THE EFFECT OF PERSONAL INNOVATIVENESS

ON TECHNOLOGY ACCEPTANCE AND USE

By

PETER A. ROSEN

Bachelor of Arts
University of California, Santa Barbara
Santa Barbara, CA
1993

Master of Business Administration
San Diego State University
San Diego, CA
1996

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
July, 2005

THE EFFECT OF PERSONAL INNOVATIVENESS

ON TECHNOLOGY ACCEPTANCE AND USE

Dissertation Defense:

Rick L. Wilson

Nikunj P. Dalal

Mark Gavin

Marylin G. Kletke

A. Gordon Emslie
Dean of the Graduate College

ACKNOWLEDGMENTS

I wish to thank the following people:

Chair: Dr. Rick Wilson for his guidance throughout the PhD program

Committee Members: Drs. Nik Dalal, Mark Gavin and Meg Kletke for their time and expertise

Faculty: Drs. Rathindra Sarathy and Ramesh Sharda for their insight

Family: Brooke, Hannah, Elijah, Ira, Laura, and Wayne Rosen for their support

Peers: Mohammad Al-Ahmadi, Stephen Barnes, Brad Carlson, Susan Chinburg, Christie Fuller, David Furman, Bob Greve, Ashish Gupta, Deana Jelovac, Dave Kern, Han Li, Joyce Lucca, Charles McCann, Susan Michie, Don Kluemper, Mark Phillips, Hank Ramsey, Deepa Ray, and John Signftz for their friendship and support

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Organizations of all types, from corporations to not-for profit firms, are constantly updating their information technology (IT) in an attempt to gain competitive advantages. Expected benefits of successful IT implementation include increases in productivity and efficiency, better communication across organizational units, and a more effective distribution of work activities (Al-Gahtani 2004; Fisher et al. 2004). In a study on office automation, productivity gains from new IT systems were found to be greater than 15% in every company surveyed (Hirschheim 1986). The Illinois National Bank of Springfield, for example, reported an increase in productivity of 340% in its support staff after a new IT implementation (Hirschheim 1986). While not all projects produce such results, top-level management would not support new IT projects as frequently as they do if they believed that the benefits of implementation did not outweigh the costs.

End-user acceptance of IT is one of many critical success factors to IT project implementation, and lack of acceptance can lead to project failure (Pinto et al. 1990). When IT projects fail, the costs can be significant. A recent KPMG survey of 134 companies (mostly European) found that the average cost of IT project failures was $14 million, with the worst example citing a loss of $240 million (Anonymous 2003). One way IT projects can fail is project abandonment. In a study of IT project abandonment, 23 of 49 companies surveyed had either totally, substantially, or partially abandoned an

IT project in the recent past (Ewusi-Mensah et al. 1991). Besides total abandonment, another way IT projects can fail is underutilization of systems (Gefen et al. 1998). Lack of user acceptance can be a contributing factor to both IT project abandonment and underutilization of implemented systems.

While early articles on user acceptance studied basic word-processing and e-mail technologies (Davis 1989; Davis et al. 1989), user acceptance issues are not germane to just simple office products. For instance, end-user reluctance or unwillingness to accept systems has been cited as a cause of failure in many studies done on Enterprise Resource Planning (ERP) software as well (Nah et al. 2004).

Given this, it is not surprising that individual level technology acceptance is one of the most researched topic areas in the field of information systems (IS). A recent review of the Technology Acceptance Model (TAM), a model frequently used to predict individual acceptance of technology, found over 100 such studies from leading IS journals and conferences during the past 17 years (Lee et al. 2003).

As the acceptance literature is well established and contains a variety of explanatory models, Venkatesh, Morris, Davis and Davis (2003) created a synthesized model that portrayed a more complete picture of the acceptance process than any previous individual models. Eight models previously used in the IS literature were merged in an integrated model, all of which had origins in psychology, sociology, and communications. These models were Social Cognitive Theory (Bandura), Innovation Diffusion Theory (Rogers), Theory of Reasoned Action and Theory of Planned Behavior (Fishbein and Ajzen), Technology Acceptance Model (Davis), Combined TAM-TPB, PC

Utilization Model (Triandis), and the Motivation Model. Each model attempts to predict and explain user behavior using a variety of independent variables.

