2008

Intentions to Use Information Technologies: An Integrative Model

Ron Thompson
Wake Forest University

Deborah Compeau
University of Western Ontario

Chris Higgins
University of Western Ontario

Nathaniel C. Lupton
University of Western Ontario, nathaniel.lupton@sjsu.edu

Recommended Citation

Ron Thompson, Deborah Compeau, Chris Higgins, and Nathaniel C. Lupton. "Intentions to Use Information Technologies: An Integrative Model" *End User Computing Challenges and Technologies: Emerging Tools and Applications* (2008): 79-101. https://doi.org/10.4018/978-1-59904-295-4.ch006

Chapter VI
Intentions to Use Information Technologies:
An Integrative Model

Ron Thompson
Wake Forest University, USA

Deborah Compeau
University of Western Ontario, Canada

Chris Higgins
University of Western Ontario, Canada

Nathan Lupton
University of Western Ontario, Canada

ABSTRACT

An integrative model explaining intentions to use an information technology is proposed. The primary objective is to obtain a clearer picture of how intentions are formed, and draws on previous research such as the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989) and the decomposed theory of planned behavior (Taylor & Todd, 1995a). The conceptual model was tested using questionnaire responses from 189 subjects, measured at two time periods approximately two months apart. The results generally supported the hypothesized relationships, and revealed strong influences of both personal innovativeness and computer self-efficacy.

INTRODUCTION

Understanding the process by which individuals adopt and use information technologies in the workplace and the factors that influence their decisions about what technologies to use to aid in the performance of their work tasks remains an important focus of IS research (Venkatesh, Morris, Davis, & Davis, 2003). While our ultimate interest is often in the achievement of organizational benefits from technology, the behavior of the individual represents a critical prerequisite for achieving these larger goals (Seddon, 1997).

Our review of current research on individual technology acceptance reveals, among other things, two overarching themes in the models. The first theme reflects the importance of pursuing parsimonious models. Parsimony is an important element in the development of theory and is one of the key contributions of the Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warsaw, 1989). The second theme reflects the dominance of what we will refer to as an instrumental view of technology adoption decisions. Under this perspective, the dominant influences on intentions to use technologies are those involving beliefs about the degree to which using an information technology will result in objective improvements in performance.

The pursuit of parsimony and the focus on instrumental determinants have served the technology adoption stream well. The relative simplicity of TAM has made it a fertile ground for extensive study (Venkatesh & Davis, 2000). Similarly, the focus on an instrumental view of technology adoption has allowed us to explore this aspect of the influences on adoption in relatively deep fashion. On the other hand, both characteristics have had a limiting effect in other respects. Plouffe, Hulland, and Vandenbosch (2001) argue that an exclusive focus on parsimony, while sufficient if the research goal is prediction, may produce a narrower understanding of the phenomenon and perhaps limit our ability to influence it by not recognizing the myriad forces involved. Agarwal and Karahanna (2000) make a similar argument with respect to the focus on instrumental beliefs. They argue that a more holistic assessment of technology adoption is necessary, incorporating elements more related to intrinsic than extrinsic motivation. In part, they suggest this is necessary because of the nature of modern information technologies. What is also apparent, however, is the need to examine holistic perceptions in order to improve our understanding of the phenomenon of technology acceptance.

The purpose of this study, then, is to build on existing technology adoption theory in a more holistic and integrative fashion. Specifically, we seek to extend the Decomposed Theory of Planned Behavior (DTPB) (Taylor & Todd, 1995a). This theory was chosen as it represents a broader perspective, yet has enjoyed less ongoing development than TAM. Our extensions focus on three areas. First, we seek to explore the linkages among the independent variables proposed by Taylor and Todd (1995a). Second, we extend DTPB to be consistent with TAM. Third, we incorporate the trait of personal innovativeness with information technology (Agarwal & Prasad, 1998) into the model. This is a small step towards broadening our view from the more instrumental focus that has guided us to date. Finally, we seek, as have others (Agarwal, Sambamurthy, & Stair, 2000; Karahanna, Straub, & Chervany, 1999; Venkatesh & Davis, 2000) to understand the influence of experience within our model. While several previous authors have examined the role of experience within the context of TAM, to our knowledge, only one study (Taylor & Todd, 1995b) has done so within the TPB perspective. Before discussing the research design in more detail, we turn to the theoretical background and the research model to be tested.

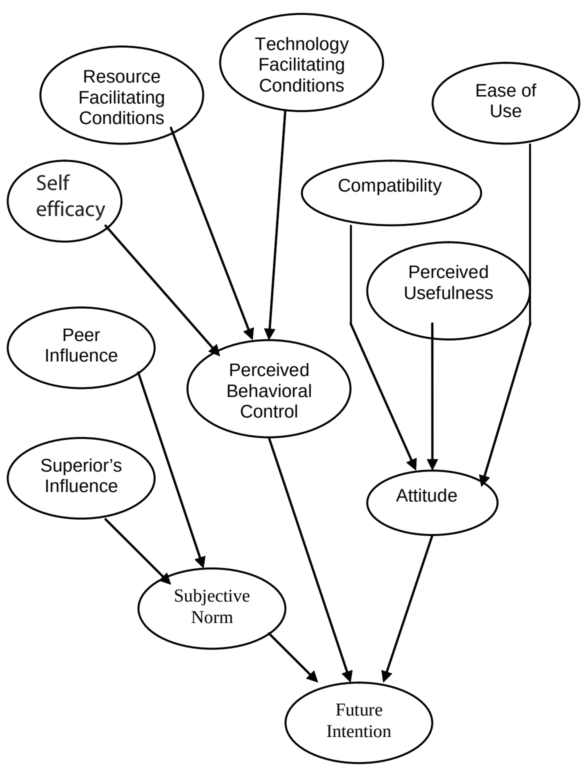
THEORETICAL BACKGROUND AND RESEARCH MODEL

Decomposed Theory of Planned Behavior

The Theory of Planned Behavior (TPB) (Ajzen, 1991) was constructed as an extension to the Theory of Reasoned Action, or TRA (Fishbein & Ajzen, 1975) including, in addition to attitude and subjective norm, the construct of perceived behavioral control. Taylor and Todd (1995a) compared TAM with an adaptation of TPB, finding that perceived behavioral control and subjective norm added little in terms of explained variance in intentions to use technology. Taylor and Todd (1995a) went further, however, by proposing what they termed a decomposed theory of planned behavior (see Figure 1). Their intent was not to try to improve on TAM or TPB in terms of explaining variance in intentions or use of a technology, but rather to identify additional components of belief structures that would provide more explanation of the antecedents to attitude, subjective norm, and perceived behavioral control.

