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RESEARCH NOTE

Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study[1]

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Abstract

A model, based on Bandura's Social Cognitive Theory, was developed to test the influence of computer self-efficacy, outcome expectations, affect, and anxiety on computer usage. The model was tested using longitudinal data gathered from 394 end users over a one-year interval. Significant relationships were found between computer self-efficacy and outcome expectations, and between self-efficacy and affect and anxiety and use. Performance outcomes were found to influence affect and use, while affect was significantly related to use. Overall, the findings provide strong confirmation that both self-efficacy and outcome expectations impact on an individual's affective and behavioral reactions to information technology.

Keywords: IS usage, self-efficacy, causal models, longitudinal

ISRL Categories: AP, GB02, GB03

Introduction

The study of individual reactions to computing technology has been an important topic in recent information systems research. Many authors have studied different aspects of the phenomenon, from a variety of theoretical perspectives, including Diffusion of Innovations (DOI) (e.g., Compeau and Meister 1997; Moore and Benbasat 1991), the Technology Acceptance Model (TAM) (e.g., Davis et al. 1989; Venkatesh and Davis 1996), the Theory of Planned Behavior (TPB) (e.g., Mathieson 1991; Taylor and Todd, 1995), and Social Cognitive Theory (SCT) (e.g., Compeau and Higgins 1995a, 1995b; Hill et al. 1986, 1987). This research has produced useful insights into the cognitive, affective, and behavioral reactions of individuals to technology, and into the factors which influence these reactions.

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In each of the theories noted above, behavior (e.g., the use of computers) is viewed as the result of a set of beliefs about technology and a set of affective responses to the behavior. The beliefs are represented by the perceived characteristics of innovating in innovation diffusion research, by perceived usefulness and perceived ease of use in TAM, by behavioral beliefs and outcome evaluations in TPB, and by outcome expectations in SCT. They have been referred to as the net benefits (realized or expected) accruing from use of the system (Seddon 1997). Affective responses are typically measured by attitudes toward use, an individual's evaluation of the behavior as either positive or negative. These commonalities in the models reflect a belief in the cognitive basis of behavior.

However, while the TAM and DOI perspectives focus almost exclusively on beliefs about the technology and the outcomes of using it, SCT and TPB include other beliefs that might influence behavior, independent of perceived outcomes. The TPB model incorporates the notion of perceived behavioral control as an independent influence on behavior, recognizing that there are circumstances in which a behavior might be expected to result in positive consequences (or net benefits), yet not be undertaken due to a perceived lack of ability to control the execution of the behavior. Perceived behavioral control encompasses perceptions of resource and technology facilitating conditions, similar to those measured by Thompson et al. (1991), as well as perceptions of ability, or self-efficacy (Taylor and Todd 1995). SCT gives prominence to the concept of self-efficacy—defined as beliefs about one's ability to perform a specific behavior—recognizing that our expectations of positive outcomes of a behavior will be meaningless if we doubt our capability to successfully execute the behavior in the first place. IS research has demonstrated a strong link between self-efficacy and individual reactions to computing technology, both in terms of adoption and use of computers (Compeau and Higgins 1995b; Hill et al. 1986, 1987; Taylor and Todd 1995), and in terms of learning to use computers and computer software (Compeau and Higgins 1995a; Gist et al. 1989; Webster and Martocchio 1993). Our beliefs about our capabilities to use technology successfully are related to our decisions about whether and how much to use technology, and the degree to which we are able to learn from training.

The addition of perceived behavioral control and self-efficacy beliefs to our models of individual adoption and use of technology is critical to the recognition that adoption is not just about convincing people of the benefits to be derived from a technology (selling the technology). It must also be about coaching, teaching, and encouraging individuals to ensure that they have the requisite skills and confidence in their skills to be successful in their use.