Venkatesh, Morris, Davis, and Davis' (2003) unification model sought to improve upon predictive ability of the individual models by identifying commonalities and capitalizing on their best aspects. They created the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The UTAUT model explained about 70 percent of the variance in intention to use technology, vastly superior to variance explained by the eight individual models, which ranged from 17 and 42 percent.

The conclusion of the study was that the UTAUT model explained user acceptance in a more complete and realistic manner than past models. By consolidating and improving upon existing IT acceptance models, the UTAUT model, it was argued, should now serve as a benchmark for the acceptance literature, much like TAM has over the past 15 years.

As the number of TAM studies increased over the recent past, researchers also explored antecedents of perceived ease of use and perceived usefulness, key components of TAM. The goal of these studies was to broaden the scope of TAM and to generalize results across many different contexts.

The study in this paper will augment the UTAUT model by utilizing the individual innovativeness construct. First introduced in 1998, the construct of Personal Innovativeness in the Domain of Information Technology (PIIT) is designed to measure "the willingness of an individual to try out any new information technology" (Agarwal et al. 1998). While the UTAUT model measures many variables, it fails to investigate individual traits, such as innovativeness, that could further help explain the process of technology acceptance and use.

Therefore, this study, investigated the effect of the PIIT construct in a modified UTAUT model framework. By including PIIT, it is expected that the amount of variance explained in both behavioral intentions to use and actual use of new technology should increase, providing a more realistic picture of individual level IT acceptance.

A few studies have previously used PIIT as a construct in their research model. Interestingly, PIIT has been used as an antecedent to other variables, as a consequent of other variables, and as moderator between variables. As an antecedent, PIIT has been shown to influence computer self-efficacy (Agarwal et al. 2000; Kishore et al. 2001; Thatcher et al. 2002), computer anxiety (Thatcher et al. 2002), relative advantage (Karahanna et al. 2002), perceived ease of use and perceived usefulness (Kishore et al. 2001; Lewis et al. 2003; Lu et al. 2003), and intention to use technology (Thatcher 2004). As a moderator, it has been used to better explain the relationship between perceived ease of use and intention to use, and between perceived usefulness and intention to use (Agarwal et al. 1998). Finally, as a consequent, the variables of trust (McKnight et al. 2002), playfulness and flow state (Woszczynski et al. 2002) are hypothesized to influence PIIT.

With the lack of consensus, this study therefore also explored the “position” that PIIT should be included in the technology acceptance process. First, PIIT was tested as a main effect variable, predicting behavioral intentions to use a new IT. Next, PIIT was tested as a moderator of the relationship between perceptions of IT and behavioral intentions to use IT. Finally, PIIT was tested as a predictor of technology use. By examining PIIT in three different logical locations in the research model, this study attempted to clarify where PIIT fits in the acceptance context.

In summary, the goals will be: 1) to determine if the inclusion of PIIT better explains the technology acceptance process 2) to determine where PIIT best fits in this context, and 3) to test a modified version of the UTAUT model to evaluate its efficacy as the model of choice for future technology acceptance studies.

CHAPTER II

REVIEW OF LITERATURE

The acceptance and use of technology has been a topic of much discussion in the MIS literature. As this study explores innovativeness within the context of technology use, the review of relevant literature will start with a brief introduction of the UTAUT model, followed by a discussion of innovativeness. Additionally, in the marketing literature, numerous articles have focused on the innovativeness concept, and its relationship to consumer purchase behavior. Hypotheses for innovativeness will be provided first, followed by those related to the replication of UTAUT.

UTAUT Model

A recent study proposed a model of IT acceptance that combined elements from eight oft-used models found in the MIS literature. A complete discussion of the eight models, and the resultant creation of the Unified Theory of Acceptance and Use of Technology (UTAUT) model can be found in (Venkatesh et al. 2003).

The eight existing models of IT acceptance shared one thing in common; they explain behavioral intentions or usage behavior at the individual user level. Thus, IT adoption studies that predict success or task fit do not fall in the scope of this study, as in (DeLone et al. 1992; Goodhue et al. 1995) . As this study focuses on individual level user acceptance, studies whose focus is on organizational adoption of new technology will also not be considered (Klein et al. 1996; Leonard-Barton et al. 1988).