In an empirical test of their model, Taylor and Todd (1995a) found support for most of the hypothesized relations. Others have since built on the model, focusing on the constructs of technology and resource facilitating conditions (Mathieson, Peacock, & Chin, 2001), the interaction of age and gender to influence user perceptions and use (Morris, Venkatesh, & Ackerman, 2005) and applying the model to the adoption of IT by health

Figure 1. Decomposed theory of planned behavior (Taylor & Todd, 1995a)

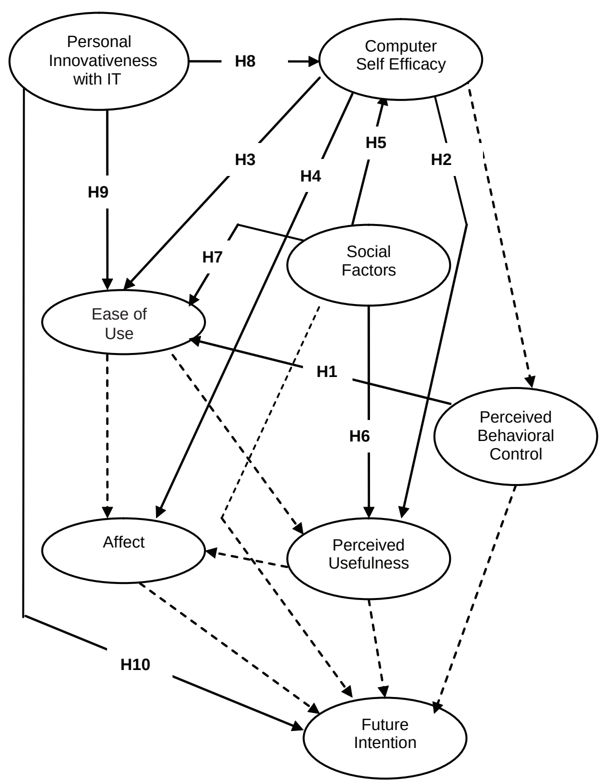


care professionals (Chau & Hu, 2001) and use of EDSS (Workman, 2005). Collectively, these studies suggest that the TPB perspective is reasonable, though it does not add significantly to explained variance except when fully integrated with TAM (Riemenschneider, Harris, & Mykytyn, 2003). Attitude and control beliefs are consistently and significantly related to adoption intention. The role of normative beliefs is mixed and suggests a weaker effect than the others.

Our extended conceptual model is shown in Figure 2. The model extends DTPB by including more concepts related to non-instrumental influences on technology adoption, and by including a more complex web of relationships among the antecedents. We adopted DTPB as the foundation for our model, rather than TAM, as DTPB represents a more general theoretical model. To highlight the differences between DTPB and our model, we provide a brief overview of our model and then describe the rationale for the hypothesized relationships in more detail.

Intention to use Microsoft Access (the target system) is influenced by affect (attitude), social factors (subjective norms), and perceived behavioral control. Consistent with TAM (e.g., Davis et al., 1989; Taylor & Todd, 1995a), intention is also hypothesized to be influenced directly by perceived usefulness. Affect is influenced by three factors, two of which (perceived usefulness and perceived ease of use) were predicted in the original TAM (Davis et al., 1989) and in DTPB

Figure 2. Research model



Note: *Dotted lines represent relationships previously established by DTPB (Taylor & Todd, 1995a) and TAM (Davis, et al, 1989)*

(Taylor & Todd, 1995a). The third influence on affect is self-efficacy. Perceived usefulness is hypothesized to be influenced by perceived ease of use, computer self-efficacy, and social factors, while perceived ease of use is hypothesized to be influenced by self-efficacy, social factors, perceived behavioral control, and personal innovativeness with IT. Perceived behavioral control is influenced by self-efficacy as well. Finally, self-efficacy is influenced by personal innovativeness with IT and social factors.

Our model builds on previous literature in several ways. First, we have opened up the paths across the avenues of behavioral, normative, and control beliefs. In earlier models (e.g., TAM, DTPB), these antecedents were viewed as separate and distinct influences, with no linkages among them. As we discuss in detail in the following section, however, there are theoretical reasons and empirical support for the existence of linkages across these influences.

Second, we have incorporated the personality trait of personal innovativeness with information technology as an attempt to begin the reintegration of general tendencies into our understanding of individual behavior with respect to IT. An explicit aim of TRA and TPB, when they were developed, was to move away from trying to associate general personality traits with behaviors. At the time, it was felt that such predictors were not as good as beliefs and attitudes (Ajzen, 1991). Yet now that we have begun to understand these specific beliefs and attitudes, there is a benefit to re-examining the role of personality variables in our models.

In addition, we consider the model at two time periods to examine the influence of experience in changing the model parameters. Other specific differences between our model and previous ones (e.g., TAM, DTPB) are discussed in later sections. The primary goal of the study is not to try and increase the amount of variance explained in intentions or use of an IT, but rather to obtain a clearer picture of the antecedent factors that influence attitudes, subjective norms, and perceived behavioral control, as well as the inter-relations among them.

CONSTRUCTS AND HYPOTHESES

For space reasons, we do not provide detailed definitions of the constructs employed in the model. Interested readers can refer to previous sources for intentions to use a specific information technology in the future (Davis et al., 1989; Venkatesh et al., 2003), affect (Compeau & Higgins, 1995a; Thompson, Higgins, & Howell, 1991), perceived usefulness (Davis et al., 1989), perceived ease of use (Davis et al., 1989), perceived behavioral control (Ajzen, 1991; Taylor & Todd, 1995a), computer self-efficacy (Compeau & Higgins, 1995a; Taylor & Todd, 1995a), social factors (Compeau & Higgins, 1995a), and personal innovativeness in the domain of information technology (Agarwal & Prasad, 1998). Explanations and working definitions for all constructs are also available from the authors upon request.

To avoid unnecessarily repeating the rationale for hypotheses and relationships that have been well established by previous research, we simply list relationships that are not considered controversial and then focus on those that are extensions to DTPB and TAM. Relationships that have been previously established (and represented with dotted lines on Figure 2) include:

- Affect toward using an information technology will have a positive influence on intentions to use the technology (DTPB, TAM).
- The perceived usefulness of an information technology will exert a positive influence on affect toward using the technology (DTPB, TAM).
- Perceived usefulness of an information technology will exert a positive influence on intentions to use the information technology (TAM).

- The perceived ease of use of an information technology will have a positive influence on affect toward using the technology (DTPB, TAM).
- Perceived ease of use of an information technology will exert a positive influence on perceived usefulness of the technology (TAM).
- Perceived behavioral control will exert a positive influence on intentions to use an information technology (DTPB).
- Computer self-efficacy will exert a positive influence on perceived behavioral control (DTPB).
- Social factors will exert a positive influence on intentions to use an information technology (DTPB).

In addition to a direct influence on intentions as depicted above, there may be additional roles for perceived behavioral control (PBC). In their study of technology adoption and use, Mathieson et al. (2001) argued that perceived resources (a subset of PBC) included personal assets such as an individual's expertise. In addition, they suggested that perceived ease of use would be influenced by expertise. As a result, Mathieson et al. (2001) concluded that perceived resources should influence perceived ease of use, and they observed empirical support for this relationship. The resulting hypothesis is:

H1: Perceived behavioral control will exert a positive influence on perceived ease of use of an information technology.

In addition to the potential influence of computer self efficacy (CSE) on PBC, there is evidence from other research that CSE might influence additional factors within the DTPB model. If an individual is confident in his or her ability to learn to use an information technology, he or she is more likely to believe that he or she will be able to put the technology to productive use. Although we would anticipate that the influence of specific self-efficacy would be stronger than general CSE, general CSE has been shown to exert a positive influence on perceived usefulness of a specific IT (e.g., Compeau & Higgins, 1995a; Compeau, Higgins, & Huff, 1999). The associated hypothesis is:

H2: Computer self-efficacy will have a positive influence on perceived usefulness of an information technology.

