction with the computer system and system use was measured at this time. The analysis in this study was conducted on the data derived at the follow-up evaluation, which occurred six weeks after the completion of training.

Training Interventions

Instruction. The instruction condition was conducted in a conference room, using a deductive or traditional classroom approach. General rules were presented to trainees, followed by specific examples. A computer-driven slide show was used to provide standardized information to all sessions. Trainees were given corresponding written information and were free to take notes if they desired. Questions and discussion were encouraged at any time during the training.

Exploration. The exploration condition was conducted in a computer classroom, where trainees were seated at workstations. An inductive approach was used. Trainees received a manual at the beginning of the session, as well as a disk needed to work through the exercises. From that point on, they were instructed to work independently on the computer, as if completing a self-study course. They were advised that the trainer was there to help them if they reached an impasse or failed to understand the material. When questioned, the trainer primarily referred trainees to the appropriate portion of the manual. Trainees who completed the manual and exercises in less than two hours were asked to stay at their workstations and continue interacting with the computer.

Behavior modeling. The modeling condition was conducted in the same computer classroom used for the exploration condition. General concepts were presented to trainees in a lecture format, with emphasis placed on specific learning points. Trainees were shown the same visual aids, and provided the same written materials as the instruction condition. They were encouraged to participate during the presentation if they desired. To learn specific procedures, trainees were directed to observe the trainer, who performed the procedures on a computer with the image projected on a screen. Then they were to attempt the task themselves. Disks were provided to each trainee, as in the exploration condition. Trainees were given time to experiment on the computer, to find other ways of carrying out the assignments, i.e., they were not expected to learn "one way only" to complete the tasks.

Measures

Manipulation check. An eight-item measure was developed, patterned after one used by Werner et al. (1994). Using a five-point Likert scale, with anchors from strongly agree to strongly disagree, trainees rated the extent to which the trainer engaged in certain behaviors in their training. (The questionnaire is available from the author.) If the manipulations were carried out as intended, the groups should vary in the extent to which they agreed that the trainer in their session carried out the roles of "instructor" versus "advisor" versus "model." ANOVAs were separately conducted on each of the eight items. Differences between the treatments were statistically significant for each item ($p < .01$). As expected, trainees in the behavior modeling treatment rated the trainer significantly higher than trainees in exploration or instruction in terms of concentrating on specific learning points, giving opportunity to practice learning points, and acting as a role model. Trainees in the exploration treatment rated the trainer significantly higher than behavior modeling and instruction trainees in terms of encouraging a trial-and-error approach, progressing from examples to general conclusions, and acting as an advisor. Trainees in the instruction treatment rated the trainer significantly higher than behavior modeling and exploration trainees in terms of acting as an instructor and in progressing from facts to general conclusions. Given the strength of these findings, it was clear that manipulations were carried out as intended.

Reaction. A six-item measure of reactions to training was developed, patterned after Werner et al. (1994). A five-point Likert scale was used, with anchors from strongly agree to strongly disagree. (The questionnaire is available from the author.) Sample items included, "I would recommend this training program to others," and "The training program got me more excited about becoming more computer literate." Cronbach's alpha (Cronbach & Snow, 1977) equaled .92 in this sample. No specific hypotheses were made concerning reactions to training. However, differential trainee reactions might serve as a possible explanation for differences across the conditions on other measures. Also, as mentioned above, scores on this scale can be used to measure trainees' perceptions of training quality in each condition. Reactions were favorable to all three training approaches. Differences between the conditions were not statistically significant ($F=.46$, $p=.96$).

Learning styles. The Kolb Learning Styles Inventory was used to measure the cognitive learning style of trainees. This instrument asked the trainees to characterize themselves on a series of nine scales. Results of the instrument were used to plot the trainees' positions on each axis and in the four quadrants as described earlier. Trainees completed the instrument prior to training, being informed that there were no right or wrong answers, only that people varied as to how they obtained knowledge.

Comprehension outcomes. Cognitive learning measures were developed for this study to capture general and procedural comprehension. *General comprehension* was measured using 11 items, which included six multiple choice and five true/false questions. Items captured general or background information which trainees needed to know to operate the computer system and which were covered in all training sessions. This included general questions about booting a computer, directories and subdirectories, logging in (i.e., does it help maintain security?), and formatting disks (i.e., does formatting destroy all data stored on the disk?). Five points were assigned for each correct answer, so scores could range from 0-55. Cronbach's alpha equaled .83.