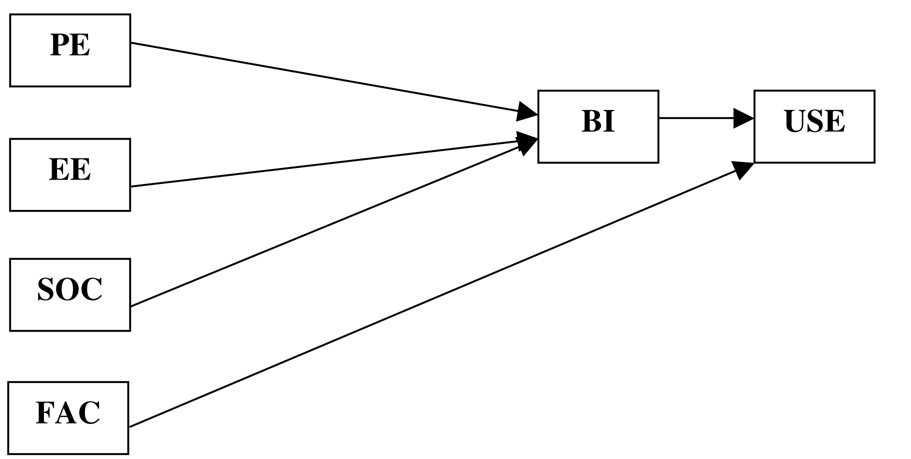
The first step in the creation of the UTAUT model was to identify areas of overlap and the most important variables. Five new constructs were defined (Table 1) that incorporated the similarities of previous constructs. Performance expectancy, effort expectancy, social influence, facilitating conditions, and attitude were created by combining elements taken from the eight existing models of individual level IT user acceptance. Two of the seven constructs listed below, anxiety and self-efficacy, came directly from the Social Cognitive Theory model (Compeau et al. 1995; Compeau et al. 1999) and were not changed in any way. These constructs were deemed to be influential enough to be included in the new model, even though they did not overlap with other models per se.

Table 1 – UTAUT Model Constructs

New Construct Name	Model	Old Construct Name
Performance Expectancy	TAM, Combined TAM-TPB, Motivation Model	Perceived Usefulness
	PC Utilization	Job Fit
	Innovation Diffusion Theory	Relative Advantage
	Social Cognitive Theory	Outcome Expectations
Effort Expectancy	TAM, Combined TAM-TPB, Motivation Model	Perceived Ease of Use
	PC Utilization	Complexity
	Innovation Diffusion Theory	Ease of Use
Social Influence	Theory of Reasoned Action, TPB, Combined TAM-TPB	Subjective Norm
	PC Utilization	Social Factors
	Innovation Diffusion Theory	Image
Facilitating Conditions	TPB & Combined TAM-TPB	Perceived Behavioral Control
	PC Utilization	Facilitating Conditions
	Innovation Diffusion Theory	Compatibility
Attitude	Theory of Reasoned Action, TPB, & Combined TAM-TPB	Attitude Toward Behavior
	Motivation Model	Intrinsic Motivation
	PC Utilization	Affect Toward Use
	Social Cognitive Theory	Affect
Anxiety	Anxiety	Self-Efficacy
Self-Efficacy	Social Cognitive Theory	Self-Efficacy

Figure 1 shows the core UTAUT model without the moderators (gender, age, voluntariness and experience) and without the constructs that were shown to not significantly impact behavioral intentions (computer self efficacy, anxiety, and attitude). This serves as the technology framework within which the impact of innovativeness will be tested.

Figure 1 – UTAUT Model



General Innovativeness

There is much disagreement about the concept, as differences exist regarding the level of abstraction (global vs. domain specific vs. product specific), the timing of measurement (predictive vs. post hoc), whether it is a personality trait or cognitive style, and how it should be operationalized.