A second difference between the theories of individual adoption and use is also relevant for this study: the differences in their causal structures. Most of the perspectives (TAM, TPB, DOI) view the causal relationships as essentially unidirectional, with the environment influencing cognitive beliefs, which influence attitudes and behaviors. SCT, in contrast, explicitly acknowledges the existence of a continuous reciprocal interaction between the environment in which an individual operates, his or her cognitive perceptions (self-efficacy and outcome expectations), and behavior (Bandura 1986). Thus, self-efficacy is viewed in SCT as an antecedent to use, but successful interactions with technology (e.g., enactive mastery) are also viewed as influences on self-efficacy. The same is true for emotional responses, such as affect and anxiety, which are both influenced by self-efficacy and also sources of information on which self-efficacy judgments are based. Thus, an individual judgment of self-efficacy, measured at one point in time, can be viewed as both a *cause* and an *effect.*

The implication of this difference in causal sequencing is twofold. First, it allows for a richer understanding of how capability and confidence develop over time. Recognizing the potential for positive and negative spirals of self-efficacy and usage (Lindsley et al. 1995) that result from the reciprocal interactions is an important step to being able to successfully manage the development process. Of more immediate and pragmatic concern for this study is the fact that the reciprocal nature of the relationships between self-efficacy and outcome expectations, and affect, anxiety, and usage, makes drawing causal conclusions more difficult. In any research, without longitudinal separation of hypothesized causes from effects, it is difficult to draw conclusions about the causal implications of the relationships observed (Vitalari 1991). Given the reciprocal relationships posed by Social Cognitive Theory, this problem is magnified.

Thus, the current study tests a model of individual reactions to computing technology in a longitudinal context. This allows us to make stronger causal arguments regarding the observed relationships, even given the complex theoretical context from which the model is derived. Moreover, studying the effects of self-efficacy and outcome expectations over time allows us to understand whether their influences are relatively short in duration or whether they are more enduring. This evidence will help in building programs (training, support, etc.) and managing implementation based on these factors.

Research Model and Hypotheses

The research model used to guide the study is shown in Figure 1. This model is a subset of the one first tested by Compeau and Higgins (1995b). The model identifies the linkages between cognitive factors (self-efficacy, performance-related outcome expectations, and personal outcome expectations), affective factors (affect and anxiety), and usage.

The constructs are defined as follows. Self-efficacy reflects an individual's beliefs about his or her capabilities to use computers. Outcome expectations, defined as the perceived likely consequences of using computers, has two dimensions. Performance-related outcomes are those associated with improvements in job performance (efficiency and effectiveness) associated with using computers. Personal outcome expectations

