1995

Computer learning motivation and indicators of computer skill in employee populations

Silvia Swigert

COMPUTER LEARNING MOTIVATION AND INDICATORS OF COMPUTER SKILL IN EMPLOYEE POPULATIONS

A Thesis

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Psychology

---

by

Silvia Swigert

June 1995

COMPUTER LEARNING MOTIVATION AND INDICATORS OF

COMPUTER SKILL IN EMPLOYEE POPULATIONS

A Thesis

Presented to the

Faculty of

California State University,

San Bernardino

---

by

Silvia Swigert

June 1995

Approved by:

[redacted] 5/31/95

Janet L. Kottke, Ph.D., Chair, Psychology Date

[redacted]

Matt L. Riggs, Ph.D.

[redacted]

Joanna S. Worthley, Ph.D.

ABSTRACT

Based on evidence that volitional computer interaction patterns such as information search, quick start, active experimentation, and production bias are associated with computer skill development, a correlational analysis of the relationship between the established computer learning motivation variables of computer self-efficacy, learning style, and microcomputer playfulness and two new variables, computer achievement motivation and time urgency, to the established criterion variables of computer knowledge, years of microcomputer experience, average weekly number of applications used, average weekly depth of use at work, and the new variable of expert and naive computer interaction, was conducted in a sample of employees who had discretion over computer use at work within two companies at three locations. Measures for the new variables were developed in the Pilot Study, using a sample of students, and in the Thesis Study, using the employee sample, after which seven hypotheses were made such that there would be: (a) positive relationships between computer self-efficacy, computer achievement motivation, and learning style and the criterion variables (Hypotheses 1, 2, and 3); (b) negative relationships between time urgency the criterion variables (Hypothesis 4); (c) a positive relationship between computer playfulness and computer achievement motivation (Hypothesis 5); and (d) moderation by computer achievement motivation of the relationships of computer self-efficacy and time urgency with the criterion variables (Hypotheses 6 and 7). Using a conservative combination of criteria composed of: (a) a Bonferroni family-wise error rate of .05, (b) a valued effect size of .10, and (c) a pattern of significance across the criterion variables, the results confirmed Hypotheses 1, 2, and 5 only. The effect sizes for the confirmed hypotheses were as follows: (a) .04 to .27 for the relationship between computer self-efficacy and the criterion variables, (b) .04 to .38 for the relationship between computer achievement motivation and the criterion variables, and (c) .44 for the relationship between computer playfulness and computer achievement motivation. Indicators which had nonsignificant relationships with the first two predictors included computer knowledge, one out of seven measures describing expert interaction (i.e., going back and

improving a document), and three out of six measures describing naive interaction (i.e., learning new software only when it saves considerable time, developing skills while working on a project rather than take classes, and using the arrow keys to move around a document).

ACKNOWLEDGMENT

To my husband, Randy B. Garcez, my advisor, Janet L. Kottke, and my mentor, Diane Pfahler, for their generous support, unwavering belief in me, and wonderful words of encouragement, and to the Chair of my Thesis Committee, Janet L. Kottke, and the members, Matt L. Riggs and Joanna S. Worthley, for their enthusiasm and accommodation throughout the process and across the miles.

This effort was truly cooperative, with special thanks to Janet L. Kottke and Diane Pfahler for administering the Pilot survey in their classes, Randy B. Garcez and Donna Carvalho for administering the Thesis survey in their organizations, and all of the research participants for making this project possible.

TABLE OF CONTENTS

APPENDIX--Continued

LIST OF TABLES

Table

List of Tables--Continued

List of Tables--Continued

List of Tables--Continued

List of Tables--Continued

LIST OF FIGURES

INTRODUCTION

It is often said that there is never a good time to buy a computer. In fact, the aura of perpetual progress in computer technology can be traced to the four generations of increasingly efficient and affordable computers that have evolved within a mere forty-five years (Mandell, 1988). The last generation brought the personal computer (PC; a.k.a. microcomputer) which was first marketed to businesses and consumers in the 1980s and is now a ubiquitous sight in today's work organizations.

As is true with many job-specific skills, employees often rely on the workplace to provide computer training. The most common source of this training is the _help desk_, or information center. Help desks are usually located in the information systems or computer services area, and were originally created to train employees to use _custom_ applications software. With the proliferation of microcomputers, an explosion of off-the-shelf or commercial applications software occurred which placed new demands on the help desk. These demands included managing end-user computing, a term in the information services' jargon which describes employees who interact with the computer (e.g., inputting data, creating reports, etc.) without the direct supervision of information services personnel (Thompson, Higgins, & Howell, 1991).

Throughout the computer revolution, effective support from information services personnel has been vital to the implementation of information technology in work organizations. However, managing end-user computing has proved to be more challenging than imagined, and most end-user computing policies continue to be experimental. Some of these policies include emphasizing internal resources, such as training information services personnel to become organizational consultants (Nelson, 1991), and outsourcing help desk services in the belief that end-user computing is ancillary to the core work of computer services (e.g., programming).

One of the primary issues facing organizations devising computer training policies is the fact that employee computer skill levels are often wide-ranging (O'Shea & Muralidhar, 1990; Francis & McMullen, 1989). Information services personnel frequently work simultaneously with expert and novice users and thus must provide a wide range of service. Expert users, for example, often wish to influence technology policies that have traditionally been the purview of information services, while novice users regularly inundate help desks with requests for basic instruction.

Regardless of whether a policy of insourcing (i.e., internal training resources) or outsourcing is adopted, most organizations inadvertently rely on the initiative of the employees to either contact the help center, sign up for computer classes, or, if no policy exists, devise self-teaching methods. However, once employees begin attending computer classes or contacting help desks, organizations have little knowledge about how to keep employees motivated to increase their skills beyond the level acquired during initial training.

Information services personnel who work on the front lines often exasperate, "why won't they learn?" (Hayen, Cook, & Jecker, 1990). Their frustration indicates that much more needs to be known about how to devise and implement computer training for the majority of employees who use computers in the workplace. Technology and business management researchers are also becoming concerned, as projected productivity gains continue to be based on the assumption that skill levels will steadily increase (Nelson, 1991).

One approach to the problem is to motivation variables which either affect interaction patterns that promote learning or are related to other indicators of computer skill acquisition. In doing so, the nature of intrinsic motivation in computer skill acquisition may be discovered which may in turn support the investigation of such factors in the design and delivery of computer training in the workplace.

Research Background

The shortage of proven guidelines for computer training in the workplace might be related to the relative recency and multidisciplinary nature of the research (Gattiker, 1992). For example, the disciplines of education (instructional design and school psychology), computer science (artificial intelligence and computer science education), psychology (human factors and industrial and organizational psychology), and management (information technology, technology innovation, and human resource management) are all associated with computer training research.

Education and computer science researchers have been interested in whether computers can improve the instructional process and increase student learning performance. The primary focus of this group has been on <u>computer-assisted teaching</u> (CAT), which encompasses testing cognitive and social theories of learning using <u>intelligent tutoring systems</u> (ITS) and, to a lesser extent, the effectiveness of computer programming education through the study of computer skill acquisition in computer science students.

Psychology researchers have concentrated on studying human-computer interactions in the context of artificial intelligence applications. The degree of control the user has over the task, the characteristics of the program <u>interface</u> (portion of the program that the user interacts with), and computer usability are the main variables of interest. Industrial and organizational psychology researchers have focused on social factors in computer adoption in the workplace and on other aspects of human experience in automated environments.

With some exceptions, management researchers concerned about the adoption of technology have generated the largest amount of computer training research. In doing so, they often borrow theoretical constructs from sociology, psychology, technological innovation science, and instructional design.

In spite of the variety of research being done, some generalizations about the computer training literature can be made:

First, aside from the specific skills that are derived from the training content, definitions of computer skill are usually not given. Instead, research participants are typically classified in terms of one or more experience variables. These variables include experience related to procedural or declarative knowledge, experience related to frequency of use, experience related to control over use, and experience related to length of use.

Second, in terms of design, most of the studies have investigated the relationship between trainee characteristics, instructional design, and training delivery. Significant results have been obtained with learning (declarative and procedural) and attitude outcome measures. However, most of the effects have been linked to trainee characteristics such as computer attitudes (satisfaction, interest, instrumentality, and anxiety), computer self-efficacy, gender, age, learning style, and microcomputer playfulness, with motivational variables being more effective than cognitive ability (spatial, quantitative, visual) variables. In addition, there appears to be some evidence for aptitude-training-interactions (e.g., Bostrom, Olfman, & Sein, 1990, 1993; Webster & Martocchio, 1992), although more replications need to be conducted with generalizable designs before any conclusions can be made.

Third, computer attitude, computer learning, and computer experience measures have been the most common outcome measures. Computer attitudes have generally correlated with computer learning outcomes, which have in turn correlated with intentions to use computers in the future. In general, computer attitude and computer experience measures have proven to be good outcome measures for cross-sectional studies (e.g., Howard & Mendelow, 1991; Thompson, Higgins & Howell, 1991; McQuarrie, 1989). Recently, however, more attention has been given to computer experience measures over computer attitude measures in the hope that computer attitudes will be understood better in relationship to computer experience (Arthur & Olson, 1991). At the same time, traditional measures of computer experience such as length of experience have proved to be problematic as users may experience the computer in different ways (Santhanam & Wiedenbeck, 1993; Howard & Mendelow, 1991).

What is Computer Skill?

Computer skill taxonomies and theories of computer skill acquisition are still rare and tend to be undeveloped. From the efforts of those who have tried, it seems that part of the difficulty rests in the fact that although the computer is a tangible, concrete thing (e.g., a tool), it is the centerpiece of a new type of work organization that is inherently malleable and thus dependent upon transformative skills.

Importance of Sequencing

Panko (1988) created a computer skills hierarchy which includes: (1) basic use, (2) comfortable use, (3) good practice, and (4) innovation skills. Basic use skills are usually acquired in introductory courses. Comfortable use skills are developed as the user becomes familiar with the system and begins to develop a pattern of use. Good practice skills are knowing how to (1) manage the hardware and systems components (e.g., working safely and efficiently with computers, (2) automate frequent operations, and (3) maintain and fix equipment in addition to software components (e.g., knowing how to manage data and how the computer impacts work systems). At the top of the hierarchy are innovation skills which enable the user to change or transform local work processes.

Panko (1988) uses Harmon's (1985; cited in Panko, 1988) theory of sequencing to describe computer skill acquisition. Harmon (1985; cited in Panko, 1988) states that skill acquisition occurs best when users engage in concrete, formal, and meta-formal thinking in the proper sequence (in the Piagetian sense). Users who attempt skills which are at the formal (problem-solving) or meta-formal (monitoring, evaluating, and directing learning) level before they have acquired skills at the concrete (mechanical) level will become confused and demotivated. For example, in a proper learning sequence, a user would first learn commands or algorithms in a rote manner without connecting them to the system itself (concrete operations). Then, the user would start to understand the principles behind the commands and be able to interpret what is taking place when the commands are selected (formal operations). Finally, the user would integrate his or her joint knowledge of the task domain and the computer domain to correctly apply the technology to problems in the task domain (meta-cognitive understanding).

While sequencing seems to be a necessary condition for acquiring computer skills, it may not be a sufficient condition. For example, Panko (1988) and others have observed a phenomenon called "plateauing". Plateauing occurs when users stay at comfortable use levels instead of progressing to the good practice and innovation levels.

Panko (1988) suggests this occurs because users stop developing their skills before they have acquired the understanding to progress to higher levels.

Importance of General Skills

Unlike Panko (1988), Gattiker (1992) defines computer skill in a broader fashion. To Gattiker, computer skills are composed of general skills which are simply applied to the task of using a computer in an effective way. His general skill taxonomy is composed of five levels which are ordered along a continuum of ease of transferability: (1) basic, (2) social, (3) conceptual, (4) technology, and (5) task. Basic skills are the easiest to transfer, while task skills are the most difficult. (Contrary to what the name implies, computer skills are technology skills only when they help employees prevent the accidents or breakdowns associated with the inappropriate use of the technology.)

Gattiker (1992) believes that general skill levels probably represent only one of several factors that are important to computer skill development. Some of the other factors include individual abilities or characteristics (cognitive and motor processes, motivation, and sociodemographics), task characteristics (substantive complexity and degree of control), and training delivery variables (training time and training content).

Motivation in Computer Training Research

While there is some evidence that computer skill acquisition may be influenced by the sequencing of learning (e.g., quick-start manuals; see "Computer Experience" section) and by the application of general task-relevant skills in computer learning situations (e.g., research on social integration skills of computer buffs), the larger question has been what motivates voluntary computer learning. As indicated earlier, researchers have begun to recognize that potential interactions between individual differences and training strategies are particularly salient when computer skill development is voluntary. This recognition, in combination with the fact that users have distinct ways of acquiring computer skills, has motivated research with three promising variables: (1) computer self-efficacy, (2) learning style, and (3) microcomputer playfulness.

Computer Self-Efficacy

Self-efficacy describes an individual's judgment of his or her performance capabilities on a particular task (Stipek, 1993). As such, self-efficacy is a judgment of competence which is believed to determine the affect and persistence of a learner. Thus, the higher the self-efficacy of the learner, the more likely he or she is to have positive feelings and engage in mastery behavior (e.g., Gist and Mitchell, 1992; Gist, 1987).

Several studies have examined computer self-efficacy in connection with other variables such as: (a) computer experience and computer course enrollment (Hill, Smith, & Mann, 1987); (b) computer use, interest, course enrollment, and gender (Mirua, 1987); (c) software training performance and training method (Gist, Schwoerer, & Rosen, 1989); 4) computer experience and perceived training opportunity (Martocchio & Webster, 1992); and (d) computer attitudes (Harrison & Ranier, 1992). Overall, the results indicate that computer self-efficacy is predictive of computer course enrollment but not computer experience; that females have significantly lower scores than males; and that computer self-efficacy is predictive of computer ownership and college major as well as previous computer course enrollment.

With the exception of Harrison and Ranier's (1992) study, all of the scales in the studies cited were unique. In contrast, Harrison and Ranier (1992) used a previously developed scale by Murphy, Coover, and Owen (1989). Murphy et al.'s scale has three dimensions, each measuring the level of confidence subjects have in their ability to perform increasingly difficult computer-related tasks. The first dimension represents beginning computer skills, the second dimension represents intermediate to advanced skills, and the third dimension represents mainframe computer skills. In Harrison and Ranier's study, the overall scale correlated negatively with computer anxiety and positively with computer attitudes.

Learning Style

Learning style has been defined as "characteristic cognitive, affective, and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment"

(Keefe, 1987, p. 5). Learning style and other personality variables (e.g., Myers Briggs Type Indicator; Eysenck's introversion-extroversion scale) have been measured in computer trainee and programmer populations in an effort to discover whether motivation and learning can be increased by matching treatments with style traits (e.g., Foxall & Hackett, 1982; Geisert, 1990; Bostrom, Olfman, & Sein, 1990; and Sein & Robey, 1991).

Currently, the most popular measure in computer training research is Kolb's (1985; 1976) Learning-Style Inventory (LSI). The LSI measures learning preferences by juxtaposing preferences for abstraction versus concreteness on the one hand, with preferences for action versus reflection the other hand. To measure preference, difference scores between the bipolar abilities of concrete experience (affective, sense-feeling skills) and abstract conceptualization (cognitive, or thinking skills), in the case of abstraction, and between active experimentation (acting or behavior skills) and reflective observation (observing skills), in the case of activity, are calculated and combined to create a typology of four styles. The four basic learning abilities underlying the styles are grounded in a four-stage developmental model of experiential learning which describes learning as it occurs in all areas of an individual's life, not just the classroom. In the model, development occurs when all of the abilities are used in the proper sequence. For example, individuals would first obtain subjective impressions of an experience (concrete experience) then begin to incorporate the views of others (reflective observation), after which concepts or theories would be created to understand the experience (abstract conceptualization), ending with a theory which would then be tested (active experimentation). However, Kolb believes this sequence seldom occurs; instead, most individuals prefer certain abilities over others, and hence develop particular strategies which help them excel in situations requiring those abilities.

In the style typology, individuals who prefer to receive information in an abstract (e.g., symbols) rather than concrete way, and who process the information in a reflective rather than active way are classified as <u>assimilators</u>. Assimilators prefer inductive reasoning, and are primarily interested in abstract concepts although not so much for practical purposes (and therefore prefer theory over fact) as for the experience of being logical and precise.

Individuals who prefer to receive information in a concrete way (e.g., feeling, subjective) and who process the information in a reflective way are classified as <u>divergers</u>. Divergers perform well in brainstorming exercises as they like to generate a variety of ideas. They are interested in people, and are imaginative and emotional.

Individuals who prefer to receive information in a concrete way and who process the information in an active way are classified as <u>accommodators</u>. Accommodators are often risk-takers who like to involve themselves in new experiences and are excellent adaptors. Accommodators are very different from assimilators in that they will reject theories in favor of facts.

Finally, individuals who prefer to receive information in an abstract way and who process the information in an active way are classified as <u>convergers</u>. Convergers do best when there is a single correct answer to a problem as they prefer to learn by testing hypotheses. In addition, they are described as unemotional individuals who prefer things over people.

The LSI (1985; 1976) is currently being used in computer software training research to identify which preferred modes of learning are associated with training success (Sein & Robey, 1991; Bostrom, Olfman & Sein, 1990; Hudak & Anderson, 1990). Bostrom et al. and Sein and Robey have hypothesized that active experimenters (AE) and abstract conceptualizers (AC) (hence convergers) will be more suited for computer interaction than reflective observers (RO) and concrete experiencers because hands-on experience and logical thinking lead to computer skill acquisition. Furthermore, Kolb (1984) and Hudak and Anderson (1990) have hypothesized that active experimenters will prefer to learn from projects and trial-and-error methods, compared to reflective observers who will prefer to learn from lectures; thus, the former may develop skills through more frequent exposure when compared to the latter.

After much review by investigators (Allison & Hayes, 1990; Buetell & Kressel, 1984; Pinto & Geiger, 1991; and

Ruble & Stout, 1991), the LSI (1985; 1976) was changed from an adjective checklist to its present form, however the new version is still considered problematic because of low classification rates in test-retest studies. Recently, Geiger, Boyle, and Pinto (1993) conducted an investigation with a normative version which produced encouraging results in terms of internal consistency and factor structure.

Microcomputer Playfulness

According to Martocchio and Webster (1992; also Webster & Martocchio, 1990), microcomputer playfulness is a promising new learning motivation variable in computer training research. Microcomputer playfulness was derived from the cognitive playfulness variable, in which spontaneity, joy, and a sense of humor are manifested. Cognitively playful persons are described by Barnett (1991; quoted in Martocchio & Webster, 1992) as follows

> 'Individuals with playful dispositions are said to be guided by internal motivation, and have an orientation toward process with self-imposed goals, a tendency to attribute their own meanings to objects or behaviors (that is, not to be dominated by a stimulus), a focus on

(Barnett, 1991; continued)

> pretense and nonliterality, a freedom from externally imposed rules, and active involvement' (p. 556).

Martocchio and Webster (1992) conducted several studies in which they predicted that trainees who were high in microcomputer playfulness would: (a) perform well in computer software training, (b) tend to be more creative in their interactions with the computer (e.g., innovative), and (c) have higher mood and affect than those low in microcomputer playfulness. The results of their studies confirmed their predictions and showed microcomputer playfulness to be incrementally more predictive of learning, mood, and satisfaction than computer anxiety and computer attitudes in subjects learning a commercial wordprocessing software. In addition, microcomputer playfulness contributed more variance than did a measure of computer self-efficacy.

Although Martocchio and Webster (1992; also Webster and Martocchio, 1990) predicted that microcomputer playfulness would be associated with higher learning outcomes in their experiments, they also mentioned that cognitive playfulness may not always be conducive to performance because playful individuals are steered by their own goals.

Experience in Computer Training Research

The most frequently appearing outcome variables in the literature are (1) computer skill and knowledge in training content and (2) length of computer experience. Computer skill and knowledge levels are used to contrast expert knowledge and performance with novice beliefs and performance. Length of computer experience, which often serves as a classification variable, is used as an outcome variable when intermediate or voluntary use is being examined (Howard & Mendelow, 1990; McQuarrie, 1989; and Thompson, Higgins, & Howell, 1991).

Classification of Experience

Fisher (1991) states that the current research is difficult to interpret because different terms have been used to describe subject groups. Even when the research occurs within the same context (e.g., type of computer software), terms such as _beginner_, _casual_, _infrequent_, _occasional_, _experienced_, _expert_, _discretionary_, _novice_, and _naive_ are all used without referring to a common definition.

To illustrate, the term novice is not used uniformly throughout the research; sometimes it means very little to no experience. At other times, it means generally experienced users who lack knowledge in a particular area. And, on occasion, it is used in a very narrow sense to classify users who are simply less knowledgeable than others in particular are of computing.

In the more useful classification schemes, researchers of programming behavior have used the terms naive and novice with intermediate and advanced to measure length and breadth of experience across studies. However, attributes such as intention, level of task involvement, and goals are not embodied in these schemes. To address this, Fisher (1991) has proposed a classification which makes distinctions between expert and naive users on the one hand, and novice and naive and experienced users on the other hand. Novices are always naive, while experienced users can be either naive or expert. The novice gains experience over time, although the extent to which this experience will lead to greater expertise is related to the novice's degree of task-openness and motivation to understand the operating system.

In contrast, naive users are motivated to use computers in an effective way, but do not necessarily wish to understand the operating system.

Carrying this reasoning forward, all users are both naive and novice in the beginning of skill acquisition. Some users become expert over time; others remain relatively naive as their skills are limited to the demands of the task at hand (e.g., comfortable use skills). Therefore, the quality of exposure or participation is also an important factor in becoming an expert.

Fisher (1991) believes that classification schemes such as his can improve the generalizability of the research and allow needed comparisons between studies, especially when statements about experience are included in the sample descriptions (e.g., duration, frequency, and types of training or instruction).

Optional vs required use. Users whose occupational or professional tasks do not require them to use computers are variously classified as discretionary, casual, infrequent, or occasional. These users typically have a fair amount of job autonomy. In contrast, users whose occupations are heavily impacted by computer technology such as secretaries and accounting clerks are more likely to be considered experts or regular users. As a result, discretionary users are considered to be distinct from expert users in terms of the intensity or frequency of their use.

Because discretionary users often view the computer as a tool that is incidental to their occupation, they are able to select the software they use and will often use it narrowly to perform a small group of particular tasks. Consequently, they may not experience the computer in the same way that experts do. In terms of knowledge and performance, discretionary users are also more likely to have intermediate skill levels, in the sense that they may perform expertly on one specific computer function but naively or novice-like on another conceptually related function. Usually, the functions which are less understood are functions which are, by user choice, used less frequently in the task activity. In fact, these users may not be intermediate at all in that their knowledge is procedural and hence easily forgotten without practice.

Perhaps as a result of poor classification, more research has been conducted with either full-novices (naive and inexperienced) or full-experts than with subjects who are naive-experienced. In fact, with the exception of one study by Santhanam and Wiedenbeck (1993), there are virtually no published empirical studies of knowledge or skill levels which characterize discretionary users. Yet, important information on the motivational aspects of computer skill acquisition may be derived from the interaction patterns of discretionary (i.e., naive-experienced) users precisely because their experience is voluntarily acquired.

Performance Consequences of Observed Behavior Patterns

Based on the evidence collected so far, some computer interaction behaviors, such as information search, are more associated with skill acquisition than others. For example, computer interaction studies have identified behaviors such as quick-start behavior, active experimentation, and production bias, which appear to be debilitative to learning.

Currently, several methods are being used to obtain cognitive and behavioral information which might distinguish the different types of users. These methods are described in the next section, followed by a short discussion of observed computer interaction patterns in novice, intermediate, and discretionary users.

Methods of measuring performance. Much of the literature on computer interaction behavior has been generated by software engineers who are interested in computer usability. A system is usable if its operating procedures can be learned quickly and performed efficiently by everyone. Since the type of information that is available on computer interaction behavior reflects these concerns, it is helpful to be acquainted with the ways in which usability is determined.

Briggs (1987) provides a good overview in her article on usability issues, in which she describes four criteria for usability. These include: (a) performance efficiency such as speed, error, or qualitative analysis; (b) user understanding; (c) user satisfaction; and (d) training costs.

The first two criteria, performance efficiency and knowledge-based assessment, have been the most important for uncovering patterns of behavior. When combined with performance efficiency techniques, knowledge-based assessment techniques which measure user understanding by tapping knowledge type and structure (procedural and declarative) have been particularly effective for discovering cognitive bases of motivation.

According to Briggs (1987), the best methods for generating these criteria are: (a) critical incident, (b) prompted recall, (c) protocol analysis, and (d) kelly repertory grid methods. Investigators using critical incident methods seek out user misconceptions about the system which relate to problems in the workplace. Prompted recall methods gauge the extent to which the user is dependent upon the temporal context of procedures when executing some specific task, as well as the degree to which the user is aware of information that is present concerning the state of the system. Protocol analysis methods provide information on whether the system conforms or maps with the user's expectation or conception of it. Kelly repertory grid methods identify specific areas where users are or are not informed.

While these methods have been used extensively in software development and other computer product investigations, they have provided rich information on computer interaction behaviors in a few studies involving novice, expert, and discretionary users.

Information search. In a longitudinal study, Dutke and Schonpflug (1987) studied novices (no prior experience) learning a text processing and communication system (TELEX) through structured interviews (critical incidents) over a period of nine months. Users who attained a level of skill and knowledge that allowed them to manage unknown situations were different in that they voluntarily encountered uneasy situations and took the risk of committing errors.

As a result, Dutke and Schonpflug (1987) concluded that novices who wish to acquire advanced skills must be able to put up with the additional costs of searching for information even though these costs cannot be justified by the task or project itself (e.g., it is an investment).

When performance problems occurred during the study, further learning depended on the user's epistemic curiosity (e.g., desire to learn) and intention to attain the task goal. For example, not every user in the study considered operating problems to be opportunities to learn. Often, attributive processes seemed to influence effort. Some users believed that the demands were too high compared to their abilities, and felt overloaded. These users deferred problem-solving to others when operating errors were encountered. On the other hand, users who considered a problem to be appropriate with respect to their state of knowledge and the task demands did not defer the problem and persisted in solving it.

Searching for appropriate sources of information and using the information properly was a key factor in whether users acquired more advanced skills. At the same time, solving problems with a manual or a passive help system was successful only when the user could define the problem properly. Thus, when users asked another person for help, they were essentially delegating the task of identifying the problem to whoever assisted. Over time, this activity seemed to prevent them from acquiring more advanced skill.

Quick-start behavior. Researchers at IBM identified a specific pattern in wordprocessing users which they named quick-start behavior (cited in Panko, 1988). Quick-start behavior occurs when users prefer to jump in rather than use a manual or follow tutorials.

Quick-starters were less patient, as evidenced by their comments (in reaction to being offered a manual or tutorial), such as: " I want to do something, not learn how to do everything", and "I could have typed 3,000 words by now" (Panko, 1988, p. 174). When they did use the manual, they tended to flip through it and only stopped at parts that interested them.

As an initiating behavior, quick-start behavior is probably beneficial. However, in the long run, it tended to cause learning deficits, which later became translated into constant trouble for these users.

A main accommodation for quick-start behavior has been to use truncated manuals which expressly instruct users to watch the video display as they work. According to Panko (1988), when quick-start users don't understand why something occurs, they tend to dismiss it rather than try to learn why it occurred.

Active experimentation. Santhanam and Wiedenbeck (1993) used performance measures and a verbal protocol technique to record the performance and self-monitoring characteristics of novice, discretionary, and expert users using a wordprocessing software. The subjects were asked to perform as many of sixteen different editing tasks as they could by using any method they liked (i.e., they could leave a task unfinished and complete it later). The tasks were classified as either novice or expert according to whether they were routine or non-routine. In addition, the subjects were also asked to verbalize their thoughts as they completed the tasks.

A classification scheme was designed with codes reflecting previous research on novice and expert text processing characteristics. For example, novice codes included the act of (a) hesitating or showing a lack of confidence, (b) wanting to experiment, (c) being confused about system behavior, (d) exhibiting a lack of knowledge about the semantic structure of the system, (e) forgetting commands or syntax, or (f) displaying a production bias (i.e., performance valued over learning). On the other hand, expert codes included being able to (a) categorize problems, (b) show knowledge and understanding of the system and the commands, (c) coordinate large amounts of information (chunking ability; see next section), or (d) recover from errors routinely.

The results showed discretionary users to generally be expert on the simpler routine tasks, although they still encountered difficulties and used suboptimal commands at times. Some subjects would actively experiment in different ways when they could not remember a command. When doing so, these subjects indicated that they needed to verify the results of their experimentation rather than read about the command in the manual. When they did experiment, however, they were confused about the system's behavior because they were unable to make connections between their actions and the results.

Santhanam and Wiedenbeck also noted that these users tended to exhibit a steady-state of knowledge in a core set of commands and procedures and that they were entirely satisfied with this level of knowledge. For example, in an instance in which the task was to format a six-page document, one subject formatted each paragraph while exclaiming, "oh, this is taking forever to format but I don't want to know more commands" (p. 212). Another subject did the same thing while saying, "I am sure there is a quicker way to do this, but I don't care to find out" (p. 212).

<u>Production bias</u>. In addition to a bias towards active experimentation, discretionary users strongly exhibited a production bias, or a bias to perform rather than learn. For example, Santhanam and Wiedenbeck (1993) found that the subjects "loathed reading instructions given in the guidebook or manual and read the minimum amount possible" (p. 214). In one instance, a subject read the first few lines of the instructions in which a related command was listed and immediately applied it, rather than read the next few sentences which explained that the first command was not capable of achieving the goal. In addition, the subject did not verify the results and assumed the action was correct. When these users used suboptimal commands, they often verbalized thoughts which were consistent with making a conscious decision to perform rather than learn. For example, while deleting lines one by one instead of using a blocking function, these subjects would say: "let me just go and delete sentence by sentence" or, when asked to center a

line, "I don't remember the command, so let me just eyeball it" (Santhanam & Wiedenbeck, 1993, p. 212).

Overall, the apparent lack of motivation to learn about the software on the part of the discretionary users was quite startling. One subject was particularly clear about this when he said, "this is better than learning a new command" (Santhanam & Wiedenbeck, 1993, p. 215), while setting the top margin of a document by inserting lines instead of using a formatting function.

Additional Motivational Influences Derived from the Results of the Computer Experience Research

Computer Achievement Motivation

The computer experience research summarized above raised some ideas about other motivational influences which might be related to indicators of computer skill development. In particular, the lack of motivation to achieve shown by users who displayed the production bias in their performance and verbalized thoughts was striking.