As a starting point in this study Everett M. Rogers' definition of an innovation is used. He defines an innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers 2003). A related term, innovativeness, is defined as the "the degree to which an individual is relatively earlier in adopting an innovation than other members of his (social) system" (Rogers et al. 1971). This definition is insightful in its use of time and its post-hoc measurement (as it is only measured after an innovation has been adopted). While this measurement method allows researchers to explain the adoption of an innovation, it is not useful for prediction. This can be considered a major drawback of the Rogers and Shoemaker's (1971) definition. Another major drawback of this definition and measurement method of innovativeness is that it is tied to a specific innovation. For example, an employee adopter of Microsoft Excel is considered innovative just for Microsoft Excel. If that same person adopts Microsoft Word later than her peers, she would not be considered innovative for Microsoft Word. Thus, the individual is considered highly innovative for one product and not innovative for another very similar software product. Thus, by tying the definition of innovativeness to the innovation itself, the concept cannot be generalized across innovations (or products). Regardless of these two major shortcomings of Rogers and Shoemaker's definitions, many future studies built upon their groundbreaking work.

A second definition of innovativeness views the concept as "a basic dimension of personality relevant to the analysis of organizational change" (Kirton 1976). Kirton proposed that "everyone can be located on a continuum ranging from an ability 'to do things better' to an ability 'to do things differently,' and the ends of the continuum are labeled adaptive and innovative, respectively" (Kirton 1976). A 32-item questionnaire, called the Kirton Adaption-Innovation Inventory (KAI) was used to determine an individual's location point on the continuum. The KAI inventory was based in part on the descriptors (characteristics) for adaptors and innovators from the earlier work of Rogers and Shoemaker (1971).

The major difference between Kirton's work and Rogers and Shoemaker is that KAI could be used to predict an individual's level of innovativeness before adoption. Thus, the results of the questionnaire could be applied to an individual and generalized across all innovations (not just one specific innovation). Thus, KAI scores could be used in a more practical way for marketing professionals. Since individuals who are innovative could be identified in advance, early advertising efforts could be targeted on these individuals for increased product adoption.

In the field of communications, researchers also created a predictive measure of general innovativeness. These authors defined innovativeness as "a normally distributed, underlying personality construct, which may be interpreted as a willingness to change" (Hurt et al. 1977). The 20-item Innovativeness Scale (IS) was designed to predict an individual's level of innovativeness on a global level, which could be applied to all types of innovations, much like KAI scores. The authors found that their 20-item measure could place individuals into five categories of innovativeness (innovators, early adopters, early majority, late majority and laggards), in a normally distributed fashion, exactly as defined by Rogers and Shoemaker (1971). An interesting point in the Hurt, et al (1977) study is that innovativeness was defined as a willingness to change, and not the change itself. Therefore, they measure intention to change, and are not concerned with whether the behavior actually changed. Interestingly, this is analogous to behavioral intentions used in the MIS literature and has an important ramification for this study.

Multiple Levels of Innovativeness

While Rogers and Shoemaker (1971), Kirton (1976) and Hurt et al. (1977) defined innovativeness as a general level construct, others took a different. In their theoretical paper, Midgley and Dowling (1978), propose multiple levels of innovativeness. The most general level of innovativeness that which can be applied across product categories is termed innate innovativeness. This concept is very similar to the concepts presented earlier. Actualized innovativeness is another level of innovativeness proposed in the same study, and is defined as “what is observed and measured as innovative behavior” i.e., the actual purchase of a new product (Midgley et al. 1978). While these two levels of innovativeness are related, complex situational effects, communications, and interest in the product category mediate the relationship between innate innovativeness (general type) and actualized innovativeness (behavior). The authors propose a relationship between these two levels of innovativeness as “individuals with a high degree of innate innovativeness [should] display high actualized innovativeness on more occasions than other, less innovative individuals”.

While Midgley and Dowling agree with earlier authors that innovativeness is a basic personality trait, there are a few interesting differences between their work and that of the previous literature. Midgley and Dowling assert that innovativeness must be tied to observable behavior or else it is meaningless, differentiating from Hurt et al and Kirton who measure innovative intentions.

Also, Midgley and Dowling’s view that “in the context of any specific innovation, complex situational and communication effects intervene between individuals’ innovativeness and their observed time of adoption” (Midgley et al. 1978) is another major difference. Therefore, instead of proposing a direct link between innovativeness and actual behavior, Midgley and Dowling posit that other factors contribute to the understanding of the innovativeness-behavior relationship.