Procedural comprehension. Procedural comprehension was measured using 11 open-ended questions. Three primary researcher-developed scenarios were presented, and trainees were asked to respond in writing as to what would appear next on the computer screen. After each scenario, either two or three follow-up questions were provided, and trainees were asked to comment on what would occur in response to various commands. All answers were scored by two raters, the author and a computer expert unaffiliated with the study, according to the following scheme: For the three primary questions, absolutely correct answers received 10 points, partially correct answers were assigned five points, and incorrect answers received zero points. The eight other questions were considered of lesser importance; thus, absolutely correct answers received five points, partially correct answers three points, and incorrect answers received zero points. Scores could range from 0-70.

Skill-based learning outcomes. A hands-on measure was developed for this study to capture skill-based learning and transfer, based on the work of Baldwin and Ford (1988). Each trainee received a computer disk and was asked to complete six tasks on the computer. The first four tasks were very similar to what had been covered in training, and assessed *skill reproduction*, i.e., using skills in situations very similar to those encountered in training (Baldwin, 1992). Eight sub-tasks were completed as part of these four questions. Examples include finding and recording the contents of the root directory, changing directories, and Micro-SNAP entry procedures. The final two tasks were designed to measure *skill generalization*. They required trainees to combine tasks that they should have learned in training, in order to perform a different activity than the one they had tried in training (Baldwin, 1992). One task entailed creating a new directory, and the other developing Micro-SNAP reports. Trainee responses were scored by the author, with three points assigned for absolutely correct answers, two points for partially correct solutions, one point for solutions that were incorrect, but somewhat similar to the correct solutions, and zero points for solutions that were incorrect or not provided. Scores could range from 0-30.

End-user computing satisfaction. User satisfaction measures focus on a broad range of computer functions. It has been suggested that end-user satisfaction can be evaluated in terms of knowledge or the user's understanding of the system and its applications. The more effective the training, the more a trainee would be expected to be satisfied with the system. The Doll and Torkzadeh (1988) instrument used in this study employs twelve questions such as, "The system is easy to use," and "The output is presented in a useful format." Trainees responded to these items using a five-point Likert scale, with 1 labeled as "Disagree," 3 as "No opinion," and 5 as "Agree." Cronbach's alpha reliability for this instrument was .98.

System use. System use can be a surrogate indicator of system success (Ives et al., 1983). Trainees were instructed to maintain a log of hours they spent on the system. The author concedes that there are flaws in self-reported measures and that some trainees might have inflated their actual time interacting with the system, but with this system there was no electronic means to track system use. Despite the fact that system use was required for the trainees to complete their duties, it was recognized that some trainees might have the opportunity or be inclined to use the system more than others. If there was a large degree of variance among individual users or treatment groups the results would be unduly influenced.

Analysis

Structural equation modeling without latent variables was used to conduct the analysis. Structural equation modeling can be used to test theoretical models that specify causal relationships among a number of observed variables. Structural equation modeling determines whether a theoretical model successfully accounts for the actual relationships observed in the sample data. The output of the analysis provides indices that demonstrate whether the model, as a whole, fits the data, as well as significance tests for specific causal paths. The procedure deals only with causal models in which all variables are manifest (observed) variables. It does not deal with path models that specify causal relationships between latent or unobserved variables; such models are called "LISREL-type" models (Hatcher, 1994; SAS Institute, 1989). As with most statistical procedures, structural equation modeling requires several necessary conditions be met to insure the validity of the analysis. All variables assessed should be either interval- or ratio-level data. The statistical tests conducted with the analysis (e.g., the model chi-square test and significance tests for path coefficients) assume a multivariate normal distribution. Relationships between variables should be linear and additive with variables free of multicollinearity. To test for goodness of fit, the initial causal model must be overidentified. An overidentified model is one that includes more equations than unknowns. Finally, there should be a ratio of at least five subjects for each parameter (total parameters equal path coefficients plus variances and covariances) to be estimated. Some researchers argue that the analysis is best conducted on samples greater than 200 (March et al., 1988).