Venkatesh and Davis (1996) posited that computer self-efficacy should act as a precursor to perceived ease of use. Individuals who are confident in their ability to learn to use information technologies are likely to view specific information technologies as easier to use than their counterparts who are less confident in their ability to learn. The results from their empirical testing provided support for this proposition. Agarwal et al. (2000) also observed a positive influence of self-efficacy on perceived ease of use, as did Venkatesh (2000). This leads to the following hypothesis:

H3: Computer self-efficacy will exert a positive influence on perceived ease of use of an information technology.

Compeau and Higgins (1995b) argued that computer self-efficacy should influence affect toward using an information technology. If an individual is confident in his or her ability to learn to use an information technology, he or she is more likely to have positive affective reactions to using the technology. In testing this relation, Compeau and Higgins (1995b) observed a statistically significant, though small, influence in a cross-sectional design. Compeau et al. (1999) further observed that self-efficacy measured at one point in time exerted an influence on affect measured one year later. From these findings, the associated hypothesis is:

H4: Computer self-efficacy will exert a positive influence on affect toward using an information technology.

There are possible influences for social factors beyond a direct effect on intentions, as well. Bandura (1997) argues that social persuasion is an important source of information that can influence the formation of self-efficacy judgments and expectations of outcomes. Encouragement by others in the reference group to use technology may carry with it a sense of encouragement regarding one's skills; in other words, you should use this technology *and you are capable of it.* Even if unspoken, this evaluation is implied; after all, why would a friend or colleague encourage you to do something wholly outside your capabilities? To the extent that this skills evaluation is present, social factors would be expected to influence self-efficacy. Compeau and Higgins (1995b) observed a positive influence of social persuasion on self-efficacy. These observations lead to the following hypothesis:

H5: Social factors will exert a positive influence on computer self-efficacy.

Social factors also influence perceived usefulness. Klein and Sorra (1996) argue that social influence operates through either a process of compliance or one of internalization. Compliance involves acting as the others desire because of perceived pressure. Internalization involves taking on the views of the other for oneself. Thus, an individual who feels persuaded to use technology by his or her reference group attributes the persuasion to a rational judgment on the part of the group; the group is encouraging the use of the technology because they see it as useful. Given that, the individual also decides that the technology is useful. Thus, through a process of internalization, the social factors result in increased perceptions of perceived usefulness.

H6: Social factors will exert a positive influence on perceived usefulness of an information technology.

Similarly, we anticipate that perceptions about ease of use of a technology could be influenced by social factors, especially in the absence of direct experience. In a training environment, for example, communication cues from the instructor regarding the relative ease (or difficulty) of learning to become proficient with the technology could influence initial perceptions on the part of the individual. This leads us to propose that:

H7: Social factors will exert a positive influence on perceived ease of use of an information technology.

Agarwal et al. (2000) argued for a direct influence of personal innovativeness on computer self-efficacy. Their rationale was that, consistent with the original formulation of social cognitive theory (Bandura, 1986), individual personality exerts an indirect influence on performance, through self-efficacy. Their empirical test found support for a positive influence of PIIT on general computer self-efficacy. The corresponding hypothesis is:

H8: Personal innovativeness will exert a positive influence on computer self-efficacy.

We also anticipate that personal innovativeness will influence perceived ease of use. If I am someone who is more innovative with respect to technology use, I will tend to view new technologies as being easier to use, above and beyond any indirect influence through self-efficacy. This is supported by learning theory (Ford, Smith, Weissbein, Gully, & Salas, 1998) that shows the ability to generalize skills across related domains. This hypothesis has also been verified in research based on TAM (Lu, Yao, & Yu, 2005; Yi, Fiedler, & Park, 2006). Since the underlying software structures (i.e., menus, concepts, functions) tend to be similar across technology domains, an individual who experiments actively with new technologies has the opportunity to engage in greater learning which can then be transferred to other domains. This results in perceptions of greater ease of use. The resulting hypothesis is:

H9: Personal innovativeness will exert a positive influence on perceived ease of use of an information technology.

Finally, since we are investigating intentions to use an information technology in the future, we would expect more innovative individuals to have stronger intentions (once again, above and beyond any indirect influences through intervening variables). This hypothesis reflects, at least to a degree, the influence of habit on behavior (Triandis, 1980) and the relationship between innovativeness and system use (Larsen & Sorebo, 2005). All things being equal, we would expect those who have habitually been ready adopters of technology in the past to continue to do so in the future, irrespective of specific attitudes and beliefs as they continue a set behavior pattern that has become habitual. Hence:

H10: Personal innovativeness will exert a positive influence on intentions to use information technology.

Experience

Considerable research has shown that computer experience influences many of the constructs and relations within a nomological network that involves intentions, use, and/or performance (e.g., Compeau & Higgins, 1995b; Compeau et al., 1999; Davis et al., 1989; Karahanna et al., 1999; Lippert & Forman, 2005; Szajna, 1996; Taylor & Todd, 1995b; Thompson, Higgins, & Howell, 1994; Venkatesh et al., 2003).

The experience level, or skill level, of an individual can be considered to fall across a continuum. When we assess experience and skill at specific points in time, we are essentially taking a snapshot of a potentially changing phenomenon (Marcolin, Compeau, Munro, & Huff, 1998). When an individual has no personal experience with a specific information technology, his or her attitudes, beliefs, and expectations toward using the technology may be influenced by factors such as social influences from peers and superiors, and personal experience with similar technologies. As the individual gains experience with the technology, he or she has objective outcomes (positive and/or negative) that are internalized, and which in turn influence beliefs about expected outcomes (Triandis, 1980), perceived usefulness (Bhattacherjee & Premkumar, 2004), and ease of use (Hackbarth, Grover, & Yi, 2003).

Thus, we expect that some of the constructs and the relations in the model will be influenced by the increased experience (skill level) of the respondent. As a result, we conducted supplemental analysis (described later) to examine the influence of experience in more detail.

RESEARCH METHODOLOGY

The data collection and analysis reported here is a subset of a larger research program that encompassed data collected in several related studies. For the overall research program, we wished to measure a relatively large number of constructs. In the interest of keeping the research questionnaire to a reasonable length (to increase participation rates and reduce the possibility of errors caused by respondent fatigue or declining interest), the number of items for most constructs was reduced to three. Although most of the individual items used here have been employed in previously published studies, some were developed or modified specifically for this research program.

The primary risks in using this approach were (1) some of the measures could prove to be unreliable, reducing the number of measures per construct even further; and (2) the limited number of measures might tap only a subset of a given construct. To reduce these risks, the choice of items was made partially on a face validity basis (in an effort to identify the most relevant measures), and partially from the results of a pilot study. The pilot study allowed us to refine the measures, resulting in the final set used in the main study. Note that most of the items used in this study were also included in the empirical work conducted by Venkatesh et al. (2003) as they tested for commonality across measures from previous work. Since Venkatesh et al. (2003) found that these measures were similar to others purporting to measure the same constructs (i.e., they loaded together in a factor analytic sense), we have more confidence that the measures selected for this study are in fact reasonable measures of the constructs (further details of the pilot study and a table showing the similarities between the measures used in this study and measures used in related work is available upon request from the authors).