Similar to Midgley and Dowling (1978), Hirschman (1980) also defines the innovativeness construct with a number of different levels. In her study, three levels of innovativeness are presented; vicarious, adoptive, and use innovativeness (Hirschman 1980). Vicarious innovativeness is the "acquisition of information regarding a new product", while adoptive innovativeness "refers to the actual adoption of a new product". Use innovativeness is applied to products that have already been adopted by a consumer and occurs "when the consumer uses a product that s/he already possesses to solve a problem that has not been previously encountered". Hirschman proposes a theoretical model of the innovativeness process by introducing antecedents to innovativeness, including novelty seeking, role accumulation, consumer creativity, and socialization influences.

Additionally, Hirschman disagrees with all previous authors and suggests that innovativeness may not be a stable personality trait. "Given the fact that innovativeness has been found highly correlated with such variables as educational attainment, occupational status, and urbanization, it would seem more plausible that it is not a genetic constant, but rather socially influenced" (Hirschman 1980).

Since both the Midgley and Dowling (1978) and Hirschman (1980) studies were theoretical, and not empirically tested, it is difficult to determine which concept of innovativeness (general vs. multi-level) is more practical. The two types of innovativeness were presented to show the historical disagreement in the marketing literature on precise definitions and use of the innovativeness construct.

Consolidation of Innovativeness Literature

The previous five authors each had a slightly different opinion on the definition and use of innovativeness. In response to this, Goldsmith (1986) undertook a study that examined the similarities and differences of the various types of innovativeness. In his study, the convergent validity of the Open Processing Scale (OPS) (Leavitt et al. 1975), the Jackson Innovation (JI) innovativeness subscale (Jackson 1976), and the previously mentioned KAI (Kirton 1976) and Innovativeness Scale (Hurt et al. 1977) was examined. At the time, they were the most commonly used innovativeness scales. OPS was utilized to measure a distinctive cognitive style presumed to underlie innovative consumer behavior (Leavitt et al. 1975), while the JI describes an innovator as a "creative and inventive individual, capable of originality of thought; motivated to develop novel solutions to problems; values new ideas; like to improvise" (Jackson 1976).

Goldsmith found that though the four definitions underlying the scales were different, the results supported the convergent validity of the four scales, suggesting they are measuring similar or nearly similar traits (Goldsmith 1986). While IS and OPS measure the willingness of an individual to try new things, JI measures divergent thinking (creativity), and KAI measures different cognitive styles of problem solving. The commonality per Goldsmith, was their "ability to measure the traits of sensation seeking and risk taking as components of 'innovativeness', however it is defined" (Goldsmith 1986). The Goldsmith study highlighted the lack of consensus in the innovativeness literature, but supported the notion that the term had been used throughout in a similar fashion. Note that Goldsmith did not use the Midgley and Dowling (1978), or Hirschman (1980) studies, as they proposed no operationalization of the innovativeness construct.

Domain Specific Innovativeness

Goldsmith also researched the concept of domain specific innovativeness (DSI), an idea based upon the concept of the cross-sectional approach to measuring innovativeness (Gatignon et al. 1985; Midgley et al. 1978; Robertson et al. 1969). DSI "reflects the tendency to learn about and adopt innovations (new products) within a specific domain of interest" (Goldsmith et al. 1990). Their initial research described six studies used to develop and test a DSI scale. This resulted in a six-item, unidimensional scale which measured innovativeness of an individual in a specific area of interest. Questions could be modified to fit any domain of interest, and the results could then be generalized within that domain. Using the example from their study, one who is innovative in the domain of music is not necessarily innovative in fashion, so to measure the global innovativeness of an individual as in (Hurt et al. 1977; Kirton 1976) would add little value (Goldsmith et al. 1990).