The analysis began with the overidentified model (see Figure 1). The data set's covariance matrix was used to determine the fit between the data and the model. The analysis was conducted for three separate data sets, (1) aggregated (skills-based plus comprehension), (2) skill-based, and (3) comprehension evaluations. All analysis was conducted using SAS System's PROC CALIS procedure, using the maximum likelihood method of parameter estimation. Several key tests were performed to determine model-to-data fit. First, the chi-square statistic provided a test of the null hypothesis that the covariance matrix had the specific model structure. Two other tests to determine model fit were also considered, Bentler and Bonnett's (1980) normed fit index (NFI) and Bentler's (1989) comparative fit index (CFI). Both range in value from 0 to 1 where 0 represents the goodness of fit associated with a null model where all variables are uncorrelated and 1, for a model that perfectly reproduces the original covariance matrix. Good fit is indicated by values greater than .9, with Bentler's CFI considered the most precise measure of fit. If the indicators fail to show acceptable fit then model modification is required.

The first step in modification is a review of the path coefficients to determine if any paths in the initial model should be deleted. The t-values for all path coefficients should be statistically significant ($p < .05$) or the paths are removed. Under certain conditions it might become necessary to add paths to the model. This is determined by a review of the normalized residual matrix, which represents the normalized difference between the original covariance matrix and the predicted model matrix. Absolute values that exceed 2.00 should be considered problematic and suggest the need for an additional path between the indicated variables. Fortunately, this did not occur in this analysis. It is important to note that the deletion or addition of paths to the model should conform to the theoretical grounds underlying the study. Once paths are deleted from (or added to) the model, it is reanalyzed. A new predicted model matrix is then estimated and compared against the original covariance matrix. The analysis proceeds in an iterative manner until the statistics indicate good fit or no improvement.

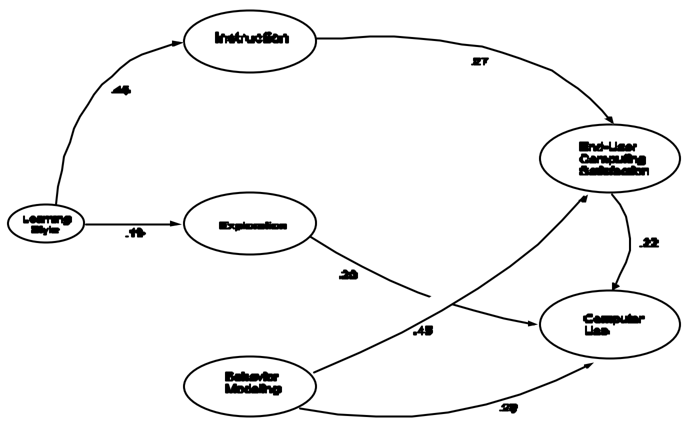
Results

Aggregated Data Model

This section discusses the analysis of the three models beginning with the aggregated data model. The results are presented with the standardized path coefficients and the supported hypotheses for the significant paths. As stated earlier, each data set's covariance matrix was tested initially against the overidentified model. The initial model for the aggregated data set failed to provide a good fit between the data and the theoretical model. Estimation of this model revealed a significant model chi-square value, $\chi^2 = 226.27$, $p < .001$. The values for NFI and CFI were .35 and .33 respectively. Analysis indicated that several of the paths did not meet the desired statistical significance level. Given these results, the original model was rejected and modifications were attempted to improve the model's fit.

Three iterations of the procedure described in the previous section yielded the final aggregated data model (see Figure 4). This model differs widely from the original model, providing a much better fit between the data and the theoretical model than any of the previous iterations. Estimation of this model revealed a non-significant model chi-square value, $\chi^2 = 4.59$, $p < .97$. The values for NFI and CFI were .97 and .93 respectively. The results indicated that several paths were not significant at the .05 level; these paths were deleted from the model. Paths that remained in the model are labeled with their standardized path coefficients, facilitating interpretation. Learning style had a significant influence on instruction treatment trainees (path coefficient .45) and a moderate effect (path coefficient .19) on the trainee in the exploration treatment. To test for a significant difference

Figure 4: Aggregate Data Path Model



Chi Square = 4.59 CFI = .93 NFI = .97
p-value = .97

between learners within each training treatment a z-test was conducted on the scores of the AE and RO learners after the structural equation modeling was completed. Within the instruction treatment, the mean score of RO learners surpassed that of AE learners (57.58 and 46.46 respectively), significant at Z = 11.67, p = .02, rejecting the null hypothesis of equal means. Within the exploration treatment the mean score of AE learners (93.55) was significantly different from the mean score of RO learners (74.36) (Z = 9.75, p = .03). The results support hypotheses H1(A) and H2(A). Interestingly, learning style had no effect on the trainees in the behavior modeling treatment. There was no significant difference (Z = .95, p = .23) between the mean scores (AE = 130.4, RO = 129.73), supporting hypotheses H3(A).