Kanfer (1990) has noted that theories which incorporate cognitive and motivational processes constitute one of the contemporary trends in the study of intrinsic motivation and skill acquisition. An example of such a theory comes from Dweck (1986) and colleagues (Elliott & Dweck, 1988; Dweck & Leggett, 1988), who have essentially extended concepts such as Atkinson's need for achievement, Weiner's attribution processes, and White's mastery orientation from a global and trait-like perspective to a domain-specific and interactionist perspective. In this approach, each learner is motivated by one of two classes of goals that are derived from two implicit theories of ability or intelligence (Dweck & Leggett, 1988; Dweck, 1986). In entity theory, intelligence is considered to be fixed; individuals who hold entity theories are motivated by performance goals in which the objective is to gain positive or avoid negative judgments of competence. In incremental theory, intelligence is malleable; individuals who hold incremental theories are motivated by learning goals in which the objective is to increase competence.

Entity learners are more likely to avoid challenge and have lower levels of persistence when obstacles are present. As a result, they are more likely to exhibit helplessness or avoidance. In contrast, incremental learners actively seek challenges and have high persistence when obstacles are present. Thus, the sharpest distinction between these two types of learners occurs when confidence is low.

Campbell (1989) has recommended that more attention be paid to Dweck's (1986) notion of learner dispositions regarding mastery or performance needs as an important component of learning motivation. According to the research of Dweck and colleagues, individuals with performance orientations in a specific knowledge domain may adopt computer learning behaviors once the social context is changed (see Dweck, 1986, for discussion of evaluative versus non-evaluative social contexts and their impact on this type of learner).

Time Urgency

In Santhanam and Wiedenbeck's (1993) study, the production bias associated with novice and discretionary interaction patterns (on advanced tasks) was explained, along with the coding rule, in the following way:

> A [production bias] code was used when subjects expressed a desire to complete a task as quickly as possible, regardless of

> whether they used the most appropriate method. A production bias may not be strictly a characteristic of novices, but all learners. We have treated it as a novice characteristic here because the gaps in knowledge which are likely to lead to a production bias occur most often in novices (p. 208).

From their description, Santhanam and Wiedenbeck (1993) suggest that the production bias may be an inherent part of skill learning; however, this explanation does not address the fact that experts did not behave this way even when they were not familiar with a task. In addition, not all of the novices exhibited this type of behavior either.

Landy, Rastegary, Thayer, and Colvin (1991) recently investigated the construct of time in connection with the _Type A behavior pattern_ (TABP). Landy et al. combined the most commonly used measures of TABP and time orientation (e.g., Jenkins Activity Survey, Bortner scale, and the Framington scale) and examined the dimensionality of the combined measures in a sample of undergraduate psychology students. The five dimensions which emerged form the analysis were: (1) competitiveness, (2) eating behavior, (3) general hurry, (4) task-related hurry, and (5) speech patterns. Because the production bias is a time-sensitive concept, it is conceivable that time urgency, and its subcomponents of competitiveness, general hurry, and task-related hurry, may represent a dispositional (i.e., genetic) influence that is detrimental to the development of computer skill, and hence related to computer learning motivation.

Experience in the Form of Computer Interaction Patterns

Santhanam and Wiedenbeck's (1993) study of behavior patterns associated with high performance stimulated some thought about how computer interaction might predict skill development. For example, certain interaction behaviors were identified as naive based on a combination of measures tapping performance efficiency and learning goals. As a result, a conception of computer interaction in which behaviors were characterized as leading to either expert or naive experience emerged.

Expert Experience

Expert users completed all of the tasks and generally showed no performance differences between routine and non-routine tasks. No instances of production bias were observed because the experts knew how to achieve the results optimally. In addition, they were twice as fast as discretionary users in completing the tasks and they never showed confusion about system behavior. And, unlike the discretionary users, expert users were able to perform the tasks which were not frequently used in their jobs because they had broad knowledge and were able to categorize the problems properly. Expert users were also more likely to use <u>chunking abilities</u>, or the ability to represent a complex series of commands in chunks so that a single unit, rather than a series of commands which must be linked together, can be executed.

Naive Experience

Since novice users did not attempt all of the tasks, there was less comparison information than with discretionary and expert users. As expected, novice users generally showed novice-like behavior on all of the tasks.

Typically, they worked very slowly (four times as long as discretionary users and eleven times as long as experts) and became frustrated or asked the experimenter if they could stop. These users consulted manuals far more frequently than the discretionary users (32 times compared to 5 times on comparable task occasions) who were more likely to consult the on-line help menus. Novices used far fewer suboptimal commands when compared to the discretionary users because they were more likely to consult the manual or the help system. However, novices were similar to discretionary users in the sense that they also appeared to use active experimentation to learn and expressed the need to verify the results. In addition, they too exhibited some instances of production bias. On occasion, novices would accomplish a task in an expert fashion after considerable experimentation, however, based on their performance on other related tasks, they appeared to have a shallow understanding of the function.

Discretionary users were classified as novice in 90% of the non-routine task incidents. This was a surprising finding for the researchers because the subjects were specifically selected for their long experience with the software. In general, the average time taken was higher, more errors were made, and more instances of non-performance were recorded when compared to expert users. Although these users had fewer instances of suboptimal commands on the non-routine tasks because they spent time looking up commands in the manual or help system, they tended to scan the menus, which indicated that they did not know where the task fit into the system structure (i.e., semantics).

PURPOSE OF THE STUDY

The purpose of this study was to explore the relationship between potentially related motivation variables and computer experience. An amalgamated approach, as opposed to a converging operations (findings fall in more than one theory; Kanfer, 1990) or new paradigm approach (integrate constructs from different fields; e.g., Gattiker, 1994; Kanfer, 1990), was selected so that multiple computer learning motivation variables could be analyzed together in an effort to check for redundancy and linkages, while simultaenously returning a value to the participating organizations by providing an organizational profile of important variables in the field. To this end, Hypotheses 1 through 3 were made which pertained to the relationship of computer achievement motivation (Hypothesis 1), computer self-efficacy (Hypothesis 2), and learning style (Hypothesis 3), to the computer experience variables of (a) computer interaction, (b) computer knowledge, (c) length of computer experience, (d) intensity or depth of computer experience, and (e) versatility or breadth of computer software experience. Hypothesis 4 was a more limited version of the above in which time urgency, as a potentially salient proximal motivator to the production bias, was hypothesized to be positively related to naive interaction.

To address relationships between potentially-related motivation variables, microcomputer playfulness, as an indicator of the interest or curiosity component of achievement motivation, was hypothesized to be positively related to computer achievement (Hypothesis 5). Finally, moderator effects were hypothesized between computer achievement motivation and computer self-efficacy and time urgency based on Dweck's (1986) theory that self-concept and learning goals will result in learning persistence, which may in turn act as a guard against other demotivating effects (e.g., external or internal demotivation effects such as self-efficacy or impulsivity) (Hypotheses 6-7). The hypotheses described above were stated as follows:

Hypothesis 1: Computer achievement motivation will be positively related to:

1) expert computer interaction

2) computer knowledge

Hypothesis 1 (con't)

3) length of experience

4) depth of experience

5) breadth of experience

Hypothesis 2: Computer self-efficacy will be positively related to:

1) expert computer interaction

2) computer knowledge

3) length of experience

4) depth of experience

5) breadth of experience

Hypothesis 3: The learning abilities of active experimentation learning style and abstract conceptualization will be positively related to:

1) expert computer interaction

2) computer knowledge

3) length of experience

4) depth of experience

5) breadth of experience

Hypothesis 4: Computer achievement motivation will be positively related to computer playfulness.

Hypothesis 5: Time urgency will be positively associated with naive interaction.

Hypothesis 6: Computer achievement motivation will moderate the relationship between computer self-efficacy and:

1) expert computer interaction
2) computer knowledge
3) length of experience
4) depth of experience
5) breadth of experience

Hypothesis 7: Computer achievement motivation will moderate the relationship between time urgency and naive computer interaction.

RESEARCH DESIGN

A cross-sectional survey design was chosen to obtain descriptive information on employees who engage in discretionary use in order to explore the relationships which were hypothesized between measures of computer learning motivation (e.g., computer achievement motivation, computer self-efficacy, computer playfulness, learning style, and time urgency) and measures of computer skill acquisition (e.g., computer interaction, computer knowledge, and computer experience). Since the self-report survey is often used to measure motivational and attitudinal variables (Schmitt & Klimoski, 1991), it was considered appropriate for measuring the computer learning motivation variables. While the design was perhaps less ideal for measuring the behavioral variables of computer skill (e.g., interaction and experience), it was deemed the most practical for the present project due to the multiple constraints of time, cost, and the exploratory nature of the research.

Pilot Study

Several instruments were pilot-tested prior to the Thesis Study because they were either new measures created by the author (e.g., computer interaction and computer achievement motivation) or criterion measures which had been altered to suit the purpose of the Thesis Study (e.g., computer knowledge and computer experience). Measures of the variables in the Pilot Study were imbedded in a single self-report questionnaire which contained seven parts (see Appendix A).

Thesis Study

Measures of the variables in the Thesis Study were imbedded in a single self-report questionnaire which contained nine parts (See Appendix B).

Origin of the Measures

Pre-existing measures were used to operationalize the variables whenever possible to aid interpretation. While each of the measures is described in the respective Method sections, a brief overview of their origins is given below.

The computer self-efficacy measure (Murphy, Coover, & Owen, 1989), computer playfulness measure (Webster &

Martocchio, 1992), and time urgency measure (Landy, Rastegary, Thayer, and Colvin, 1991) were each obtained from the published literature. The learning style measure (Kolb, 1985) was obtained from the test publisher (McBer & Company), with the response format being the only element changed. The computer experience variables (Anderson & Ortinau, 1988; Arthur & Olson, 1991; Fisher & Kaplan, 1990; Howard & Mendelow, 1990; Prumper, Zapf, Brodbeck, & Frese, 1992; and McQuarrie, 1989) were also obtained from the published literature and were used with minor revisions.

Parts of the computer achievement motivation measure and the computer knowledge measure were changed to accommodate the purpose of the Thesis Study. The computer achievement motivation measure was created by adding new items to a set of modified items from an existing general self-efficacy scale (Sherer, Maddux, Mercandange, Prentice-Dunn, Jacobs, & Rogers, 1982; cited in Woodruff & Cashman, 1993). The computer knowledge measure (Massoud, 1991) was altered by adding application-related items from an existing test bank (Blissmer, 1990).

The computer interaction measures were new as no other self-report inventory of computer interaction behaviors was found in the literature.

The demographic items of age, gender, level of formal education, were obtained from the literature, while the job status and job type items were suggested by site personnel.

Order of the Measures

Several concerns about the order of the measures in the questionnaires were identified at the start, and were as follows: (1) respondents' self-reported frequency of computer interaction behaviors might be influenced by their responses to the motivational measures, (2) respondents' assessment of their computer self-efficacy might be influenced by their performance on the computer knowledge measure, (3) respondents' responses to the computer experience and demographic items might influence their responses to the motivational measures, and (4) respondents may choose not to persist in completing the survey if the computer experience items were placed before the end of the survey. As a result of these concerns, the computer interaction measure was placed first, followed by the computer self-efficacy measure, the computer knowledge measure, the computer experience measures, and finally the demographic items.

Variables, hypotheses, and corresponding items in the Thesis Study are shown in Table 1 (see pages 51 through 57).

Table 1

Variables, Hypotheses, and Items in the Thesis Study

Variable Name	Hypothesis	Items on Survey
Independent Variable #1: Computer achievement motivation (CAM)	Hypothesis #1: CAM will be positively associated with indicators of computer skill acquisition	See Questions 14 through 29: positive persistence and self-concept in computer skill learning
Independent Variable #2: Computer self-efficacy (CSE)	Hypothesis #2: CSE will be positively associated with indicators of computer skill acquisition	See Questions 30 through 60: confidence in completing increasingly difficult computer tasks

Table 1--<u>Continued</u>

Variable Name	Hypothesis	Items on Survey
Independent Variable #3: Abstract conceptualization (AC)	Hypothesis #3: The convergent learning style will be positively associated with indicators of computer skill acquisition	See Questions 63, 67, 71, 74, 78, 82, 85, 89, 93, 100, 104, 108: thinking abstractly and planning systematically
Indepedent Variable #4: Active experimentation (AE)	Hypothesis #3	See Questions 64, 68, 72, 75, 79, 83, 86, 90, 94, 97, 101, 105: being active when applying knowledge (e.g., jumping in)

Table 1--Continued

Variable Name	Hypothesis	Items on Survey
Independent Variable #5: Competitiveness	Hypothesis #4: Time urgency will be positively associated with naive interaction	See Questions 143, 144, 145, 149, 152, 153, 155: hard-driving or ambitious orientation
Independent Variable #6: Task hurry	Hypothesis #4	See Questions 140(R), 142(R), 151(R), 154, 157, 160: completing work or tasks in a fast way

Table 1--Continued

Variable Name	Hypothesis	Items on Survey
Independent Variable #7: General hurry	Hypothesis #4	See Questions 141, 146, 147, 148(R), 150, 156(R), 158(R), 159: rushed or nervous orientation
Independent Variable #8: Microcomputer playfulness	Hypothesis #5: Microcomputer playfulness will be positively associated with computer achievement motivation	See Questions 133, 134(R), 135, 136, 137, 138(R), 139(R): inventive and imaginative when using computers

Table 1--<u>Continued</u>

Variable Name	Hypothesis	Items on Survey
Dependent Variable #1: Expert computer interaction	Hypotheses #1, #2, #3, #6, #7	See Questions 2, 3, 5, 7, 8, 11, 12: invests time, practices, generally attempts to understand the overall system
Dependent Variable #2: Naive computer interaction	Hypotheses #1, #2, #3, #4, #6, #7	See Questions 1, 4, 6, 9, 10, 13: uses resources in a stop-gap manner, structures learning through projects

Table 1--Continued

Variable Name	Hypothesis	Items on Survey
Dependent Variable #3: Computer knowledge	Hypotheses #1, #2, #3, #6, #7	See Questions 109 through 132: Conceptual and applied declarative knowledge about microcomputer hardware and software
Dependent Variable #4: Number of years of computer experience by hardware type	Hypotheses #1, #2, #3, #6, #7	See Question 165: number of years of experience with mainframe, mini, and micro computers

Table 1--Continued

Variable Name	Hypothesis	Items on Survey
Dependent Variable #5: Intensity of computer use during an average week	Hypotheses #1, #2, #3, #6, #7	See Questions 166 and 167: percent ratio of hours of computer use to hours of work in an average week
Dependent Variable #6: Number of types of applications used during an average week	Hypotheses #1, #2, #3, #6, #7	See Questions 168 and 169: breadth of use (i.e., number of applications selected)
Moderating Variable #1: Computer achievement motivation (CAM)	Hypotheses #6 and #7	See Independent Variable #1

PILOT STUDY

Method

Participants

Approximately one-hundred and twenty students taking classes at two southwestern universities were surveyed. Sixty-three percent (*n* = 76) participated, with twenty-three males (30%) and fifty-three females (70%) responding. While the age range was 17 to 46 years, most of the respondents were between the ages of 17 and 28 years (68%). In addition, the majority of the respondents (68%) had completed either high school or two years of college, with about one-third (32%) having completed four years of college or more.

Instrumentation

Measures of computer interaction, computer achievement motivation, computer self-efficacy, computer knowledge, computer experience, and demographics were imbedded in a single questionnaire which was presented in seven parts (see Appendix A).

Computer interaction. A twenty-one item inventory of computer interaction behaviors (Part One) was created based on the naive and expert behavior descriptions discussed in the literature review.

Thirteen items (items 2, 3, 5, 7, 8, 10, 12, 13, 14, 15, 16, 18, and 19) were descriptive of naive behaviors while eight items (items 1, 4, 6, 9, 11, 17, 20, and 21) were descriptive of expert behaviors. All of the items were preceded by the stem, "When using computers, I PREFER TO"; a sample naive ending was "learn new computer features while working only when it saves considerable time", and a sample expert ending was "try out new commands or features rather than use the ones I already know".

The response format was a four-point Likert scale in which respondents were asked to circle the number which described how often they preferred to engage in the behavior when using computers. The scale anchors ranged from 0 (never) to 3 (always).

Computer achievement motivation. A twenty-item scale was created by combining thirteen new items with seven modified items (Part Two).

The new items were written with the interaction research and Dweck's theory of self-concept and learning goals in mind (e.g., Dweck, 1986; Dweck & Leggett, 1988; Elliott & Dweck, 1988; Jagacinski & Nicholls, 1987) (see Table 2 on page 62 for item descriptions).

Eight items measured self-concept, with two being negatively-written (items 32 and 41) and five being positively-written (items 23, 25, 35, 38, and 40). Six items measured goals, with three being negatively-written (items 24, 30, and 31) and three being positively-written (items 36, 37, and 39).

The seven pre-existing items (items 22, 26, 27, 28, 29, 33, and 34) (Sherer, Maddux, Mercandante, Prentice-Dunn, Jacobs, & Rogers, 1982; cited in Woodruff & Cashman, 1993) were treated as measures of persistence and were altered to include a computer context. According to Woodruff and Cashman (1993), five of the selected items (items 22, 26, 27, 33, and 34) measured magnitude, or intensity level within activity (e.g., "If something looks complicated, I won't even try it"), and two of the items measured strength (items 28 and 29) (e.g., "If I can't do a job the first time, I keep trying until I can").

In order to add a computer context to the items, each item was modified simply adding the word computer (e.g., "If something about the computer looks complicated, I won't even try it") in most cases.

One potential problem that was noted at the outset was the fact that the two types of items (one type was negatively-written and the other type was positively-written) loaded on separate factors in Woodruff and Cashman's (1993) study. This would not be expected if the items were indeed measuring the same dimension.

Achievement motivation has often been operationalized as persistence, interest, and task absorption. The new items were written to operationalize the incremental and entity self-concepts and corresponding learning and performance goals which appear to be relevant in the context of computer learning.

A five-point Likert response format was used in which respondents were asked to circle the number indicating their level of agreement with the item. The scale anchors ranged from 1 (strongly disagree) to 5 (strongly agree).

Table 2

Conceptual Components and Scoring Direction for the Computer Achievement Items in the Pilot Study

Item Number and Type	Scoring Direction
<u>Persistence</u>	
22. If something about the computer looks complicated, I won't even bother to try it.	Negative
26. When trying to learn something new about the computer, I soon give up if I am not initially successful.	Negative
27. I avoid facing difficulties with the computer.	Negative
28. If I can't do a job with the computer the first time, I keep trying until I can.	Positive
29. Failure with the computer just makes me try harder.	Positive

Table 2--<u>Continued</u>

Item Number and Type	Scoring Direction
<u>Persistence</u> (con't)	
33. I avoid trying to learn new things about the computer when they look too difficult for me.	Negative
34. I give up learning about the computer easily.	Negative
<u>Self-Concept</u>	
23. When I am learning how to use a computer, I am most concerned about developing my ability.	Positive
25. I feel I have learned more when I exert a lot of effort.	Positive
32. I like computer tasks that are hard enough to show that I am intelligent.	Negative

Table 2--<u>Continued</u>

Item Number and Type	Scoring Direction
<u>Self-Concept</u> (con't)	
35. I am not bothered when I experience problems with the computer because I believe I will get better over time.	Positive
38. If a computer task is too easy, I usually get bored even though others are impressed with my ability.	Positive
40. When I am thinking about computers, I feel like I can become an expert if I just keep at it.	Positive
41. If I fail when I am working with the computer, I usually figure I have exhausted my computer ability at that point.	Negative

Table 2--Continued

Item Number and Type	Scoring Direction
Goals	
24. I like to do fun and easy things with the computer so that I don't have to worry about making mistakes.	Negative
30. When working with a computer, I would rather do things that I already know how to do.	Negative
31. I like to work on computer tasks that are fairly easy so that I'll do well.	Negative
36. When I have difficulty learning how to use the computer, I think about what I am doing as I am learning.	Positive
37. I feel compelled to attempt challenging goals even though there is a good chance that I will fail.	Positive

Table 2--Continued

Item Number and Type	Scoring Direction
Goals (con't)	
39. I like to do computer-related things that are hard, new, and different so that I can learn from them.	Positive

Computer self-efficacy. Computer self-efficacy was measured with a thirty-two item scale (Murphy, Coover, & Owen, 1989) (Part Three). Murphy et al. used Bandura's (1986; cited in Murphy et al.) theory of self-efficacy and Schunk's (1989; cited in Murphy et al.) theory of classroom learning to measure confidence at increasing levels of computer skill. As defined by Murphy et al., self-efficacy consists of "self-percepts of efficacy [which] influence choice of activities and environmental settings, effort expenditure, and persistence regardless of whether such appraisals are faulty or accurate" (p. 894).

Murphy et. al administered the scale to a sample of 414 graduate students, vocational students, and nurses taking university computer courses. Three factors were obtained in a principal factors analysis with oblique rotation. Factor 1 was labeled beginning skill, Factor 2 was labeled advanced skill, and Factor 3 was labeled mainframe skill. Coefficient alpha for the factors were .97, .96, and .92, respectively. In addition, the magnitude of the factor intercorrelations increased across factors in a linear fashion (e.g., each skill level correlated higher with the next highest level).

In the present study, a five-point Likert format was used in which respondents were asked to circle the number which corresponded to their level of agreement with statements that began with "I feel CONFIDENT". A sample ending from the beginning scale was "calling up a data file to view on the monitor screen"; a sample ending from the advanced scale was "organizing and managing files"; and a sample ending from mainframe scale was "logging onto a mainframe computer system". The scale anchors ranged from 1 (strongly disagree) to 5 (strongly agree).

Computer knowledge. The computer knowledge measure was composed of two tests. The Computer Competence Instrument (Educational Testing Service [ETS]; cited in Massoud, 1991) was the first test, and consisted of thirty-three items (mostly multiple choice) (Part Four). The second test was composed of thirty multiple-choice items that were selected by the author from a published test bank (Blissmer, 1990) (Part Five).

The Computer Competence Instrument was originally developed to measure computer vocabulary and knowledge about computers in adult remedial education populations (Massoud, 1991). Substantive areas of the test included knowledge of specific hardware and software components, how to interact with the IBM disk operating system (DOS), history of computers and electronics, and knowledge of the utility of computers in business, industry, and the professions.

Both tests were combined because a measure of computer knowledge in populations using multiple applications was desired and the Computer Competence Instrument lacked applied questions about microcomputer application software. In addition, a more difficult test was desired based on the fact that the remedial students in Massoud's (1991) study had higher pass rates than the ETS (national) norm study participants. A sample item stem from the Computer Competence Instrument was "what does a modem do?", and a sample item stem from the application test was "to edit a letter, you need to learn". Most of the items were multiple choice and respondents were asked to select the best response. Appendix C shows the corresponding content area for each item.

Computer experience. As discussed in the literature review, the decision to select several types of computer experience items was based on recent evidence suggesting that the relationship between computer skill and computer experience encompasses more than length of experience.

The main types of computer experience items included were: (a) computer access (Item 136 and Item 137), (b) intensity of computer use (Item 138 and Item 142), (c) length of computer experience by hardware type (Item 139), (d) intensity and breadth of computer application use (Item 140 and Item 141) and (e) formal computer education by type (Item 143). Each of these items is listed in Part Six; the main purpose of including them was to test the instructions.

Demographics. The demographic variables of age (Item 144), gender (Item 145), and education level (Item 146) were included to determine sample characteristics (see Part Seven).

Administration

The questionnaires were administered to the students by the instructors during class time. As an incentive, each student was given course credit for participating. An informed consent statement was delivered orally prior to administration (see Appendix D). After administration, a written debriefing statement was given to each participants (see Appendix E).

PILOT STUDY

Results

Computer Interaction

Item distributions. Item skew statistics ranged from -1.4 to 3.5 standard units for the naive items, and 0.2 to 3.6 standard units for the expert items. Except for items 14 and 15, a slight negative pattern of skewness was apparent in the naive items, while a slight positive pattern of skewness was apparent in the expert items (see Table 3 on page 74). Item means ranged from .66 to 1.96, and standard deviations ranged from .80 to 1.15. As the pattern of skewness implies, the expert items tended to have the lowest means, while the naive items tended to have the highest means.

Principal components analysis. Seven factors accounting for approximately 64% of the variance were extracted in a principal components analysis. Although the overall sampling adequacy was low (KMO = .57), the scree plot showed two main components which accounted for approximately 30% of the variance. In addition, the loadings on the first two components were generally consistent with the proposed categories of expert and naive behaviors, however there were enough exceptions to create some doubt as to whether the classification was supported.

<u>Scale development</u>. No changes to the items were made on the basis of the principal components analysis. Instead, the Pilot Study was treated as a preliminary tryout of the items. This meant that the development of the items proceeded on a logical rather than empirical basis. This approach was taken because the sample had a lower than expected amount of computer experience (see Computer Experience section), and it was felt that this characteristic might have biased the responses. In addition, unknown differences between the student sample and the target employee made interpretation difficult at times. For example, Item 14, "ask peers or coworkers to complete portions of a project which require more computer skill than I have" was strongly rejected in the student sample. While this type of response might be expected in a school setting, it would not necessarily be expected in a work setting.

Table 3

Results of the Item Analysis of the Computer Interaction Inventory in the Pilot Study

Item	Item Responses (%) 0	1	2	3	Mean	SD	Z_{skew}
Retained							
2--Naive	11.8	23.7	46.1	18.4	1.71	.91	-1.37
7--Naive	14.4	36.8	38.2	10.5	1.45	.87	-1.40
10--Naive	18.4	36.8	32.9	11.8	1.38	.92	.35
14--Naive	48.7	28.9	10.5	11.8	.86	1.03	3.54
15--Naive	15.8	52.6	22.4	9.2	1.25	.84	1.76
16--Naive	7.9	28.9	42.1	19.7	1.75	.87	-.84
1--Expert	21.1	47.4	27.6	3.9	1.14	.80	.81
4--Expert	18.4	48.7	22.4	10.5	1.25	.88	1.61
9--Expert	36.8	34.2	15.8	13.2	1.05	1.03	2.32
11--Expert	25.0	28.9	34.2	11.8	1.33	.98	.23
17--Expert	39.5	36.8	21.1	2.6	.87	.84	1.93
20--Expert	14.5	46.1	27.6	11.8	1.37	.88	1.06
21--Expert	55.3	26.3	15.8	2.6	.66	.84	3.62

Table 3--*Continued*

Item	Item Responses (%) 0	1	2	3	Mean	*SD*	Z_{skew}
Not Retained							
3--Naive	6.6	27.6	28.9	36.8	1.96	.96	-1.40
5--Naive	7.9	43.4	36.8	11.8	1.53	.81	.53
8--Naive	6.6	36.8	28.9	27.6	1.78	.93	- .15
12--Naive	17.1	39.5	31.6	11.8	1.38	.91	.52
13--Naive	10.5	26.3	28.9	34.2	1.87	1.01	-1.32
18--Naive	2.6	26.3	48.7	22.4	1.91	.77	- .73
19--Naive	15.8	39.5	36.8	7.9	1.37	.85	.07
6--Expert	26.3	26.3	21.1	26.3	1.47	1.15	.24

The point range was changed to start with 1 instead of 0; in addition, a few respondents suggested that the response format include more options. To this end, a fifth category was added, *4* (most of the time), which simply created a middle category between *3* (often) and *5* (all of the time).

Even though most of the item distributions were adequate, a decision was made to improve the items by increasing their behavioral specificity. Thus, eight items (items 6, 3, 5, 8, 12, 13, 18, and 19) were eliminated because they either required too much alteration or were similar to items that would require less alteration.

Of the thirteen items that were retained, ten appeared to have either vague or double-barreled flaws and were re-written. For example, the phrase, "develop computer skills when I need them", in Item 16 was considered too vague and was changed to "develop computer skills while working on a project". In another example, the phrase, "use the arrow keys to move around a document when I am pressed for time", was changed to "use the arrow keys to move around a document" to eliminate a possible double-barreled effect (see Appendix F for a list of these changes). To illustrate how the items were correlated, a principal components analysis was conducted with the items which were retained (albeit some of the items were altered according to the description above (see Table 4 on page 77).

Table 4

Results of the Principal Component Loadings for the Computer Interaction Items in the Pilot Study

		Component[a]				
Item[b]	Type	1	2	3	4	5
4	Expert	.81	.22	.22	.04	.06
9*	Expert	.79	.14	.33	.20	-.09
1	Expert	.69	.29	.24	-.11	-.26
21	Expert	.67	-.05	.04	.17	.27
16*	Naive	-.54	.17	.29	.32	.00
20	Expert	.51	.32	-.42	-.29	.05
11	Expert	.41	-.12	-.18	.04	.23
7*	Naive	-.15	.79	-.06	.04	-.06
10*	Naive	-.42	.65	-.16	.20	-.16
2*	Naive	.11	.28	-.66	-.29	.19
15*	Naive	-.24	.46	.50	-.35	.16
17	Expert	.12	.12	-.22	.86	.07
14*	Naive	-.19	.14	.21	.02	.85

[a] loadings in excess of .40 are underlined. [b] asterisked items were rewritten.

Computer Achievement Motivation

Item distributions. Item skew statistics ranged from -1.5 to 2.4 standard units for the reverse-scored items, and -3.8 to 0.8 standard units for the positively-scored items. Item means for the reverse-scored items ranged from 2.14 to 3.69, and 2.76 to 3.88 for the positively-scored items. Standard deviations ranged from 1.05 to 1.39 in the former, and .90 to 1.18 in the latter.

Principal components analysis. Four components accounting for approximately 60% of the variance were extracted in a principal components analysis (see Table 5). The overall sampling adequacy was fair (KMO = .77). The scree plot showed two main components which accounted for approximately 46% of the variance. The first component, accounted for 33%, while the second component, accounted for an additional 13%. With the exception of items 32, 24, 31, and 30, most of the reverse-scored items clearly loaded on the first component. In addition, three positive self-concept items and positive goal item (items 39, 35, 40, and 23) clearly loaded negatively on the first component and only marginally on the second component. In contrast, the remaining six items (items 29, 37, 28, 38, 25, and 36) consisting of two positive goal, two positive persistence, and two positive self-concept items, loaded negatively on the first component and positively on the second component.

Table 5

Principal Component Factor Loadings for the Computer Achievement Motivation Items in the Pilot Study

Item	Type/Direction	Component 1	2	3	4
26	Persistence/negative	.<u>74</u>	.27	.17	.29
33	Persistence/negative	.<u>72</u>	.06	.16	.22
34	Persistence/negative	.<u>71</u>	.14	-.19	.35
30	Goals/negative	.<u>67</u>	.<u>51</u>	.02	-.03
22	Persistence/negative	.<u>66</u>	.06	.38	.00
27	Persistence/negative	.<u>60</u>	.21	.35	-.21
31	Goals/negative	.<u>60</u>	.<u>58</u>	.14	-.19
24	Goals/negative	.39	.<u>64</u>	-.08	-.18
41	Self-Concept/negative	.<u>50</u>	.06	-.<u>61</u>	.21
32	Self-Concept/negative	-.<u>44</u>	.33	-.<u>55</u>	.01

Table 5--Continued

Item	Type/Direction	Component 1	2	3	4
39	Goals/positive	-.77	.27	.00	.11
35	Self-Concept/positive	-.66	-.02	.27	.31
40	Self-Concept/positive	-.57	.01	.08	-.16
29	Persistence/positive	-.56	.51	.22	.16
37	Goals/positive	-.56	.40	-.04	.44
28	Persistence/positive	-.53	.36	.37	.21
38	Self-Concept/positive	-.38	.38	-.31	.01
25	Self-Concept/positive	-.01	.58	-.40	-.17
36	Goals/positive	-.38	.43	.41	.04
23	Self-Concept/positive	-.47	.25	.06	-.58

Note. Underlined factor loadings are ≥ .40

A forced two-factor principal axis factor analysis with varimax rotation was conducted, as there appeared to be no other significant correlation patterns, to determine whether the empirical and the common factor structure would be similar (Tabachinick & Fidell, 1989, p. 634).