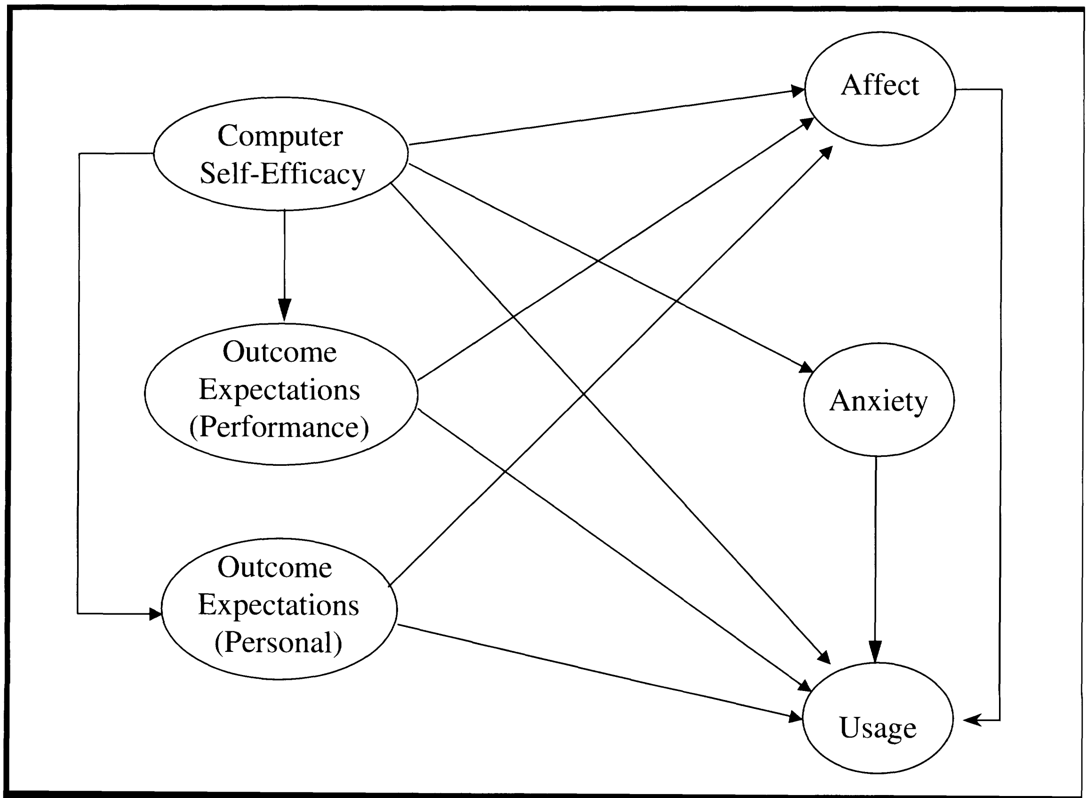

Figure 1. Research Model

relate to expectations of change in image or status or to expectations of rewards, such as promotions, raises, or praise. Affect and anxiety represent the affective responses of individuals toward using computers. Affect represents the positive side—the enjoyment a person derives from using computers—while anxiety represents the negative side—the feelings of apprehension or anxiety that one experiences when using computers. Use represents the degree of use of computers at work and at home.

The hypotheses tested are those originally proposed by Compeau and Higgins (1995b). These are outlined in Table 1. According to the model, self-efficacy influences both personal and performance-related outcome expectations (H1 and H2), since it is often difficult for individuals to separate the anticipated consequences of the behavior from their expectations of performance attainments (Bandura 1986). That is, if I believe I will be able to use a computer with great skill, I am more likely to expect positive outcomes from

Table 1. Hypotheses to be Tested

	Hypothesis	Supporting References
H1.	The higher the individual's computer self-efficacy, the higher his/her performance-related outcome expectations.	Bandura et al. 1977; Betz and Hackett 1981; Compeau and Higgins 1995b; Stumpf et al. 1987
H2.	The higher the individual's computer self-efficacy, the higher his/her personal outcome expectations.	Bandura et al. 1977; Betz and Hackett 1981; Compeau and Higgins 1995b; Stumpf et al. 1987
H3.	The higher the individual's computer self-efficacy, the higher his/her affect (or liking) of computer use.	Bandura et al. 1977; Betz and Hackett 1981; Compeau and Higgins 1995b; Stumpf et al. 1987
H4.	The higher the individual's computer self-efficacy, the lower his/her computer anxiety.	Betz and Hackett 1981; Bandura et al. 1977; Compeau and Higgins 1995b; Stumpf et al. 1987
H5.	The higher the individual's computer self-efficacy, the higher his/her use of computers.	Burkhardt and Brass 1990; Compeau and Higgins 1995a; Hill et al. 1987
H6.	The higher the individual's performance-related outcome expectations, the higher his/her affect (or liking) for the behavior.	Bandura 1986
H7.	The higher the individual's personal outcome expectations, the higher his/her affect (or liking) for the behavior.	Bandura 1986
H8.	The higher the individual's performance-related outcome expectations, the higher his/her use of computers.	Compeau and Higgins 1995b; Davis et al. 1989; Hill et al. 1987; Thompson et al. 1991
H9.	The higher the individual's personal outcome expectations, the higher his/her use of computers.	Compeau and Higgins 1995b; Davis et al. 1989; Hill et al. 1987; Thompson et al. 1991
H10.	The higher the individual's affect for computer use, the higher his/her use of computers.	Bandura 1986; Compeau and Higgins 1995b; Engle et al. 1986
H11.	The higher the individual's computer anxiety, the lower his/her use of computers.	Compeau and Higgins 1995b; Igbaria et al. 1989; Webster et al. 1990

my computer use than if I doubt my capabilities. Similarly, I am more likely to derive enjoyment (H3) and less likely to experience anxiety (H4) from activities that I feel confident in performing, since feelings of confidence influence emotional responses.

Outcome expectations (professional and personal) are expected to influence affect (H6 and H7) and usage (H8 and H9). Such effects are central to both Social Cognitive Theory and to other theories of individual adoption. Finally, affect and anxiety are each expected to influence usage (H10 and H11), since individuals will tend seek out activities they enjoy and avoid those that are anxiety producing.