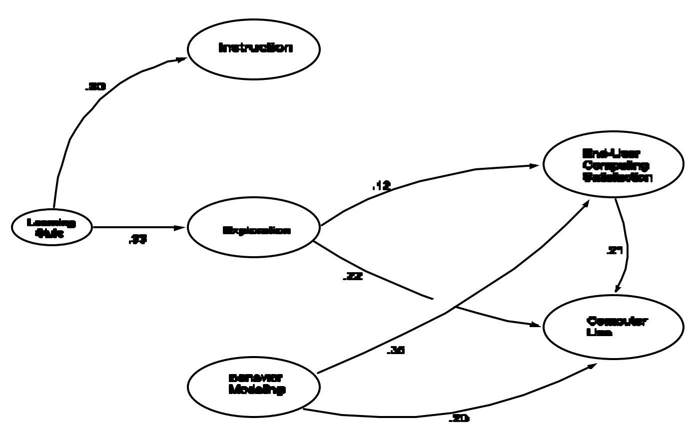
The path between the instruction intervention and end-user computing satisfaction was statistically significant (standardized coefficient of .27), indicating a .27 unit increase in satisfaction for each unit of instruction training and supporting hypothesis H4(A) that instruction training successful outcomes will influence EUCS. A comparison of EUCS path coefficients indicates that the behavior modeling intervention path (standardized path coefficient .45) is almost twice as strong as the instruction path coefficient, which supports hypothesis H6(A) that behavior modeling outcomes will influence EUCS. The paths between exploration and behavior modeling and computer use (path coefficients .20 and .29 respectively) were also significant (supporting H8(A) and H9(A)), again with modeling providing the strongest relationship.

Skills-Based Data Model

The second data set to be analyzed was the skills-based evaluation model. This data set was based on the results of the hands-on evaluations and followed exactly the same procedure as the analysis for the aggregated data set model. The initial model for the skills-based data set also failed to provide a good fit between the data and the theoretical model. Estimation of this model revealed a significant model chi-square value, $\chi^2 = 26.27$, $p < .003$. The values for NFI and CFI were .73 and .65 respectively. Given these results, the original model was rejected and modifications were attempted to improve the model's fit. Two iterations resulted in the skills-based model found in Figure 5. Estimation of this model revealed a non-significant model chi-square value, $\chi^2 = 0.81$, $p < .99$. The values for NFI and CFI were .99 and .97 respectively.

This model denotes no significant change in the paths between the learning styles and the three

Figure 5: Skills-Based Evaluation Path Model



Chi Square = .81 CFI = .97 NFI = .99
p-value = .99

training interventions. Surprisingly, the analysis discovered a significant difference between AE and RO learners in the instruction technique. The mean score of AE learners (5.50) was significantly different (Z = 7.69, p = .03) from the scores of RO learners (3.81), rejecting the hypothesis of equal means. The mean score of the AE learners (24.83) in the exploration treatment was significantly different (Z = 9.74, p = .00) from the mean score of RO learners (14.01), contributing to support for hypotheses H2(S). Supporting hypothesis H3(S), the analysis discovered no significant difference (Z = .81, p = .24) between the mean scores of trainees within the behavior modeling treatment (AE = 26.07, RO = 25.44).

Not surprisingly, the paths from the lecture treatment and end-user computing satisfaction and computer use were not significant and were deleted. The skills-based evaluation required trainees to repeat and expand upon items practiced during the exploration and modeling training sessions that were not included in instruction sessions. It was puzzling that the instruction trainees did not build hands-on skills during the six weeks between training and evaluation since trainees were working with the computer system. The paths between exploration and satisfaction and use were significant, supporting hypotheses H5(S) and H8(S), with path coefficients of .12 and .22 respectively. The paths between modeling and satisfaction (path coefficient .35) and use (path coefficient .20) were also significant, supporting hypotheses H6(S) and H9(S). In this case, the differences in the strengths of the paths were not as dramatic as those in the aggregated data model.