The two-factor solution accounted for approximately 40% of the variance, with the negative factor (Factor 1; negative items) accounting for 21% and the mixed factor (Factor 2; positive and negative items) accounting for 19% of the variance. This time, the reverse-scored goal and persistence items loaded positively on the first factor, while the positively-scored self-concept, persistence and goal items loaded positively on the second factor.

A repeat analysis with oblique rotation (as a further check on the validity of the varimax solution; Crocker & Algina, 1986; p. 300) revealed similar groupings, although the variance distributions were more intertwined. For example, the reverse-scored persistence items loaded positively on both factors. The loadings for the negative achievement factor (Factor 2) were unique in that no other items loaded significantly on the factor, and they were larger than their loadings on the first factor. At the same time, the negative or reverse-scored self-concept and goal items defined the negative factor and were independent of the mixed factor (Factor 2). The results of both rotations are given below in Table 6.

Table 6

Two-Factor Orthogonal and Oblique Loadings for the Computer Achievement Motivation Items in the Pilot Study

		Factor Loadings[a]			
		Orthogonal		Oblique	
Item	Type/Direction	1	2	1	2
30	Goals/negative	.83	-.08	.02	.83
31	Goals/negative	.82	.02	-.09	.84
26	Persistence/positive	.70	-.30	.26	.65
24	Goals/negative	.66	.17	-.23	.71
34	Persistence/negative	.58	-.38	.35	.51
33	Persistence/negative	.54	-.43	.40	.46
27	Persistence/negative	.54	-.25	.22	.49

Table 6--Continued

Item		Factor Loadings			
		Orthogonal		Oblique	
		1	2	1	2
22	Persistence/negative	.50	-.38	.35	.43
32	Self-Concept/negative	-.13	.46	-.47	-.04
41	Self-Concept/negative	.36	-.29	.27	.30
29	Persistence/positive	-.07	.73	-.75	.08
39	Goals/positive	-.37	.72	-.72	-.23
37	Goals/positive	-.15	.62	-.63	-.03
28	Persistence/positive	-.14	.58	-.59	-.03
36	Goals/positive	-.02	.50	-.52	.08
38	Self-Concept/positive	-.06	.46	-.47	.04
23	Self-Concept/positive	-.18	.44	-.44	-.10
35	Self-Concept/positive	-.46	.42	-.40	-.39
40	Self-Concept/positive	-.38	.37	-.36	-.31
25	Self-Concept/positive	.29	.34	-.37	-.31

Note. _n_ =76; Underlined loadings are ≥ .40.

Scale Development

In general, the factor analysis results were supportive of a negative factor, with negative or reverse-scored items defining the factor against which positive or positively-scored items were negatively correlated. However, the presence of the second, mixed factor made the analysis complex. This was especially true when the factor could be defined as a positive factor (and was thus independent of the negative persistence factor) in the varimax rotation; yet be defined as a separate and independent dimension of the negative factor in the oblique rotation.

While most of the items loaded according to one of the several patterns discussed, some of the items did not load very strongly (less than .50) on either factor. The content of these items and their intercorrelations were further examined to determine whether they should be eliminated from the item pool. As a result, negative or reverse-scored self-concept items 32 and 41 were eliminated, as was positive or positively-scored Item 25. Negative or reverse-scored Item 33 was eliminated because its content was similar to a better constructed item (Item 34). Finally, the contents of items 22, 38, 37, and 39 were changed for the reasons shown in Table 7 on page 86.

A total scale measuring computer achievement motivation was constructed with the remaining sixteen items. The seven negative or reverse-scored items were summed with the nine positive or positively-scored items to obtain a total score. The revised scale was normally distributed (M = 51.1; Mdn = 51.0; Mo = 52.0; z_{skew} = -.62), although the score range of 23 to 76 points was somewhat short of the possible range of 16 to 80 points.

Reliability. Coefficient alpha for the computer achievement motivation scale was .87 ($\underline{SE}_{alpha}$ = .016; $\bar{r}$ = .30).

Table 7

Changes Made to the Computer Achievement Items for the Thesis Study

Item	New Content	Reason for Change
22	I will not even bother to try something with the computer if it looks complicated.	Changed emphasis in sentence
38	I usually get bored when a computer task is too easy.	More at effort that is expended.
37	I have an urge to attempt challenging goals with the computer even when there is a good chance I will fail.	Context as a possibility rather than a certainty of failure.
39	I like to do computer-related things that are hard, new, and different.	More at challenge to keep socially-desirable responding to a minimum.

Computer Knowledge

Item difficulty and point-biserial correlations were used to select items that would discriminate between high and low scorers.

Item difficulty. Difficulty rates for the initial pool of 63 items ranged from .05 to 1.0. Although middle passing rates (e.g., .50) are recommended for broad tests (Crocker & Algina, 1986), a larger passing range of .30 to .80 percent was selected for the initial pool because of the small number of middle passing items. Only 26 items (41%) had passing rates in this range.

Item discrimination. Crocker & Algina (1986) recommend that only items whose point-biserial correlations are statistically significant by at least two standard deviations be selected for inclusion in an item pool. Thus, the minimally acceptable correlation in the present case was .24 (see Appendix G for formula).

Item selection. Based on respondents' comments, five items (items 107, 108, 109, 110, and 121) were eliminated due to content. For example, Item 107 and Item 108 used the term wordprocessor instead of microcomputer or PC, and items

109, 110, and 121 made specific references to non-generic software features. Since Item 121 was within the difficulty range, the item pool was thus reduced to 25 items when this item was removed. An additional item (Item 96) was eliminated due to formatting problems (matching items had very high passing rates). Three more items (item 85, 90, and 128) were eliminated due to low point-biserial correlations, leaving twenty-one items in the pool. Two items (items 126 and 127) were added as experimental items because, while they performed poorly in the development sample (low passing), their content indicated that they should be discriminating. Finally, Item 101 and Item 115 were added because their point-biserial correlations were high ($\underline{r}_{pb}$ = .31 and $\underline{r}_{pb}$ = .46, respectively) although their passing rates exceeded the initial set rate of .80.

Altogether, 24 items were retained (see Table 8 on page 89). The scale distribution was slightly skewed ($\underline{M}$ = 13.1; $\underline{SD}$ = 4.2; Mdn = 13.5; Mo = 14.0; $\underline{z}_{skew}$ = -1.2), although the actual range of 1 to 23 points was very close to the possible range of 1 to 24 points.

Table 8

Results of the Item Analysis of the Computer Knowledge Test in the Pilot Study

Item	p	r_{pb}
1. 80	.57	.55
2. 79	.57	.50
3. 116	.55	.48
4. 115	.83	.46
5. 106	.71	.42
6. 119	.65	.42
7. 88	.48	.40
8. 82	.60	.39
9. 124	.55	.38
10. 81	.56	.37
11. 105	.39	.37
12. 104	.68	.36
13. 111	.49	.35
14. 123	.47	.35
15. 87	.31	.34
16. 122	.48	.34

Table 8--Continued

Item	p	r_{pb}
17. 113	.71	.33
18. 120	.63	.33
19. 131	.36	.32
20. 101	.87	.31
21. 134	.36	.31
22. 125	.64	.26
23. 127	.20	.24
24. 126+	.36	.02

+: r_{pb} < .24, or less than 2 SDs above chance.

Reliability. Coefficient alpha for the entire scale was .72, with a mean inter-item correlation of .10. Corrected item-total correlations ranged from -.02 to .42, while squared multiple correlations (SMCs) ranging from .31 to .78. Based on their respective SMCs of .70 and .78, the most related items to the other items were items 81 and 82.

However, these items did not have the highest point-biserial correlations. Finally, separate coefficient alpha estimates were obtained for the items grouped according to the content classification shown in Appendix 3. The system components group (13 items) had a coefficient alpha of .63 and mean inter-item correlation of .12; the wordprocessing items in the applications group (4 items) had a coefficient alpha of .40 and mean inter-item correlation of .14; the programming items in the applications group (3 items) had a coefficient alpha of .37 and mean inter-item correlation of .16; and the instrumentality items (2 items) which measured usefulness of computers in society had an inter-item correlation of .16. A small amount of improvement was obtained when the worst performing items were removed (e.g., experimental Item 126; coefficient alpha would have been .68 without this item), however the results indicated that the content groupings were not internally consistent.

Computer experience. The primary purpose of testing the computer experience items was to determine whether the instructions were clear. As it turned out, missing data was within an acceptable range (M = 4%; maximum = 9%).

Judging from their distributions, the items captured the representativeness of computer experience in the sample. Fifty-one percent owned a computer and 79% had access to a computer; most of the sample used wordprocessing software (65%) compared to spreadsheet (21%), database (28%), graphics (21%), communication (13%) or other types of software (35%). The sample was also more likely to have taken introductory courses (58%) over applications courses (28%) or programming courses (22%). Finally 63% spent eight hours or less per week using the computer. For number of applications used during an average week, the mean was 2.22 applications (SD = 1.34; Mdn = 2), with scores ranging across the possible range of one to six applications.

Aside from checking for missing data, the next most important task was to cross-check the estimates made from Item 138, "about how many hours of computer work do you do, on average, per week?", with the estimates made from Item 142, "what approximate percentage of your total time is spent using computers".

In order to check the accuracy of the respondents' estimates of total time (Item 142), defacto hourly base rates was determined (see Appendix H for formula; assumes that if every hour of the week were counted, the ideal base number would be 168 hours). The results showed that about 23% of the respondents used 15 hours or less as a base for their estimate, 20% used between 32 and 63 hours, and 5% used between 200 and 400 hours. The rest of the respondents were somewhere in between these ranges.

As a result, Item 142 was replaced with "about how many hours per week, on average, are you involved in activities? (e.g., 70 hours per week = 10 hours per day)" and preceded Item 138, which remained "about how many hours of computer work do you do, on average, per week?".

Computer Self-Efficacy

Scale distributions. The distribution for the total self-efficacy scale was skewed (M = 109.4; SD = 24.7; Mdn = 114.0; z_{skew} = -2.7). The range of scores was 36 to 154, slightly short of the possible range of 31 to 155. The distribution for the beginning subscale was also skewed (M = 63.3; SD = 13.9; Mdn = 64.5; z_{skew} = -3.67), due to the same outliers mentioned above (without the outliers, the score range shrank from 60 to 38). The distribution for the advanced subscale was slightly skewed ($\underline{M}$ = 37.2; $\underline{SD}$ = 10.2; Mdn = 37.0; $\underline{z}_{skew}$ = -.98), with scores ranging between 12 and 60 (possible range was 12 to 50). Finally, the distribution for the mainframe subscale was uniform ($\underline{M}$ = 8.7; $\underline{SD}$ = 3.7; Mdn = 9.0) with multiple modes across the actual and possible range of 3 to 15 points.

Reliability. Coefficient alphas for the scales were .96 for the total scale, .94 for the beginning subscale, .97 for the advanced subscale, and .96 for the mainframe subscale. These results were very similar to those obtained by Murphy et al. (1989) with factor scores.

Subscale intercorrelations. Pearson $\underline{r}$ correlations between the beginning, advanced, and mainframe scales were as follows: .76 ($\underline{p} \leq .001$) between beginning and advanced; .52 ($\underline{p} \leq .001$) between advanced and mainframe; and .42 ($\underline{p} \leq .001$) between beginning and mainframe. These correlations were also very similar to those obtained by Murphy et al. (1989).

Convergent validity. Pearson $\underline{r}$ correlations between computer self-efficacy and the computer interaction, computer achievement motivation, and computer knowledge measures indicated that the selected expert interaction items and the computer achievement motivation scale were positively correlated with self-efficacy, while the selected naive interaction items, with the exception of naive Item 2, were either negatively correlated or were unrelated to the self-efficacy scales. Finally, the computer knowledge scale was only weakly correlated with self-efficacy (see Table 9 below).

Table 9

Pearson _r_ Between Computer Self-Efficacy and Measures of Computer Interaction, Computer Achievement Motivation, and Computer Knowledge in the Pilot Study

Measure	Computer Self-Efficacy
Computer Interaction:	
Expert--Item 1	.52*
Naive---Item 2	.26*
Expert--Item 4	.41*
Naive---Item 7	.08

Table 9--Continued

Measure	Computer Self-Efficacy
Expert--Item 9	.54*
Naive---Item 10	.05
Expert--Item 11	.20*
Naive---Item 14	-.17
Naive---Item 15	-.23
Naive---Item 16	-.18
Expert--Item 17	.21*
Expert--Item 20	.23*
Expert--Item 21	.45*
Computer Achievement Motivation	.55*
Computer Knowledge	.26*

*$p \leq .01$

PILOT STUDY

Discussion

A majority (77%) of the retained computer interaction items were subsequently revised for the Thesis Study. However, some of the rewriting decisions were bolstered by the results of the item correlations with computer self-efficacy in that the stronger items that were left unchanged had the strongest correlations with computer self-efficacy, when compared to the weaker items which were eventually rewritten.

The computer achievement motivation measure, being composed of negative and positive dimensions of persistence, self-concept, and goals, was multidimensional. After removing the items which appeared unique, a revised computer achievement motivation scale was created which was only moderately correlated with computer self-efficacy. No further judgements were made, although the differential loading pattern between the positively-written persistence items and the negatively-written persistence items that was found in Woodward and Cashman's (1993) study was also found in the present study. This seemed to indicate that the items were not measuring the same dimension, as the reverse-scoring procedure would require. On the other hand, no action was taken beyond eliminating the poorest-performing items until the cross-validation had occurred in the Thesis Study. This was done because it was felt that there was a chance that the new items might help define these positively-written persistence items.

The computer knowledge test was complex in that no clearly consistent content domains could be identified either logically or empirically. Although the relatively small correlation between computer knowledge and computer self-efficacy ($\underline{r}$ = .26) was puzzling, this finding may be related to deficiencies in declarative knowledge (e.g., mental models) acquired outside of the classroom.

The nature of asking for respondents' estimates of intensity of use (e.g., weekly depth) as a measure of computer experience was better understood as a result of the hypothetical estimation exercise, and it was decided that a bounded framework would be essential in the Thesis Study.

THESIS STUDY

Method

Site Descriptions

Three survey sites within the offices of two different western organizations were opportunistically selected for sampling. Site personnel at each location confirmed that the extent of microcomputer use was essentially voluntary for the employees who would be surveyed.

Site A. Site A was a manufacturing unit within a western subsidiary of a multinational pharmaceutical organization. Approximately twenty-five percent (n = 140) of the employees were included in the survey; the remaining seventy-five percent (n = 420) worked within the factory and had very little exposure to microcomputers.

Site B. Site B was a division within the same pharmaceutical subsidiary which housed personnel from several research units within the company. Approximately eighty percent (n = 660) of the employees were included in the survey; the remaining twenty percent (n = 165) were identified as nonusers by site personnel.

Site C. Site C was a human resource department within a western scientific research organization that housed personnel involved in personnel administration, organizational development, and information systems. Approximately ninety-two percent (_n_ = 120) of the employees were included in the survey.

Participants

Site A. Fifty-one percent (_n_ = 69) of the target population at Site A responded to the survey, with thirty-one males (45%) and thirty-eight females (55%) responding. The mean age of the respondents was 45 years (_SD_ = 9.7; Mdn = 45), with ages ranging from 26 to 65 years. The mean level of education was 15 years (_SD_ = 2.6; Mdn = 14). Forty-five of the respondents had exempt status, (66%), sixteen had non-exempt status (23%), and seven had hourly status (10%). Seventeen (30%) respondents had jobs classified as administrative, fourteen (25%) as professional, twenty-three (41%) as manufacturing, one (1%) as facilities and one (1%) as computer-related.

Site B. Thirty-five percent of the target population at Site B responded to the survey (_n_ = 232), with one-hundred and sixteen males (50%) and one-hundred and fifteen females (50%) responding. The mean age of the respondents was 39 years (SD = 9.7; Mdn = 39), with ages ranging from 21 to 71 years. The mean level of education was 16 years (SD = 2.6; Mdn = 16). One-hundred and sixty-three respondents (71%) had exempt status, forty-three (20%) had nonexempt status, and twenty-two (9%) had hourly status. Seventy-one (31%) respondents had jobs classified as administrative, ninety-nine (43%) as professional, forty-one (18%) as manufacturing, thirteen (6%) as facilities, and five (2%) as computer-related.

Site C. Thirty-eight percent of the target population at Site C responded to the survey (n = 46), with seven males (16%) and thirty-eight females (84%) responding. The mean age of the respondents was 42 years (SD = 9.7; Mdn = 41), with ages ranging from 23 to 59 years. The mean level of education was 16 years (SD = 2.6; Mdn = 16). Twenty-three respondents (53%) had exempt status, six (14%) had nonexempt status, and fourteen (33%) had hourly status. Thirty-eight respondents had jobs classified as administrative (84%) and seven had jobs classified as computer-related (16%).

Instrumentation

Measures of 1) computer interaction; 2) computer achievement motivation; 3) computer self-efficacy; 4) learning style; 5) microcomputer playfulness; 6) time urgency; 7) computer knowledge; 8) computer experience; and 9) demographics were included in the survey (see Appendix B).

Computer interaction. The thirteen computer interaction items (Part One) that were developed in the Pilot Study were used to operationalize computer interaction in the present study.

Computer achievement motivation. Computer achievement motivation was measured with the 16-item scale (Part Two) that was developed in the Pilot Study and consisted of nine positively-worded and seven reverse-scored items. Coefficient alpha for the scale in the Pilot Study was .87 ($\underline{SE}_{alpha}$ = .016; r = .30). Possible scores ranged from 16 to 80.

Computer self-efficacy. Computer self-efficacy was measured with the thirty-two item scale (Murphy, Coover, & Owen, 1989) (Part Three) described in the Pilot Study.

Learning style. A normative version of Kolb's (1985) Learning-style Inventory (LSI-1985) was used to measure learning style. As discussed in the literature review, the normative version changes the instructions so that all responses are independent rather than dependent (i.e., ipsative).

To create the normative version, the ipsative format was replaced with a Likert format that ranged from 1 (strongly disagree) to 5 (strongly agree) and the sentence stems and endings were combined to obtain 48 statements. For example, a sample item with the stem "When I am learning" was "When I am learning, I am a reserved person"; a sample item with the stem "I learn best" was "I learn best when I rely on my ideas".

These statements were then scrambled in the manner described by Geiger, Boyle, and Pinto (1993). Geiger et al. used different scale anchors (e.g., 1 [not like me] to 7 [very much like me]), however the form in the present study was very similar in that respondents were asked to indicate how strongly they agreed with each statement.

Each of the four learning styles (active experimentation, concrete experience, reflective observation, and abstract conceptualization) was measured with a scale consisting of twelve items. Possible scores for each scale ranged from 12 to 60 points.

Coefficient alpha in Geiger et. al's (1993) study of 455 students at two universities was .83 for concrete experience (CE); .77 for reflective observation (RO); .86 for abstract conceptualization (AC); and .84 for active experimentation scale (AE). These coefficients were similar to the coefficients reported by Kolb (1985) in the LSI-1985 norm study for the ipsative version (.82, .73, .83, and .78, respectively).

Microcomputer playfulness. Microcomputer playfulness was measured with Webster and Martocchio's (1992) seven-item adjective list. As discussed in the literature review, these items are associated with a spontaneous and creative factor. A Likert response format was used which ranged from 1 (strongly disagree) to 7 (strongly agree). Respondents were asked to indicate how well the words characterized them when interacting with computers. For example, "spontaneous" was a sample item that was scored in the positive direction, while "unoriginal" was a sample item that was reverse-scored.

Coefficient alpha for the scale was reported to range from .86 to .90 in a series of development studies published by Webster and Martocchio (1992). Possible scores ranged from 7 to 49 points.

Time urgency. Three scales developed by Landy, Rastegary, Thayer, and Colvin (1991) were used to measure time urgency. The first scale, competitiveness, consisted of seven items. A sample item from this scale was "I have a strong need to excel in most things". The second scale, task-oriented hurry, consisted of six items. A sample item from this scale was "I usually work fast". Finally, the third scale, general hurry, consisted of eight items. A sample item from this scale was "I am usually pressed for time". Coefficient alpha for the scales was reported to be .81, .72, and .81, respectively, in a sample of 190 students (Landy et al.).

A Likert format was used which ranged from 1 (strongly disagree) to 5 (strongly agree). Respondents were asked to indicate how well the statements characterized them. Possible scores ranged from 7 to 35 points for the competitiveness scale; 6 to 30 points for the task-oriented scale; and 8 to 40 points for the general hurry scale.

Computer knowledge. The twenty-four item computer knowledge test developed in the Pilot Study was used to measure computer knowledge. Coefficient alpha for the scale was .73 ($\underline{SE}_{alpha}$ = .008; r = .10) in the Pilot Study. Possible scores ranged from 0 to 24.

Computer experience. With the exception of Item 138 and Item 142, the same items described in the Pilot Study were used in the present study. As discussed in the Pilot Study, Item 138 (Item 166 in the Thesis Study) was changed to "about how many hours per week, on average, are you involved in activities? (e.g., 70 hours per week = 10 hours per day)", and Item 142 (Item 167 in the Thesis Study) was changed to "about how many hours of computer work do you do, on average, per week?".

Shortly after survey administration at Site A, respondents indicated that they were confused about what was being asked in Item 166. As a result, participants at Site

A were advised to respond to Item 166 and Item 167 as though they pertained to worktime only. This meant that no information on other places of use (i.e., home) was available for this sample.

Item 166 and Item 167 were then revised prior to administration at Site B and Site C to reflect estimates of use at work only. The new version was administered in the form of "about how many hours do you work per week? (average week)" (Item 166) and "about how many hours per week do you use the computer at work?" (Item 167). In addition, Item 170 ("about how many hours per week do you use the computer at home for nonwork purposes") was added in an attempt to obtain estimates of overall use.

To measure intensity of use at work, a ratio variable (percent of average work hours spent using the computer) was created by dividing average weekly hours spent using the computer by average weekly (total) hours at work.

<u>Demographics</u>. The demographic variables measured in the present study included age, gender, education, employee status (hourly, non-exempt, and exempt), and job type

(administrative, professional, manufacturing, facilities, computer-related, and other) (see Part Nine).

Administration

To stimulate response at Site A and Site B, the questionnaires were administered anonymously and a raffle prize series was offered to all participants. Each respective site contact signed an interoffice memorandum describing the survey, raffle program, and consent stipulations. Packages containing the memorandum, raffle tickets, and questionnaire were then distributed to employees through interoffice mail. Drawings were conducted at two separate intervals to provide an incentive for early response. After each drawing, company-wide electronic mail was used to announce the winning numbers.

At Site C, the questionnaires were administered anonymously but without incentives by a manager within the department through inter-office mail. The manager attached a memorandum which described the purpose of the survey and the consent stipulations.

THESIS STUDY

Results

Consolidation of the Samples

All of the samples were combined into a single sample for the subsequent analyses. Although some of the differences between the sample means were statistically significant, the majority of the differences were associated with job type. For example, when compared to employees in administrative (38%), professional (34%), manufacturing (20%), and other jobs (4%), employees in computer-related jobs (4%) were higher on microcomputer experience (M = 9.0 years), average weekly hours of computer use (M = 23.8 hours), average weekly percent of time spent using computers (M = 55%), average weekly number of applications used (M = 4.3), and computer self-efficacy (M = 138.4). In addition, manufacturing employees were generally lower on these variables when compared to administrative and professional employees. As a result, although two of the samples (Site A and Site B) were obtained from the same company, the distribution of these variables across the sites was different due to an inversely-related percentage of professional to manufacturing jobs. For example, Site B had 43% professional jobs and 18% manufacturing jobs, compared to Site A which had 25% professional jobs and 41% manufacturing jobs.

Finally, Site C represented a single department in a different company, in which 84% of the jobs were administrative compared to 30% at Site A and 31% at Site B. The remaining 16% of the jobs at Site C were computer-related, which was also higher than the rates at sites A and B (2% and 6%, respectively).

Adjusted Pilot Study Measures

After examining the analysis, further adjustments to the Pilot Study measures of computer achievement motivation and computer knowledge were made to maximize the unidimensionality and internal consistency of these measures for the Thesis Study.

Computer achievement motivation. The coefficient alpha and principal component analysis results indicated that the Pilot Study computer achievement scale could be further improved by eliminating items 15, 16, 21, 22, and 24(items 23, 24, 31, 36, and 38 in the Pilot Study, respectively). These items created a second component that accounted for an additional 12% of the variance over and above the 39% that was accounted for by the first component. The second component was eliminated after the items listed above were removed, and a single component was extracted which accounted for 51% of the variance (see Table 10 on page 113). (Note: a principal axis factor analysis was not conducted as a single factor was desired, confirmation of shared variance was unnecessary.)

Two of the rejected items were positive self-concept items, one was a positive goal, and two were negative goal items. These items were only similar in that they represented attempts to operationalize Dweck's entity and incremental self-concepts of intelligence. For example, the rejected Item 16, "I like to do fun and easy things with the computer so that I don't have to worry about making mistakes", and Item 21, "I like to work on computer tasks that are fairly easy so that I'll do well" represented two out of the three negative (i.e., entity) goal items in the scale. On the incremental or positive side, Item 15, "When I am learning how to use a computer, I am most concerned about developing my ability" and Item 24, I usually get bored when a computer task is too easy" were self-concept items, representing two out of four positive self-concept items. Item 22, "When I have difficulty learning how to use the computer, I think about what I am doing as I am learning", was a positive goal item, representing one out of three positive goal items.

It was not immediately clear why these items did not load with the other self-concept and goal items (items 18, 23, 26, 27, and 29) or the persistence items (items 14, 17, 19, 20, 25, and 28)(i.e., in terms of item class). However, the persistence items hung together, which was notable as these items were derived from the existing general self-efficacy scale (e.g., Sherer, et al., 1982). After the revision, the proportion of items assigned to each class were as follows: (1) 55% for persistence (6 items), (2) 27% for goal items (3 items), and (3) 18% for self-concept items (2 items). Based on the content of the surviving items, the goal items measured the respondents' valuation of new versus

Table 10

Component Loadings for the Pre-Adjusted and Adjusted Computer Achievement Motivation Scales in the Thesis Study

		Pre-Adjusted Scale Components		Revised Scale Component
Item	Type/Direction	1	2	1
26	Goals/pos	.79	.17	.80
28	Persist/neg	-.77	.03	-.79
25	Persist/neg	-.74	.18	-.74
20	Persist/pos	.73	.26	.74
14	Persist/neg	-.73	.16	-.72
23	Goals/pos	.68	.13	.70
29	Self/pos	.69	.08	.70
27	Self/pos	.68	.23	.68
17	Persist/neg	-.67	.29	-.67
19	Persist/pos	.66	.26	.68
18	Goals/neg	-.64	.20	-.64
24	Self/pos	.30	.28	--

Table 10--Continued

Item	Type/Direction	Pre-Adjusted Scale Components 1	Pre-Adjusted Scale Components 2	Revised Scale Component 1
16	Goals/neg	-.45	.64	--
15	Self/pos	.21	.61	--
21	Goals/neg	-.53	.55	--
22	Goals/pos	.34	.53	--

existing skills, and the self-concept items measured respondents' belief that skills would improve over time.

Coefficient alpha in the Pilot Study (16 items) was .88 (SE_{alpha} = .015; $\bar{r}$ = .32), as it was in the Thesis Study. In contrast, coefficient alpha for the revised scale (11 items) was .90 (SE_{alpha} = .010; $\bar{r}$ = .46). The distribution for the revised scale was slightly skewed (z_{skew} = - 3.7; M = 40.1; SD = 7.6; Mdn = 41.0). Actual scores ranged between 18 and 55, which was somewhat short of the possible range of 11 to 55.

Computer knowledge. The distribution of the computer knowledge test was negatively skewed and kurtic ($\underline{z}_{skew}$ = -7.6; $\underline{z}_{kurtosis}$ = 4.3; $\underline{M}$ = 16.5; $\underline{SD}$ = 4.4; Mdn = 17.0), with scores ranging from 0 to 23 points out of a possible 24 points. Item difficulty levels ranged from .22 to .93, resulting in a mean difficulty level of .69. Coefficient alpha for the scale was .81 ($\underline{SE}_{alpha}$ = .010; $\bar{r}$ = .15).

As was done in the Pilot Study, separate coefficient alphas were obtained for each set of items according to the original test specification. However, just as in the Pilot Study, the coefficients turned out to be very small.

After examining the inter-item correlations, only five items (items 112, 113, 116, 117, and 126) were found to be consistently related to each other. Coefficient alpha for these items was lower at .70, ($\underline{SE}_{alpha}$ = .001; $\bar{r}$ = .33) however the point-biserial correlations ranged from .58 to .65 and were the best in the group (see Table 11 on page 116).

Table 11

Results of the Item Analysis of the Computer Knowledge in the Thesis Study

Item	*p*	r_{pb}
1. 110 (80)	.93	.45
2. 109 (79)	.79	.55
3. 122 (116)	.86	.36
4. 121 (115)	.86	.28
5. 118 (106)	.92	.45
6. 123 (119)	.91	.41
7. 114 (88)	.60	.33
8. 112 (82)	.85	.63
9. 127 (124)	.70	.45
10. 111 (81)	.81	.65
11. 117 (105)	.54	.65
12. 116 (104)	.73	.59
13. 119 (111)	.59	.36
14. 126 (123)	.73	.57

Table 11--Continued

Item	p	r_{pb}
15. 113 (87)	.56	.58
16. 125 (122)	.68	.44
17. 120 (113)	.56	.33
18. 124 (120)	.70	.36
19. 115+ (101)	.93	.18
20. 128 (125)	.60	.43
21. 129 (127)	.41	.44
22. 130 (131)	.60	.40
23. 131 (134)	.34	.46
24. 132+ (126)	.22	-.03

Note: underlined correlations correspond to items selected for the revised computer knowledge scale. +: $r_{pb} < .24$, or less than 2 SDs above chance. Parenthetical numbers correspond to Pilot Study item numbers.