SAMPLE AND PROCEDURES

Data were collected from junior and senior undergraduate students (business majors) completing a required course in management information systems (MIS). The respondents were required to use the Microsoft Access database management system for a group project (two students per group), representing 10% of their final grade. All students received some training with the software, and completed three individual assignments with it prior to completing the group project.

Measures were taken at two time periods approximately two months apart. At the time of the first measurement (T_1), the respondents had received a demonstration of the software and had completed one simple assignment using it. At the time of the second measurement (T_2), they had received additional training and had completed two additional (more complex) individual assignments as well as the group project (which required fairly extensive use of the software).

All students in five different sections of the course were asked to participate in the study. No inducements were offered, and students were given the option of not participating. All who were invited agreed to participate. Questionnaires were distributed in class to all students that were in attendance during specific class periods. 219 students completed the pretraining questionnaire, and 209 completed the postquestionnaire; those not completing both (i.e., those that were absent on one of the days) were removed from the sample. In total, 193 respondents completed both pre and postmeasures. Questionnaires from four respondents were removed due to missing data, leaving a net sample size of 189. The questionnaire responses were associated with an identification number, making it possible to match responses by respondent across the two time periods.

Of the 189 respondents, 117 were male and 72 were female. All respondents were traditional third and fourth year undergraduate students, and all had a reasonable level of familiarity with personal computers. We asked the respondents to rate their skill level with PC operating systems, word processing, spreadsheets, and e-mail using a 7-point scale with anchors of Novice (1), Intermediate (4), and Expert (7). We then summed across the four technologies to obtain a general measure of self-rated expertise. The scores ranged from 10 to 28 (out of a possible 28), with a mean of 19.3 and standard deviation of 3.3.

Although the generalizability of results will be constrained somewhat since the use of Access was mandatory for the students, many situations involving the use of information technologies by professionals are also mandatory. In addition, since our intention measure is focused on future, optional use by the respondent, the constraints on generalizability imposed by the mandatory nature of the task are mitigated somewhat.

RESULTS

The measures were tested using PLS-Graph (Chin & Frye, 2001) by running the full research model with the data collected at Time 1 and again with the data collected at Time 2. The first test of the measures was to examine the item loadings to assess individual item reliability. As in the pilot study, there were weaknesses evident in the loadings for the computer self-efficacy measures for the data collected at Time 1. These results were somewhat surprising, since the Compeau and Higgins measures of computer self-efficacy had demonstrated adequate psychometric properties in previous use (e.g., Compeau & Higgins, 1995a, 1995b; Compeau et al., 1999). Gundlach and Thatcher (2000) argue that the self-efficacy construct is multidimensional, reflecting human assisted vs. individual self-efficacy. This would be consistent with our findings. Factor analysis of the eight items also supported this view. A principal components analysis resulted in two factors, one of which included items 1, 2, 6, and 7 and the other which included 3, 4, 5, and 8. Since the variation was greater on the first set and there was less risk of a ceiling effect, we chose to retain those items.

The loadings for one measure of perceived behavioral control (PBC2) were low (below 0.5) for both time periods. In retrospect, this finding should not have been a surprise. PBC2 states that "the amount I use Access is within my control." Since the respondents were required to use Access to complete their projects, there was very little variation on this item. This issue was not a problem in the pilot study, since those respondents had the opportunity to use other software for completing the assigned task. We therefore decided to remove this item, and re-run the models. Table 1 shows the final list of items, including the means and standard deviations (at Time 1), and the item loadings obtained from the PLS run for Times 1 and 2.

Note that for social factors, both the weights and loadings (respectively) are displayed. Since the social factors construct was modeled as formative (Barclay, Higgins, & Thompson, 1995), the important indicators are the weights (not the loadings), and the criteria considered is whether or not the weights are statistically significant. In both models, and for all three social factor items, the weights were positive and significant at $p < 0.05$. For adequate item reliability for the reflective constructs, ideally loadings should be higher than 0.7 (Barclay et al., 1995). All observed loadings were close to or above the desired level (i.e., 0.67 or greater). We also examined the loadings and cross-loadings for all items at both time periods (see Table 2), and observed no violations (i.e., all loadings were greater than 0.65, and all cross-loadings were less than 0.60).

Table 3 shows the results of further tests for the reliability and validity of the measures. The average variance extracted (AVE) is shown for each construct, as is the Fornell and Larcker (1981) measure of composite reliability (CR). For adequate scale reliability, AVE should be greater than 0.5. CR may be interpreted similarly to Cronbach's alpha. That is, 0.70 may be considered an acceptable value for exploratory research, with 0.80 appropriate for more advanced studies. Table 3 also shows the correlations between constructs, and the diagonal, shaded cells display the square root of the average variance extracted. For adequate discriminant validity, the values on the diagonal (shaded cells) should be greater than the off-diagonal elements. The corresponding test results at Time 2 are not shown here (for space reasons) but the pattern of results was similar to those shown for Time 1.

At Time 1, all constructs have composite reliabilities in excess of 0.80, with the exception of social factors. Average variance extracted is above 0.50 for all constructs except social factors

Table 1. Item reliability: Time 1 and Time 2

Item	Description	Mean	S.D.	Loading T1	Loading T2
CSE1	I could complete the job using the software… …if there was no one around to tell me what to do as I go	4.0	1.7	.87	.87
CSE2	…if I had only the software manuals available for reference	4.8	1.5	.86	.85
CSE6	…if I had a lot of time to complete the task for which the software was provided	5.6	1.2	.70	.67
CSE7	…if I had just the built-in help facility for assistance	4.4	1.7	.71	.81
PIIT1	Among my colleagues and peers, I will be among the first to try new computer tools and applications	4.4	1.6	.68	.77
PIIT2	I only use computer tools that fit a specific need; I seldom try new tools or applications just for the fun of it (R)	4.1	1.8	.87	.81
PIIT3	I must see other people using new computer tools before I will consider using them myself (R)	5.0	1.6	.74	.82
EOU1	Learning to use [software package] would be easy for me	4.3	1.5	.82	.86
EOU2	Working with [software package] is so complicated, it is difficult to understand what is going on (R)	4.9	1.4	.82	.69
EOU3	I would find it difficult to get [s/w pkg] to do what I need (R)	4.8	1.4	.81	.69
PU1	Using [software package] would… …allow me to increase my productivity	5.2	1.3	.80	.87
PU2	…increase my quantity of output for the same amount of effort	4.9	1.4	.86	.88
PU3	…increase my effectiveness	5.4	1.2	.89	.93
PBC1	I have the resources to use [s/w package] whenever I wish	5.9	1.5	.78	.78
PBC3	I have the resources, the knowledge, and the ability to make effective use of [software package]	4.6	1.7	.87	.92
AFF 1	I really dislike using [software package] (R)	5.1	1.5	.84	.83
AFF 2	Working with [software package] is a lot of fun	3.8	1.5	.91	.91
AFF 3	I really enjoy working with [software package]	4.1	1.4	.94	.93
AFF 1	I really dislike using [software package] (R)	5.1	1.5	.84	.83
AFF 2	Working with [software package] is a lot of fun	3.8	1.5	.91	.91

Continued on following page

Table 1. continued

Item	Description	Mean	S.D.	Loading T1	Loading T2
AFF 3	I really enjoy working with [software package]	4.1	1.4	.94	.93
INT1	I predict that I will use [s/w pkg] on a regular basis in the future	4.7	1.3	.87	.90
INT2	Although I will likely use outputs from [software package] quite extensively, I don't see myself directly using [software package] in the future (R)	4.9	1.5	.85	.86
INT3	I expect that I will use [software package], or a similar type of software product, quite extensively in the future	5.1	1.5	.85	.88
SF1	My colleagues and peers expect me to learn how to use computers effectively	5.6	1.4	.45 .65	.30 .65
SF2	My instructor (or boss) is supportive of my use of computers	6.3	1.0	.54 .65	.53 .70
SF3	People whose opinions I value will perceive me as being competent if I use computers effectively	5.1	1.3	.51 .68	.57 .77

Note: For SF1, SF2 and SF3, the item weight is displayed on top, and the loading below.