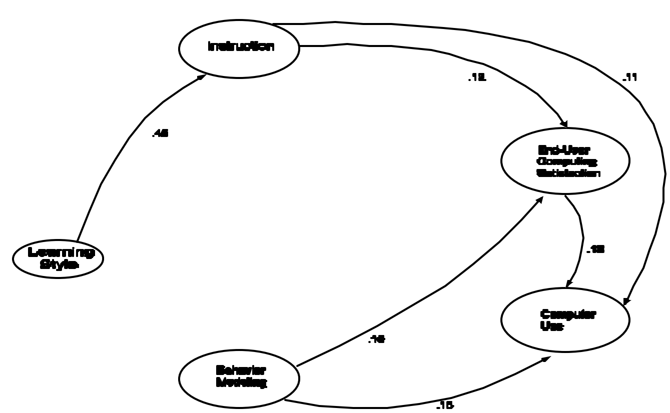
Comprehension Data Model

The last data set to be analyzed was the comprehension evaluation model. The initial model for the comprehension data set also failed to provide a good fit between the data and the theoretical model. Estimation of this model revealed a non-significant model chi-square value, $\chi^2 = 17.18$, $p < .32$, but the values for NFI and CFI were only .59 and .49 respectively. Given these results, the original model was rejected and modifications were attempted to improve the model's fit. Four iterations resulted in the comprehension evaluation model found in Figure 6. Estimation of this model revealed a non-significant model chi-square value, $\chi^2 = 11.51$, $p < .57$. The values for NFI and CFI were .89 and .86 respectively. The chi square statistic and the CFI suggest a marginal fit between the model and the data, but analysis performed after this run failed to improve the model's fit.

This model illustrates changes in the paths between the learning styles and the three training interventions. Once again, the difference between the mean scores of instruction trainees (AE = 42.65, RO = 52.08) was significant (Z = 8.67, p = 0.04) supporting hypothesis H3(C). There was no significant difference (Z = .75, p = .33) between the mean scores of trainees in the exploration technique (AE = 49.12 , RO = 48.11), supporting hypothesis H2(C) and contributing to the deletion of the LSI/Exploration path. Hypothesis H3(C) is also supported (Z = .86, p = .20), indicating no difference between the mean scores of behavior modeling trainees (AE = 92.95, RO = 90.43), no influence of learning style, and the deletion of the LSI/behavior modeling path.

The most noticeable difference between this model and the skills-based model is the difference in the instruction and exploration paths. In the current model the paths from Instruction to EUCS (coefficient .12) and Use (coefficient .11) are both

Figure 6: Comprehensive Evaluation Path Model



Chi Square = 11.51 CFI = .86 NFI = .89
p-value = .57

significant (supporting hypotheses H4(C) and H7(C)) with the paths from the exploration treatment not significant. The lack of significance of any of the exploration paths has led to the technique's elimination from this model. Again, this should come as no surprise since the literature suggests that the instruction technique should produce superior results for this type of evaluation. The paths from Behavior Modeling to EUCS (coefficient .16) and Use (coefficient .15) were again significant, supporting hypotheses H6(C) and H9(C).

Discussion and Implications

This study was motivated by the desire to support the installation of a new computer system, to determine the optimum method of training novice computer users, and to assess learning style's role in computing system training. The analysis indicates that the assumptions with regard to learning style are for the most part upheld. The reflective observation (RO) learners performed best in the instruction treatment, while active experimentation (AE) learners excelled in the exploration technique. Instruction trainees were most influenced by learning style while exploration trainees were also influenced, but to a lesser degree. The analysis revealed that learning style did not significantly influence trainees in the behavior modeling treatment in all three models/information types.