The first four items in the reduced set were ETS items (items 112, 113, 116, and 117) and the last item (Item 126) was a test bank item. Altogether, these items measured broad concepts in computer hardware and software knowledge. For example, Item 112, "Which of the following is an output device?", and Item 113, "Which of the following was used earliest with computers?" (e.g., vacuum tubes) tapped computer hardware knowledge, while Item 116, "What is an algorithm?", Item 117, "To have your microcomputer communicate with a mainframe computer in another city, you will probably need each of the following, EXCEPT:", and Item 126, "Being able to answer "what if" questions means that spreadsheets take full advantage of the computer's ability to:", tapped knowledge about software concepts. In addition, a principal components analysis (KMO = .79) extracted one factor which accounted for 50% of the variance in the items. It should be noted that these items were not as related in the Pilot sample (α = .25) in which a different group of items were related instead (items 80, 79, 106, 115, and 116 in the Pilot survey; α = .68).

The distribution for the adjusted scale was negatively skewed (z_{skew} = -5.5; $\underline{M}$ = 3.4; $\underline{SD}$ = 1.5; Mdn = 4.0), with actual responses ranging from 0 to 5 points out of a possible total of five points.

Unadjusted Pilot Study Measures

Computer interaction. Contrary to the author's belief that the Thesis sample would react differently to the computer interaction items based on work environment and computer experience factors, the item distributions in the Thesis Study were very similar to the distributions in the Pilot Study except that they were even more skewed due to the expansion of response categories (see Table 12 on page 121). Although the work environment factors could not be verified (e.g., opportunity to ask others for assistance, etc), the computer experience factors were compared and found to be similarly distributed in the sense that the distributions were also significantly positively skewed (although all values were sampled better and the average depth of usage was higher in the Thesis Study). Although similarities occurred in spite of the changes that were made in response to the Pilot Study results, the items which were strongest in the Pilot Study were also strongest in the

Thesis Study, with the exceptions of items 1, 2, 3, and 9 (14, 17, 20, and 10 in the Pilot Study). It was concluded that the changes made to the poor performing items in the Pilot Study did not cause them to hang together better in the Thesis Study.

A pattern of correlation common to both samples emerged after the results of the principal components analysis and inter-item correlations were compared between the samples. Based on the scree plot, both samples had two main components which accounted for similar amounts of variance (38% in the Thesis sample; 36% in the Pilot sample), and the same items had the strongest loadings on the components. The first component was dominated by expert items 7, 8, 11, and 12; the second component was dominated by naive items 9 and 10 (see Table 13 on page 124).

Overall, the Pilot sample had eleven significant intercorrelations between the expert items (ranging from .28 to .70), compared to twenty-one in the Thesis sample (ranging from .17 to .68), and three significant intercorrelations between the naive items (ranging from .27

to .41), compared to three in the Thesis sample (ranging from .14 to .26).

Table 12

Results of Item Analysis of the Computer Interaction Items in the Thesis Study

		Item Responses (%)							
Item	Type	1	2	3	4	5	Mean	SD	Z_{skew}
1	Naive	26	37	15	10	13	2.5	1.3	5.3
4	Naive	11	29	26	26	8	2.9	1.1	0.3
6	Naive	8	20	26	31	16	3.3	1.2	-1.8
9	Naive	14	40	26	15	5	2.6	1.1	3.6
10	Naive	17	40	25	13	5	2.5	1.1	4.1
13	Naive	20	24	23	20	14	2.9	1.3	1.0
2	Expert	17	41	19	14	9	2.6	1.2	4.5
3	Expert	19	36	21	13	10	2.6	1.2	4.8
5	Expert	12	25	19	29	14	3.1	1.3	-0.7
7	Expert	18	36	20	17	9	2.6	1.2	3.4
8	Expert	28	36	19	11	6	2.3	1.2	5.4

Table 12--Continued

		Item Responses (%)							
Item	Type	1	2	3	4	5	Mean	SD	Z_{skew}
11	Expert	9	37	35	14	5	2.7	1.0	3.1
12	Expert	38	30	17	8	7	2.2	1.2	6.8

With the exception of an increased correlation between expert items 11 and 12, all of expert inter-item correlations were reduced within a range of .02 to .19 in the Thesis sample. In addition, the correlations between the naive item pairs decreased by almost half (within a range of .15 to .17).

For the naive items, the Pilot and Thesis samples consistently selected Item 9 (using less than ideal software for the job) and Item 4 (learning software only when it saved considerable time). The correlation for Item 10 (learning software in a step-by-step manner rather than finding out how it functions) was actually larger than Item

4 in the Thesis sample, however Item 10 followed Item 4 in the Pilot sample because it was strongly negatively correlated with a third factor that was dominated by Item 13 (using the arrow keys to move around a document). Coefficient alpha for the consistent expert items was .75 in the Thesis Study, compared to .72 in the Pilot Study, and .51 for the consistent naive items in the Thesis Study, compared to .45 in the Pilot Study.

Although some of the items appeared to be successfully cross-validated, more than half of them did not. A deliberate decision was then made to keep the items as simple measures in order to explore their unique variance, as opposed to their common variance.

Table 13

Principal Component Loadings for the Computer Interaction Items in the Thesis Study[a]

		Component			
Item	Type	1	2	3	4
8	Expert	.<u>79</u>	-.08	.04	-.35
7	Expert	.<u>73</u>	-.04	.06	-.40
11	Expert	.<u>72</u>	.13	-.22	-.06
12	Expert	.<u>62</u>	-.23	.07	-.03
5	Expert	.<u>53</u>	.06	.07	.22
2	Expert	.<u>51</u>	.14	.<u>47</u>	.33
9	Naive	-.17	.<u>73</u>	-.12	-.19
10	Naive	.00	.<u>66</u>	.24	-.30
4	Naive	.01	.<u>49</u>	-.38	.25
13	Naive	.07	.<u>47</u>	-.13	-.17
6	Naive	.31	.27	-.63	.16
1	Naive	-.09	.<u>54</u>	.<u>58</u>	.08
3	Expert	.<u>48</u>	.18	.11	.<u>58</u>

[a] loadings in excess of .40 are underlined.

Computer self-efficacy. The distribution for the computer self-efficacy scale (Murphy, Coover, & Owen, 1989) was kurtic and negatively skewed ($z_{kurtosis}$ = -2.32; z_{skew} = -1.29; *M* = 119.0; *SD* = 21.0; Mdn = 118.0), with scores ranging from 52 to 155 points out of a possible 31 to 155 points. Coefficient alpha was .96 (SE_{alpha} = .007; $\bar{r}$ = .45).

The distribution for the beginning level subscale (CSE1) was negatively skewed (z_{skew} = -5.0; *M* = 68.4; *SD* = 10.1; Mdn = 69.0), with scores ranging from 26 to 80. Coefficient alpha was .95 (SE_{alpha} = .009; $\bar{r}$ = .56).

The distribution for the advanced level subscale (CSE2) was normally distributed (*M* = 41.2; *SD* = 10.4; Mdn = 41.5), with scores ranging from 13 to 60. Coefficient alpha was .97 (SE_{alpha} = .012; $\bar{r}$ = .57).

Finally, the distribution for the mainframe level subscale (CSE3) was uniform ($z_{kurtosis}$ = -3.9; *M* = 9.3; *SD* = 3.8; Mdn = 9.0), with scores ranging from 3 to 15. Coefficient alpha was .97 (SE_{alpha} = .033; $\bar{r}$ = .92).

Adjusted Thesis Study Measures

Adjustments were also made to the Thesis Study measures of time urgency, learning style, and depth of computer use (average weekly hours of worktime and average weekly hours of computer use during worktime) to improve interpretation of their effects later in the analysis.

Time urgency. Coefficient alpha was .72 ($\underline{SE}_{alpha}$ = .041; $\bar{r}$ = .31) for the competitive scale; .17 ($\underline{SE}_{alpha}$ = .066; $\bar{r}$ = .02) for the general hurry scale; and .08 ($\underline{SE}_{alpha}$ = .088; $\bar{r}$ = .01) for the task-related hurry scale. The last two coefficients were very poor, so a principal components analysis (KMO = .81) was conducted to to determine whether the observed correlation matrix would support the factors described by Landy, Rastegary, Thayer, and Colvin (1991) in their larger analysis (i.e., included two additional sets of items). In the results, five components were extracted of which two components accounted for most of the variance. A subsequent principal axis factor analysis with varimax rotation was then conducted with the rationale that the principal components analysis (e.g., how much overlap between total and common variance) would be supported by obtaining redundant results, which resulted in two primary factors as well (using the scree plot as the criterion). Items which loaded highest on Factor 1 (competitiveness) and Factor 2 (general hurry) in the principal axis analysis were selected and a second principal axis factor analysis was conducted in which the same two factors were obtained.

Based on the eigen plots, an oblique rotation fit best (probably due to a moderate inter-factor correlation of .34) (see Table 14 on page 128).

Coefficient alpha for the revised competitive and general hurry scales was .82 ($\underline{SE}_{alpha} = .026$; $\bar{r} = .48$) and .72 ($\underline{SE}_{alpha} = .036$; $\bar{r} = .40$), respectively. As can be seen from the inter-item correlations in Table 15 on page 130, the dimensions are internally homogenous but somewhat correlated.

The revised competitiveness scale had five items (compared to seven) and the distribution was slightly skewed ($\underline{z}_{skew} = -1.6$; $\underline{M} = 18.1$; $\underline{SD} = 3.4$; Mdn = 18.0), with scores ranging from 8 to 25 points out of a possible 5 to 25 points.

The revised general hurry scale had four items (compared to eight) and the distribution was normal (M = 12.0; SD = 2.9; Mdn =12.0) with scores ranging across the possible range of 4 to 20.

Table 14

Oblique Factor Loadings of Selected Items for the Time Urgent Measures of Competitiveness and General Hurry

	Factor[a]	
Item Description	1	2
1. I have a strong need to excel in most things (item 144).	.<u>74</u>	-.03
2. I am hard driving and competitive (item 153).	.<u>73</u>	.09
3. I go "all out" (item 143).	.<u>69</u>	-.10
4. I am hard driving (item 149).	.<u>65</u>	.16
5. I am ambitious (item 155).	.<u>63</u>	-.01
6. I am often in a hurry (item 159).	-.04	.<u>75</u>
7. I find myself hurrying to get to places even when there is plenty of time (item 150).	-.01	.<u>69</u>

Table 14--Continued

Item Description	Factor[a] 1	Factor[a] 2
8. People who know me well agree that I tend to do most things in a hurry (item 154).	.11	.60
9. I am more restless and fidgeting than most people (item 147).	-.01	.49

[a] Underlined loadings are equal to or greater than .40.

Table 15

Matrix of Intercorrelations by Type for Time Urgency

Type		Item	1	2	3	4	5	6	7	8	9
Compete	1.	Item 143	1.00								
	2.	Item 144	.59*	1.00							
	3.	Item 153	.41*	.52*	1.00						
	4.	Item 155	.37*	.47*	.51*	1.00					
	5.	Item 149	.43*	.42*	.62*	.44*	1.00				
Hurry	6.	Item 147	.05	.10	.16	.08	.18	1.00			
	7.	Item 150	.06	.13	.22*	.12	.30*	.34*	1.00		
	8.	Item 154	.18	.15	.27*	.19*	.32*	.33*	.38*	1.00	
	9.	Item 159	.07	.21*	.15	.14	.20	.33*	.50*	.47*	1.00

* _p_ ≤ .05

Learning style. The concrete experience (CE) scale was positively skewed (z_{skew} = 3.3; M = 38.7; SD = 7.6; Mdn = 38.0), with scores ranging from 22 to 60. Coefficient alpha was .86 (SE_{alpha} = .02; $\bar{r}$ = .34).

The reflective observation (RO) scale was also positively skewed (z_{skew} = 1.8; M = 40.7; SD = 7.6; Mdn = 40.0), with scores ranging from 20 to 60. Coefficient alpha was .86 (SE = .02; $\bar{r}$ = .34).

The abstract conceptualization (AC) scale was negatively skewed (z_{skew} = -2.1; M = 42.7; SD = 8.0; Mdn = 43.0), with scores ranging from 18 to 60. Coefficient alpha was .90 (SE = .02; $\bar{r}$ = .43).

Finally, the active experimentation scale was negatively skewed (z_{skew} = -1.2; M = 47.6; SD = 6.6; Mdn = 48.0), with scores ranging from 27 to 60. Coefficient alpha was .87 (SE = .02; $\bar{r}$ = .37).

The AC and AE scales were both negatively skewed and the most reliable. The RO scale was the next most reliable, followed by the CE scale; both of these scales were positively skewed.

The results from a principal components analysis

(KMO = .92) showed seven components with eigenvalues above 1.0. After examining the scree plot, the first four components were considered significant with corresponding eigenvalues of 14.332 (30%), 3.177 (7%), 2.855 (6%), and 1.544 (3%).

Once the four components were found to be significant, two and four factors were forced in a principal axis factor analysis with varimax rotation. These loadings were then compared with the results of Geiger, Boyle, and Pinto's (1993) study (see Table 16 on page 134; item descriptions by scale appear in Appendix I).

Using the scree test and the pattern of significant loadings (greater than or equal to .40), Geiger et al. (1993) found four distinct factors. In Geiger et al.'s study, the factors represented AC, AE, CE, and RO with eigenvalues of 5.365, 5.019, 4.059, and 3.881, respectively. In the present study, the factors represented AC, AE, RO, and CE with most of the shared variance being accounted for by the AC items (7.372, 6.543, 4.583, and 3.593, respectively).

The 2-factor results in Geiger et al.'s study showed the AC items loading on the first factor and the CE and AE items loading on the second factor, with eigenvalues of 5.854 and 5.615, respectively. In describing these results, Geiger et al. noted that none of the RO items loaded significantly on the factors. In the present study, the AC items and the RO items loaded on the first factor and the CE and AE items loaded on the second factor with eigenvalues of 9.589 and 7.729, respectively.

Finally, separate principal axis factor analyses with oblique rotations were performed for each scale to determine whether the poor results in the 2- and 4-factor analysis might be related to multi-dimensionality or error within the scales themselves.

For the CE scale, the results (KMO = .88) showed two factors with eigenvalues of 3.091 (26%) and 2.062 (10%), respectively, with an inter-factor correlation of .53. The first factor was a feeling factor, with the most influential item being "I learn best when I rely on my feelings" ($\underline{r}$ = .95); the second factor was an "involved and receptive" factor, with the most influential item being "When I learn, I get involved" ($\underline{r}$ = .75) (see Table 17 on page 136).

Table 16

Factor Analysis Results for Kolb's Learning Style Scales in the Thesis Study in Comparison with Geiger, Boyle, and Pinto's (1993) Study[a]

		2-Factor Patterns				4-Factor Patterns							
		Thesis		Geiger, et al.		Thesis				Geiger, et al.			
		1	2	1	2	1	2	3	4	1	2	3	4
CE	1		.48						.68			.70	
	2											.58	
	3		.55		.45							.63	
	4		.56						.74			.74	
	5		.58		.42							.41	
	6											.41	
	7		.57									.50	
	8		.52		.50				.85			.50	
	9				.42							.74	
	10		.66										
	11				.68								
	12												
RO	1							.50					.75
	2												.63
	3												.45
	4	.52						.74					.69
	5	.61				.60							.60
	6												.71
	7							.76					
	8	.53											
	9												
	10	.42											
	11	.52						.73					.72
	12	.53						.76					
AC	1	.50		.45		.58				.48			
	2	.59		.69		.61				.72			
	3	.65		.66		.77				.72			

Table 16--Continued

		2-Factor Patterns				4-Factor Patterns							
		Thesis		Geiger, et al.		Thesis				Geiger, et al.			
		1	2	1	2	1	2	3	4	1	2	3	4
AC	4	.79		.53		.77				.56			
	5	.73		.52		.73				.56			
	6	.70		.64		.70				.68			
	7			.59						.65			
	8	.64		.42		.63				.45			
	9						.50						
	10	.65		.64		.59				.65			
	11	.60		.61		.53				.63			
	12	.47		.61						.68			
AE	1		.46	.64			.48		.63		.70		
	2								.50		.40		
	3	.56				.52							
	4	.62			.68	.56		.63		.81			
	5		.51		.67		.58				.64		
	6		.65		.56		.69				.70		
	7				.68								
	8										.81		
	9				.66						.40		
	10		.63	.41			.71				.79		
	11				.66		.74						
	12		.58	.46			.67				.65		

[a] CE = Concrete Experience; RO = Reflective Observation; AC = Active Conceptualization; AE = Active Experimentation.

Table 17

Results of (Oblique) Principal Axis Factor Analysis of Concrete Experience Items

Items	Factors[a] 1	2
3. I learn best when I rely on my feelings.	.95	-.18
4. I learn by feeling.	.82	-.06
1. When I learn, I like to deal with my feelings.	.69	.00
7. When I am learning, I have strong feelings and reactions.	.61	.14
10. I learn best when I trust my hunches and feelings.	.52	.20
8. I learn best from personal relationships.	.51	.14
9. When I learn, I get involved.	-.01	.75
12. When I am learning, I am an accepting person.	-.03	.67
6. I learn best when I am receptive.	-.03	.57

Table 17--Continued

Items	Factors[a] 1	2
2. When I learn, I am open to new experiences.	.00	<u>.49</u>
11. When I am learning, I am an intuitive person.	.25	.44
5. When I learn, I feel personally involved in things.	.27	.42

[a] Loadings that exceed .40 and clearly load on one factor are underlined.

For the RO scale, the results (KMO = .85) showed three factors with eigenvalues of 3.158 (26%), 1.383 (12%), and 1.368 (11%), respectively. The first factor included "watching" items, with the most influential item being "I learn by watching" (r = .87); the second factor included "reserved" items, with the most influential item being "When I am learning, I am an observing person" (r = .91); and the third factor included "open-minded" items, with the most influential item being "When I learn, I look at all sides of the issues" (r = .80)(See Table 18 on page 139). The watching factor was more correlated with the open-minded factor (r = .53) compared to the reserved factor (r = .40); and the open-minded and reserved factors were nearly as correlated (r = .35) as the latter.

For the AC scale, the results (KMO = .92) showed two factors with eigenvalues of 3.143 (26%) and 2.213 (18%), respectively. The first factor included logical items, with the most influential item being "When I am learning, I am a logical person" (r = .87); the second factor included idea items, with the most influential item being "When I learn, I like to think about ideas" (r = .82) (See Table 19 on page 141). Although the idea items were independent of the logical or rational items, the remaining items (thinking, careful) shared variance across factors which contributed to the high inter-factor correlation of .74.

For the AE scale, the results (KMO = 88) showed two factors with eigenvalues of 3.371 (28%) and 1.895 (16%), respectively. The first factor included try out or do

Table 18

Results of (Oblique) Principal Axis Factor of Reflective Observation Items

Items	Factors 1	2	3
7. I learn by watching.	.87	.01	-.07
12. When I learn, I like to observe.	.80	-.03	.06
4. When I learn, I like to watch and listen.	.80	.01	-.02
11. When I learn, I like to observe.	.72	.07	.03
1. I learn best when I listen and watch carefully.	.59	.01	-.14
2. When I am learning, I am an observing person.	.31	.05	.28
10. I learn best from observation.	.05	.91	-.06
3. When I am learning, I am a reserved person.	-.03	.69	.02
5. When I learn, I look at all sides of the issues.	-.14	.09	.80
9. I learn best when I am open-minded.	.07	-.06	.61

Table 18--Continued

Items	Factors 1	2	3
6. I learn best when I rely on my observations.	.27	-.03	.40
8. When I learn, I take my time before acting.	.24	.24	.29

Note: Loadings in excess of .40 and which clearly loaded on one factor are underlined.

items, with the most influential item being "I learn best when I can try things out for myself" ($\underline{r}$ = .82); the second factor included responsible items, with the most influential item being "When I am learning, I am responsible about things" ($\underline{r}$ = .78)(see Table 20 on page 143). The inter-factor correlation was .52, which was probably due to undifferentiated loadings between the "being an active person" and "getting things done" items.

Table 19

Results of (Oblique) Principal Axis Factor Analysis of the Abstract Conceptualization Items

Items	Factors 1	Factors 2
5. When I am learning, I am a logical person.	.<u>87</u>	-.06
4. I learn best when I rely on logical thinking.	.<u>81</u>	.03
6. When I am learning, I am a rational person.	.<u>75</u>	-.02
2. I learn best from rational theories.	.<u>69</u>	.00
3. When I learn, I evaluate things.	.<u>58</u>	.25
1. When I am learning, I tend to reason things out.	.45	.22
7. When I learn, I like to think about ideas.	-.11	.<u>82</u>
11. When I learn, I like ideas and theories.	.04	.<u>68</u>
9. I learn best when I rely on my ideas.	-.02	.<u>61</u>

Table 19--Continued

Items	Factors 1	Factors 2
8. When I learn, I like to analyze things, break them down into parts.	.27	.54
10. I learn by thinking.	.23	.50
12 I learn best when I am careful.	.11	.22

Note: Loadings that exceed .40 and clearly load on one factor are underlined.

Table 20

Results of Oblique Principal Axis Factor of the Active Experimentation Items

	Items	Factors 1	Factors 2
12.	I learn best when I can try things out for myself.	._82_	-.08
5.	I learn best from a chance to try out and practice.	._78_	-.18
11.	When I learn, I like to try things out.	._69_	.12
6.	When I learn, I like to be active.	._67_	.05
10.	When I learn, I like to be doing things.	._60_	.21
1.	I learn by doing.	._57_	.00
8.	When I am learning, I am an active person.	.46	.34
2.	When I learn, I like to see results from my work.	._43_	.13
4.	When I am learning, I am responsible about things.	-.05	._78_
9.	When I am learning, I am a responsible person.	-.03	._77_

Table 20--Continued

Items	Factors 1	2
3. I learn best when I am practical.	.04	.49
7. I learn best when I work hard to get things done.	.28	.47

Note: Loadings that exceed .40 and clearly load on one factor are underlined.

Finally, a principal axis factor analysis with varimax rotation was conducted to confirm the unidimensional nature of the items with significant loadings on the first factors only. Using the scree plot as a guide, three significant factors were obtained, and AE, CE, RO, and AC appeared as separate factors with eigenvalues of 2.991 (14%), 3.073 (14%), 2.913 (13%), and 2.938 (13%), respectively.

The new scales were more internally consistent, in addition to providing more defined factor results and lower inter-scale correlations. For example, the original inter-scale correlation ranged from .51 to .66, compared to the new inter-scale correlations range of .17 to .39 (see Table 21 on page 146).

Coefficient alphas for the new scales were .86 ($\underline{SE}_{alpha}$ = .006; $\bar{r}$ = .50) for the CE scale (six items); .87 ($\underline{SE}_{alpha}$ = .011; $\bar{r}$ = .57) for the RO scale (five items); .87 ($\underline{SE}_{alpha}$ = .006; $\bar{r}$ = .59) for the AC scale (five items); and .85 ($\underline{SE}_{alpha}$ = .005; $\bar{r}$ = .50) for the AE scale (six items).

The distributions for the new scales were also similar in that the CE distribution ($\underline{z}_{skew}$ = 4.0; $\underline{M}$ = 16.2; $\underline{SD}$ = 5.0; Mdn = 15.5) and the RO distribution ($\underline{M}$ = 16.8; $\underline{SD}$ = 4.2; Mdn = 17.0) again had lower means compared to the AE distribution ($\underline{z}_{skew}$ = -3.9; $\underline{M}$ = 24.7; $\underline{SD}$ = 3.7; Mdn = 25.0) and AC distribution ($\underline{z}_{skew}$ = -3.6; $\underline{M}$ = 18.4; $\underline{SD}$ = 3.9; Mdn = 19.0). Thus, the main impact of using the new scales was to reduce the dimensionality of the scales in order to reduce the effects of multicollinearity.

Table 21

Results of Principal Axis Factor Analysis with Oblique Rotation with the Selected Learning Style Items in the Thesis Study

	Factor[a]			
Item[b]	1	2	3	4
AE 105	.<u>79</u>	-.03	-.01	.00
AE 101	.<u>76</u>	-.08	.06	.10
AE 79	.<u>72</u>	-.04	.02	-.05
AE 97	.<u>64</u>	.09	-.02	.10
AE 83	.<u>61</u>	.14	-.03	.03
AE 64	.<u>57</u>	.06	.00	.00
CE 69	-.10	.<u>93</u>	-.07	.03
CE 76	-.02	.<u>81</u>	.04	.03
CE 61	-.02	.<u>73</u>	.00	-.01
CE 87	.06	.<u>63</u>	.11	-.03
CE 98	.25	.<u>52</u>	.01	.06
CE 91	.16	.<u>49</u>	.10	-.05
RO 88	.00	.05	.<u>87</u>	-.07

Table 21--Continued

	Factor[a]			
Item[b]	1	2	3	4
RO 107	.08	-.02	.82	-.02
RO 103	.07	-.06	.79	-.01
RO 73	-.07	.01	.74	.09
RO 62	-.09	.11	.50	.08
AC 74	-.10	-.05	.12	.84
AC 71	-.02	.13	-.09	.78
AC 78	.12	-.08	.05	.76
AC 82	.11	-.15	.05	.72
AC 67	.02	.07	-.01	.69

[a] Loadings in excess of .40 are underlined.

[b] AE = active experimentation; CE = concrete experience; RO = reflective observation; AC = abstract conceptualization.

Computer experience. For the computer experience measures, 63% (n = 217) of the respondents owned a computer (Item 161), 96% (n = 334) had access to a computer (Item 162), and 96% (n = 331) used a computer at work (Item 163). From sites B and C only, 56% (n = 163) indicated that they used the computer at home (Item 170). The distribution for those who used the computer at home was skewed and kurtic (Z_{skew} = 10.1; $Z_{kurtosis}$ = 9.5; M = 5.3; SD = 5.2; Mdn = 4.0), with responses ranging from 1 to 25 hours per week. Although there were some outliers, most of the respondents (90%) used the computer between 1 and 10 hours per week.

For length of experience by hardware type (Item 164), 90% (n = 302) had microcomputer experience, 17% (n = 58) had minicomputer experience, and 41% (n = 140) had mainframe experience.

The distribution for microcomputer experience was positively skewed and slightly kurtic (Z_{skew} = 3.2; $Z_{kurtosis}$ = -1.49; M = 5.9; SD = 4.1; Mdn = 5.0), with responses ranging from 0 to 20 years. The distribution for minicomputer experience was highly skewed and kurtic (Z_{skew} = 40.2; $Z_{kurtosis}$ = 130.4; M = .76; SD = 2.6; Mdn = 0.0), with responses ranging from 0 to 25 years. Finally, the distribution for mainframe experience was also skewed and kurtic ($\underline{Z}_{skew}$ = 18.8; $\underline{Z}_{kurtosis}$ = 26.0; $\underline{M}$ = 2.3; $\underline{SD}$ = 4.5; Mdn = 0.0), with responses ranging from 0 to 30 years.

Sixty percent (n = 203) of all respondents worked exactly 40 hours per week (Item 166); one respondent worked 80 hours per week (1%) and was distinct when compared to respondents in the next highest group who worked 60 hours per week (3%). The distribution for this base variable was skewed and kurtic ($\underline{Z}_{skew}$ = 7.6; $\underline{Z}_{kurtosis}$ = 18.3; $\underline{M}$ = 43.0; $\underline{SD}$ = 6.3; Mdn = 40.0), with responses ranging from 20 to 80 hours per week.

For average weekly computer use at work (Item 167), the distribution was positively skewed and kurtic ($\underline{Z}_{skew}$ = 3.50; $\underline{Z}_{kurtosis}$ = -1.98; $\underline{M}$ = 15.9; $\underline{SD}$ = 10.6; Mdn = 15) with scores ranging from 0 to 50 hours per week. The ratio variable of average weekly percent of computer use at work was also skewed and kurtic ($\underline{Z}_{skew}$ = 3.0; $\underline{Z}_{kurtosis}$ = -3.1; $\underline{M}$ = 38%; $\underline{SD}$ = 26%; Mdn = 36%), with values ranging from 0 to 100%.

For breadth of experience, the distribution of the number of application types used in an average week was positively skewed ($\underline{Z}_{skew}$ = 2.8; $\underline{M}$ = 2.7; SD = 1.4; Mdn = 3.0), with responses ranging from 0 to 6 applications. Distributions for application depths (Items 168 and 169) were, with the exception of wordprocessing, highly skewed. A summary of the distribution characteristics of the application use variables is given below in Table 22.

Table 22

Descriptive Statistics for the Application Use Variables in the Thesis Study

Variable	Mean	SD	Mdn	Min.	Max.
Hours					
Wordprocesing	8.02	8.35	5.00	0.0	40.0
Spreadsheet	2.67	4.33	0.50	0.0	30.0
Database	2.62	5.50	0.00	0.0	36.0
Graphics	1.28	3.80	0.00	0.0	40.0
Communication	0.90	2.72	0.00	0.0	28.0

Variable	Mean	SD	Mdn	Min.	Max.
Hours (con't)					
Other	0.60	1.89	0.00	0.0	17.5
<u>Percentage</u>					
Wordprocesing	47.16	33.55	50.00	0.0	100.0
Spreadsheet	17.43	25.19	5.00	0.0	100.0
Database	14.09	25.34	0.00	0.0	100.0
Graphics	7.02	15.40	0.00	0.0	100.0
Communication	5.20	14.08	0.00	0.0	100.0
Other	5.19	16.66	0.00	0.0	100.0

Note: n = 331.

<u>Unadjusted Thesis Study Measures</u>

<u>Microcomputer playfulness</u>. The distribution for the microcomputer playfulness scale (Webster & Martocchio, 1992) was negatively skewed (Z_{skew} = -1.9; M = 33.2; SD = 7.4; Mdn = 33.0), with scores ranging from 7 to 49. Coefficient alpha was .87 (SE_{alpha} = .03; $\bar{r}$ = .50).

Computer education. The introductory class distribution was highly skewed and kurtic (Z_{skew} = 15.1; $Z_{kurtosis}$ = 19.8; M = 1.4; SD = 1.7; Mdn = 1.0), with responses ranging from 0 to 10 courses. Thirty-six percent of the respondents had taken 0 classes, with 90% having taken 0 to 3 classes.

The applications class distribution was highly skewed and kurtic (Z_{skew} = 30.3; $Z_{kurtosis}$ = 101.9; M = 1.9; SD = 3.0; Mdn = 1.0), with responses ranging from 0 to 30 classes. Thirty-nine percent of the respondents had taken 0 classes, with 73% having taken 0 to 2 classes.

The programming class distribution was also highly skewed and kurtic (Z_{skew} = 48.6; $Z_{kurtosis}$ = 211.1; M = .90; SD = 2.6; Mdn = 0.0), with responses ranging from 0 to 30 classes. Seventy-one percent of the respondents had taken 0 classes, with 90% having taken 0 to 2 classes.

Developed Measures

Since several measures were developed prior to testing the hypotheses, a short review of the changes that were made is given in this section in advance of the hypothesis results.

The computer learning motivation measures of computer achievement motivation, learning style, and time urgency measures were changed, as were the computer experience measures of the computer interaction and computer knowledge. On the one hand, the changes in operationalization had the effect of narrowing the construct for each measure; on the other hand, with the exception of computer interaaction, these changes improved the internal consistency and simple structure of the measures.