Personal Innovativeness in the Domain of Information Technology

The previous studies have attempted to show that a domain specific view of innovativeness gives marketers a more practical way to measure and predict purchase behavior than a global view of innovativeness. This idea was used in the Management Information Systems (MIS) field when a study was conducted to define Personal

Innovativeness in the Domain of Information Technology (PIIT) (Agarwal et al. 1998). This new construct is basically Goldsmith and Hofacker's DSI scale adapted to the domain of information systems. PIIT is defined as "the willingness of an individual to try out any new information technology" (Agarwal et al. 1998). If individuals more likely to try IT can be identified, these people can act as change agents and opinion leaders for new IT implementations in organizational settings (Agarwal et al. 1998). When considering implementation of new technology, these individuals could help champion IT project implementation, leading to fewer project failures. From the vantage point of IT producers, early marketing campaigns could be targeted the highly innovative, leading to strong early sales and potentially improved word of mouth advertising to those who are less innovative.

PIIT Moderation Hypotheses – Between Perceptions and Intentions

Agarwal and Prasad (1998) disagree marketing researchers who posited a direct link between innovativeness and purchase behavior and argue for the use of PIIT is as a moderator. They theorize PIIT to moderate the relationship between perceptions of an IT and behavioral intentions to use a new IT. As an example, consider two individuals with similar perceptions of a specific information technology. Those individuals with higher levels of PIIT are theorized to be more likely to create favorable intentions to use the new IT than those with lower levels of PIIT (Agarwal et al. 1998). PIIT as a moderator is also consistent with earlier use of innovation as an individual characteristic that moderated the relationship between managerial messages and adoption of IT (Leonard-Barton et al. 1988).

Based upon Goldsmith's argument that a domain specific view of innovativeness was more meaningful than a global view, the domain specific innovativeness in the form of PIIT was used in this study. Additionally, using the theoretical models of Agarwal and Prasad (1998) and Leonard-Barton and Deschamps (1988), innovativeness will be tested as moderator in the relationship between perceptions and behavioral intentions to adopt a new IT.

This study will use a modified version of the UTAUT model of technology acceptance, which includes two perceptions, performance expectancy (perceived usefulness of technology) and effort expectancy (perceived ease of use of the technology). These terms will be presented in more detail later, but are illustrated in Figure 1.

H1: PIIT will moderate the relationship between the performance expectancy and behavioral intentions to use the new technology.

H2: PIIT will moderate the relationship between the effort expectancy and behavioral intentions to use the new technology.

The way the relationships can be described in these two hypotheses are identical. With negative perceptions of performance expectancy (usefulness), as measured by low scores on a 1-7 Likert scale, both those with high levels of PIIT and those with low levels of PIIT will have low levels of behavioral intention to use the technology. With more positive perceptions of usefulness, as measured by higher scores on a Likert 1-7 scale, those with higher levels of PIIT will be more likely to indicate intentions to use the technology than those with lower levels of PIIT. The same holds true for effort expectancy (ease of use). Negative perceptions of effort expectancy will lead to low levels of behavioral intention to use the technology, no matter the level of PIIT. As the perceptions of effort expectancy become more positive it is hypothesized that those with higher levels of PIIT will be more likely to indicate intentions to use the technology than those with lower levels of PIIT.

Interestingly, Agarwal and Prasad (1998) found only the relationship between compatibility (one perception) and intention was significantly moderated by PIIT. Even with generally non-significant findings, their theory suggests that one proper usage of PIIT is as a moderator in the relationship between perceptions of technology and intentions to use technology.

PIIT to Behavioral Intentions & Actual Usage Behavior – Main Effect Hypotheses

In contrast to using PIIT as a moderator, others have empirically tested the direct link between traits and behavior and found a significant relationship.

Eastlick and Lotz (1999) developed a theoretical model that linked personal innovativeness traits (including opinion leadership/innovativeness, hedonic shopping involvement, and information seeking) to adoption intentions through an attitudinal construct. In the context of electronic shopping (Internet, television, or a combination of both), they found those who scored high on opinion leadership/innovative scales were more likely to intend to purchase items than those were scored lower on the same scale (Eastlick et al. 1999).

The second study supporting the link between innovativeness and intentions used a modified version of the Theory of Planned Behavior (TPB) to model Internet shopping intentions and actual shopping behavior (Limayem et al. 2000). The constructs of perceived consequences and personal innovativeness are added to attitudes, subjective norms, and perceived behavioral control to construct a picture of the factors that shape

Internet shopping intentions and behavior. The research model links personal innovativeness to purchase intentions directly. The link was found significant; giving support to innovativeness as a positive influence of behavioral intentions.