To establish the temporal sequencing of the model as presented in Figure 1, self-efficacy and outcome expectations are measured at one point in time while affect, anxiety, and usage are measured one year later.

It should be noted that the decision to focus on self-efficacy and outcome expectations as independent and affect anxiety and usage as dependent variables does not mean that the reverse paths (e.g., usage to self-efficacy) are not of interest. We have chosen to focus on these relationships as a first step. Once the role of self-efficacy and outcome expectations has been established, the factors that influence the formation of these variables can be examined. This work, however, is beyond the scope of the current study.

Methodology

Procedures

Pretest and pilot studies of the survey instrument were conducted prior to the initial data collection phase and are reported elsewhere (Compeau and Higgins 1995b). The survey design and data collection procedures were those recommended by Dillman (1978).

Data were collected at two points in time. The first survey was sent to 2,000 randomly selected subscribers to a Canadian business periodical. The response rate was 53.4%. One year later, the same survey was sent to those who responded to the first survey. The response rate for the second survey was 67%.

Respondents were identified in both phases of the research by a unique number and matched across time periods.[2] The final sample consisted of 394 matched responses. A summary of the demographic characteristics is shown in Table 2.

In order to assess non-response bias in the second survey, a comparison of demographics reported in the time 1 survey for time 2 respondents and non-respondents was undertaken. The comparisons revealed no significant differences for functional area and organizational level, but significant differences for gender ($p < .035$), age ($p < .04$), educational level ($p \leq .003$), and educational background ($p < .02$). Women made up 16% of the first survey and 14% of the second survey. The respondents to the second survey were slightly younger, had attained higher educational levels,[3] and were slightly more concentrated in business and science than the respondents to the first survey. The differences are small (2% to 3% changes at most), and the responses give no indication of why they occurred; it may represent nothing more than random fluctuation. Nevertheless, it does imply a degree of non-response bias in the second survey.

Measures

Time 1

Computer self-efficacy was measured by the 10-item instrument developed by Compeau and Higgins (1995b). Outcome expectations were measured by 11 items developed by Compeau and Higgins (1995b). Six items relate to performance outcomes, and five items relate to personal outcomes (Table 3 shows the measures for each of the constructs).

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[2]Analysis of the matching was also conducted by comparing age, gender, and educational background across the two surveys. Any inconsistent matches were removed from the final sample.

[3]Note that this analysis did **not** compare reported educational level at time 1 with educational level at time 2 (where a difference could reflect maturation in the sample). The comparison was made on the time 1 demographic data for respondents who completed only the time 1 survey and those who completed both the time 1 and time 2 surveys.

Table 2. Demographic Characteristics of the Sample (Demographics Drawn From Second Survey)

Demographic Variable	Sample Composition	
Age	Mean = 41 years; std. dev. = 9.2; range 22-64	
Gender	Men	86%
	Women	14%
Functional Areas Represented	General Management	28%
	Marketing	18%
	Accounting/Finance	17%
	Information Systems	5%
	Engineering	5%
	Production	4%
	Human Resources	4%
	Other[a]	18%
Organizational Levels Represented	Executive	40%
	Middle Management	30%
	Professional	15%
	First Line Management	9%
	Technical/Clerical	3%
	Other	3%
Highest Educational Level Attained	Graduate Degree	43%
	Some Graduate Work	5%
	University or College Degree	38%
	Some University or College	11%
	Secondary School or Less	5%
Educational Background	Business	64%
	Science	16%
	Arts	6%
	Social Science	6%
	Other	8%

[a]This response typically represented consultants or independant practitioners.

Time 2

Affect was measured by five items, drawn from the Computer Attitude Scale (Loyd and Gressard 1984). Anxiety was measured by four items[4] from the Computer Anxiety Rating Scale (Heinssen et al. 1987). These four items were found in the initial survey to best capture the feelings of anxiety associated with computer use (Compeau and Higgins 1995b). Computer use was measured by four items, reflecting the duration and frequency of use of computers at work, and the duration of computer use at home on weekdays and weekends. Frequency of use at work was measured on a six point scale ranging from less than once per month to several times per day. Duration of use at work was measured in hours per day on a typical day, and was coded into four categories (less than 30 minutes, 30 minutes to two hours, two to four hours, and more than four hours). Duration of use at home was also measured in hours and was coded into categories (not at all, up to one hour, one to two hours, more than two hours).