(where again, such measures are not considered to be relevant given the formative nature of the construct). In all cases, the variance shared between a construct and its measures is greater than the variance shared among the constructs.

The PLS results for the structural model (path coefficients and R^2 values) for Time 1 are displayed in Figure 3, and for both time periods are shown in Table 4. The path coefficients (which can be interpreted similarly to standardized path coefficients from a regression model) are provided, along with an indication of whether or not a specific path is statistically significant. The t-statistics for testing statistical significance were obtained by running a bootstrapping routine (Chin & Frye, 2001), with 500 samples, each containing 189 observations.

Table 4 shows the direct, indirect, and total effects for each of the hypothesized paths, as well as the amount of variance explained (R^2) for all of the endogenous constructs. Cohen (1988) defined strong, moderate, and weak effects for regression as corresponding to effect sizes of approximately 0.35, 0.15, and 0.02, respectively. Although similar statements have not been made specifically for PLS, since PLS uses regression in its analysis, these rules of thumb are most likely appropriate.

Table 2. Loadings and cross-loadings of indicators on constructs at Time 1

	CSE	PIIT	EOU	PU	PBC	AFF	INT
CSE1	**0.87**	0.46	0.38	0.22	0.43	0.37	0.31
CSE2	**0.86**	0.42	0.45	0.26	0.46	0.41	0.38
CSE6	**0.70**	0.26	0.20	0.34	0.29	0.30	0.34
CSE7	**0.71**	0.39	0.24	0.22	0.24	0.31	0.29
PIIT1	0.38	**0.68**	0.30	0.14	0.22	0.31	0.25
PIIT2	0.42	**0.87**	0.44	0.19	0.32	0.44	0.44
PIIT3	0.33	**0.74**	0.34	0.05	0.23	0.20	0.22
EOU1	0.44	0.37	**0.82**	0.26	0.44	0.54	0.32
EOU2	0.26	0.33	**0.82**	0.13	0.31	0.47	0.18
EOU3	0.31	0.45	**0.81**	0.11	0.27	0.49	0.29
PU1	0.27	0.13	0.14	**0.80**	0.32	0.34	0.41
PU2	0.30	0.15	0.25	**0.86**	0.31	0.40	0.45
PU3	0.26	0.16	0.14	**0.89**	0.37	0.34	0.50
PBC1	0.32	0.22	0.32	0.27	**0.78**	0.28	0.28
PBC3	0.44	0.33	0.38	0.37	**0.87**	0.47	0.34
AFF1	0.35	0.42	0.62	0.35	0.36	**0.84**	0.44
AFF2	0.39	0.33	0.48	0.39	0.38	**0.91**	0.44
AFF3	0.46	0.39	0.55	0.39	0.49	**0.94**	0.49
INT1	0.35	0.35	0.31	0.50	0.37	0.43	**0.87**
INT2	0.36	0.31	0.25	0.42	0.31	0.44	**0.85**
INT3	0.36	0.40	0.28	0.45	0.29	0.45	**0.85**

CSE – computer self-efficacy; PIIT – personal innovativeness in the domain of IT; EOU – ease of use; PU – perceived usefulness; PBC – perceived behavioral control; AFF – affect; INT – future intentions

As can be seen in Table 4, most of the relationships taken from DTPB and TAM received at least partial support, although there were exceptions. Affect was found to have a moderate and significant influence on long term intentions at both Time 1 and Time 2, suggesting that people will expect to do things that they enjoy doing. Perceived usefulness exerted a moderate and significant influence on affect and a moderate (Time 2) or strong (Time 1) influence on intentions. Thus, the influence of perceived usefulness was only partly mediated by affect.

Perceived ease of use exerted a strong influence on affect at both Times 1 and 2, but the relative influence declined somewhat at Time 2. This result is consistent with other studies that have found that the direct influence of EOU tends to decrease over time (e.g., Venkatesh et al., 2003). At Time 2, perceived ease of use exerted a moderate and significant influence on perceived usefulness; this effect was not significant (at the $p < 0.05$ level) at Time 1. This result is consistent with most prior research, suggesting that the influence of ease of use on usefulness becomes stronger with direct experience.

Perceived behavioral control showed no significant influence on intentions at Time 1, but a significant influence at Time 2. Thus, for this group of individuals, control beliefs have a stronger effect following greater experience with the behavior.

Table 3. Reliability and discriminant validity

(Revised Model at Time 1)

	CR	AVE
PIIT	.81	.59
SF	.70	.44
CSE	.87	.62
EOU	.86	.67
PU	.89	.73
PBC	.82	.69
AFF	.92	.80
INT	.89	.73

CR = Composite Reliability
AVE = Average Variance Extracted

	PIIT	SF	CSE	EOU	PU	PBC	AFF	INT
PIIT	**0.77**							
SF	0.21	**0.66**						
CSE	0.49	0.21	**0.79**					
EOU	0.47	-0.03	0.42	**0.82**				
PU	0.17	0.26	0.33	0.21	**0.85**			
PBC	0.34	0.13	0.46	0.42	0.39	**0.83**		
AFF	0.43	0.11	0.45	0.62	0.42	0.46	**0.89**	
INT	0.41	0.26	0.42	0.33	0.53	0.38	0.51	**0.85**

PIIT – personal innovativeness in the domain of IT; SF – social factors; CSE – computer self-efficacy; EOU – ease of use; PU – perceived usefulness; PBC – perceived behavioral control; AFF – affect; INT – future intentions

Diagonal elements represent the square root of the average variance extracted. Off diagonal elements represent correlations. For discriminant validity, the diagonal elements should be higher than the off-diagonal elements, indicating that the variance shared between a construct and its measures is higher than the variance shared between construct pairs.

The magnitude of the path ($\beta = 0.17$), however, still suggests a smaller effect than that of affect or perceived usefulness. No direct effect of social factors on intentions was found, although the total effects in Time 1 were substantive.

With respect to the hypotheses directly tested in this study, PBC was found to exert a moderate influence on perceived ease of use at Time 1, and a strong influence at Time 2 (H1). General computer self-efficacy exerted moderate but significant influences on both EOU and affect at both time periods (H3, H4). The influence on perceived usefulness was significant at Time 1 but not at Time 2 (H2). Interestingly, the effect on perceived ease of use was stronger at Time 2, resulting in an increased indirect effect of self-efficacy on perceived usefulness, partly compensating for the reduced direct effect. Thus, it appears that with direct experience, people can separate the potential of the software from their ability to realize that potential.