Computer learning motivation. The final computer achievement measure primarily tapped persistence in learning, but also included goals which valued new skills rather than existing skills, and a self-concept which subscribed to skills improving with time. In the final analysis, Sherer et al.'s (1982) persistence items turned out to be the most predominant items in the measure.

The learning style measure was changed to include constructs which were closer to being independent of each other when compared to the original scales. This meant that the concrete experience ability scale was restricted to feeling as opposed to including involvement; the reflective observation ability scale was restricted to watching and observing as opposed to including being reserved and being open-minded; the abstract conceptualization scale was restricted to using logic and being rational as opposed to thinking about ideas or being careful; and the active experimentation scale was restricted to trying out things as opposed to being responsible. As a result, the final measures did not reflect or incorporate the apparent interplay between the extraneous factors that was found with the original scales.

The time urgency scales were changed so that only competitiveness and general hurry were measured. The new competitiveness scale simply had fewer items compared to the original scale, as did the general hurry scale. The task hurry items were completely eliminated as the items loaded on both scales without any particular pattern being evident. Thus, the operationalization of time urgency was restricted to the constructs of being hard-driving and ambitious and having an overall rushed or nervous orientation.

Computer experience. The final computer interaction measures consisted of thirteen single-item measures, six of which were naive and seven of which were expert behavior.

The computer knowledge test was drastically reduced from sixty-three items to five items. In the final analysis, the measure tapped general knowledge about computer hardware and software, with only one item measuring knowledge within a specific application. These items were internally consistent, which was the best that could be achieved, however it probably means that the results are reflective of the particular experience of the Thesis sample only. For example, the items that were consistent in the Pilot sample were not in the Thesis sample, and vice versa.

Extant Measures

Of the measures that were not changed, computer playfulness and computer self-efficacy had good distributions and high internal consistencies. Furthermore, unlike the computer education, application depth, and mini- and mainframe-hardware type variables which were not sampled well enough, the distributions for the number of applications used (component variables for the breadth of average weekly computing) and the microcomputer hardware type variables were normal enough to maintain multivariate normality in the subsequent hypothesis tests. These variables were then used to operationalize depth, breadth, and length of computer experience, respectively.

Testing of Hypotheses

Hypotheses 1 and 2: Computer achievement motivation and computer self-efficacy will be positively related to indicators of computer skill acquisition.

Pearson *r* correlations between the predictors of computer achievement motivation and computer self-efficacy and the criterion variables are shown in Table 23 on page 159.

With the exception of Item 2, Item 4, Item 6, Item 13, and computer knowledge, all of the correlations between the two predictors and the criterion variables were significant (*FW* [153] $\leq$ .05) and in the expected direction. Effect sizes for computer achievement motivation ranged from .04 to .21, while computer self-efficacy effect sizes ranged from .04 to .20. Variables for which computer achievement motivation had a minimum effect size of .10 to a maximum of .21 included (1) asking others to complete projects (negative--Item 1), (2) learning computer software for the sake of learning (Item 8), (3) using the software I know even though the result might be less than ideal (negative--Item 9), (4) trying out new commands rather than the ones already known (Item 11), (5) using the computer manual to develop skills (Item 12), and (6) average depth of computer experience. For computer self-efficacy, a minimum effect size of .10 and a maximum of .20 included all of the interaction variables listed above (except Item 9 [r^2 = .06]), in addition to computer knowledge, years of microcomputer experience, and average number of applications used per week. Thus, with the exception of depth of experience in which r^2 was .08, computer self-efficacy had more significant relationships with the criteria than computer achievement motivation, although not as powerful.

Continuing to look at the predictors together, computer achievement motivation was moderately correlated with computer self-efficacy (r = .64), and both predictors had a similar pattern of correlation with most of the computer interaction items.

On the other hand, computer achievement motivation was significantly correlated with Item 2 (go back and improve a document after learning new skills) in contrast to computer self-efficacy, and computer self-efficacy was significantly correlated with Item 6 (develop skills while working on a project rather than take classes) and computer knowledge in contrast to computer achievement motivation. Furthermore, the magnitude of the correlation between microcomputer experience (length) was twice as large for computer self-efficacy (r = .40) compared to computer achievement motivation (r = .21), and almost twice as large for number of applications used (r = .45 and r = .27, respectively).

In general, however, the hypotheses were confirmed for each predictor except in the cases of nonsignificance and Item 6 which noted at the beginning of this section. Both predictors were positively correlated with Item 6, although only computer self-efficacy was significantly so (r = .21). Thus, the hypothesis was not confirmed for Item 6, chiefly because it was originally classified as a naive interaction in that projects may not provide proper frameworks for learning computer skills.

Table 23

Matrix of Intercorrelations Between Predictor and Criterion Variables in the Thesis Study

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. CAM	1.00												
2. CSE	.64*	1.00											
3. NEWAE	.14	.17	1.00										
4. NEWRO	.11	.09	.21*	1.00									
5. NEWAC	.25*	.31*	.38*	.35*	1.00								
6. NEWCE	.10	.08	.39*	.33*	.15	1.00							
7. COMP	.29*	.19	.32*	.08	.22*	.12	1.00						
8. HURRY	-.08	-.02	.02	-.11	.04	.03	.30*	1.00					
9. PLAY	.66*	.65*	.15	.03	.21*	.12	.24*	-.03	1.00				
10. ITEM 1	-.31*	-.32*	.00	.12	-.08	.07	.07	.05	-.26*	1.00			
11. ITEM 2	.30*	.15	.09	.22*	.02	.13	.05	-.16	.16	.11	1.00		
12. ITEM 3	.20*	.19	-.01	.15	.09	.03	.12	.03	.16	.11	.30*	1.00	

Table 23--Continued

Variable	1	2	3	4	5	6	7	8	9	10	11	12
13. ITEM 4	-.13	.01	.05	.06	.12	-.03	.03	.13	-.15	.04	.07	.09
14. ITEM 5	.32*	.29*	.03	.02	.15	-.01	.05	.00	.26*	.00	.22*	.22*
15. ITEM 6	.16	.21*	.09	-.02	.14	-.01	.06	.10	.19	-.09	.07	.17
16. ITEM 7	.35*	.30*	.12	.04	.14	.09	.12	.02	.30*	-.07	.27*	.17
17. ITEM 8	.44*	.40*	.19	.03	.13	.15	.22*	.04	.39*	-.08	.26*	.21*
18. ITEM 9	-.38*	-.25*	.04	-.08	.03	-.04	-.07	.10	-.35*	.26*	-.10	.02
19. ITEM 10	-.24*	-.28*	.09	-.08	.03	.10	.02	.00	-.27*	.27*	.10	-.01
20. ITEM 11	.46*	.42*	.24*	.05	.22*	.05	.20*	.03	.41*	-.06	.27*	.24*
21. ITEM 12	.44*	.44*	.01	.12	.20*	.06	.15	.07	.37*	-.09	.21*	.19
22. ITEM 13	-.01	-.05	.04	.06	.03	.02	.02	.03	-.09	.13	.02	.07
23. MICROEXP	.21*	.40*	.05	-.11	.17	-.06	-.03	.03	.34*	-.28*	-.02	.03
24. CKNOW	.16	.38*	.09	-.20	.21*	-.14	.08	.16	-.26*	-.13	-.13	.07
25. APPNUM	.27*	.45*	.02	-.07	.08	-.06	-.01	.02	.36*	-.10	.06	.13
26. TOTDEP	.31*	.28*	.07	-.08	-.04	-.01	.02	-.08	.33*	-.15	.21*	-.02

Table 23--Continued

Variable	13	14	15	16	17	18	19	20	21	22	23	24	25
13. ITEM 4	1.00												
14. ITEM 5	.04	1.00											
15. ITEM 6	.12	.12	1.00										
16. ITEM 7	.00	.26*	.10	1.00									
17. ITEM 8	-.04	.31*	.14	.68*	1.00								
18. ITEM 9	.26*	-.02	.14	-.07	-.10	1.00							
19. ITEM 10	.14	.02	.03	.03	-.02	.36*	1.00						
20. ITEM 11	.12	.30*	.31*	.40*	.50*	-.04	.03	1.00					
21. ITEM 12	-.07	.33*	.06	.36*	.41*	-.19	-.14	.38*	1.00				
22. ITEM 13	.14	.03	.11	-.03	.03	.22*	.14	.13	.07	1.00			
23. MICROEXP	-.01	.20	.26*	.15	.16	.09	-.06	.21*	.21*	-.01	1.00		
24. CKNOW	.08	.14	.25*	.07	.08	.12	-.16	.19	.09	.01	.44*	1.00	
25. APPNUM	.01	.15	.26*	.20	.25*	-.10	-.18	.27*	.27*	-.03	.40*	.42*	1.00
26. TOTDEP	.01	.16	.05	.13	.17	-.11	-.05	.21*	.21*	.02	.32*	.05	.31*

* $\underline{FW}_{153} \leq .05$. Note: Due to missing data, $\underline{n}$ ranges from 317 to 345. CAM = computer achievement motivation; CSE = computer self-efficacy; NEWAE = trying out things; NEWRO = watching and observing; NEWAC = using logic and rationality; NEWCE = feeling; COMP = competitiveness; HURRY = general hurry; PLAY = microcomputer playfulness; MICROEXP = years of microcomputer experience; CKNOW = computer knowledge; APPNUM = average number of applications used per week; TOTDEP = average depth of computer use as a proportion of worktime.

Hypothesis 3: The active experimentation and abstract conceptualization learning styles will be positively related to indicators of computer skill acquisition.

Altogether, there were six small but statistically significant correlations (FW [68] $\leq .05$) between the learning style variables and the criteria (see Table 23 on page 159). Active experimentation was positively related to Item 8 ($r = .19$) and Item 11 ($r = .24$), while abstract conceptualization was positively related to Item 11 ($r = .22$), Item 12 ($r = .20$), and computer knowledge ($r = .21$). Finally, reflective observation was positively related to Item 2 ($r = .22$) and negatively related to computer knowledge ($r = -.20$).

Since the learning style variables were somewhat correlated (e.g., ranging from .17 to .39, listwise), a series of standard multiple regressions was performed in which each statistically significant computer skill indicator was regressed on the set of learning style variables. As shown below in Tables 24 through 28, the sample sizes in the regressions ranged from 312 to 314. However, with the exception of reflective observation and computer knowledge (r = -.17 compared to r = -.20), the relationships above remained significant in the reduced sample.

In the regressions, active experimentation did not share unique variance with Item 8 (a preference for learning new software just for the sake of learning it) although it was a stronger predictor than abstract conceptualization and concrete experience and could effectively capture almost all of the explained variance that was contributed by the set (R^2 = .06) (see Table 24 on page 164).

On the other hand, active experimentation and abstract conceptualization each contributed unique variance (sr^2 = .02 and .03, respectively) in the regression of Item 11 (a preference for trying out new commands or features rather than using the ones already known) (see Table 25 on page 165).

Table 24

Results of the Standard Multiple Regression of Item 8 on Learning Styles

Variables[a]	Item 8 (DV)	AC	RO	CE	AE	B	β	sr^2 (unique)
AC	.16					0.036	0.12	
RO	.02	.34*				-0.021	-0.08	
CE	.16	.14	.32*			0.027	0.12	
AE	.20*	.38*	.20*	.39*		0.038	0.12	
					Intercept	0.568*		
Mean	2.27	18.46	16.80	16.26	24.84			
SD	1.15	3.86	4.16	5.06	3.64			

$R^2 = .06$[b]

Adjusted $R^2 = .05$

$R = .25$***

* $\underline{FW}_{68} \leq 05$ [a] $\underline{n} = 312$ [b] Unique variability = .00; shared variability = .06

Table 25

Results of the Standard Multiple Regression of Item 11 on Learning Styles

Variables[a]	Item 11 (DV)	AC	RO	CE	AE	B	β	sr^2 (unique)
AC	.24*					0.050**	0.20	.03
RO	.02	.34*				-0.017	-0.07	
CE	.04	.14	.32*			-0.007	-0.04	
AE	.23*	.38*	.20	.39*		0.047**	0.18	.02
					Intercept	0.987*		
Mean	2.68	18.46	16.80	16.26	24.84			
SD	0.96	3.86	4.16	5.06	3.64		R^2 = .08[b]	
						Adjusted	R^2 = .07	
							R = .29***	

* FW ≤ .05 [a] n = 312 [b] Unique variability = .05; shared variability = .03

Abstract conceptualization essentially accounted for all of the variance in Item 12 (a preference for reading computer manuals and magazines to develop computer skills) ($\underline{sr}^2$ = .04) as none of the other styles shared variance with it (see Table 26 on page 167).

Abstract conceptualization, reflective observation, and concrete experience shared unique variance with computer knowledge ($\underline{sr}^2$ = .06, .04, and .01, respectively). The results also indicated that the combination of the three variables increased prediction as abstract conceptualization alone explained 4 percent of the variance and the other two styles had nonsignificant bivariate correlations (see Table 27 on page 168).

Finally, reflective observation was the only significant unique predictor for Item 2 (preference for going back and improving a document after learning new skills) and could by itself account for most of the explained variance (see Table 28 on page 169). The only instance where the hypothesis of a joint effect between active experimentation and abstract conceptualization was in the case of Item 11.

Table 26

Results of the Standard Multiple Regression of Item 12 on Learning Styles

Variables[a]	Item 12 (DV)	AC	RO	CE	AE	B	β	sr^2 (unique)
AC	.19					0.067***	0.21	.04
RO	.08	.34*				0.003	0.01	
CE	.05	.14	.33*			0.012	0.05	
AE	.02	.38*	.19	.39*		-0.028	-0.08	
					Intercept	1.356**		
Mean	2.15	18.46	16.82	16.28	24.86			
SD	1.21	3.86	4.18	5.07	3.62		R^2 =	.04[b]
						Adjusted	R^2 =	.03
							R =	.21**

* FW ≤ .05 [a] n = 312 [b] Unique variability = .04; shared variability = .00

Table 27

Results of the Standard Multiple Regression of Computer Knowledge (CKNOW) on Learning Styles

Variables[a]	CKNOW(DV)	AC	RO	CE	AE		B	β	sr^2 (unique)
AC	.20						0.109***	0.28	.06
RO	-.17	.34*					-0.085***	-0.23	.04
CE	-.14	.14	.33*				-0.040*	-0.13	.01
AE	.08	.38*	.19	.38*			0.030	0.08	
						Intercept	2.809***		
Mean	3.46	18.44	16.80	16.27	24.83				
SD	1.52	3.88	4.18	5.05	3.63			R^2 = .12[b]	
						Adjusted		R^2 = .11	
								R = .35***	

* <u>FW</u> ≤ .05 [a] <u>n</u> = 314 [b] Unique variability = .11; shared variability = .01

Table 28

Results of the Standard Multiple Regression of Item 2 on Learning Styles

Variables[a]	Item 2 (DV)	AC	RO	CE	AE	B	β	sr^2 (unique)
AC	.01					-0.031	-0.10	
RO	.22*	.34*				0.062***	0.22	.04
CE	.15	.14	.32*			0.016	0.07	
AE	.11	.38*	.19	.39*		0.026	0.08	
					Intercept	1.228*		
Mean	2.60	18.47	16.84	16.31	24.85			
SD	1.19	3.86	4.17	5.04	3.64			

R^2 = .07[b]

Adjusted R^2 = .05

R = .26***

* FW ≤ .05 [a] n = 312 [b] Unique variability = .04; shared variability = .03

On the other hand, the hypothesis was confirmed for the individual styles in the case of Item 8 for active experimentation and Item 12 and computer knowledge in the the case of abstract conceptualization.

Hypothesis 4: Time urgency will be positively related to indicators of computer naiveté.

Landy, Rastagary, Thayer, and Colvin (1991) suggested that the separate constructs of hurriedness and competitiveness might be confounded in popular measures of time urgency. Consequently, although both scales were treated as dimensions of time urgency in the present study, it was conceivable that hurriedness might be more positively related to naiveté than competitiveness because a motivation to hurry in most instances would seem to interfere with the considerable amount of time it takes to acquire computer skills.

As discussed earlier, the competitive and general hurry scales were significantly correlated (r = .30) (FW [34] $\leq$ .05) with an effect size of .09. However, competitiveness was positively correlated to Item 8 (learning new software for the sake of learning) (r = .22) and Item 11 (trying out new commands) (r = .20), compared to general hurry, which was not statistically significantly correlated with any of the criteria (see Table 23 on page 159). Thus, the hypothesis was not confirmed in this case, especially to the extent that competitiveness is a dimension of time urgency and time urgency was positively correlated with Item 8.

Hypothesis 5: Computer achievement motivation will be positively related to computer playfulness.

The Pearson r correlation between computer playfulness and computer achievement motivation was positively statistically significantly (r = .66) (FW [153] $\leq$ .05), with an effect size of .44 (see Table 23 on page 159). Thus, the hypothesis of a significant positive relationship between the two predictors was confirmed.

Both variables similarly correlated with computer interaction, although the correlations for computer achievement motivation were often stronger than computer playfulness. However, computer playfulness was stronger for the remaining indicators of computer knowledge, years of microcomputer experience, and number of applications used

(r = .26; r = .34; and r = .36, respectively) compared to computer achievement motivation (r = .14; r = .21; and r = .27, respectively). Both predictors were approximately equal in the magnitude of their correlations with depth of experience.

Hypothesis 6: Computer achievement motivation will moderate the relationship between computer self-efficacy and indicators of computer skill acquisition.

A series of moderated regressions with centered predictors and a step-down approach (Aiken & West, 1991) was conducted to test whether computer achievement would moderate the relationship between computer self-efficacy and the computer skill indicators.

The only statistically significant interaction (effect size = .03; see Table 29 on page 173) found was between computer self-efficacy and Item 1 (asking others for help in completing portions of a project). The form of the relationship was negative in that higher levels of computer achievement motivation were associated with an increasing negative slope (high [+1 SD], medium [M], and low [-1 SD]; see Table 30 on page 174).

Table 29

Hierarchical Regression of Item 1 on the Interaction (CSE*CAM) of the Centered Predictors of Computer Self-Efficacy (CSE) and Computer Achievement Motivation (CAM)

Variables[a]	Item 1 (DV)	CSE*CAM	CSE	CAM	B	β	sr^2 (incremental)
CSE*CAM	.17				0.001**	0.17	.03
CSE	-.31*	-.09			-0.013**	-0.20	.02
CAM	-.31*	.21*	.64*		-0.026*	-0.15	.01
					0.001*	0.12	
				Intercept	2.372***		
Mean	2.46	102.44	.21	.11			
SD	1.32	184.08	20.90	7.62	R^2 =	.13	
					Adjusted R^2 =	.12	
					R =	.36**	

* FW ≤ .05 [a] n = 327

Table 30

Simple Regression Equations for the Hierarchical Regression of Item 1 on the Interaction (CSE*CAM) Between Computer Self-Efficacy (CSE) and Computer Achievement Motivation (CAM)

---

(1) Regression of Y on X (CSE) at Specific Values of Z (CAM) for Centered Data:

In general: $Y = (.013^{**}+.001Z^{*})X' + (-.026Z^{*}+2.372)$

At Z_H = 7.621:	$Y = -.021X^{**} + 2.174$
At Z_M = 0.000:	$Y = -.013X^{*} + 2.272$
At Z_L = -7.621:	$Y = -.005X + 2.570$

(2) Regression of Y on X (CAM) at Specific Values of Z (CSE) for Centered Data:

In general: $Y = (-.026^{**}+.001Z^{*})X' + (-.013Z^{*}+2.372)$

At Z_H = 20.976:	$Y = -.005X + 2.099$
At Z_M = 00.000:	$Y = -.026X^{*} + 2.372$
At Z_L = -20.976:	$Y = -.047X^{**} + 2.645$

In addition, the same form of interaction was revealed when computer self-efficacy was assumed to be the moderator and simple slopes for computer achievement motivation were likewise computed at high values of computer self-efficacy (recommended by Aiken & West, 1991). (Note that centering predictors changes the interpretation of the parameters such that the effects are present at the <u>average</u> value of the other predictor; in this case, the mean value of computer self-efficacy was 119 points, or somewhat above the normal mean, and the mean value of computer achievement motivation was 40.10 points, also somewhat [more] above the normal mean.) The form of the interaction was consistent with the hypothesis in that the relationship between computer self-efficacy and the criterion (naive, in this case) would be stronger when computer achievement motivation values are high. Thus, computer self-efficacy was a better predictor of this particular interaction when computer achievement motivation was high.

By the same token, computer achievement motivation was a stronger (negative) predictor of this particular computer interaction when computer self-efficacy is low. Even so, only one instance of the hypothesis was confirmed, which meant that the weight of the evidence was not supportive of the hypothesis.

Hypothesis 7: Computer achievement motivation will moderate the relationship between time urgency and indicators of computer skill acquisition.

Just as in Hypothesis 6 above, a series of moderated regressions with centered predictors and a step-up approach was conducted to test whether computer achievement would moderate the relationship between the time urgency variables and the computer skill indicators. The hypothesis of a moderator effect was not confirmed in this case, as no significant interactions were found.

Overview of Contributions of Unique Variance

A series of standard multiple regressions in which each criterion was regressed on the entire set of predictors was performed to evaluate whether the bivariate correlations between the predictors and the criteria would remain significant when all of the predictors were present.

Seventeen regressions were performed, of which Item 6 (developing new computer skills while working on a project rather than take computer classes) and Item 13 (using the arrow keys to move around a document) were not statistically significant. (Note: Item 13 had no statistically significant bivariate correlations with the predictors, while Item 6 had small but statistically significant bivariate correlations [$\underline{FW}$ (153) ≤ .05) with computer self-efficacy efficacy [$\underline{r}$ = .21] and computer playfulness [$\underline{r}$ = .19]). The sample sizes for the regressions ranged from 277 to 287, compared to 317 to 345 in the bivariate correlations. As a result of the reduced sample sizes, the minimum correlation was raised from .19 to either .21 or .22, depending upon whether the sample size was above or below 281 ($\underline{FW}$ [153] ≤ .05). In spite of this, all of the statistically significant bivariate relationships remained significant in the reduced samples.

Of the predictors that shared unique variance with the criteria, computer achievement motivation contributed the most often with ten instances, followed by computer self-efficacy with six instances, abstract conceptualization with four instances, reflective observation with three instances, and active experimentation, general hurry, competitiveness, and computer playfulness with two instances each.

The results of the regressions are discussed below under sections which correspond to each criterion (see Tables 31 through 45 beginning on page 184 and ending on page 198).

Item 1: Asking others to complete projects. Computer achievement motivation (sr^2 = .03), in contrast to the only other significant bivariate correlates of computer self-efficacy and computer playfulness, was the only predictor to show unique variance. On the other hand, the insignificant bivariate correlates of competitiveness (sr^2 = .03) and reflective observation (sr^2 = .02) were significant in the presence of the other predictors (R^2 = .18).

Item 2: Going back and improving a document. Both of the two significant bivariate correlates of computer achievement motivation (sr^2 = .07) and reflective observation (sr^2 = .03) were significant. At the same time, the insignificant bivariate correlates of abstract conceptualization (sr^2 = .02) and general hurry (sr^2 = .02) were significant in the presence of the other predictors

(R^2 = .21).

Item 3: Use the computer help function when problems develop. None of the significant bivariate correlates (e.g., computer achievement motivation, computer self-efficacy, and microcomputer playfulness) contributed unique variance to this criterion (R^2 = .08).

Item 4: Learn new software features only when it saves considerable time. None of the bivariate correlations between the predictors and this item were significant; however general hurry (sr^2 = .02) contributed unique variance in the presence of the other predictors (r = .16; R^2 = .08).

Item 5: Use the manual when having difficulties. Computer achievement motivation was the only significant bivariate correlate to contribute unique variance (sr^2 = .02) to this item, compared to the other significant bivariate correlates of computer self-efficacy and microcomputer playfulness. In addition, abstract conceptualization, which was a nonsignificant bivariate correlate, also contributed unique variance in the presence of the other predictors (sr^2 = .01)(R^2 = .14).

Item 7: Learning new features when no projects are due. Only computer achievement motivation, one of the three significant bivariate correlates, contributed unique variance to this item ($\underline{sr}^2 = .04$), even though this item was one of the core four expert items (albeit more peripherally) that correlated with computer self-efficacy and microcomputer playfulness ($\underline{R}^2 = .15$).

Item 8: Learn new features just for the sake of learning about a program. Altogether, there were five significant bivariate correlates for this item, including computer achievement motivation, computer self-efficacy, microcomputer playfulness, abstract conceptualization, and comptetitiveness. However, only computer achievement motivation contributed unique variance to this item ($\underline{sr}^2 = .04$) ($\underline{R}^2 = .25$).

Item 9: Use the software known even though the result might be less than ideal. Three predictors had significant bivariate correlations with this item, including computer achievement motivation, computer self-efficacy, and microcomputer playfulness. Of these, only computer achievement motivation ($\underline{sr}^2 = .04$) and microcomputer playfulness contributed unique (negative) variance (sr^2 = .02). In addition, abstract conceptualization, a nonsignificant bivariate correlate, contributed unique (positive) variance (sr^2 = .02) in the presence of the other predictors (R^2 = .22).

Item 10: Learn software commands in a step-by-step manner. Computer achievement motivation, computer self-efficacy, and microcomputer playfulness were the only significant bivariate correlates for this item. Computer self-efficacy was the only predictor in this group to contribute unique (negative) variance (sr^2 = .03), in conjunction with the nonsignificant bivariate correlate of abstract conceptualization, which contributed positive unique variance (sr^2 = .02) (R^2 = .15).

Item 11: Try out new commands rather than use the ones already known. Five bivariate correlates were significant for this item, including computer achievement motivation, computer self-efficacy, microcomputer playfulness, active experimentation, and abstract conceptualization. Of these, only computer achievement motivation (sr^2 = .03), computer self-efficacy (sr^2 = .02), and active experimentation

($\underline{sr}^2$ = .02) contributed unique variance.

Item 12: Read computer manuals and magazines to develop skills. Computer achievement motivation, computer self-efficacy, and microcomputer playfulness were significant bivariate correlates for this item, however only computer achievement motivation ($\underline{sr}^2$ = .05) and computer self-efficacy ($\underline{sr}^2$ = .02) contributed unique variance ($\underline{R}^2$ = .27).

Years of microcomputer experience. Computer achivement motivation, computer self-efficacy, and microcomputer playfulness were significant bivariate correlates for this item. Computer self-efficacy ($\underline{sr}^2$ = .03) and microcomputer playfulness ($\underline{sr}^2$ = .03) contributed the same amount of unique variance, in contrast to computer achievement motivation, which was nonsignificant. Abstract conceptualization ($\underline{sr}^2$ = .01) and competitiveness ($\underline{sr}^2$ = .02) were nonsignificant bivariate correlates which contributed unique variance (positive and negative, respectively) in the presence of the other predictors.

Computer knowledge. Computer self-efficacy ($\underline{sr}^2$ = .09) had the largest bivariate correlation ($\underline{r}^2$ = .40) as well as the highest unique contribution to this measure, followed by general hurry ($sr^2 = .03$), and computer achievement motivation, reflective observation (negative), abstract conceptualization, and concrete experience (negative), which had semi-partial correlations of .02. Of the predictors, only computer self-efficacy, microcomputer playfulness, and abstract conceptualization had significant bivariate correlations with the item.

Number of applications used during an average week. Computer achievement motivation, computer self-efficacy, microcomputer playfulness, and abstract conceptualization were the only significant bivariate correlates of this item, and computer self-efficacy was the only predictor to share unique variance with it ($sr^2 = .07$) ($R^2 = .21$).

Depth of use during an average week. The only significant bivariate correlates for this item was computer achievement motivation, computer self-efficacy, and microcomputer playfulness. Only computer achievement motivation contributed unique variance ($sr^2 = .02$), in conjunction with abstract conceptualization ($sr^2 = .01$) which contributed in the presence of the others ($R^2 = .16$).

Table 31

Standard Multiple Regression of Item 1 on Computer Learning Motivation Variables

Var[a]	ITEM 1 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	-.34*										-0.042*	-0.25	.03
CSE	-.32*	.66*									-0.009	-0.15	
PLAY	-.30*	.68*	.64*								-0.014	-0.08	
AE	-.02	.12	.15	.14							-0.190	-0.05	
RO	.09	.11	.10	.05	.19						0.037*	0.12	.02
AC	-.06	.27*	.32*	.22*	.17	.36*					0.000	0.00	
CE	.05	.09	.07	.09	.39*	.30*	.16				0.014	0.06	
COMP	.08	.25*	.16	.22*	.30*	.05	.19	.13			0.072*	0.19	.03
HURRY	.06	-.05	.00	-.03	.05	-.09	.04	.09	.36*		-0.006	-0.01	
									Intercept		4.060*		
<u>M</u>	2.44	40.12	119.22	33.22	24.79	16.64	18.43	16.12	18.08	12.06			
SD	1.31	7.78	21.09	7.44	3.62	4.13	3.85	5.01	3.40	2.89		R^2 = .18[b]	
											Adjusted	R^2 = .16	
												R = .43*	

* <u>FW</u> ≤ .05 [a] <u>n</u> = 286 [b] Unique variability = .06; shared variability = .12

Table 32

Results of the Standard Multiple Regression of Item 2 on Computer Learning Motivation Variables

Var[a]	ITEM 2 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.34*										0.062*	0.39	.07
CSE	.18	.66*									-0.002	-0.03	
PLAY	.18	.68*	.65*								-0.012	-0.07	
AE	.14	.11	.15	.13							0.033	0.10	
RO	.23*	.11	.10	.05	.19						0.059*	0.20	.03
AC	.05	.27*	.32*	.22*	.36*	.36*					-0.046*	-0.15	.02
CE	.14	.08	.07	.09	.39*	.29*	.16				0.013	0.05	
COMP	.09	.25*	.16	.22*	.30*	.05	.19	.13			0.016	0.04	
HURRY	.05	-.05	.00	-.03	.05	-.09	.04	.09	.36*		-0.066*	-0.16	.02
									Intercept		0.135		
M	2.62	40.15	119.20	33.24	24.80	16.66	18.43	16.14	18.08	12.05			
SD	1.22	7.76	21.12	7.44	3.62	4.13	3.86	5.00	3.40	2.89		R^2 =	.21[b]
											Adjusted	R^2 =	.18
												R =	.45*

* FW ≤ .05 [a] n = 285 [b] Unique variability = .14; shared variability = .07

Table 33

Results of the Standard Multiple Regression of Item 3 on Computer Learning Motivation Variables

Var[a]	ITEM 3 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.22*										0.015	0.09	
CSE	.22*	.65*									0.007	0.12	
PLAY	.19	.68*	.64*								0.006	0.03	
AE	.00	.11	.15	.13							-0.024	-0.07	
RO	.12	.10	.09	.04	.18						0.034	0.11	
AC	.10	.26*	.31*	.21*	.35*	.35*					0.000	0.00	
CE	.02	.07	.06	.08	.39*	.28*	.16				0.007	0.12	
COMP	.13	.27*	.17	.22*	.31*	.06	.20*	.15			0.034	0.09	
HURRY	.02	-.05	.00	-.03	.05	-.10	.04	.08	.36*		0.002	0.00	
									Intercept		0.464		
M	2.60	40.07	119.11	33.20	24.77	16.07	18.42	16.07	18.11	12.05			
SD	1.24	7.75	21.04	7.44	3.61	4.97	3.85	5.97	3.38	2.89	R^2 =	.08[b]	
										Adjusted	R^2 =	.05	
											R =	.28*	

*FW ≤ .05 [a]n = 285 [b] Unique variability = .00; shared variability = .08.