[4]These four items were used in the assessment of the final model by Compeau and Higgins (1995b).

Data Analysis

Assessment of the research model was conducted using Partial Least Squares (PLS) Version

Table 3. Individual Item Loadings

Item	Measure	Factor Loading
	I COULD COMPLETE THE JOB USING THE SOFTWARE . . .	
SE 1	. . . if there was no one around to tell me what to do as I go	0.807
SE 2	. . . if I had never used a package like it before	0.791
SE 3	. . . if I had only the software manuals for reference	0.822
SE 4	. . . if I had seen someone else using it before trying it myself	0.814
SE 5	. . . if I could call someone for help if I got stuck	0.821
SE 6	. . . if someone else had helped me get started	0.799
SE 7	. . . if I had a lot of time to complete the job for which the software was provided	0.791
SE 8	. . . if I had just the built-in help facility for assistance	0.711
SE 9	. . . if someone showed me how to do it first	0.740
SE 10	. . . if I had used similar packages before this one to do the same job	0.805
	IF I USE A COMPUTER . . .	
Perf. Out. 1	. . . I will be better organized	0.565
Perf. Out. 2	. . . I will increase my effectiveness on the job	0.830
Perf. Out. 3	. . . I will spend less time on routine job tasks	0.663
Perf. Out. 4	. . . I will increase the quality of output of my job	0.835
Perf. Out. 5	. . . I will increase the quantity of output for the same amount of effort	0.721
Perf. Out. 6	. . . I will be less reliant on clerical support staff	0.523
Pers. Out. 1	. . . My co-workers will perceive me as competent	0.734
Pers. Out. 2	. . . I will increase my sense of accomplishment	0.580
Pers. Out. 3	. . . I will increase my chances of obtaining a promotion	0.830
Pers. Out. 4	. . . I will be seen as higher in status by my peers	0.698
Pers. Out. 5	. . . I will increase my chances of getting a raise	0.821
Affect 1	I like working with computers	0.869
Affect 2	I look forward to those aspects of my job that require me to use a computer	0.816
Affect 3	Once I start working on the computer, I find it hard to stop	0.646
Affect 4	Using a computer is frustrating for me (R)	0.721
Affect 5	I get bored quickly when working on a computer (R)	0.693
Anxiety 1	I feel apprehensive about using computers	0.873
Anxiety 2	It scares me to think that I could cause the computer to destroy a large amount of information by hitting the wrong key	0.792
Anxiety 3	I hesitate to use a computer for fear of making mistakes I cannot correct	0.892
Anxiety 4	Computers are somewhat intimidating to me	0.909
Use 1	Frequency of use at work	0.776
Use 2	Duration of use at work	0.731
Use 3	Duration of use at home on weekdays	0.710
Use 4	Duration of use at home on weekends	0.657

n = 394

2.91.02.08 (Chin and Fry 1995), a regression-based technique that can analyze structural models with multiple-item constructs and direct and indirect paths. PLS produces loadings between items and constructs (similar to principal components analysis) and standardized regression

Table 4. Reliability and Discriminant Validity Coefficients

Construct	ICR	1.	2.	3.	4.	5.	6.
1. Self-efficacy	0.94	0.79					
2. Performance. Out. Exp.	0.85	0.31	0.70				
3. Personal Out. Exp.	0.86	0.21	0.53	0.74			
4. Affect	0.87	0.48	0.43	0.27	0.75		
5. Anxiety	0.92	-0.54	-0.30	-0.11	-0.64	0.87	
6. Use	0.81	0.43	0.40	0.15	0.50	-0.44	0.72

ICR = Internal Consistency Reliability.
Diagonal elements (shaded) are the square root of the variance shared between the constructs and their measures. Off diagonal elements are the correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

coefficients between constructs.[5] R^2 values for dependent constructs are also produced. PLS was preferred to LISREL for this study since the interest in this study was to assess the predictive validity of self-efficacy and outcome expectations measured separately from affective and behavioral responses, making a focus on the paths rather than the model appropriate. In addition, PLS does not require distributional assumptions regarding the underlying data, and tests of univariate normality (Kolmogorov-Smirnov test) showed that none of the manifest variables in this study was normally distributed (all $p < 0.001$).[6]