Table 4. Tests of hypotheses (direct effects), indirect and total effects for Time 1 and Time 2

	Time 1			Time 2		
Relationship	**Total Effects**	**Direct Effects**	**Indirect Effects**	**Total Effects**	**Direct Effects**	**Indirect Effects**
AFF - INT	0.24	0.24**	0.00	0.31	0.31**	0.00
PU - AFF	0.27	0.27**	0.00	0.25	0.25**	0.00
PU - INT	0.42	0.36**	0.06	0.32	0.24**	0.08
EOU - AFF	0.53	0.50**	0.03	0.39	0.35**	0.04
EOU - PU	0.12	0.12+	0.00	0.16	0.16**	0.00
PBC - INT	0.08	0.04	0.04	0.23	0.17**	0.06
CSE - PBC	0.46	0.46**	0.00	0.44	0.44**	0.00
SF - INT	0.19	0.09	0.10	0.09	-0.05	0.14
H1: PBC-EOU	0.25	0.25**	0.00	0.35	0.35**	0.00
H2: CSE-PU	0.25	0.23**	0.02	0.15	0.10	0.05
H3: CSE-EOU	0.17	0.17**	0.00	0.29	0.29**	0.00
H4: CSE-AFF	0.36	0.15**	0.21	0.41	0.21**	0.20
H5: SF-CSE	0.12	0.12+	0.00	0.12	0.12+	0.00
H6: SF-PU	0.24	0.21**	0.03	0.38	0.36**	0.02
H7: SF-EOU	-0.14	-0.17*	0.03	0.03	-0.02	0.05
H8: PIIT-CSE	0.47	0.47**	0.00	0.57	0.57**	0.00
H9: PIIT-EOU	0.47	0.34**	0.13	0.36	0.11	0.25
H10: PIIT-INT	0.37	0.22*	0.15	0.33	0.18**	0.15

Amount of Variance Explained (R^2)	**Time 1**	**Time 2**
Future intentions	44%	40%
Affect	49%	38%
Perceived Usefulness	15%	23%
Perceived Ease of Use	34%	35%
Perceived behavioral control	21%	19%
Computer self efficacy	26%	39%

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$

The influence of social factors was mixed. The influence of social factors on self-efficacy (H5) was positive but not significant at $p < 0.05$. Since social persuasion is one of the weaker sources of self-efficacy information and, more importantly, since the persuasion that was examined here was encouragement to use computers rather than specific encouragement about one's skills, this is not overly surprising. Social factors did exert a moderate influence on perceived usefulness (H6) at Time 1 and strong influence at Time 2. This is consistent with the notion of internalization suggested by Klein and Sorra (1996). The influence of social factors on perceived ease of use (H7) was surprising, with a significant negative influence at Time 1 and no influence at Time 2. This finding was unexpected and bears further consideration.

Figure 3. PLS results

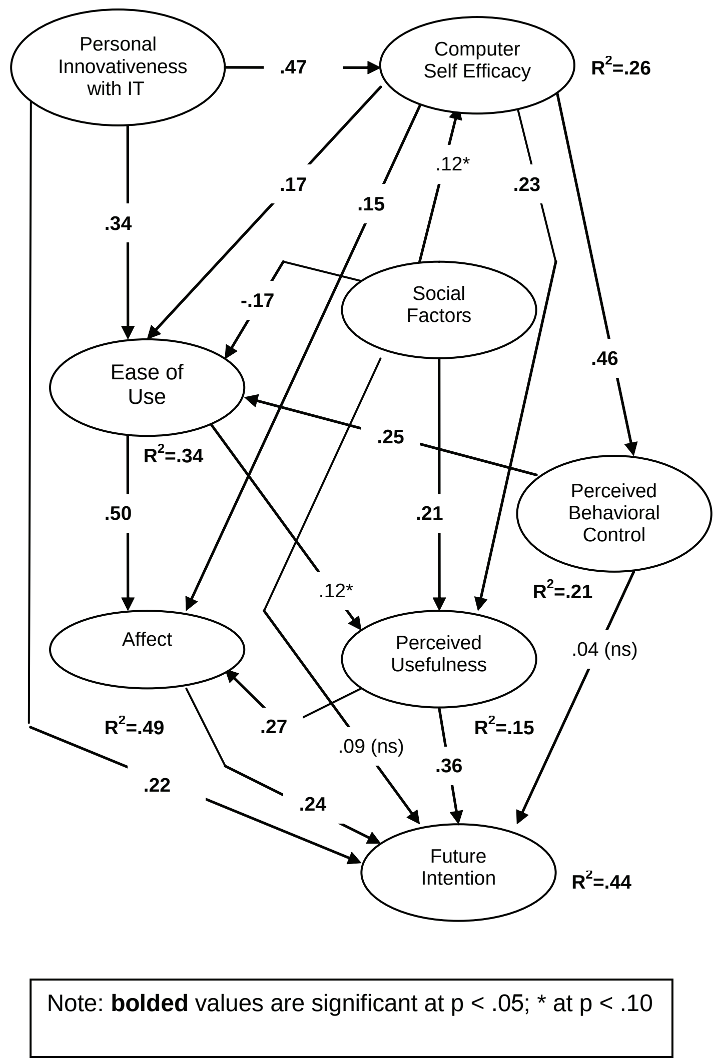


Table 5. Comparison of construct means

	Mean (Std. Deviation)		
	Time 1	**Time 2**	**p-value**
GENERAL FACTORS			
Personal Innovativeness	13.5 (3.8)	13.2 (3.9)	.22
Computer Self-efficacy	18.8 (4.8)	19.2 (4.8)	.21
Social Factors	17.0 (2.5)	17.4 (2.4)	.01
SPECIFIC FACTORS			
Perceived Usefulness	15.5 (3.2)	16.3 (3.7)	.001
Perceived Ease of Use	14.1 (3.5)	14.6 (3.6)	.88
Affect	13.1 (3.9)	13.4 (4.1)	.005
Perceived Behavioral Control	10.5 (2.7)	11.6 (2.2)	.001
Future Intentions	14.7 (3.7)	14.4 (4.2)	.65

Personal innovativeness with information technology exerted a strong positive influence on computer self-efficacy (H8) at both time periods, and a strong positive influence on perceived ease of use (H9) at Time 1. At Time 2, there was no influence of personal innovativeness on perceived ease of use. This is consistent with the arguments of Venkatesh and Davis (1996) who suggest that through experience, ease of use perceptions become more rooted in specific features of the software and less influenced by general personal traits. Personal innovativeness also exhibited a direct influence on intentions at both time periods (H10).

Supplemental Analysis Concerning Experience

Our analysis, discussed above, suggests that experience moderates many of the relationships between constructs in technology acceptance models. As subjects gain in experience, their intentions are more strongly influenced by affect and perceived behavioral control and less influenced by perceived usefulness and personal innovativeness. Computer self-efficacy exerts a stronger influence on perceived ease of use and affect, but a weaker influence on perceived usefulness. Thus, individuals become able to separate the potential of the software from their ability to use it. Personal innovativeness exerts a stronger influence on self-efficacy following experience but becomes a nonsignificant predictor of perceived ease of use.