Table 34

Results of the Standard Multiple Regression of Item 4 on Computer Learning Motivation Variables

Var[a]	ITEM 4 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	-.14										-0.016	-0.11	
CSE	-.04	.65*									0.004	0.10	
PLAY	-.16	.68*	.64*								-0.024	-0.16	
AE	.04	.09	.13	.12							0.008	0.03	
RO	.06	.10	.09	.05	.19						0.017	0.06	
AC	.10	.25*	.30*	.20*	.34*	.36*					0.030	0.10	
CE	-.01	.06	.05	.07	.38*	.30*	.14				-0.012	-0.06	
COMP	.01	.27*	.18	.22*	.32*	.08	.20*	.14			-0.010	-0.03	
HURRY	.16	-.06	.00	-.03	.05	-.09	.04	.08	.36*		0.064*	0.17	.02
									Intercept		2.291*		
M	2.93	40.05	119.17	33.15	24.77	16.64	18.41	16.04	18.06	12.05			
SD	1.12	7.68	20.98	7.43	3.60	4.10	3.84	4.95	3.37	2.91	R^2 =	.08[b]	
											Adjusted R^2 =	.05	
											R =	.28*	

* FW ≤ .05 [a] n = 282 [b] Unique variability = .02; shared variability = .06

Table 35

Results of the Standard Multiple Regression of Item 5 on Computer Learning Motivation Variables

Var[a]	ITEM 5 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.31*										0.033*	0.20	.02
CSE	.29*	.66*									0.005	0.09	
PLAY	.28*	.68*	.64*								0.014	0.08	
AE	.02	.12	.16	.14							0.000	0.00	
RO	-.01	.11	.10	.05	.19						-0.018	-0.06	
AC	.18	.27*	.31*	.22*	.36*	.35*					0.045*	0.14	.01
CE	-.07	.09	.08	.09	.39*	.29*	.17				-0.024	-0.10	
COMP	.00	.26*	.17	.22*	.30*	.06	.20*	.13			-0.040	-0.11	
HURRY	-.01	-.05	.00	-.03	.05	-.09	.05	.09	.36*		0.014	0.03	
									Intercept		1.073		
M	3.12	40.18	119.34	33.26	24.80	16.68	18.46	16.13	18.05	12.04			
SD	1.25	7.76	21.13	7.46	3.62	4.13	3.86	5.00	3.40	2.90		R^2 = .14[b]	
											Adjusted	R^2 = .12	
												R = .38*	

* FW ≤ .05 [a] n = 283 [b] Unique variability = .03; shared variability = .11.

Table 36

Results of the Standard Multiple Regression of Item 7 on Computer Learning Motivation Variables

Var[a]	ITEM 7 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.37*										0.049*	0.32	.04
CSE	.27*	.66*									0.000	0.00	
PLAY	.29*	.68*	.64*								0.010	0.06	
AE	.12	.12	.15	.14							0.022	0.07	
RO	.07	.11	.10	.05	.19						0.001	0.00	
AC	.14	.27*	.32*	.22*	.36*	.36*					0.003	0.01	
CE	.11	.09	.07	.09	.39*	.30*	.17				0.012	0.05	
COMP	.09	.25*	.16	.22*	.30*	.05	.19	.13			-0.015	-0.04	
HURRY	.02	-.05	.00	-.03	.05	-.09	.05	.09	.36*		0.017	0.04	
									Intercept		-0.473		
<u>M</u>	2.58	40.12	119.22	33.22	24.79	16.64	18.43	16.12	18.05	12.06			
SD	1.18	7.78	21.09	7.44	3.62	4.13	3.85	5.01	3.40	2.89		R^2 = .15[b]	
											Adjusted	R^2 = .12	
												R = .39*	

* <u>FW</u> ≤ .05 [a] <u>n</u> = 286 [b] Unique variability = .04; shared variability = .09

Table 37

Results of the Standard Multiple Regression of Item 8 on Computer Learning Motivation Variables

Var[a]	ITEM 8 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.44*										0.044*	0.30	.04
CSE	.36*	.66*									0.003	0.06	
PLAY	.39*	.68*	.64*								0.019	0.12	
AE	.21*	.12	.14	.14							0.035	0.11	
RO	.02	.11	.10	.05	.19						-0.021	-0.07	
AC	.17	.27*	.32*	.22*	.36*	.36*					0.004	0.01	
CE	.16	.09	.07	.09	.39*	.30*	.17				0.019	0.08	
COMP	.20*	.25*	.16	.22*	.30*	.05	.19	.13			0.007	0.02	
HURRY	.06	-.05	.00	-.03	.05	-.09	.08	.09	.36*		0.020	0.05	
									Intercept		1.848*		
<u>M</u>	2.24	40.12	119.22	33.22	24.79	16.64	18.43	16.12	18.085	12.06			
SD	1.14	7.78	21.09	7.44	3.62	4.13	3.85	5.01	3.40	2.89		R^2 = .25[b]	
											Adjusted	R^2 = .22	
												R = .50*	

* <u>FW</u> ≤ .05 [a] <u>n</u> = 286 [b] Unique variability = .04; shared variability = .21.

Table 38

Results of the Standard Multiple Regression of Item 9 on Computer Learning Motivation Variables

Var[a]	ITEM 9 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	-.41*										-0.043*	-0.31	.04
CSE	-.28*	.66*									0.000	0.01	
PLAY	-.37*	.68*	.64*								-0.026*	-0.18	.02
AE	.03	.12	.15	.14							0.018	0.06	
RO	-.08	.12	.10	.05	.19						-0.027	-0.10	
AC	.02	.27*	.32*	.22*	.36*	.36*					0.046*	0.16	.02
CE	.00	.09	.07	.09	.39*	.30*	.17				0.004	0.02	
COMP	-.11	.25*	.16	.22*	.30*	.05	.19	.13			-0.021	-0.07	
HURRY	.08	-.05	.00	-.03	.05	-.09	.08	.09	.36*		0.023	0.06	
									Intercept		4.402*		
<u>M</u>	2.60	40.12	119.22	33.22	24.79	16.64	18.43	16.12	18.085	12.06			
SD	1.08	7.78	21.09	7.44	3.62	4.13	3.85	5.01	3.40	2.89	R^2 =	.22[b]	
										Adjusted	R^2 =	.20	
											R =	.47*	

* <u>FW</u> ≤ .05 [a] <u>n</u> = 286 [b] Unique variability = .08; shared variability = .14

Table 39

Results of the Standard Multiple Regression of Item 10 on Computer Learning Motivation Variables

Var[a]	ITEM 10 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	b	sr^2
CAM	-.24*										-0.012	-0.09	
CSE	-.29*	.65*									-0.012*	-0.24	.03
PLAY	-.25*	.69*	.65*								-0.014	-0.10	
AE	.09	.12	.15	.14							0.005	0.02	
RO	.09	.10	.09	.05	.20*						0.007	0.03	
AC	.02	.27*	.31*	.22*	.36*	.36*					0.040*	0.14	.02
CE	.13	.09	.07	.09	.40*	.30*	.18				0.024	0.12	
COMP	.04	.26*	.16	.22*	.30*	.05	.19	.12			0.026	0.08	
HURRY	.03	-.04	.00	-.02	.05	-.10	.04	.10	.36*		-0.010	-0.03	
									Intercept		3.162*		
M	2.49	40.21	119.41	33.19	24.80	16.65	18.46	16.16	18.11	12.06			
SD	1.06	7.74	21.06	7.50	3.66	4.16	3.85	5.04	3.40	2.91		R^2 = .15[b]	
												Adjusted R^2 = .12	
												R = .39*	

* FW ≤ .05 [a] n = 278 [b] Unique variability = .05; shared variability = .10

Table 40

Results of the Standard Multiple Regression of Item 11 on Computer Learning Motivation Variables

Var[a]	ITEM 11(DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.47*										0.034*	0.28	.03
CSE	.45*	.66*									0.009*	0.20	.02
PLAY	.41*	.68*	.64*								0.010	0.08	
AE	.20*	.12	.15	.14							0.040*	0.15	.02
RO	.03	.11	.10	.05	.19						-0.010	-0.04	
AC	.19	.27*	.32*	.22*	.36*	.36*					0.002	0.01	
CE	.06	.09	.07	.09	.39*	.30*	.16				-0.007	-0.04	
COMP	.16	.25*	.16	.22*	.30*	.05	.19	.13			-0.003	-0.01	
HURRY	.01	-.05	.00	-.03	.05	-.10	.04	.09	.36*		0.008	0.02	
									Intercept		-0.867		
M	2.65	40.12	119.22	33.22	24.79	16.64	18.43	16.12	18.08	12.06			
SD	0.94	7.78	21.09	7.44	3.62	4.13	3.85	5.01	3.40	2.89	R^2 =	.28[b]	
										Adjusted	R^2 =	.26	
											R =	.53*	

* FW ≤ .05 [a]n = 286 [b] Unique variability = .07; shared variability = .14

Table 41

Results of the Standard Multiple Regression of Item 12 on Computer Learning Motivation Variables

Var[a]	ITEM 12 (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.48*										0.051*	0.33	.05
CSE	.43*	.66*									0.012*	0.21	.02
PLAY	.36*	.68*	.64*								0.000	0.00	
AE	.03	.12	.15	.14							-0.027	-0.08	
RO	.11	.11	.10	.05	.19						0.014	0.05	
AC	.19	.27*	.32*	.22*	.36*	.36*					0.010	0.03	
CE	.07	.09	.07	.09	.39*	.30*	.16				0.006	0.03	
COMP	.16	.25*	.16	.22*	.30*	.05	.19	.13			0.009	0.03	
HURRY	.06	-.05	.00	-.03	.05	-.10	.05	.09	.36*		0.031	0.07	
									Intercept		-1.716		
M	2.12	40.12	119.25	33.22	24.81	16.64	18.08	16.12	18.08	12.07			
SD	1.20	7.79	21.12	7.45	3.61	4.14	3.41	5.02	3.41	2.89	R^2 =	.27[b]	
										Adjusted	R^2 =	.24	
											R =	.52*	

* FW $\leq$ .05 [a]n = 285 [b]Unique variability = .07; shared variability = .20

Table 42

Results of the Standard Multiple Regression of Microcomputer Experience (MICRO) on Computer Learning Motivation Variables

Var[a]	ITEM	MICRO(DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.21*											-0.065	-0.12	
CSE	.36*	.66*										0.052*	0.27	.03
PLAY	.34*	.68*	.65*									0.148	0.27	.03
AE	.01	.12	.15	.14								-0.023	-0.02	
RO	-.05	.13	.10	.05	.20*							-0.101	-0.10	
AC	.17	.28*	.32*	.23*	.33*	.38*						0.149*	0.14	.01
CE	-.03	.10	.07	.11	.38*	.29*	.14					-0.021	-0.03	
COMP	-.06	.26*	.18	.22*	.31*	.07	.22*	.15				-0.021*	-0.17	.02
HURRY	.00	-.05	.00	-.03	.07	-.09	.06	.11	.37*			0.060	0.04	
										Intercept		0.542		
<u>M</u>	6.13	39.95	118.77	33.26	24.72	16.60	18.31	16.00	18.05		12.09			
SD	4.11	7.88	21.25	7.47	3.60	4.15	3.45	4.95	3.34		2.89	R^2 =	.20[b]	
											Adjusted	R^2 =	.17	
												R =	.45*	

* <u>FW</u> ≤ .05 [a]<u>n</u> = 278 [b] Unique variability = .09; shared variability = .11.

Table 43

Results of the Standard Multiple Regression of Computer Knowledge (KNOW) on Computer Learning Motivation Variables

Var[a]	KNOW (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	*sr*^{2}
CAM	.16										-0.038*	-0.20	.02
CSE	.40*	.66*									0.030*	0.43	.09
PLAY	.27*	.67*	.64*								0.025	0.12	
AE	.06	.12	.15	.14							0.016	0.04	
RO	-.13	.12	.10	.05	.19						-0.058*	-0.16	.02
AC	.21*	.28*	.32*	.21*	.35*	.36*					0.067*	0.18	.02
CE	-.11	.19	.07	.09	.39*	.30*	.17				-0.041	-0.14*	.02
COMP	.07	.26*	.16	.21*	.30*	.05	.20*	.13			-0.028	-0.06	
HURRY	.18	-.05	.00	-.03	.05	-.09	.04	.09	.36*		0.096*	0.19	.03
									Intercept		0.551		
M	3.55	40.06	119.14	33.23	24.79	16.62	18.40	16.00	18.05	12.09			
SD	1.48	7.83	21.10	7.43	3.61	4.14	3.88	4.95	3.34	2.89	R^2 =	.28[b]	
											Adjusted R^2 =	.25	
											R =	.52*	

* *FW* $\leq$ .05 [a]*n* = 287 [b] Unique variability = .20; shared variability = .08.

Table 44

Results of the Standard Multiple Regression of Number of Applications (APPNUM) on Computer Learning Motivation Variables

Var[a]	APPNUM (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.29*										-0.001	-0.01	
CSE	.43*	.66*									0.026*	0.39	.07
PLAY	.34*	.68*	.65*								0.024	0.13	
AE	-.02	.10	.14	.13							-0.012	-0.03	
RO	.01	.12	.11	.05	.20*						0.004	0.01	
AC	.21*	.27*	.31*	.21*	.33*	.37*					-0.014	-0.04	
CE	.07	.08	.06	.09	.40*	.29*	.17				-0.014	-0.05	
COMP	-.01	.28*	.18	.23*	.31*	.06	.21*	.14			-0.041	-0.10	
HURRY	-.01	-.05	.00	-.02	.05	-.11	.04	.07	.36*		0.017	0.04	
									Intercept		0.219		
_M_	2.76	40.02	119.36	33.27	24.81	16.50	18.43	16.08	18.09	12.06			
SD	1.38	7.83	20.98	7.51	3.60	4.13	3.87	4.96	3.38	2.90		R^2 = .21[b]	
											Adjusted	R^2 = .18	
												R = .46*	

* _FW_ ≤ .05 [a]_n_ = 277 [b] Unique variability = .07; shared variability = .14

Table 45

Results of the Standard Multiple Regression of Depth of Computer Use (%DEP) on Computer Learning Motivation Variables

Var[a]	%DEP (DV)	CAM	CSE	PLAY	AE	RO	AC	CE	COMP	HURRY	B	β	sr^2
CAM	.32*										0.006*	0.19	.02
CSE	.28*	.66*									0.001	0.11	
PLAY	.32*	.68*	.64*								0.005	0.15	
AE	.04	.11	.15	.13*							0.004	0.06	
RO	-.05	.13	.11	.05	.19						-0.003	-0.06	
AC	-.04	.27*	.31*	.21*	.34*	.37*					-0.009*	-0.14	.01
CE	.00	.09	.07	.09	.39*	.30*	.15				0.000	0.00	
COMP	.00	.25*	.16	.21*	.30*	.06	.20*	.13			-0.003	-0.04	
HURRY	-.12	-.05	.00	.03	.05	-.09	.04	.08	.37*		-0.008	-0.09	
									Intercept		0.108		
<u>M</u>	0.39	40.04	119.36	33.22	24.78	16.61	18.43	16.13	18.04	12.05			
SD	0.25	7.86	21.08	7.49	3.61	4.15	3.87	5.00	3.40	2.90	R^2 =	.16[b]	
										Adjusted	R^2 =	.13	
											R =	.40*	

* <u>FW</u> ≤ .05 [a]<u>n</u> = 281 [b] Unique variability = .03; shared variability = .13.

Variables Related to Integrated Use

A series of direct discriminant function analyses was also performed to determine whether the notion of integrated or intense, versatile use might differentiate motivated and skilled users from unmotivated and unskilled users. Prior to the analysis, the author believed that integrated use might be an indicator of training transfer (e.g., between applications) in that intense, versatile use stands in contrast to intense use within a single application. Thus, integrated use was operationalized by combining intense and versatile use.

Grouping variables.

The nine computer learning motivation variables and fifteen computer skill variables served as group membership predictors in the analysis. The learning motivation predictors included computer achievement motivation, computer playfulness, computer self-efficacy, time urgency (competitiveness and hurriedness), and learning style (concrete experience, abstract conceptualization, active experimentation, and reflective observation). The skill predictors included expert and naive interaction behaviors, computer knowledge, and years of microcomputer experience.

Four groups were formed according to whether respondents were above or below the medians of average weekly application use at work (breadth; Mdn = 3.0) and average weekly microcomputer use at work (depth; Mdn = 36%). Group 1 was below both medians with a mean use of 1.42 applications and a mean intensity rate of 14% ($n = 92$); Group 2 was above the median of application use, with a mean use of 3.57 applications, but below the median of intensity, with a mean rate of 20% ($n = 68$); Group 3 was above both medians with a mean use of 3.9 applications and a mean intensity rate of 60% ($n = 99$); and Group 4 was below the median of application use, with a mean use of 1.63 applications, but was above the median of intensity, with a mean rate of 58% ($n = 63$).

Initial analysis. Of the original 347 cases, 98 cases (28%) were dropped from the analysis because of missing data. For the most part, these cases were evenly distributed across groups. However, the one exception was Group 1 which had a slightly higher number of cases with missing data on the learning style scales of concrete experience (CE) and abstract conceptualization (AC). For the remaining 249 cases, assumptions of linearity and normality for grouped data were deemed met through residuals analysis, however a significant Box's M ($F[900] = 1.21$; $p \leq .001$) was obtained so the equality of the group variance-covariance matrices was not confirmed.

After conducting univariate tests of homogeneity of variance for all of the variables, significant differences (Barlett-Box F) were found for computer knowledge, Item 9, and Item 12. To reduce Box's M and to boost the power of the analysis, computer knowledge was dropped first because it had the largest discrepancy (between Group 1 and Group 2). Variables which had insignificant univariate F statistics, such as concrete experience, reflective observation, abstract conceptualization, active experimentation, competitiveness, general hurry, Item 4, Item 7, and Item 13, were also dropped and the analysis was repeated for a second time. During the second analysis, Item 10 became nonsignificant, so it was removed as well and the analysis was repeated for a third time.

The univariate F statistics for the twelve remaining predictors were all less than .01, however the familywise (FW) Type I error rate exceeded .01. In order to keep the FW Type I error rate at .01, Item 1, Item 3, and Item 11 were dropped as well. A fourth, and final, analysis was conducted, which is described below.

Only 18 percent ($\underline{n}$ = 61) of the cases were dropped from the analysis because of missing data this time, primarily due to the removal of the learning style variables. However, just as before, these cases were evenly distributed across groups. This left 286 cases for the analysis, with 80 cases in Group 1, 64 cases in Group 2, 89 cases in Group 3, and 53 cases in Group 4. Box's M (108) at 116.81 was nonsignificant at p = .41.

The overall chi-square statistic (χ^2 [24]= 122.86) for the three functions that were extracted was significant at less than .001. After removal of the first function, only the second function remained significant (χ^2 [1]= 24.82; $\underline{p}$ = .04). The first two functions accounted for 93% of the between group variability; the first function accounted for 82% of the variance ($\underline{r}$ = .54), while the second function accounted for an additional 11% of the variance ($\underline{r}$ = .23).

Final analysis. In order to consider predictor correlations for significant functions only, a subanalysis was conducted in which only two functions were requested. Using a minimum loading of .40 as a criterion, the variables with the best loadings for the first function were microcomputer experience, computer self-efficacy, computer playfulness, computer learning motivation, Item 5, and Item 12; the variable with the best loading on the second function was Item 6. The canonical discriminant functions at the group centroids indicated that the first function maximally separated Group 3 from Group 1, and the second function maximally separated Group 2 from the other groups (see Table 46 on page 205).

Thus, intense, versatile users had 1) more years of microcomputer experience (M = 8.42) and higher levels of 2) computer self-efficacy (M = 130.38), 3) computer playfulness (M = 36.97), 4) computer achievement motivation (M = 43.20), 5) using the software manual when difficulties develop (M = 3.37), and 6) reading computer manuals and magazines to develop computer skills (M = 2.70). On the other hand, non-intense, versatile users, when compared to all of the other groups, had a higher level of preference for developing new skills while working on a project rather than taking classes (Item 6) (_M_ = 3.70). In exception, the last variable, Item 8 (preference for learning new software features for the sake of learning about a program), had a loading that, at .37, did not reach the threshold of .40 (see Table 47 on page 206) for a list of group means for each predictor).

Table 48 on page 206 lists the predictor loadings, univariate _F_ statistics, and pooled within-group correlations among the predictors.

Table 46

Group Centroids in the Integrated Discriminant Function Analysis in the Thesis Study

		Function	
Group		1	2
1	Low Breadth, Low Depth	-.89	-.08
2	High Breadth, Low Depth	.14	.43
3	High Breadth, High Depth	.77	-.16
4	Low Breadth, High Depth	-.12	-.14

Table 47

Group Means for the Predictors in the Discriminant Function Analysis in the Thesis Study

Group[a]	MICRO	PLAY	CSE	CAM	Q5	Q6	Q8	Q12
1 Low Low	3.83	29.34	106.71	36.56	2.56	2.95	1.94	1.76
2 High Low	6.34	33.69	122.64	39.36	3.19	3.70	2.23	2.14
3 High High	8.42	36.97	130.38	43.19	3.37	3.46	2.66	2.70
4 Low High	5.92	33.55	117.72	41.09	3.23	3.32	2.32	1.92
Total	6.21	33.47	119.68	40.09	3.08	3.35	2.30	2.17

Note. n = 286 [a] Low Low = low breath/low depth; High Low = high breadth/low depth; High High = high depth/high breadth; Low High = low breadth/high depth.

Table 48

Results of Integrated Use Discriminant Function Analysis with Computer Learning Motivation and Computer Skill Variables

	Correlations of predictor variables with discriminant functions			Pooled within-group correlates among predictors[a]						
Predictor	1	2	Univariate *F* (3, 282)	MICRO	PLAY	CAM	Q12	Q5	Q8	Q6
MICRO	.74*	-.16	21.89		.23	.13	.11	.10	.10	.18
PLAY	.64*	-.15	16.37			.66	.28	.21	.37	.17
CAM	.51*	.41	11.59				.42	.28	.40	.16
Q12	.48*	-.20	10.28					.29	.41	.04
Q5	.40*	.06	7.11						.27	.13
Q8	.37*	-.26	5.86							.14
Q6	.30	.62*	5.77							
Canonical *R*	.54	.23								
Eigenvalue	.42	.06								

* higher loading on function [a] n = 286

DISCUSSION

The present investigation was designed to explore the relationship between computer learning and computer skill indicators in employee populations where the extent of computer use was essentially voluntary. In the course of the investigation, two separate studies were conducted; the first study (Pilot Study) served as the development study for the computer interaction, computer achievement motivation, computer knowledge, and computer experience measures, while the second study (Thesis Study) served as the primary investigation.

The primary investigation entailed testing seven hypotheses which were derived from a tentative model of variable relations (see Figure 1 on page 213). Three of the seven hypotheses were confidently confirmed. The results of these hypothesis tests are discussed below, followed by a discussion of the results of the unconfirmed hypothesis tests.

Confirmed Hypotheses

The general hypotheses that computer achievement motivation and computer self-efficacy would each be positively related to computer experience were confirmed (Hypotheses 1 and 2), with the exception of computer knowledge in the case computer achievement motivation, and Item 2 (preference for going back and improving a document (expert interaction) in the case of computer self-efficacy, which were null. In addition, although not formally stated, it was assumed that the predictors would negatively correlate with the naive interaction items; this occurred for the most part, with the exception of preferences for: (1) learning software only when it saves considerable time (Item 4--both predictors null), (2) using the arrow keys to move around a document (Item 13--both predictors null), and (3) learning software from projects rather than classes (Item 6--only computer self-efficacy null).

Taking the relationships whose effects exceeded .10 (e.g., $\underline{r} > .30$; a medium effect) into account, computer self-efficacy was not only equally related to the expert factor in computer interaction (e.g., items 7, 8, 11, and

12), but was also more related to all of the computer experience variables, except average weekly depth of use. This result suggests that skill or task-level inventories, when compared to computer achievement motivation (e.g., persistence and belief in incremental ability), may be more effective at measuring actual skill levels. On the other hand, computer achievement motivation was a more effective predictor, based on bivariate and partialled correlations, of the interaction behaviors when compared to computer self-efficacy. This latter finding suggests that confidence in skill (e.g., computer self-efficacy) and persistence in learning may not represent redundant constructs.

Finally, the hypothesis that computer playfulness and computer achievement motivation would be positively related (Hypothesis 4) was also confirmed, with an effect size of .41. This result suggests that persistence and incremental skill values are related to a creative and imaginative orientation to computer interaction.

Unconfirmed Hypotheses

The remaining four hypotheses (Hypotheses 3, 5, 6, and 7) were not confidently (e.g., globally) confirmed.

For the learning abilities underlying the converger learning style, there were three small effects. In the first effect, the finding of a joint effect with Item 11 fits the description of the converger who likes to actively experiment, as long as the action is hypothesized to produce a particular effect (e.g., testing rather than exploring).

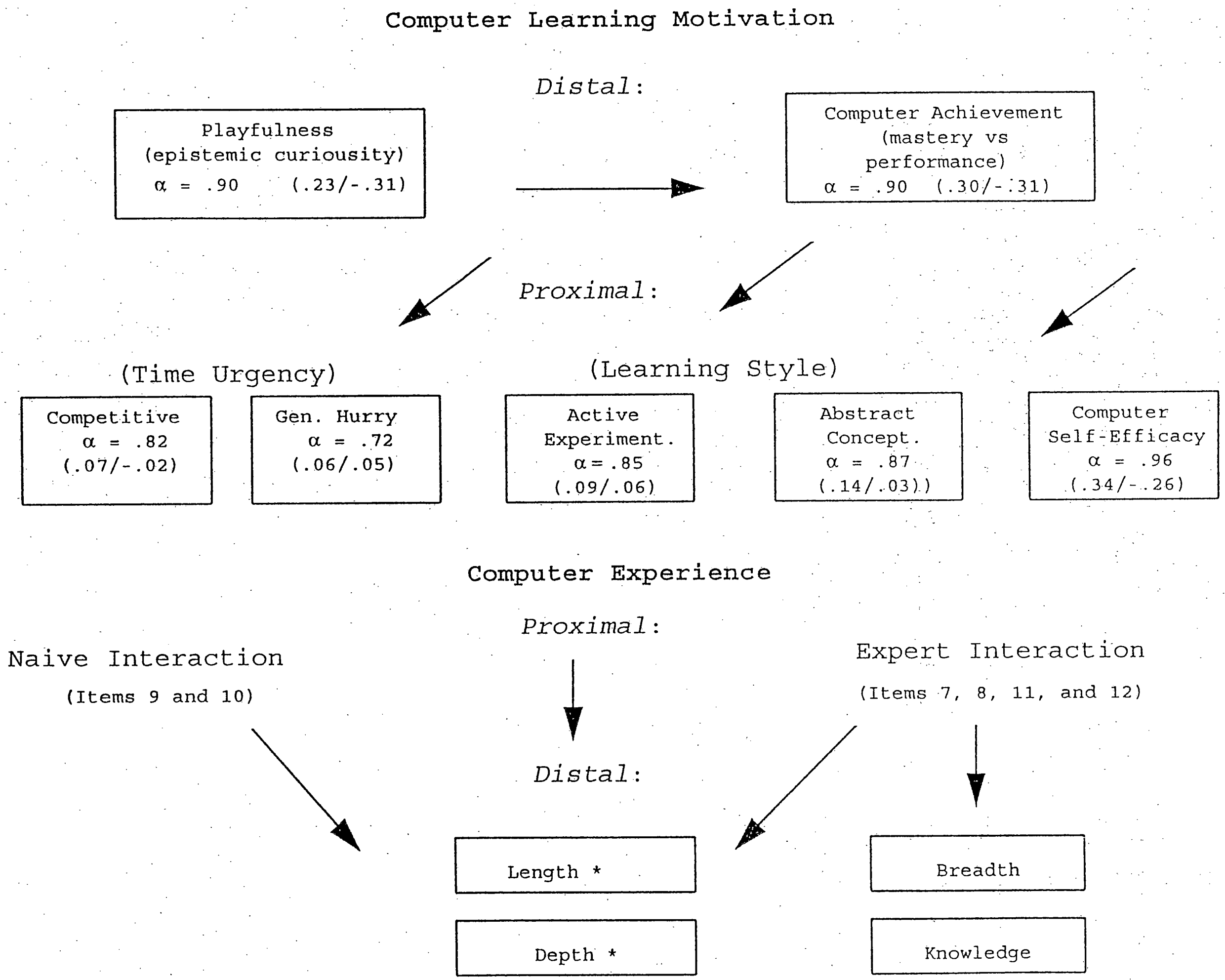
In the second effect, abstract conceptualization was uniquely related to the activity of reading computer manuals and magazines (Item 12), which fits the notion that abstract conceptualizers like to receive information in an abstract way rather than through interaction with the environment or through feelings (e.g., concrete experience). In the third effect, abstract conceptualization was uniquely related to computer knowledge, which might be acquired through the activities described above (i.e., Item 12).

Hypothesis 5 was unconfirmed for either dimension of time urgency (i.e., competitiveness or general hurry) in the prediction of naive interaction. Instead, competitiveness was positively related to two indicators of the expert factor, and general hurry was unrelated to either the expert or naive factor. In the case of general hurry, the reason for this finding was not entirely clear, except that general hurry was clearly not related to even the strongest indicators of naive interaction (e.g., Item 9--using software that is less than ideal and Item 10--learning software in a non-chunking manner).

The hypothesis that computer achievement motivation would moderate the relationship between computer self-efficacy and the computer experience variables (Hypothesis 6) was confirmed in one instance of interaction between computer self-efficacy and asking others to help complete projects (Item 1); while the effect size was rather small (i.e., 3%), it indicated that a definite effect was present.

Related to Hypothesis 6 was Hypothesis 7, which was also unconfirmed. This indicated that computer achievement motivation did not moderate the relationship between the measures of time urgency and the computer experience variables. This result was surprising, as the production bias in the computer experience literature did not appear to be dictated by any situational pressure. Nonetheless, the result suggests that a general orientation towards hurrying is not associated with naive interaction.