The measurement model in PLS is assessed in terms of item loadings, internal consistency, and discriminant validity. Individual item loadings and internal consistencies greater than 0.7 are considered adequate (Fornell and Larcker 1981). For discriminant validity, items should load more strongly on their own construct than on other constructs in the model, and the average variance shared between each construct and its measures should be greater than the variance shared between the construct and other constructs.

The structural model and hypotheses are tested by examining the path coefficients (which are standardized betas). In addition to the individual path tests, the explained variance in the dependent constructs is assessed as an indication of the overall predictive strength of the model.

[5]In the model tested here, as in Compeau and Higgins (1995b), all of the constructs were modeled as reflective. That is, the manifest variables were viewed as reflections of the underlying construct rather than as an index.

[6]Inspection of the histograms showed that most of the items were negatively skewed

Results

Measurement Model

Individual item loadings (Table 3) for the computer self-efficacy and anxiety constructs were all above 0.70. While each of the other constructs showed some weak (< 0.70) loadings, the internal consistency reliabilities were all greater than 0.7 (see Table 4) so no items were dropped. This allowed consistency with the measures used in the previous study (Compeau and Higgins 1995b). Further examination of Table 4 shows that all constructs were more strongly correlated with their own measures than they were with any of the other constructs; thus, discriminant validity was observed.

Structural Model

The path coefficients from the PLS analysis are shown in Figure 2. Consistent with recommended procedures (Barclay et al. 1995), jackknifing was used to generate standard errors and t-statistics. A jackknife size of 10, yielding 39 sub-samples, was used.

Hypotheses 1 through 5 were supported. Self-efficacy was shown to exert a significant positive influence on both performance-related (H1) and personal (H2) outcome expectations, a significant