The analysis supports the literature's assumptions that learning style is a factor in training and education and is a significant factor in the design of training programs/courses. To achieve optimum results from training and education programs, courses and materials should be designed with the trainees' learning style and material content in mind. For instance, if material is conceptual or general in nature and trainees are oriented toward reflective observation, the instruction technique is the best approach. For a combination of material and learning styles, the situation that is most likely found in real world information system settings, the behavior modeling technique should provide the best results. This approach, in which learners were not significantly influenced by learning style, provided optimum results for both types of information, procedural and general concepts, and included all elements of Kolb's model, justifying its placement at the origin of the Comprehensive Training Model.

Surprisingly, the instruction trainees' performance lagged behind that of exploration and behavior modeling trainees in the skills-based evaluation. Clearly, instruction trainees were at a disadvantage since their training failed to provide the direct hands-on guidance that was provided during the other treatments. It was assumed that since they received the same information as the other trainees, only presented in a different manner, their skill levels would equalize after a period of interaction with the computer system. Unfortunately for the instruction trainees, this was not the case. This finding has serious implications for training/learning programs based on the instruction technique that requires trainees to apply skills-based knowledge.

There were no formal hypotheses discussed in this study with regard to the link between EUCS and computer use. The information systems literature and common sense suggest that if computer users are satisfied with the system they will be more prone to use it. The findings of this study support that assumption. In all three models, the path between EUCS and computer use was significant. Post-experiment interviews conducted with a random sample of trainees indicated that trainees who were satisfied with the system and their training, regardless of treatment, were more apt to use the computer. In several cases, trainees reported that they were encouraged, as a result of training, to experiment with the system. Some even sought additional training, both formal and independent. Since these interviews were random and in two cases initiated by trainees, they are included in the discussion for interest only and are not included as part of the analysis.

A note of caution should be exercised when considering these findings. The results indicate the advantages of behavior modeling, the importance of learning style, and those factors' role in the success of EUCS and computer use. The experiment from which the results were derived was conducted within the narrow domain of computer system training and the subjects, while novices and randomly selected, might not be fully representative of other workforce segments, having been drawn from the military. However, the results of this experiment may have wider implications and could encourage other researchers to further investigate this topic.

This analysis has important implications for both managers and researchers as businesses strive to increase productivity through the process of upgrading and upskilling workers' knowledge, while simultaneously adjusting to the demands from growing numbers of computer end users.

Implications for managers/organizations

The training area is composed of pieces that fit together similar to a jigsaw puzzle. Unfortunately, the pieces can be assembled to create different images. The key objective for managers and organizations is to assemble the pieces in a coherent manner that will provide the optimum training solution for a minimal investment of time and money. The following items have been listed to assist managers in creating that optimum image.

Learning styles play an integral role in the understanding of trainees' abilities and as a predictor in the effectiveness of training programs. The understanding of learning style by managers and organizations can contribute to the more effective application of training budgets. If a trainee's learning style can be identified, then a training program could be designed to match that individual's style. This understanding and tailoring has the potential to reduce the cost and time required for training and result in more effective transfer of knowledge, leading to a worker who is more productive and perhaps more satisfied in the work place. Given the growing demands for knowledge workers as the work place becomes more sophisticated, and the competitive demands for increasing productivity, cost savings plus more effective training programs hold a possible key for marketplace success.

Information type has a direct link to both learning style and training technique. Information type, like learning style, provides an additional piece to the training puzzle. Based on the results of this study, the type of information imparted to the trainee has serious implications for which specific training technique should be used to facilitate training/learning. In any training endeavor that involves a technically based topic such as computers or information systems, a variety of information will be covered. The designers of training programs, based on this study's results, should create programs composed of modules that are adaptable to the different information and learning styles.

A technique such as behavior modeling can facilitate an all-in-one approach to training. Behavior modeling trainees in this study excelled regardless of their learning style or information type. Generalization of the results of this study suggests that the utilization of an approach similar to behavior modeling can lead to highly successful outcomes in all training situations. This finding has the potential to increase worker productivity while reducing training costs and problems associated with multiple topic course design. This analysis can be expanded to cover the growing area of computer based instruction, which includes both CD-ROM based learning as well as distance learning via the Internet. Designers of these programs could incorporate elements of modeling into their programs, insuring their applicability for a wider range of subjects and topics.