Figure 1. Conceptual Scheme of Proposed Variable Relations in the Thesis Study[a]



[a] average correlation for expert criteria over naive criteria is in parantheses
* not included in average correlations

Combining Computer Experience Variables

As noted earlier, some way of combining the experience variables to arrive at a classification that captures naive versus expert use would be helpful for understanding how computer experience impacts computer skill development. As a result, a new classification variable, tentatively described as integrated use, was explored using discriminant function analysis.

The results were most informative about the extremes of use (e.g., Group 1 and Group 3) in which key variables were associated with integrated use. On the experience side, these variables included years of microcomputer experience, using the manual when problems develop (Item 5), reading manuals to develop skills (Item 12), and learning new skills for the sake of learning (Item 8) on the experience side; on the motivation side, they included computer self-efficacy, computer playfulness, and computer achievement.

In addition, there was an interesting finding in which developing skills with project stimuli rather than taking classes (Item 6) separated the high breadth, low depth users (Group 2) from the other users. Since the lowest scoring group was the group with the least use, this might indicate that <u>not</u> venturing forth without taking classes might stall skill development, as measured by average number of applications used per week.

Limitations of the Investigation

As can be seen from Figure 1, the amalgamated approach taken in the present investigation was limiting in that a closer investigation of the correlated predictors was not possible.

The use of a cross-sectional survey questionnaire also made the investigation vulnerable to all of the problems associated with self-report instruments, including common method variance, consistency motif, social desirability, and nonresponse bias (Podasakoff & Organ, 1986). Efforts such as offering incentives (i.e., nonresponse bias), applying careful wording at the instruction and item level (i.e., social desirability), and strategically placing item types throughout the survey (i.e., consistency motif), were made to address most of these threats at the outset, however no attempt was made to gauge the effectiveness of these efforts. Furthermore, none of the post-hoc statistical remedies, such as Harmon's one-factor test (e.g., first factor in a principal components analysis with all measures), that have been suggested by Podsakoff and Organ were used to estimate the impact of common method variance due to a rebuttal by Kemery and Dunlap (1986). Kemery and Dunlap used the same data to demonstrate that these methods can introduce an artifact of negative bias such that positive correlations will decrease and vice-versa, with reversals in sign possible as well; the effect of these complications can make the analysis potentially uninterpretable, especially with large numbers of items.

In the future, it would be develop complementary methods, such as archival and observation methods, to verify the results of cross-sectional surveys such as this one.

Implications

The results of this investigation contribute to the general literature on computer learning motivation and the development of computer skill in several ways. First, there has been a surgence of interest in the usefulness of measures of intrinsic motivation (e.g., self-efficacy, self-concept and goals, achievement behavior, and attribution theory) after a long period of attitude measurement. The present investigation used several measures of intrinsic motivation in an effort to understand their uniqueness in relationship to computer experience.

To this end, several computer experience variables were tested which serve a starting point towards understanding the character of different types of computer experience distributions in employee populations. In addition, a new classification of computer experience was tested using the concept of integrated use.

Computer learning motivation. For the established variables of microcomputer playfulness, computer self-efficacy, and learning style, the results were primarily supportive of computer self-efficacy and microcomputer playfulness. Furthermore, microcomputer playfulness had unique variance with the criteria in the case of computer knowledge and Item 9 only. On the other hand, microcomputer playfulness was a shorter measure, and the unique (negative) relationship to Item 9 (preference for using software even though the result might be less than ideal) suggested an intent towards mastery, a quality that was not measured by computer self-efficacy.

Although there were only a few small effects for learning style, preferences for abstract conceptualization and active experimentation were related to the selected indicators. As discussed in the literature review, both tendencies were expected to correlate with computer interaction, although active experimentation by itself was expected to be related to naive interaction and lower skill (i.e., quick-start behavior) when compared to the combination of active experimentation and abstract conceptualization.

For the new variables of computer achievement motivation and time urgency, there was support for the former but not the latter. Computer achievement motivation, as a measure of persistence and belief in the value of incremental skill development, was uniquely related to the experience variables of computer interaction, but less related to the "hard" criteria of computer knowledge, and length and breadth of experience when compared to computer self-efficacy and, to a lesser extent, computer playfulness.

On the other hand, an important interaction between computer achievement motivation and computer self-efficacy in predicting preferences for asking others to complete computer projects was found which suggests that computer skill level alone (e.g., task-specific self-efficacy) may not be sufficient to guard against the threat of "plateauing".

The results of the time urgency analysis were not supportive of the notion of the production bias being related to either of the two forms of time urgency (i.e., competitiveness and general hurry) which were tested. For the most part, this result confirms other research using similar same measures of Type A behavior in which very little effect has been found between productivity and time urgency (Taylor, Locke, Lee, and Gist, 1984; Lester, 1983). One unexpected finding, however, was the pattern of medium correlation between competitiveness and the positive motivation variables of computer achievement motivation, computer playfulness, abstract conceptualization, and active experimentation. This finding, in combination with the much smaller correlation with two expert interaction indicators (except items 8 and 11), seemed to suggest a bias towards social desirability. As a result, it might be useful to investigate this possibility in future research with self-report measures.

Computer experience. In developing measures of computer interaction that tap descriptions of naive and expert behavior in the literature, an attempt was made to measure proximal indicators of computer skill, such as computer interaction, which may in turn lead to distal indicators, such as computer knowledge, and length, depth, and breadth of experience.

From the thirteen items that were retained for the Thesis Study, two naive items and four expert items were consistently related (e.g., were cross-validated) in the two samples. The naive factor included the tendency to use a convenient or known software even when the result is less ideal, and a tendency to use steps which must be connected when learning (e.g., non-chunking). The expert factor included the tendency to search for information and to want to learn about the computer. Although these items were the best performing items in terms of suggesting common factors, three of the remaining items, Item 1, Item 2, and Item 6, were useful in different analyses, suggesting that they may tap additional features of computer experience which are worthy of exploration. On the other hand, it was clear that Item 4 and Item 13 did not discriminate between motivated and non-motivated respondents; in the former case, the type of interaction included the notion of learning skills only when it saves considerable time, and in the latter, using arrow keys to move around a document. Assuming that a desire for mastery would supersede considerations of saving time only, the results for Item 4 were puzzling; however Item 9 was somewhat positively correlated with Item 4 (r = .26) which would make sense in terms of providing an explanation for the tendency to use less than ideal software. Item 13, on the other hand, was created to tap the same tendency as described in Item 10 (e.g., a non-chunking tendency; function keys are more efficient than arrow keys for moving around a document). Instead of correlating with Item 10, Item 13 primarily correlated with Item 1 (r = .13) and Item 9 (r = .22).

In general, this author believes that more exploration with these types of measures should be conducted with attention to the experience levels within the samples, as it is quite possible that the results here are peculiar to idiosyncratic characteristics of experience within the present sample.

Computer training policy. Although the results of the present investigation are preliminary and suggest more follow-up than conclusions, the computer experience results (e.g., computer class distributions, and responses on Item 6) in particular suggest that computer classes may not constitute the most effective organizational training policy. The finding that Item 2, or a preference for going back and improving a document, was related to the learning ability of reflective observation, which was in turn unrelated to the other computer experience variables, suggests that individuals who prefer reflective observation, yet do not prefer active experimentation, may fall behind in acquiring computer skills because of a need to initiate action. This interpretation is in agreement with Kolb's (1984) finding that individuals who prefer reflective observation also prefer lectures over other types of learning environments. From an intuitive point of view, most individuals develop skills which are perceived to be needed by the organizations in which they work; this situation may in turn be related to the tendency to use projects as stimuli for learning about the computer while working. Thus, if computer skill development is somehow imbedded in the particular practices of the organization, outsourcing may not be as effective as insourcing in stimulating and supporting computer skill development in the respective employee population.

In conclusion, organizational surveys such as the one used in this investigation can provide important census information on computer use patterns within an organization, as well as check employee motivation to use available technology within different areas in the organization. This information can then be used to assess readiness for training and point to potential treatments which may be suited to either low or high states of motivation.

APPENDIX A

PILOT STUDY QUESTIONNAIRE

COMPUTER USE SURVEY

The design of effective computer training and development programs may be improved if more is known about current computer use patterns. The attached survey is an effort to learn more about these patterns of computer use.

The entire survey is composed of seven parts. You will be asked about your experience in using computers and how you feel about those experiences. We are interested in your experiences even if you have only used a computer a few times.

If you have never used a computer, please start with Part Four, #73, on page 6.

Since each part has specific instructions, please be sure to read all instructions before completing the questions.

The survey is to be answered anonymously and all responses will be kept confidential. Please try to answer all of the questions to assure that a sufficient amount of data is collected.

Thank you for participating in the survey.

PART ONE

Shown below is a list of computer learning activities. While these activities reflect different interaction styles, they DO NOT reflect actual ability.

Please CIRCLE the number which describes how often you engage in these activities.

KEY:

0 = Never
1 = Sometimes
2 = Often
3 = Always

When using computers, I PREFER TO:

	Never	Some times	Often	Always
1. Try out new commands or features rather than use the ones I already know.	0	1	2	3
2. Use the arrow keys to move around a document when I am pressed for time.	0	1	2	3
3. Use the function keys just for basic operations like save, quit, and print.	0	1	2	3
4. Learn new features just for the sake of learning about a program.	0	1	2	3
5. Find out how to get out of a jam rather than spend time learning about a particular command or feature.	0	1	2	3
6. Write down new commands as I learn them so I can refer to them later.	0	1	2	3
7. Learn new computer features while working only when it saves considerable time.	0	1	2	3
8. Scroll through pages in a document by using the arrow keys rather than using combinations of other keys or commands.	0	1	2	3
9. Learn how to use the computer when I don't have any projects that are due.	0	1	2	3
10. Use the software I know even though the result might be less than perfect (e.g., using a wordprocessing package to make a graph).	0	1	2	3
11. Use a manual to get myself out of a jam.	0	1	2	3
12. Use as few specialized features as possible when I am working on a specific project.	0	1	2	3
13. Ask a person for help when an error message prevents me from continuing to work on a document.	0	1	2	3

PART ONE (con't)

	Never	Some times	Often	Always
14. Ask peers or coworkers to complete portions of a project which require more computer skill than I have.	0	1	2	3
15. Use a step-by-step approach rather than find out about what keys perform which functions.	0	1	2	3
16. Develop computer skills when I need them rather than take computer classes.	0	1	2	3
17. Go back and change a document after I have learned new skills.	0	1	2	3
18. Choose easy to use keys while typing rather than complete any extra steps.	0	1	2	3
19. Use the demands of the project I am working on to motivate me to learn more about the computer.	0	1	2	3
20. Use the computer help features to get me out of a jam.	0	1	2	3
21. Read computer manuals and magazines to develop computer skills.	0	1	2	3

PART TWO

Please CIRCLE the number which indicates YOUR LEVEL OF AGREEMENT with the following statements.

KEY:
1 = Strongly Disagree SD
2 = Disagree D
3 = Neither Agree or Disagree N
4 = Agree A
5 = Strongly Agree SA

	SD	D	N	A	SA
22. If something about the computer looks complicated, will not even bother to try it.	1	2	3	4	5
23. When I am learning how to use a computer, I am most concerned about developing my ability.	1	2	3	4	5
24. I like to do fun and easy things with the computer so that I don't have to worry about making mistakes.	1	2	3	4	5
25. I feel I have learned more when I exert a lot of effort.	1	2	3	4	5
26. When trying to learn something new about the computer, I soon give up if I am not initially successful.	1	2	3	4	5
27. I avoid facing difficulties with the computer.	1	2	3	4	5
28. If I can't do a job with the computer the first time, I keep trying until I can.	1	2	3	4	5

PART TWO (con't)

	SD	D	N	A	SA
29. Failure with the computer just makes me try harder.	1	2	3	4	5
30. When working with a computer, I would rather do things that I already know how to do.	1	2	3	4	5
31. I like to work on computer tasks that are fairly easy so that I'll do well.	1	2	3	4	5
32. I like computer tasks that are hard enough to show that I am intelligent.	1	2	3	4	5
33. I avoid trying to learn new things about the computer when they look too difficult for me.	1	2	3	4	5
34. I give up learning about the computer easily.	1	2	3	4	5
35. I am not bothered when I experience problems with the computer because I believe I will get better over time.	1	2	3	4	5
36. When I have difficulty learning how to use the computer, I think about what I am doing as I am learning.	1	2	3	4	5
37. I feel compelled to attempt challenging goals even though there is a good chance that I will fail.	1	2	3	4	5
38. If a computer task is too easy, I usually get bored even though others are impressed with my ability.	1	2	3	4	5
39. I like to do computer-related things that are hard, new, and different so that I can learn from them.	1	2	3	4	5
40. When I am thinking about computers, I feel like I can become an expert if I just keep at it.	1	2	3	4	5
41. If I fail when I am working with the computer, I usually figure I have exhausted my computer ability at that point.	1	2	3	4	5

PART THREE

Please CIRCLE the number which corresponds to YOUR LEVEL OF AGREEMENT with the following statements.

KEY:
1 = Strongly Disagree SD
2 = Disagree D
3 = Neither Agree or Disagree N
4 = Agree A
5 = Strongly Agree SA

I feel CONFIDENT:

	SD	D	N	A	SA
42. Entering and saving data (numbers or words) in a file.	1	2	3	4	5
43. Calling up a data file to view on the monitor screen.	1	2	3	4	5

PART THREE (con't)

I feel CONFIDENT:

	SD	D	N	A	SA
44. Storing software correctly.	1	2	3	4	5
45. Handling a floppy disk correctly.	1	2	3	4	5
46. Escaping/exiting from a program or software.	1	2	3	4	5
47. Making selections from an on screen menu.	1	2	3	4	5
48. Copying an individual file.	1	2	3	4	5
49. Using the computer to write a letter or essay.	1	2	3	4	5
50. Moving the cursor around the monitor screen.	1	2	3	4	5
51. Working on a personal computer (microcomputer).	1	2	3	4	5
52. Using a printer to make a "hardcopy" of my work.	1	2	3	4	5
53. Getting rid of files when they are no longer needed.	1	2	3	4	5
54. Copying a disk.	1	2	3	4	5
55. Adding and deleting information from a data file.	1	2	3	4	5
56. Getting software up and running.	1	2	3	4	5
57. Organizing and managing files.	1	2	3	4	5
58. Understanding terms/words relating to computer software.	1	2	3	4	5
59. Describing the function of computer hardware (keyboard, monitor, disk drives, computer processing unit).	1	2	3	4	5
60. Troubleshooting computer problems.	1	2	3	4	5
61. Explaining why a program (software) will or will not run on a given computer.	1	2	3	4	5
62. Understanding the three stages of data processing: (input, processing, output.).	1	2	3	4	5
63. Learning to use a variety of programs (software).	1	2	3	4	5
64. Using the computer to analyze number data.	1	2	3	4	5
65. Learning advanced skills within a specific program (software).	1	2	3	4	5
66. Using the computer to organize information.	1	2	3	4	5
67. Writing simple programs for the computer.	1	2	3	4	5
68. Using the user's guide when help is needed.	1	2	3	4	5

PART THREE (con't)

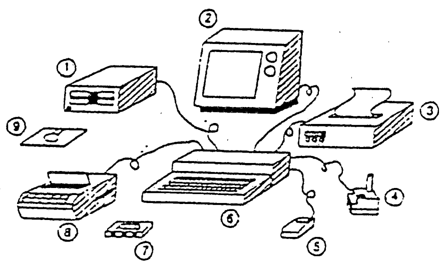
I feel CONFIDENT:

	SD	D	N	A	SA
69. Getting help for problems in the computer system.	1	2	3	4	5
70. Logging onto a mainframe computer system.	1	2	3	4	5
71. Logging off the mainframe computer system.	1	2	3	4	5
72. Working on a mainframe computer.	1	2	3	4	5

PART FOUR

For items 73-78 refer to the pictures below. Each picture has a number. Mark the category to which each example belongs.

Please fill in one box for each question.



73. Which picture shows a keyboard?

picture 1 ☐ picture 2 ☐ picture 3 ☐ picture 6 ☐

74. Which picture shows a disk drive?

picture 1 ☐ picture 2 ☐ picture 8 ☐ picture 9 ☐

75. Which picture shows a joystick?

picture 4 ☐ picture 5 ☐ picture 7 ☐ picture 9 ☐

76. Which picture shows a display screen or video monitor?

picture 1 ☐ picture 2 ☐ picture 3 ☐ picture 6 ☐

77. Which picture shows a floppy disk?

picture 4 ☐ picture 5 ☐ picture 7 ☐ picture 9 ☐

78. Which picture shows a printer?

picture 1 ☐ picture 2 ☐ picture 3 ☐ picture 6 ☐

PART FOUR (con't)

79. What is the main role of a computer program?

- ☐ To put data into the computer
- ☐ To give the computer a memory
- ☐ To tell the computer what to do
- ☐ To let the computer know if it is doing a good job

80. What does a modem do?

- ☐ It stores information in a computer's memory.
- ☐ It copies data from disk to disk.
- ☐ It lets you connect a joystick to a computer.
- ☐ It lets you connect a computer to a telephone line.

81. Which of the following is an input device?

- ☐ A plotter
- ☐ A light pen
- ☐ A dot-matrix printer

82. Which of the following is an output device?

- ☐ A keyboard
- ☐ A light pen
- ☐ A plotter

83. What does a cursor do?

- ☐ It shows the place on the display screen where you are typing.
- ☐ It holds diskettes for storage.
- ☐ It changes the brightness of the display screen.
- ☐ It changes the volume of the computer's speaker.

84. Why is it always important to make backup copies of data storage disks?

- ☐ The data may be needed for use on two different computers at the same time.
- ☐ If one computer does not work, the backup disk can be used on another computer.
- ☐ If the original data disk is damaged or lost, the data will still be available on the backup copy.
- ☐ A computer needs two disks with the same data in order to run a program.

85. Which of the following is NOT true about the historical development of computers?

- ☐ Computing mechanisms have developed from digital to analog.
- ☐ Manufacturers have been able to develop smaller computers that are more easily handled by small businesses.
- ☐ Transistors have replaced tubes as electronic devices in computers.
- ☐ Manufacturers have refined computer production so that computers have become less expensive to produce.

PART FOUR (con't)

86. When was the first general-purpose, electronic digital computer introduced?

- ☐ About the time of the invention of the telegraph.
- ☐ About the time of the invention of the phonograph.
- ☐ About the end of the Second World War.
- ☐ About the time of the launching of the first manned spacecraft.

87. Which of the following was used earliest with computers?

- ☐ Floppy disk
- ☐ Transistor
- ☐ Vacuum tube
- ☐ Integrated circuit

88. Which of the following contributed most to increased use of microcomputers?

- ☐ Cathode-ray tubes
- ☐ Useful software applications
- ☐ Letter-quality printers
- ☐ Hard disks

Questions 89-91 refer to the following table of contents page out of the XYZ operating manual.

XYZ OPERATING SYSTEM

Table of Contents

	Page
I. Introduction: Booting the system	2
II. The disk drives	4
A. Using floppy disks	4
B. Using the hard disk	6
III. Files	8
A. Copying files	8
B. Renaming files	11
C. Erasing files	13
D. Executing files	15
IV. Printing	17

- 1 -

89. In which section are you most likely to find information about "starting-up" the operating system?

- ☐ Section I
- ☐ Section II
- ☐ Section III
- ☐ Section IV

90. In which section are you most likely to find information about running a program?

- ☐ Section I
- ☐ Section II
- ☐ Section III
- ☐ Section IV

91. Which of the following operation is NOT likely to be performed by the XYZ operating system?

- ☐ Section I
- ☐ Section II
- ☐ Section III
- ☐ Section IV

PART FOUR (con't)

Questions 92-100 are examples of either computer hardware or computer software. Mark the category to which each example belongs.

	Hardware	Software
92. Electronic spreadsheet	☐	☐
93. Printer	☐	☐
94. Keyboard	☐	☐
95. Word processing program	☐	☐
96. Video display	☐	☐
97. Disk drive	☐	☐
98. Logo	☐	☐
99. Central processing unit	☐	☐
100. BASIC	☐	☐

101. Robert Jones had always paid his bills on time. However, he was denied a loan at the bank because a computer report indicated that most of his bills had not been paid. Which of the following is the most likely explanation?

- ☐ Robert Jones' memory was wrong about paying his bills.
- ☐ The computer did not work properly.
- ☐ The wrong information was entered into the computer.
- ☐ Robert Jones did not receive his bills in the mail.

102. Suppose a newspaper reporter used a word processing program to write a story. The reporter wrote the first three pages of the story and saved them. The next day the reporter loaded the story into the computer and typed the last page of the story. Then the computer's electrical plug was accidentally kicked out of its socket. Which of the following was probably true when the computer was plugged back in?

- ☐ The entire story was still in the computer.
- ☐ The entire story was lost.
- ☐ Only the last page of the story was lost.
- ☐ Only the first three pages of the story were lost.

103. A computer-equipped recording studio wishes to store information in its computer about the sound intensity of a song that is being recorded. A microphone is connected to a convertor and the converter is connected to the computer. The purpose of the converter is to convert which of the following?

- ☐ Sound waves to electrical waves
- ☐ An analog signal to a digital signal
- ☐ A digital signal to an analog signal
- ☐ A bit stream to coded information

PART FOUR (con't)

104. What is an algorithm?

- ☐ A step-by-step process for solving a given type of problem
- ☐ A word processing program for the computer language ALGOL
- ☐ A special procedure for interpreting computer output
- ☐ A special program for algebra

105. To have your microcomputer communicate with a mainframe computer in another city, you will probably need each of the following EXCEPT

- ☐ an account on the mainframe computer
- ☐ a modem
- ☐ a database program
- ☐ a terminal emulation program

PART FIVE

Please select the response which BEST completes the statements given below by placing the corresponding letter in the blank given.

____ 106. The visual aid that is electronically presented on the CRT screen to mark the location of the next point of input is called a(n):

a. mouse.
b. electronic input indicator.
c. light pen.
d. cursor.

____ 107. When operating a word processor, it is generally true that:

a. many files eventually will be created and stored by the computer.
b. only completely finished documents can be stored or archived.
c. once filed, a document will probably never be retrieved.
d. several documents should be stored using the same file name.

____ 108. When the word processor is in typeover mode:

a. new characters are added to the text as they are typed.
b. new characters take the place of characters already in the text.
c. new characters cannot be added to the text.
d. none of the above are true.

____ 109. Soft carriage returns:

a. are generated automatically by the word-wrap feature.
b. are generated by pressing [Enter] or [Return].
c. are used to indicate the end of the paragraph.
d. are characterized by both b and c.

____ 110. After a block has been marked:

a. the screen colors of the block might be reversed.
b. the characters in the block might have a different intensity.
c. it is automatically removed from the screen.
d. both a and b might occur.

PART FIVE (con't)

____ 111. Headers and footers:

a. have to be typed into each page of the file.
b. are placed in the gutter margins.
c. are placed on each page automatically.
d. have none of the above characteristics.

____ 112. Text that is justified:

a. has a flush-left margin and a ragged-right margin.
b. has flush-left or flush-right margins.
c. may use fixed-width or microspacing to achieve justification.
d. is characterized by both b and c.
e. has all of the above characteristics.

____ 113. To edit a letter, you need to learn:

a. all the features of your word processor.
b. how to move blocks of text.
c. how to search and replace.
d. how to move the cursor, scroll text, and add and delete characters.

____ 114. Spelling checkers are used to:

a. replace all misspelled words in a document.
b. identify words not found in a dictionary.
c. replace words with their synonyms.
d. do both a and b.

____ 115. After loading his new tutorial disk into the computer, James Felty was dismayed to find that no image was displayed on the unit's CRT screen. James should immediately:

a. assume the machine is broken and call a repair technician.
b. demand his money back from the vendor.
c. check the machine's disk drive.
d. unplug the computer before further damage occurs.

____ 116. Programs are actually:

a. hardware.
b. applications.
c. auxiliary equipment.
d. synchronous networks.

____ 117. Spreadsheet graphics create charts from the data in specified:

a. cells.
b. fields.
c. records.
d. ranges.

____ 118. At the intersection of each row and column of a spreadsheet is a:

a. formula
b. label.
c. cell.
d. total.

PART FIVE (con't)

____ 119. George Jones just selected an option from a bar-menu of alternatives. Suddenly another set of choices appeared on the screen. This second set of choices is called a(n):

a. icon.
b. scratch pad.
c. worksheet.
d. pull-down menu.

____ 120. Joyce Davis just selected option 7 from a list of possibilities in order to copy a file. Joyce is probably using a _______ interface.

a. command-driven.
b. graphics-oriented.
c. natural language.
d. menu-driven.

____ 121. When you delete a character from the screen using forward deletion:

a. a blank space remains where the character used to be.
b. the rest of the line shifts left to fill the void.
c. the rest of the line shifts right to fill the void.
d. none of the above happen.

____ 121. Manual search and replace:

a. will make a replacement each time a match is found.
b. asks whether the current match should be replaced or ignored.
c. will, if replacing "his" with "her", change all "history's" to "herstory's".
d. will do both a and c.

____ 123. Being able to answer "what if" questions means that spreadsheets take full advantage of the computer's ability to:

a. store large quantities of data.
b. perform multitasking functions.
c. recalculate based upon different sets of assumptions.
d. transmit data across communication lines.

____ 124. The compiler will detect _______ errors.

a. spelling.
b. grammatical.
c. syntax.
d. tense.

____ 125. Which of these statements about the computer's memory is true?

a. Each complete instruction occupies two memory cells.
b. Each data item occupies two memory cells.
c. Control units fetch the last instruction of a program first.
d. Instructions occupy one area of memory; data reside in another.

PART FIVE (con't)

____ 126. The term "bits per second" is a measure of:

a. speed.
b. length.
c. velocity.
d. capacity.

____ 127. Harvey Tuck works for a large chemical plant located on the Delaware. His specialty is in research methods. Many of his reports to his supervisor must be numerically oriented, and many of his numbers require scientific notation to be expressed. Harvey should strongly consider programming the computer in:

a. COBOL.
b. FORTRAN.
c. PC-DOS.
d. UNIX.

____ 128. A BBS is:

a. an abbreviation for bulletin board system.
b. only available on mainframe computers.
c. also called a public access message system.
d. both a and c.

____ 129. To create a very precise drawing, you would use:

a. a paint graphics editor.
b. a vector graphics editor.
c. a presentation graphics package.
d. none of the above.

____ 130. If a character's font is stored in memory as a bit map, the character:

a. can be scaled to any size.
b. can be rotated to print sideways or at an angle.
c. can be manipulated as in both a and b.
d. cannot be manipulated as in any of the above.

____ 131. When a block is deleted from the document:

a. it is usually thrown away permanently.
b. it is moved into a separate area of memory called a buffer.
c. it is highlighted.
d. it is displayed in reverse video.

____ 132. Advanced Company has promised a computer circuitry breakthrough that will result in faster speeds than previously thought possible. Advanced must now find a way to make circuits:

a. more cheaply.
b. larger.
c. from materials that resist electric current more efficiently.
d. smaller.

PART SIX (con't)

143. Please list the number of computer courses you have had in the following areas (if none, put a "0"):

___ Introductory ___ Applications ___ Programming

PART SEVEN

144. Please indicate your age: _____ years

145. Please indicate your gender (check one): ____ Male ____ Female

146. How many years of formal education have you completed? _____ years.

(Guide: High School Graduate=12; Junior College=14; Four-year College=16 Graduate School=18-20)

You have now completed the survey. Thank you again for your participation.

If you have any comments you would like to make about the survey, please do so in the space below.

APPENDIX B

THESIS STUDY QUESTIONNAIRE

COMPUTER USE SURVEY

The design of effective computer training and development programs may be improved if more is known about current computer use patterns. The attached survey is an effort to learn more about these patterns.

The entire survey is composed of nine parts. Throughout the survey, you will be asked about your experiences with computers and, in some sections, you will be asked how you feel about those experiences.

Each part of the survey has specific instructions, so please be sure to read all of the instructions before you respond to the questions. Please try to answer all of the questions to ensure that a sufficient amount of data is collected.

The survey is to be answered anonymously and all responses will be kept confidential. At no time will your name be reported along with your responses. All data will be reported in group form only.

Your participation in this research is completely voluntary and you are free to withdraw at any time during the study. In addition, you may receive a report of the results at the conclusion of the study.

PART ONE

Shown below is a list of statements describing computer interaction activities. While these statements describe general interaction styles, they do not reflect actual ability.

Please CIRCLE the number which describes how often you engage in these activities.

KEY:

1=Almost never	N
2=Sometimes	S
3=Often	O
4=Most of the time	M
5=All of the time	A

I PREFER TO:	N	S	O	M	A
1. Ask others to help me complete portions of a project when it requires more computer skill than I have.	1	2	3	4	5
2. Go back and improve an existing document after I have learned new computer skills.	1	2	3	4	5
3. Use the computer help function to assist me when problems develop.	1	2	3	4	5
4. Learn new software features only when it saves considerable time.	1	2	3	4	5
5. Use the software manual when I am having difficulties.	1	2	3	4	5
6. Develop new computer skills while working on a project rather than take computer classes.	1	2	3	4	5
7. Learn new software features when I don't have any projects that are due.	1	2	3	4	5
8. Learn new software features just for the sake of learning about a program.	1	2	3	4	5
9. Use the software I know even though the result may be less than ideal.	1	2	3	4	5
10. Learn software commands in a step-by-step manner rather than find out what functions the software performs.	1	2	3	4	5
11. Try out new commands or features rather than use the ones I already know.	1	2	3	4	5
12. Read computer manuals and magazines to develop computer skills.	1	2	3	4	5
13. Use the arrow keys to move around a document.	1	2	3	4	5

PART TWO

Please CIRCLE the number which indicates your LEVEL OF AGREEMENT with the following statements.

KEY:
1=Strongly disagree SD
2=Disagree D
3=Neither agree or disagree N
4=Agree A
5=Strongly agree SA

		SD	D	N	A	SA
14.	I will not even bother to try something with the computer if it looks complicated.	1	2	3	4	5
15.	When I am learning how to use a computer, I am most concerned about developing my ability.	1	2	3	4	5
16.	I like to do fun and easy things with the computer so that I don't have to worry about making mistakes.	1	2	3	4	5
17.	When trying to learn something new about the computer, I soon give up if I am not initially successful.	1	2	3	4	5
18.	When working with a computer, I would rather do things that I already know how to do.	1	2	3	4	5
19.	If I can't do a job with the computer the first time, I keep trying until I can.	1	2	3	4	5
20.	Failure with the computer just makes me try harder.	1	2	3	4	5
21.	I like to work on computer tasks that are fairly easy so that I'll do well.	1	2	3	4	5
22.	When I have difficulty learning how to use the computer, I think about what I am doing as I am learning.	1	2	3	4	5
23.	I have an urge to attempt challenging goals with the computer even when there is a good chance I will fail.	1	2	3	4	5
24.	I usually get bored when a computer task is too easy.	1	2	3	4	5
25.	I avoid facing difficulties with the computer.	1	2	3	4	5
26.	I like to do computer-related things that are hard, new, and different.	1	2	3	4	5
27.	I am not bothered when I experience problems with the computer because I believe I will get better with time.	1	2	3	4	5
28.	I give up learning about the computer easily.	1	2	3	4	5
29.	When I am thinking about computers, I feel like I can become an expert if I just keep at it.	1	2	3	4	5

PART THREE

Please CIRCLE the number which corresponds to your LEVEL OF AGREEMENT with the following statements.