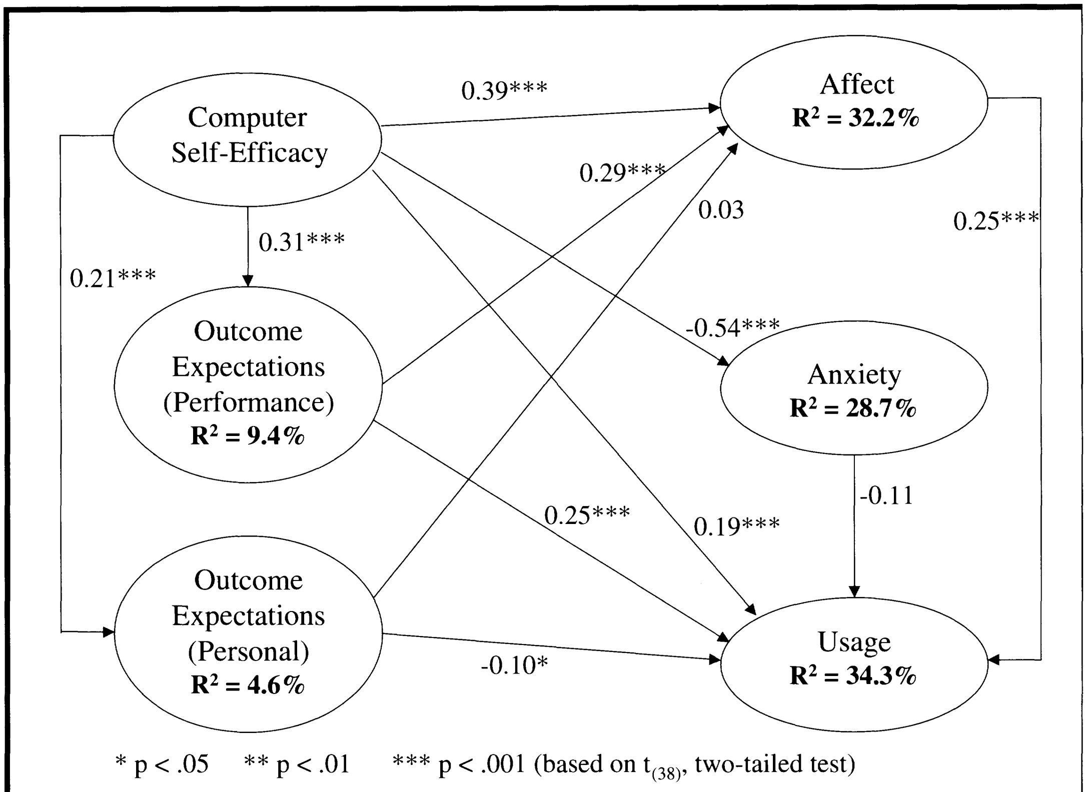

Figure 2. Results

positive influence on affect (H3), a significant negative influence on anxiety (H4), and a significant positive influence on use (H5).

Hypotheses 6 and 7 were also supported; performance outcome expectations exerted a significant positive influence on both affect (H6) and use (H7). Hypothesis 8, which posited a significant relationship between personal outcome expectations and affect, was not supported. With respect to hypothesis 9, a significant relationship between personal outcome expectations and use was observed, but this relationship was negative, contrary to the hypothesized relation.

Affect for computer use was found to exert a significant positive influence on usage (H10). Hypothesis 11 was not supported. The path from anxiety to use was not significant.

Figure 2 also shows the explained variance for each of the constructs in the model. Approximately 34% of the variance in usage is explained by the model. This is consistent with other research in the area (e.g., Davis et al. 1989; Igbaria 1990; Thompson et al. 1991). It is also slightly higher than the 32% explained variance obtained by Compeau and Higgins (1995b).

Discussion

The results of this study confirm many of the results of the earlier cross-sectional study (Compeau and Higgins 1995b), and strengthen the findings by showing the continuing predictive capability of self-efficacy and performance-related outcome expectations, even when measured one year prior to affective and behavioral responses. Self-efficacy is a strong and significant predictor of affect, anxiety, and use one year later. When both the direct and indirect effects are taken into account, self-efficacy explains a total of 18% of the variance in an individual's usage (total effect = 0.43).

Personal outcome expectations, on the other hand, appear to have little impact. Personal outcome expectations had no effect on affect (β = 0.03 n.s.) and a small, but negative effect on usage (β = -0.10 $p < .05$). This is somewhat consistent with Compeau and Higgins (1995b), although the negative finding is somewhat surprising. Research on users' expectations of technology (e.g., Ginzberg 1981; Marcolin 1994) provides a partial explanation for these findings. Expectation research finds that users who have unrealistic expectations of the benefits of technology tend to be less satisfied and ultimately use the technology less than those with more realistic assessments. If one examines the items used to measure personal outcome expectations (I will get a raise or promotion; I will gain in status or perceived competence), it may well be that these expectations represent more unrealistic expectations. After all, as technology becomes more pervasive in organizations, it becomes a necessary skill, but perhaps also one that is not sufficient for future reward. Thus, those people at time 1 who believed they would gain in such rewards by virtue of using technology had, by time 2, become disillusioned with the technology and were using it less. This explains the negative relationship between personal outcome expectations and usage. However, it should be noted that the correlation between personal outcome expectations and usage is actually positive (r = 0.15); it is only the direct effect of personal outcome expectations on use, taking into account all other paths in the model, that is negative. Thus, in the absence of other information, the prediction is that those people with higher perceptions of the personal benefits of information technology will use it more. However, when other kinds of expectations (those about self-efficacy and the performance-related benefits of technology) are factored in, the net contribution of these personal outcome expectations is negative. We must, therefore, be extremely careful in assessing the relationship between such expected benefits and behavior as their predictive capacity changes depending on the other information available.