The findings that experience moderates some relationships in the model are important for researchers to understand as we attempt to comprehend the forces involved in technology adoption decisions. But it is equally important to understand the direct effects of experience on the constructs in the model. To examine this aspect of the role of experience, we conducted supplemental analyses, comparing the means of each of our model constructs across the two month time period. We expected greater change in the software specific constructs (usefulness, ease of use, affect, perceived behavioral control) than in the more general constructs (social factors, personal innovativeness, self-efficacy). To perform this test, we computed a summed scale score for all constructs at Time 1 and Time 2, and then employed a t-test to see if the difference was statistically significant.

The results (shown in Table 5) partly support our expectation. Of the general factors, neither PIIT nor self-efficacy changed. However, the mean perception of social influence did increase from Time 1 to Time 2. For the specific factors, perceived usefulness, affect, and perceived behavioral control all increased. However, perceived ease of use did not change, nor did long term intentions.

DISCUSSION

In general, the results supported the hypothesized relations. The model explained 44% of the variance in intention at Time 1 and 40% at Time 2. While improving on prediction was not our primary aim in this chapter, examination of explained variance is nonetheless a critical element of PLS analysis. The R^2 values we obtained are less than some other models have explained (e.g., Taylor & Todd, 1995 explained more than 60% of the variance in intention). To provide an internally consistent basis of comparison, we ran a model at each time period based on TAM, using just PU, EOU, and Future Intentions. These models explained 34% and 30% of the variance in intention, compared to 44% and 40% for our expanded model.

We also ran models based on DTPB, eliminating the interlinkages among the independent constructs. These models explained 34% of the variance in intention (same at both time periods).

In general, then, an integrated model acknowledging the linkages between behavioral, control, and normative beliefs, and including general factors such as personal innovativeness, seems to be appropriate for describing technology adoption decisions. The areas where results were not as predicted, or where the paths changed from the first to second time periods, bear particular attention. First, perceived behavioral control exerted a positive influence on intentions at Time 2, but not Time 1. In addition, we noted that the responses to the perceived behavioral control items increased significantly from Time 1 to Time 2. Keeping in mind that one of the PBC items referred to having the "… resources, the knowledge, and the ability to make effective use of Access," this suggests that as the respondents gained experience with the software, they gained more confidence in their ability to control their decisions to use it.

This finding is not completely consistent with Taylor and Todd (1995b), who noted a positive influence of PBC on intentions for both inexperienced and experienced users. The influence was much stronger for experienced users, with path coefficients of 0.16 for inexperienced and 0.50 for experienced (Taylor & Todd, 1995b). In addition, Taylor and Todd (1995b) tested their model within a different context (use of a computer resource center), which could explain the discrepancy in results. In our study, respondents were required to use Access for a course project. Even though our questions focused on long-term, rather than short-term intentions, it is possible that the mandatory nature of the course project interfered with their perceptions of control, and resulted in intentions at Time 1 that were more based on the course requirement than on their future plans. If this were so, it is possible that there was both a negative and positive influence at play, and these cancelled each other.

Social factors did not exert an influence on intentions at either time period. Keeping in mind that the use of the software "in the future" would be completely voluntary for the respondents, these results are consistent with those of Venkatesh and Davis (2000), who observed an influence of social norms in mandatory, but not voluntary, settings. We observed another interesting finding with respect to the hypothesized influence of social factors on perceived EOU. Recall that the scores on the EOU scale did not change significantly from Time 1 to Time 2, while the increase in the scores on the social factors scale was statistically significant. In addition, we hypothesized three other factors as influencing EOU: self-efficacy, personal innovativeness, and perceived behavioral control. At Time 1, self-efficacy, personal innovativeness, and perceived behavioral control all had positive influences on EOU, while the path from social factors to EOU was negative. At Time 2, only the influences of self-efficacy and perceived behavioral control were statistically significant.

There were at least two additional observations worth noting. First, computer self-efficacy provided a strong, positive influence on PBC, EOU, Affect, and PU (at Time 2). These results show a much stronger role for self-efficacy than what Taylor and Todd (1995a) and Venkatesh et al. (2003) hypothesized in their models. In addition, CSE exerted a strong (indirect) influence on intentions to use technology. Second, personal innovativeness was also shown to exert an influence on intentions, both directly and indirectly through CSE and EOU (at Time 1).

IMPLICATIONS FOR RESEARCH AND PRACTICE

One limitation of the study was the use of student subjects, which limits the generalizability to some extent (Compeau, Marcolin, & Kelley, 2001). This provides an opportunity for future research, in that it would be very useful to replicate the study in an applied field setting with knowledge workers who are being asked to adopt and use a new information technology. A second limitation was the use of a limited number of items (generally three) to measure many of the constructs in the model. Future research should include the development and testing of more appropriate scales for each of the constructs.

The results of our analysis have several implications for research on technology adoption, as well as for organizational practice. The most important implication for research is to reinforce the arguments of authors such as Agarwal and Karahanna (2000) and Plouffe et al. (2001) who call for richer models of technology adoption. Moreover, the results suggest that integration, as well as richness, is of value to improving our understanding of an individual's technology adoption choice. Our integrative model shows multiple mechanisms through which personal innovativeness, self-efficacy, and social factors influence technology adoption choices, and adds to our understanding of how judgments of perceived usefulness and perceived ease of use are formed.

The results also show the influence of general factors on specific software beliefs, suggesting a degree of generality in perceptions relating to computers. Bandura (1997) and others (e.g., Agarwal et al., 2000) argue persuasively for the need to match self-efficacy judgments to the specific task. This makes sense from the standpoint of maximizing prediction, yet our results show that these general influences can also influence beliefs about specific software packages. Further study of the generalizability of self-efficacy perceptions (following the work of Agarwal et al., 2000) would be valuable in building this understanding.

In addition, the strong influence of personal innovativeness on self-efficacy and ease of use perceptions (as well as on future intentions) suggests that measuring personal innovativeness and self-efficacy perceptions could help in developing more effective training programs prior to the introduction of new information technologies. For example, knowing that a group of workers scored highly on personal innovativeness would suggest that less time and effort would be needed to ensure they had positive beliefs about the ease of use of a new information system. Further, the relatively small influence of PBC at Time 1, followed by the medium influence at Time 2, suggests that the influence of PBC increases as users gain experience. This suggests that managers should ensure that potential users perceive they have adequate access to resources (including training) after they have had some initial experience with the technology, and not just when it is introduced to them.

Finally, the results confirm the importance of incorporating experience into models of technology acceptance. Several authors have shown changes in technology adoption models, and we confirm their findings. We further show that it is specific, more than general, measures that tend to change with experience. The conceptualization of experience is challenging however. As we noted earlier, experience partly reflects exposure to the tool and partly reflects the skills and abilities that one gains through using a technology. Experience also probably reflects habit to some extent. Our research findings, including previous authors and those in this study, do not clearly differentiate between these types of effects. Nonetheless, it seems reasonable that there might be different sorts of influences depending on the extent to which experience reflects habit, skill, or simply exposure. Thus, we believe it is important for future research to more fully examine the conceptualization of experience and its influence in technology adoption models.

CONCLUSION

In summary, our results provide support for an extended model based on the decomposed theory of planned behavior. They confirm existing findings within the technology adoption stream, but also show the possibility of a more holistic and integrative approach to our models. Such an approach allows for the inclusion of less instrumental beliefs (e.g., personal innovativeness with IT) as influences on technology adoption, demonstrates the complexity of the mechanisms through which general beliefs such as personal innovativeness and self-efficacy influence adoption intention, and aids in building our understanding of the antecedents of perceived usefulness and perceived ease of use, the critical constructs in the Technology Acceptance Model. We further echo the calls of other researchers (e.g., Sun & Zhang, 2006) to extend our conceptualization and understanding of the role of experience in the formation of judgments about information technologies.