KEY:

1=Strongly disagree	SD
2=Disagree	D
3=Neither agree or disagree	N
4=Agree	A
5=Strongly agree	SA

I FEEL CONFIDENT:

	SD	D	N	A	SA
30. Entering and saving data (numbers or words) in a file.	1	2	3	4	5
31. Calling up a data file to view on the monitor screen.	1	2	3	4	5
32. Storing software correctly.	1	2	3	4	5
33. Handling a floppy disk correctly.	1	2	3	4	5
34. Escaping/existing from a program or software.	1	2	3	4	5
35. Making selections from an on screen menu.	1	2	3	4	5
36. Copying an individual file.	1	2	3	4	5
37. Using the computer to write a letter or essay.	1	2	3	4	5
38. Moving the cursor around the monitor screen.	1	2	3	4	5
39. Working on a personal computer (microcomputer).	1	2	3	4	5
40. Using a printer to make a "hardcopy" of my work.	1	2	3	4	5
41. Getting rid of files when they are no longer needed.	1	2	3	4	5
42. Copying a disk.	1	2	3	4	5
43. Adding and deleting information from a data file.	1	2	3	4	5
44. Getting software up and running.	1	2	3	4	5
45. Organizing and managing files.	1	2	3	4	5
46. Understanding terms/words relating to computer software.	1	2	3	4	5
47. Describing the function of computer hardware (keyboard, monitor, disk drives, etc.)	1	2	3	4	5
48. Trouble shooting computer problems.	1	2	3	4	5
49. Explaining why a program (software) will or will not run on a given computer.	1	2	3	4	5
50. Understanding the three stages of data processing (input, processing, output).	1	2	3	4	5

PART THREE (con't)

KEY: 1=Strongly disagree SD 2=Disagree D 3=Neither agree or disagree N 4=Agree A 5=Strongly agree SA

I FEEL CONFIDENT:	SD	D	N	A	SA
51. Learning to use a variety of programs.	1	2	3	4	5
52. Using the computer to analyze numbers.	1	2	3	4	5
53. Learning advanced skills within a specific program.	1	2	3	4	5
54. Using the computer to organize information.	1	2	3	4	5
55. Writing simple programs for the computer.	1	2	3	4	5
56. Using the user's guide when help is needed.	1	2	3	4	5
57. Getting help for problems in the computer system.	1	2	3	4	5
58. Logging onto a mainframe computer system.	1	2	3	4	5
59. Logging off the mainframe computer system.	1	2	3	4	5
60. Working on a mainframe computer.	1	2	3	4	5

PART FOUR

Please CIRCLE the number which corresponds to how well the statements below DESCRIBE YOU.

KEY:
1=Almost never N
2=Sometimes S
3=Often O
4=Most of the time M
5=All of the time A

	N	S	O	M	A
61. When I learn, I like to deal with my feelings.	1	2	3	4	5
62. I learn best when I listen and watch carefully.	1	2	3	4	5
63. When I am learning, I tend to reason things out.	1	2	3	4	5
64. I learn by doing.	1	2	3	4	5
65. When I learn, I am open to new experiences.	1	2	3	4	5
66. When I am learning, I am an observing person.	1	2	3	4	5
67. I learn best from rational theories.	1	2	3	4	5
68. When I learn, I like to see results from my work.	1	2	3	4	5
69. I learn best when I rely on my feelings.	1	2	3	4	5

***PART FOUR** (con't)*

KEY: 1=Almost never N 2=Sometimes S 3=Often O 4=Most of the time M 5=All of the time A

	N	S	O	M	A
70. When I am learning, I am a reserved person.	1	2	3	4	5
71. When I learn, I evaluate things.	1	2	3	4	5
72. I learn best when I am practical.	1	2	3	4	5
73. When I learn, I like to watch and listen.	1	2	3	4	5
74. I learn best when I rely on logical thinking.	1	2	3	4	5
75. When I am learning, I am responsible about things.	1	2	3	4	5
76. I learn by feeling.	1	2	3	4	5
77. When I learn, I look at all sides of issues.	1	2	3	4	5
78. When I am learning, I am a logical person.	1	2	3	4	5
79. I learn best from a chance to try out and practice.	1	2	3	4	5
80. When I learn, I feel personally involved in things.	1	2	3	4	5
81. I learn best when I rely on my observations.	1	2	3	4	5
82. When I am learning, I am a rational person.	1	2	3	4	5
83. When I learn, I like to be active.	1	2	3	4	5
84. I learn best when I am receptive.	1	2	3	4	5
85. When I learn, I like to think about ideas.	1	2	3	4	5
86. I learn best when I work hard to get things done.	1	2	3	4	5
87. When I am learning, I have strong feelings and reactions.	1	2	3	4	5
88. I learn by watching.	1	2	3	4	5
89. When I learn, I like to analyze things, break them down into parts.	1	2	3	4	5
90. When I am learning, I am an active person.	1	2	3	4	5
91. I learn best from personal relationships.	1	2	3	4	5
92. When I learn, I take my time before acting.	1	2	3	4	5
93. I learn best when I rely on my ideas.	1	2	3	4	5

PART FOUR *(con't)*

KEY: 1=Almost never N 2=Sometimes S 3=Often O 4=Most of the time M 5=All of the time A

		N	S	O	M	A
94.	When I am learning, I am a responsible person.	1	2	3	4	5
95.	When I learn, I get involved.	1	2	3	4	5
96.	I learn best when I am open-minded.	1	2	3	4	5
97.	When I learn, I like to be doing things.	1	2	3	4	5
98.	I learn best when I trust my hunches and feelings.	1	2	3	4	5
99.	When I am learning, I am quiet and reserved.	1	2	3	4	5
100.	I learn by thinking.	1	2	3	4	5
101.	When I learn, I like to try things out.	1	2	3	4	5
102.	When I am learning, I am an intuitive person.	1	2	3	4	5
103.	I learn best from observation.	1	2	3	4	5
104.	When I learn, I like ideas and theories.	1	2	3	4	5
105.	I learn best when I can try things out for myself.	1	2	3	4	5
106.	When I am learning, I am an accepting person.	1	2	3	4	5
107.	When I learn, I like to observe.	1	2	3	4	5
108.	I learn best when I am careful.	1	2	3	4	5

PART FIVE

Please select the response which BEST answers the question by marking the appropriate box.

109. What is the main role of a computer program?
- [ ] to put data into a computer.
- [ ] to give the computer a memory.
- [ ] to tell the computer what to do.
- [ ] to let the computer know if it is doing a good job.

110. What does a modem do?
- [ ] it stores information in a computer's memory.
- [ ] it copies data from disk to disk.
- [ ] it lets you connect a joystick to a computer.
- [ ] it lets you connect a computer to a telephone line.

***PART FIVE** (con't)*

111. Which of the following is an input device?
[ ] a plotter.
[ ] a light pen.
[ ] a dot-matrix printer.

112. Which of the following is an output device?
[ ] a keyboard.
[ ] a light pen.
[ ] a plotter.

113. Which of the following was used earliest with computers?
[ ] floppy disk.
[ ] transistor.
[ ] vacuum tube.
[ ] integrated circuit.

114. Which of the following contributed most to increased use of microcomputers?
[ ] cathode-ray tubes.
[ ] useful software applications.
[ ] letter-quality printers.
[ ] hard disks.

115. Robert Jones had always paid his bills on time. However, he was denied a loan at the bank because a computer report indicated that most of his bills had not been paid. Which of the following is the most likely explanation?
[ ] Robert Jones' memory was wrong about paying his bills.
[ ] The computer did not work properly.
[ ] The wrong information was entered into the computer.
[ ] Robert Jones did not receive his bills in the mail.

116. What is an algorithm?
[ ] a step-by-step process for solving a given type of problem.
[ ] a word processing program for the computer language ALGOL.
[ ] a special procedure for interpreting computer output.
[ ] a special program for algebra.

117. To have your microcomputer communicate with a mainframe computer in another city, you will probably need each of the following EXCEPT:
[ ] an account on the mainframe computer.
[ ] a modem.
[ ] a database program.
[ ] a terminal emulation program.

118. The visual aid that is electronically presented on the CRT screen to mark the location of the next point of input is called a(n):
[ ] mouse.
[ ] electronic input indicator.
[ ] light pen.
[ ] cursor.

***PART FIVE** (con't)*

119. Headers and footers:
   [ ] have to be typed into each page of the file.
   [ ] are placed in the gutter margins.
   [ ] are placed on each page automatically.
   [ ] have none of the above characteristics.

120. To edit a letter, you need to learn:
   [ ] all the features of your word processor.
   [ ] how to move blocks of text.
   [ ] how to search and replace.
   [ ] how to move the cursor, scroll test, and add and delete characters.

121. After loading his new tutorial disk into the computer, James Felty was dismayed to find that no image was displayed on the unit's CRT screen. James should immediately:
   [ ] assume the machine is broken and call a repair technician.
   [ ] demand his money back from the vendor.
   [ ] check the machine's disk drive.
   [ ] unplug the computer before further damage occurs.

122. Programs are actually:
   [ ] hardware.
   [ ] applications.
   [ ] auxiliary equipment.
   [ ] synchronous networks.

123. George Jones just selected an option from a bar-menu of alternatives. Suddenly another set of choices appeared on the screen. This second set of choices is called a(n):
   [ ] icon.
   [ ] scratch pad.
   [ ] worksheet.
   [ ] pull-down menu.

124. Joyce Davis just selected option 7 from a list of possibilities in order to copy a file. Joyce is probably using a _____ interface.
   [ ] command-driven.
   [ ] graphics-oriented.
   [ ] natural language.
   [ ] menu-driven.

125. Manual search and replace:
   [ ] will make a replacement each time a match is found.
   [ ] asks whether the current match should be replaced or ignored.
   [ ] will, if replacing "his" with "her", change all "history's" to "herstory's".
   [ ] will do both a and c.

126. Being able to answer "what if" questions means that spreadsheets take full advantage of the computer's ability to:
   [ ] store large quantities of data.
   [ ] perform multitasking functions.
   [ ] recalculate based upon different sets of assumptions.
   [ ] transmit data across communication lines.

PART FIVE (con't)

127. The compiler will detect _____ errors.
   - [ ] spelling
   - [ ] grammatical
   - [ ] syntax
   - [ ] tense

128. Which of these statements about the computer's memory is true?
   - [ ] each complete instruction occupies two memory cells.
   - [ ] each data item occupies two memory cells.
   - [ ] control units fetch the last instruction of a program first.
   - [ ] instructions occupy one area of memory; data reside in another.

129. Harvey Tuck works for a large chemical plant located on the Delaware. His specialty is in research methods. Many of his reports to his supervisor must be numerically oriented, and many of his numbers require scientific notation to be expressed. Harvey should strongly consider programming the computer in:
   - [ ] COBOL.
   - [ ] FORTRAN.
   - [ ] PC-DOS.
   - [ ] UNIX.

130. When a block is deleted from the document:
   - [ ] it is usually thrown away permanently.
   - [ ] it is moved into a separate area of memory called a buffer.
   - [ ] it is highlighted.
   - [ ] it is displayed in reverse video.

131. Firmware is best defined as:
   - [ ] a software that has undergone complete debugging and testing.
   - [ ] ROM computer circuits functioning under programmed instructions.
   - [ ] hardware that has been tested to meet laboratory specifications.
   - [ ] integrated circuits controlled by an arithmetic logic unit.

132. The term "bits per second" is a measure of:
   - [ ] speed.
   - [ ] length.
   - [ ] velocity.
   - [ ] capacity.

PART SIX

Please CIRCLE the number that best matches your LEVEL OF AGREEMENT with how each adjective characterizes you when you interact with microcomputers.

		Strongly Disagree			Neutral			Strongly Agree
133.	Spontaneous	1	2	3	4	5	6	7
134.	Unimaginative	1	2	3	4	5	6	7
135.	Flexible	1	2	3	4	5	6	7
136.	Creative	1	2	3	4	5	6	7
137.	Playful	1	2	3	4	5	6	7
138.	Unoriginal	1	2	3	4	5	6	7
139.	Uninventive	1	2	3	4	5	6	7

PART SEVEN

The following statements describe a person's behavior with respect to the usage of time. Please CIRCLE the number which corresponds to your LEVEL OF AGREEMENT with the way the statement characterizes you.

KEY:
1=Strongly Disagree SD
2=Disagree D
3=Neutral N
4=Agree A
5=Strongly Agree SA

		SD	D	N	A	SA
140.	I am slow doing things.	1	2	3	4	5
141.	I often feel pressed for time.	1	2	3	4	5
142.	I like work that is slow and deliberate.	1	2	3	4	5
143.	I go "all out".	1	2	3	4	5
144.	I have a strong need to excel in most things.	1	2	3	4	5
145.	I am bossy or dominating.	1	2	3	4	5
146.	I am usually pressed for time.	1	2	3	4	5
147.	I am more restless and fidgeting than most people.	1	2	3	4	5
148.	I never feel in a rush, even under pressure.	1	2	3	4	5
149.	I am hard driving.	1	2	3	4	5
150.	I find myself hurrying to get to places even when there is plenty of time.	1	2	3	4	5
151.	I often work slowly and leisurely.	1	2	3	4	5
152.	I set deadlines or quotas for myself at work and other things.	1	2	3	4	5
153.	I am hard driving and competitive.	1	2	3	4	5
154.	People who know me well agree that I tend to do most things in a hurry.	1	2	3	4	5
155.	I am ambitious.	1	2	3	4	5
156.	My spouse or a close friend would rate me as definitely relaxed and easygoing.	1	2	3	4	5
157.	I usually work fast.	1	2	3	4	5
158.	Nowadays, I consider myself to be definitely relaxed and easygoing.	1	2	3	4	5
159.	I am often in a hurry.	1	2	3	4	5
160.	I ordinarily work quickly and energetically.	1	2	3	4	5

PART EIGHT

161. Do you currently own a computer? ____ Yes ____ No

162. If "No", do you have access to a computer? ____ Yes ____ No

163. Do you use computers at work? ____ Yes ____ No

164. Please list the number of computer courses you have had in the following areas: (if none, put a "0")

Introductory _____ Applications _____ Programming _____

165. How many years of experience do you have for the following types of computers: (if less than one year, put a "1"; if none, put a "0")

Mainframe _____ Miniframe _____ Microcomputer (PC) _____

The next few questions ask you to approximate the number of hours and the percentage of time you spend using various types of computer programs at work. The combination of these items will help us understand computer use patterns more precisely.

166. About how many hours do you work per week? _______ hours (average week)

167. About how many hours per week do you use the computer at work?

_______ hours

KEY: WP=Wordprocessing SP=Spreadsheet DB=Database GR=Graphics COM=Communications OT=other ______________________________________ (please specify)

	WP	SP	DB	GR	COM	OT
168. What approximate percentage of your total computer time is spent using:	___	___	___	___	___	___
169. About how many hours does the above percentage represent? (Use #167 _____ as a guide)	___	___	___	___	___	___

170. About how many hours per week do you use the computer at home for nonwork purposes?

_______ hours

PART NINE

170. Please indicate your age: ____ years

171. Please indicate your gender: ____ Male ____ Female

172. How many years of formal education have you completed? (high school graduate=12; junior college=14; 4-year college=16; graduate school=18-20) ______ years

173. What is your employee status? _____ Hourly _____ Nonexempt _____ Exempt

174. Please either indicate your job title or describe the type of work you do:

____

You have now completed the survey. Thank you for your participation.

APPENDIX C

COMPUTER KNOWLEDGE CONTENT AREAS

Content Area	Pilot Study Items	Average Difficulty	Thesis Study Items[a]	Average Difficulty
System Components/ Interacting with DOS	73-84, 89-99, 101, 105, 115, 116, 119, 120, 124, 125, 126, 132	.72	79(109) 105(117) 120(124) 124(127) 125(128)	.65
Applications	100, 102, 104, 106-114, 117, 118, 121-123, 127-131, 133-135	.44	104(116) 111(119) 113(120) 121(125) 123(126) 131(130)	.68
History of Computer Hardware	103	.21		

APPENDIX C--Continued

Content Area	Pilot Study Items	Average Difficulty	Thesis Study Items[a]	Average Difficulty
Usefulness of Computers	85-88	.38	87-88(113-114)	.58
Total	63	.58	13	.65

[a]Parenthetic item numbers coincide with numbering in Thesis Survey.

APPENDIX D

INFORMED CONSENT

ORAL INFORMED CONSENT FORM

The study in which you are about to participate is designed to investigate current patterns of computer use. This study is being conducted by Silvia Swigert under the direction of Dr. Janet L. Kottke, professor of Psychology. This study has been approved by the Psychology Department Human Subject Review Board, California State University, San Bernardino.

In this study, you will be asked to answer approximately 146 questions. It is estimated that the survey will take about twenty minutes to complete. The survey is to be completed anonymously, so please do not put any form of identification on the survey.

Please be assured that any information you provide will be held in strict confidence by the researcher. At no time will your name be reported along with your responses. All data will be reported in group form only. At the conclusion of this study, you may receive a report of the results.

Please understand that your participation in this research is totally voluntary and you are free to withdraw and/or remove data at any time during this study without penalty.

APPENDIX E

DEBRIEFING STATEMENT

DEBRIEFING STATEMENT

The primary purpose of this study was to investigate potential motivational and predispositional determinants of computer skill acquisition. These potential determinants include computer interaction patterns, computer achievement motivation, computer self-efficacy, learning style, time urgency, and microcomputer playfulness.

If you have any questions about the survey, please contact Dr. Janet L. Kottke, Department of Psychology, California State University, San Bernardino, at (909) 880-5585. A report of the general results will also be provided by Dr. Kottke upon request after it becomes available during the next three to four weeks.

In the meantime, it would be appreciated if you would not reveal the nature of this study to other potential subjects.

Thank you for participating in the survey.

APPENDIX F

REVISED COMPUTER INTERACTION ITEMS FROM THE PILOT STUDY

Item	Old Content	New Content[a]
Q2	Use the arrow to move around a document when I am pressed for time.	Use the arrow keys to move around a document (Q13).
Q7	Learn new computer features while working only when it saves considerable time.	Learn new skills only when it saves considerable time (Q4).

APPENDIX F--Continued

Item	Old Content	New Content[a]
Q10	Use the software I know even though the result might be less than perfect (e.g., using a wordprocessing package to make a graph).	Use the software I know even though the result may be less than ideal (Q9).
Q14	Ask peers or coworkers to complete portions of a project which require more computer skill than I have.	Ask others to help me complete portions of a project when it requires more computer skill than I have (Q1).

APPENDIX F--Continued

Item	Old Content	New Content[a]
Q15	Use a step-by-step approach rather than find out about what keys perform which functions.	Learn software commands in a step-by-step manner rather than find out what functions the software performs (Q10).
Q16	Develop computer skills when I need them rather than take computer classes.	Develop computer skills when working on a project rather than take computer classes (Q6).
Q9	Learn how to use the computer when I don’t have any projectes that are due.	Learn new software features when I don’t have any projects that are due (Q7).

APPENDIX F--Continued

Item	Old Content	New Content[a]
Q11	Use a manual to get myself out of a jam.	Use the software manual when I am having difficulties with the software (Q5).
Q17	Go back and change a document after I have learned new skills.	Go back and improve an existing document after I have learned new computer skills (Q2).
Q20	Use the computer help features to get me out of a jam.	Use the computer help function to assist me when problems develop Q3).

[a] New item numbers appear in parentheses.

APPENDIX G

STANDARD ERROR FOR THE POINT BISERIAL CORRELATION

$$\sigma_P = 1 \div \sqrt{N-1}$$

APPENDIX H

DEFACTO HOURLY BASE RATE FOR INTENSITY OF USE IN THE PILOT STUDY

1. Divide percent in Item 142 by 100

Example: 5% ÷ 100% = 20

2. Multiply the result by the number of hours in Item 138

Example: 20 X 20 hours = 400 hours

APPENDIX I

SCALE ITEMS FOR KOLB'S (1985) LEARNING-STYLE INVENTORY

Prehension: Concrete Experience (CE)

1) When I learn, I like to deal with my feelings. (61)

2) When I learn, I am open to new experiences. (65)

3) I learn best when I rely on my feelings. (69)

4) I learn by feeling. (76)

5) When I learn, I feel personally involved in things. (80)

6) I learn best when I am receptive. (84)

7) When I am learning, I have strong feelings and reactions. (87)

8) I learn best from personal relationships. (91)

9) When I learn, I get involved. (95)

10) I learn best when I trust my hunches and feelings (98).

11) When I am learning, I am an intuitive person. (102)

12) When I am learning, I am an accepting person. (106)

Prehension: Reflective Observation (RO)

1) I learn best when I listen and watch carefully. (62)

APPENDIX I--Continued

Reflective Observation (RO) (Con't)

2) When I am learning, I am an observing person. (66)

3) When I am learning, I am a reserved person. (70)

4) When I learn, I like to watch and listen. (73)

5) When I learn, I look at all sides of issues. (77)

6) I learn best when I rely on my observations. (81)

7) I learn by watching. (88)

8) When I learn, I take my time before acting. (92)

9) I learn best when I am open-minded. (96)

10) When I am learning, I am quiet and reserved. (99)

11) I learn best from observation. (103)

12) When I learn, I like to observe. (107)

Transformation: Abstract Conceptualization (AC)

1) When I am learning, I tend to reason things out. (63)

2) I learn best from rational theories. (67)

3) When I learn, I evaluate things. (71)

4) I learn best when I rely on logical thinking. (74)

5) When I am learning, I am a logical person. (78)

6) When I am learning, I am a rational person. (82)

APPENDIX I--Continued

Abstract Conceptualization (AC) (Con't)

7) When I learn, I like to think about ideas. (85)

8) When I learn, I like to analyze things, break them down into parts. (89)

9) I learn best when I rely on my ideas. (93)

10) I learn by thinking. (100)

11) When I learn, I like ideas and theories. (104)

12) I learn best when I am careful. (108)

Transformation: Active Experimentation (AE)

1) I learn by doing. (64)

2) When I learn, I like to see results from my work. (68)

3) I learn best when I am practical. (72)

4) When I am learning, I am responsible about things. (75)

5) I learn best from a chance to try out and practice. (79)

6) When I learn, I like to be active. (83)

7) I learn best when I work hard to get things done. (86)

APPENDIX I--Continued

Active Experimentation (AE) (Con't)

8) When I am learning, I am an active person. (90)

9) When I am learning, I am a responsible person. (94)

10) When I learn, I like to be doing things. (97)

11) When I learn, I like to try things out. (101)

12) Learn best when I can try things out for myself. (105)

[a]Scale items are listed in the order in which they appear in the survey; the numbers in parentheses correspond to the actual survey number.

REFERENCES

Aiken, L. S., and West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Newbury Park, CA: Sage Publications.

Anderson, R. L., and Ortinau, D. J. (1988). Exploring consumer's postadoption attitudes and use behaviors in monitoring the diffusion of a technology-based discontinuous innovation. Journal of Business Research, 17, 283-298.

Arthur, W. Jr., and Olson, E. (1991). Computer attitudes, computer experience, and their correlates: An investigation of path linkages. Teaching of Psychology, 18(1), 51-54.

Bandura, A. (1986). Social foundations of thought and action-A social cognitive theory. Englewood Cliffs, NJ: Prentice- Hall.

Blissmer, R. H. (1990). Test bank to accompany Introducing Computers: Concepts, systems, and applications (1990-1991 ed.). New York, NY: John Wiley & Sons.

Bostrom, R. P., Olfman, L., and Sein, M. K. (1990). The importance of learning style in end-user training. MIS Quarterly, 14(1), 101-118.

Bostrom, R. P., Olfman, L., and Sein, M. K. (1993). Learning styles and end-user training: A first step. MIS Quarterly, 17(1), 118-120.

Briggs, P. (1987). Usability assessment for the office: Methodological choices and their implications. In M. Frese, E. Ulich, and W. Dzida (Eds.) Psychological issues of human-computer interaction in the work place. North-Holland: Elsevier Science Publishers B. V.

Crocker, L., and Algina, J. (1986). Introduction to classical and modern test theory. Fort Worth, TX: Harcourt Brace Jovanovich College Publishers.

Dutke, S., and Schonpflug, W. (1987). When the introductory period is over: Learning while doing one's job. In M. Frese, E. Ulich, and W. Dzida (Eds.) Psychological issues of human-computer interaction in the work place. North-Holland: Elsevier Science Publishers B. V.

Dweck, C. S. (1986). Motivational processes affecting learning. American Psychologist, 41(10), 1040-1048.

Dweck, C. S., and Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. Psychological Review, 95(2), 256-273.

Eason, K. D. (1984). Towards the experimental study of usability. Behaviour & Information Technology, 3, 133-143.

Elliott, E. S., and Dweck, C. S. (1988). Goals: An approach to motivation and achievement. Journal of Personality and Social Psychology, 54(1), 5-12.

Fisher, J. (1991). Defining the novice user. Behaviour & Information Technology, 10(5), 437-441.

Francis, B., and McMullen, J. (1989). New demands on PC support. Datamation, 35(21), 101-102.

Gattiker, U. E. (1992). Computer skill acquisition: A review and future directions for research. Journal of Management, 18(3), 547-574.

Geiger, M. A., Boyle, E. J., and Pinto, J. K. (1993). An examination of ipsative and normative versions of Kolb's revised Learning Style Inventory. Educational and Psychological Measurement, 53(3), 717-726.

Gist, M. E., and Mitchell, T. R. (1992). Self-efficacy: A theoretical analysis of its determinants and malleability. Academy of Management Review, 17(2), 183-211.

Gist, M. E., Schwoerer, C., and Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. Journal of Applied Psychology, 74(6), 884-891.

Gist, M. E. (1987). Self-efficacy: Implications for organizational behavior and human resource management. Academy of Management Review, 12(3), 472-485.

Harrison, A. W., and Ranier, R. K., Jr. (1992). An examination of the factor structures and concurrent validities for the computer attitude scale, the computer anxiety rating scale, and the computer self-efficacy scale. Educational and Psychological Measurement, 52(3), 735-745.

Hayen, R. L., Cooke, W. C., and Jecker, G. H. (1990). End user training in office automation: Matching expectations. Journal of Systems Management, 41(3), 7-12.

Hill, T., Smith, N. D., and Mann, M. F. (1987). Role of efficacy expectations in predicting the decision to use advanced technologies: The case of computers. Journal of Applied Psychology, 72(2), 307-313.

Howard, G. S., and Mendelow, A. L. (1991). Discretionary use of computers: An emprically derived explanatory model. Decision Sciences Journal, 22(2), 241-265.

Hudak, M. A., and Anderson, D. E. (1990). Formal operations and learning style predict success in statistics and computer science courses. Teaching of Psychology, 17(4), 231-234.

Jagacinski, C. M., and Nicholls, J. G. (1987). Competence and affect in task involvement and ego involvement: The impact of social comparison information. Journal of Educational Psychology, 79(2), 107-114.

Jagacinksi, C. M., LeBold, W. K., and Salvendy, G. (1988). Gender differences in persistence in computer-related fields. Journal of Educational Computing Research, 4(2), 185-202.

Keefe, J. W. (1987). Learning style: Theory and practice. Reston, VA: National Association of Secondary School Principals.

Kemery, E. R., and Dunlap, W. P. (1986). Partialling factor scores does not control method variance: A reply to Podsakoff and Todor. Journal of Management, 12(4), 525-530.

Kolb, D. A. (1985). Learning-Style Inventory. Boston: McBer and Company.

Kolb, D. A. (1985). Learning-Style Inventory: Technical specifications. Boston: McBer and Company.

Landy, F. J., Rastegary, H., Thayer, J., and Colvin, C. (1991). Time urgency: The construct and its measurement. Journal of Applied Psychology, 76(5), 644-657.

Mandell, S. L. (1988). Principles of information processing, (4th ed.). St. Paul, MN: West Coast Publishing Company.

Martocchio, J. J., and Webster, J. (1992). Effects of feedback and cognitive playfulness on performance in microcomputer software training. Personnel Psychology, 45(3), 553-578.

Massoud, S. L. (1991). Computer attitudes and computer knowledge of adult students. Journal of Educational Computing Research, 7(3), 269-291.

McQuarrie, E. F. (1989). The impact of discontinuous innovation: Outcomes experienced by owners of home computers. Computers in Human Behaviour, 5(4), 227-240.

Miura, I. T. (1987). The relationship of computer self-efficacy expectations to computer interest and course enrollment in college. Sex Roles, 16(5-6), 303-311.

Murphy, C. A., Coover, D., and Owen, S. V. (1989). Development and validation of the computer self-efficacy scale. Educational and Psychological Measurement, 49(4), 893-899.

Nelson, R. R. (1991). Educational needs as perceived by IS and end-user personnel: A survey of knowledge and skill requirements. MIS Quarterly, 15(4), 503-511.

O'Shea, K., and Muralidhar, K. (1990). The function and management of information centers. Journal of Systems Management, 41(12), 7-9.

Panko, R. R. (1988). End user computing: Management, applications, and technology. New York: John Wiley & Sons, Inc.

Podsakoff, P. M., and Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of Management, 12(4), 531-544.

Prumper, J., Zapf, D., Brodbeck, F. C., and Frese, M. (1992). Some surprising differences between novice and expert errors in computerized office work. Behaviour & Information Technology, 11(6), 319-328.

Santhanam, R., and Wiedenbeck, S. (1993). Neither novice nor expert: The discretionary user of software. International Journal of Man-Machine Studies, 38(2), 201-229.

Schmitt, N. W., and Klimoski, R. J. (1991). Research methods in human resources management. Cincinnati, OH: South-Western Publishing Co.

Sein, M. K., and Robey, D. (1991). Learning style and the efficacy of computer training methods. Perceptual and Motor Skills, 72(1), 243-248.

Sherer, M., Maddux, J. E., Mercandante, B., Prentice-Dunn, S., Jacobs, B., and Rogers, R. W. (1982). The Self-Efficacy Scale: construction and validation. Psychological Reports, 51, 663-671.

Stipek, D. J. (1993). Motivation to learn, (2nd ed.). Needham Heights, MA: Allyn and Bacon, a division of Simon & Schuster, Inc.

Thompson, R. L., Higgins, C. A., and Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS Quarterly, 15(1), 125-141.

Webster, J., and Martocchio, J. J. (1992). Microcomputer playfulness: Development of a measure with workplace implications. MIS Quarterly, 16(2), 201-226.

Woodruff, S. L., and Cashman, J. F. (1993). Task, domain, and general efficacy: A reexamination of the self-efficacy scale. Psychological Reports, 72, 423-432.

Yaverbaum, G. J., and Culpan, O. (1990). Exploring the dynamics of the end-user environment: The impact of education and task differences on change. Human Relations, 43(5), 439-454.