The results of this study are strengthened by the longitudinal nature of the data. Nevertheless, the study's limitations should be borne in mind. The primary limitation relates to the issue of panel attrition and the possibility of non-response bias. It has been noted that attrition bias was evident in the second survey. While the response rates to the individual surveys were both above 50%, the net sample (after matching) represents only 20% of the initial sampling frame. Furthermore, there were significant (though small) demographic differences between respondents and non-respondents to the second survey. Women, older people, those with lower educational levels, and those with educational backgrounds in arts and social sciences were somewhat less likely to respond to the follow-up survey. These findings are consistent (with the exception of gender) with findings on response rates to mail surveys in general (Ratneshwar and Stewart 1989). Women have been identified as more likely to respond to surveys (Manser et al. 1990). There are many potential reasons for non-response, ranging from difficulty in contacting respondents,[7] to differences in personality characteristics, such as approval seeking and authoritarianism (Rosenthal and Rosnow 1969), to differences in personal interest in the phenomenon. Without further data on survey delivery or follow-up with non-respondents, it is not possible to isolate the importance of specific reasons in this study. However, the differential response rate does mean that the generalizability of the results may be in question.

The second limitation relates to what was not tested in this study. None of the analyses presented here attempts to predict changes in behavior. To fully establish a causal relationship, such a test must be carried out. For example, to show conclusively the impact of self-efficacy on usage behavior, it would be necessary to induce a change in an individual's self-efficacy perception, and then observe whether this change in self-efficacy resulted in a commensurate change in behavior, while controlling for other influences on usage (such as technical constraints, task requirements, etc.). This particular aspect of the data was not examined because the data do not lend themselves well to an assessment of

[7]Because the addresses were one year out of date at the time of the second survey, many non-respondents may simply have not received the questionnaire.

change. The interval between measurements is long (12 months), and none of the measurements specifically addressed the factors that lead to change. For example, change in usage would be expected to occur if an organization adopted a new system, for example, or embarked on a major campaign to promote increased use. Such issues were not addressed in this study, and thus, it is not possible to attribute changes in behavior to self-efficacy since alternative explanations cannot be ruled out.

Despite the limitations, the findings of this study have several implications for managers. First, they remind us that low self-efficacy, if not managed, will pervade an individual's behavior to a significant extent over a prolonged period of time. In fact, there is evidence to suggest that the relationship is one of spiraling significance (Lindsley et al. 1995), where low self-efficacy leads to low performance, which leads to even lower estimations of self-efficacy and so on.

Second, if successful use requires users who are confident in their ability to use available technologies, training programs and other support mechanisms to increase self-efficacy may need to be undertaken. Since computer training has been found to represent an important means of increasing self-efficacy (Compeau and Higgins 1995a; Gist et al. 1989; Webster and Martocchio 1993), this does not represent a new requirement, but rather provides additional evidence for the arguments in favor of investing in computer training. More broadly, given the enduring effects observed here, we believe that investments, during the implementation of new technologies, in activities which may influence individuals' self-efficacy and outcome expectations will pay off both in the short and longer terms.

Finally, the results also tend to contradict the belief that low self-efficacy is a time-limited phenomenon. As technology is adopted in all aspects of our work and personal lives, there are those who predict that concerns over low self-efficacy will simply vanish as we gain experience. The results of this study show that self-efficacy continues to predict use, even over a lengthy time period. Moreover, when we examine research from the domain of psychology, where self-efficacy is shown to vary across the entire range of human functioning (including supervisory skill [Latham and Saari 1979], attendance behavior [Frayne and Latham 1987], mathematics skill [Schunk 1981], and academic productivity [Taylor et al. 1989]), it becomes evident that self-efficacy with respect to information technology use will continue to be a factor in our choices about what technologies to adopt, how much to use them (if we have that choice), and how much to persist in the face of obstacles to successful use of such technologies.

For researchers, the findings of the longitudinal extension of Compeau and Higgins (1995b) provide evidence of the robustness of the Social Cognitive Theory model of individual reactions to computing technology, at least in part. Given the similarities between the Social Cognitive Theory model and other models of technology adoption and use discussed earlier, it is reasonable to extend this conclusion, albeit with some caution, to these other models. Outcome expectations, measured in this study, are similar to the concepts of perceived usefulness (Davis 1989), relative advantage and image (Compeau and Meister 1997; Moore and Benbasat 1991) and behavioral beliefs (Mathieson 1991; Taylor and Todd 1995). Thus, the findings that performance-related outcome expectations at one point in time predict affect and use one year later can reasonably be extended to these closely related constructs. It would appear that cognitively based models of technology use evidence predictive validity, even over time separations of one year.

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