A successful match of learning style, information type, and training/learning technique can lead to higher levels of EUCS, which in turn could lead to higher levels of computer use. The bottom line for managers and organizations is indeed the bottom line! If productivity increases can be achieved and maintained by coordination of learning style, information type, and training technique, then the result for the organization should be increased competitiveness and more profit. This study illustrated that the suggested match among the elements should result in higher levels of EUCS, which in turn leads to increased computer use. This connection is not surprising given the past studies on the subject (Amoroso & Cheney, 1991; Buyukkurt & Vass, 1993; Davis & Davis, 1990; Hackathorn, 1988; Harrison & Rainer, 1992), but its application in a real-world environment provides managers with even greater incentives to insure that trainees succeed during training. Clearly, increasing skills leads to increased productivity, and satisfied workers should be more productive with regard to the systems through which they perform their job function.

Implications for Research

People learn differently based on their learning style, which will affect their transfer of knowledge. Within the domain of this experiment, learners obtained knowledge at different levels of success based on the match between their learning style, information type, and training technique. The growing numbers of computer end users suggests that there will continue to be demand for the investigation of computer systems training and computer-based learning. Learning style proved a successful indicator for knowledge transfer, based on training methodology. In what other areas might learning style be applicable? If people learn differently and learning style is a predictor, perhaps learning style could become an indicator as to how people perceive and interact with computer systems either before or after training. This along with previous indicators of computer interaction, e.g., playfulness (Webster & Martocchio, 1993), could help predict which workers should be selected to receive computer training or indicate job skills. Further, this study did not investigate if learning style had a direct link to EUCS or computer use, a topic suggested for future research.

Behavior modeling has proven to be a superior training technique. In researching this work, no study was found that investigated the fit between learning style and behavior modeling with regard to computer or computer-based training. The modeling technique has been used in only a handful of IS past studies (Compeau & Higgins, 1995; Gist et al., 1989; Hellman, 1992) that discovered the technique to be highly successful when applied to information systems research. The technique warrants additional investigation to determine other applicable areas within the information systems area. Potential applications include the use of modeling in group related activities, e.g., group decision support, team and group projects, and software development. The technique has been widely used in the management area for projects including those related to attitude change. If these studies can be linked to information systems research, perhaps the attitudes of people who are technophobic or experience computer anxiety could be understood and altered to encourage these people to interact with information systems. Additionally, the technique has been widely researched in the management and educational psychology fields. The opportunities for cross-disciplinary studies between these fields and IS researchers appear to be excellent.

Conclusion

In conclusion, the findings indicate a correlation between learning style, training technique, user satisfaction, and computer use. Learning style impacts the results of training based on the agreement of training treatment, user style, and information type. This result has particular implications as business and industry attempt to upscale their workforce to undertake increasingly technically oriented tasks and as computer tasks permeate all levels of the workforce. Instruction and exploration training produced positive results based on the match between the technique and the information type. Based on this experiment, only the use of a technique like behavior modeling should produce optimum result in most training/learning situations with a variety of learning styles. Further, levels of EUCS and computer use should be higher for trainees learning in behavior modeling. Clearly, developers of course material and training programs should seriously consider the integration of behavior modeling in their work. Additionally, the designers of computer based training material, in particular CD-ROMs, would be advised to incorporate the interactive method in their programs. The inclusion of the modeling technique could extend the applicability of the training to learners who might not otherwise excel under the exploration technique which many CBTs use.

The findings of this study suggest that tools such as the Kolb Learning Styles Inventory can be utilized to help predict trainee success. The use of this type of instrument could assist trainers in determining which trainees require more in-depth and detailed training while helping them to tailor training programs to the needs of specifically oriented learning groups. It is highly likely, though not explored in this study, that a trainee's learning style would be applicable in areas other than computer-related training, and that an instrument such as Kolb's would be a useful predictor, especially in areas of structured task training similar to those in the computer training environment.

To maintain their positions in the increasingly competitive global environment, businesses must insure that their work forces are as productive as possible. Further, the number of computers and computer-driven operations in most organizations is constantly increasing, and as a result so is the number of computer users. To maintain the productivity of their computer users many organizations are increasing the amounts of their budgets spent on computer-related training and education programs. The IS literature has identified computer-related training as a critical success factor in the implementation and success of a wide variety of systems. The results of this study answer questions for researchers, educators, and managers that help expand the knowledge of predictors and training methods which are factors in the success of computing systems and a component in the drive toward organization computing satisfaction and productivity.

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