While it has been argued that technology acceptance is a mature model (Venkatesh, 2006; Venkatesh et al, 2003), we believe there is substantial work to be done in further understanding the process of adoption. We agree with Jasperson, Carter, and Zmud (2005) that richer models are required which take into account the varying features of different technologies, the extent to which these features are used, and the individual differences of the users themselves. Initial research in this area has found that feature specific self-efficacy predicts usage above and beyond a more generalized operationalization of self-efficacy (Hasan, 2006; Hsu & Chiu, 2003). In addition to better prediction, richer models of adoption can better inform the design and support of information technologies in organizations.

REFERENCES

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, *24*(4), 665-694.

Agarwal, R., & Prasad, J. (1998, June). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 204-215.

Agarwal, R., Sambamurthy, V., & Stair, R.M. (2000, December). Research report: The evolving relationship between general and specific computer self-efficacy: An empirical assessment. *Information Systems Research, 11*(4), 418-430.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179-211.

Bandura, A. (1986). *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: W.H. Freeman & Co.

Barclay, D.W., Higgins, C.A., & Thompson, R.L. (1995). The partial least squares approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies: Special Issue on Research Methodology, 2*(2), 285-324.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *Management Information Systems Quarterly, 28*(2), 229-254.

Chau, P., & Hu, P. (2001). Information technology acceptance by individual professionals: A model comparison approach. *Decision Sciences, 32*(4), 699-719.

Chin, W.W., & Frye, T. (2001). *PLS-Graph* (Version 03.00). Soft Modeling Inc.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillside, NJ: L. Erlbaum Associates.

Compeau, D.R., & Higgins, C.A. (1995a). Application of social cognitive theory to training for computer skills. *Information Systems Research, 6*(2), 118-143.

Compeau, D.R., & Higgins, C.A. (1995b). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189-211.

Compeau, D.R., Higgins, C.A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly, 23*(2), 145-158.

Compeau, D., Marcolin, B., & Kelley, H. (2001). Generalizability of technology acceptance research using student subjects. In A. Ramirez (Ed.), *Proceedings of the Administrative Science Association of Canada, 22*(4), 35-47.

Davis, F.D., Bagozzi, R.P., & Warshaw, P.R. (1989, August). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 983-1003.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intentions and behavior: An introduction to theory and research*. Boston: Addison-Wesley.

Ford, J., Smith, E., Weissbein, D., Gully, S., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83*, 218-233.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*, 39-50.

Gundlach, M.J., & Thatcher, J.B. (2000). *Examining the multi-dimensionality of computer self-efficacy: An empirical test.* Unpublished manuscript, Florida State University.

Hackbarth, G., Grover, V., & Yi, M.Y. (2003). Computer playfulness and anxiety: Positive and negative mediators of the system experience effect on perceived ease of use. *Information and Management, 40*, 221-232.

Hasan, B. (2006). Delineating the effects of general and system-specific computer self-efficacy beliefs on IS acceptance. *Information and Management, 43*, 565-571.

Hsu, M-H., & Chiu, C-M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems, 38*, 369-381.

Jasperson, J., Carter, P.E., & Zmud, R.W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525-557.

Karahanna, E., Straub, D.W., & Chervany, N.L. (1999, June). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly, 23*(2), 183-213.

Klein, K.J., & Sorra, J.S. (1996). The challenge of innovation implementation. *Academy of Management Review, 21*, 1055-1080.

Larsen, T.J., & Sorebo, O. (2005). Impact of personal innovativeness on the use of the Internet among employees at work. *Journal of Organizational and End User Computing, 17*(2), 43-63.

Lippert, S.K., & Forman, H. (2005). Utilization of information technology: Examining cognitive and experiential factors of post-adoption behavior. *IEE Transactions on Engineering Management, 52*(3), 363-381.

Lu, J., Yao, J.E., & Yu, C.-S. (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *Strategic Information Systems, 14*, 245-268.

Marcolin, B.L., Compeau, D.R., Munro, M.C., & Huff, S.L. (2000, March). Assessing user competence: Conceptualization and measurement. *Information Systems Research, 11*(1), 37-60.

Mathieson, K., Peacock, E., & Chin, W.W. (2001). Extending the technology acceptance model: The influence of perceived user resources. *The DATA BASE for Advances in Information Systems, 32*(3), 86-112.

McFarland, D.J., & Hamilton, D. (2006). Adding contextual specificity to the technology acceptance model. *Computers in Human Behavior, 22*, 427-447.

Morris, M.G., Venkatesh, V., & Ackerman, P.L. (2005). Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *IEEE Transactions on Engineering Management*, *52*(1), 69-84.

Plouffe, C.R., Hulland, J.S., & Vandenbosch, M. (2001). Richness versus parsimony in modelling technology adoption decisions: Understanding merchant adoption of a smart card-based payment system. *Information Systems Research, 12*(2), 208-222.

Riemenschneider, C.K., Harris, D.A., & Mykytyn, P.P., Jr. (2003). Understanding IT adoption decisions in small business: Integrating current theories. *Information and Management, 40*, 269-285.

Seddon, P.B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information Systems Research, 8*(3), 240-253.

Sun, H., & Zhang, P. (2006). The role of moderating factors in user technology acceptance. *International Journal of Human-Computer Studies, 64*, 53-78.

Szajna, B. (1996, January). Empirical evaluation of the revised technology acceptance model. *Management Science*, *42*(1), 85-92.

Taylor, S., & Todd, P.A. (1995a, June). Understanding information technology usage: A test of competing models. *Information Systems Research*, *6*(2), 144-176.

Taylor, S., & Todd, P.A. (1995b). Assessing IT usage: The role of prior experience. *MIS Quarterly, 19*, 561-570.

Thompson, R.L., Higgins, C.H., & Howell, J.M. (1991, March). Towards a conceptual model of utilization. *MIS Quarterly, 15*(1), 125-143.

Thompson, R.L., Higgins, C.H., & Howell, J.M (1994). Influence of experience on personal computer utilization: Testing a conceptual model. *Journal of Management Information Systems*, *11*, 167-187.

Triandis, H.C. (1980). Values, attitudes and interpersonal behavior. In H.E. Howe (Ed.), *Nebraska Symposium on Motivation, 1979: Beliefs, Attitudes and Values* (pp. 195-259). Lincoln, NE: University of Nebraska Press, 195-259.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342-365.

Venkatesh, V. (2006). Where to go from here? Thoughts on future directions for research on individual-level technology adoption with a focus on decision making. *Decision Sciences, 37*(4), 497-518.

Venkatesh, V., & Davis, F.D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451-482.

Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*, 186-204.

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*, 425-478.

Workman, M. (2005). Expert decision system use, disuse and misuse: A study using the theory of planned behavior. *Computers in Human Behavior, 21*, 211-231.

Yi, M.Y., Fiedler, K.D., & Park, J.S. (2006). Understanding the role of individual innovativeness in the acceptance of IT-based innovations: Comparative analyses of models and measures. *Decision Sciences, 37*(3), 393-426.