While these two studies showed empirical support for the link between innovativeness and intentions, neither used DSI as the measure of innovativeness. One study used DSI as its measure of innovativeness as it modeled Internet shopping behavior (Citrin et al. 2000). In their study, DSI was used both as a main effect variable and to moderate the relationship between Internet usage and Internet shopping behavior. This study found that both the main effects of Internet usage and DSI were significant predictors of Internet shopping behavior.

This finding of DSI directly predicting purchase behavior is contrary those who argue that the simple trait to behavior model is incomplete. Since domain specific innovativeness represents “the tendency to learn about and adopt innovations within a specific domain of interest, [it] therefore, taps a deeper construct of innovativeness more specific to an area of interest” (Citrin et al. 2000). The theory behind using DSI comes from the theory that those naturally interested and curious about a specific domain are more likely to exhibit usage or purchase behavior in that domain than those who are just generally curious. Based on this it was not surprising that it was found that DSI in Internet innovativeness was more influential than the general measure of innovativeness in predicting Internet shopping behavior (Citrin et al. 2000).

In the same vein, Goldsmith (2001) conducted a number of studies showing the link between DSI and either actual purchase behaviors or purchase intentions. The first study shows a link between both buying intentions and buying behavior online

(Goldsmith 2001). It was shown that subjects who were more innovative in Internet behavior were more likely to be currently purchasing online, and even if they were not purchasers, they were more likely to indicate the intention for future purchases (Goldsmith 2001). This was echoed in another study that linked DSI to both purchase behavior and purchase intentions (Goldsmith 2002). In the case of consumer behavior, the support for the link between DSI and purchase intentions is theorized to exist because consumers 1) may not be able to afford what they want to buy, 2) may not find available what they are currently looking to purchase, 3) may be purposely delaying the purchase (Goldsmith 2002).

The studies in the previous discussion link innovativeness to either purchase behavior or purchase intentions and all found empirical support for those links. This leads to the next two hypotheses that were tested in this study:

H3: There will be a significant positive relationship between PIIT and behavioral intentions to use a new information technology.

H4: There will be a significant positive relationship between PIIT and actual usage of a new information technology.

These first four hypotheses address the innovativeness construct, as operationalized by PIIT, and how it will be used to either moderate the relationship between perceptions of technology and behavioral intentions to use technology, or to directly predict behavioral intentions and actual use of technology. As this study attempts to extend the current technology acceptance literature with the inclusion of innovativeness, the next section will describe in more detail the aforementioned UTAUT model of technology acceptance.

At the start of this chapter, Table 1 identified the major constructs of UTAUT. Next, individual hypotheses related to the 'validation' component of this study are presented along with a detailed description of each construct.

Performance Expectancy (PE)

This construct has been found to be the most influential in predicting user intentions, and is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al. 2003). Perceived usefulness, a major construct in TAM, is almost identical in definition to performance expectancy (Davis et al. 1989; Venkatesh et al. 2000). Job fit, a component of the PC Utilization Model, measures how an individual thinks their job performance will change if they use a PC to accomplish their tasks (Thompson et al. 1991). Relative advantage, from the Innovation Diffusion Model, is "the degree to which an innovation is perceived as being better than its precursor" (Moore et al. 1991). This measures the perceived performance of IT task in relation to the same task done without IT. Outcome expectations, a construct from the Social Cognitive Theory Model, is the final component of performance expectancy and is defined as the "efficiency and effectiveness gains that are expected to occur as a result of using the computer to perform the job (Compeau et al. 1995; Compeau et al. 1999). These four previous constructs share common aspects of improving job performance due to the use of IT. Thus,

H5: There will be a significant positive relationship between performance expectancy and behavioral intentions to use a new information technology.

Effort Expectancy (EE)

System complexity and its effect on system use has been incorporated into many models. Effort expectancy encompasses the variables of perceived ease of use, complexity, and ease of use from prior models, and is "the degree of ease associated with the use of the system" (Venkatesh et al. 2003). Perceived ease of use, from TAM, is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis 1989). Complexity, from the PC Utilization Model, measures the perceived difficulty of the system to its users (Thompson et al. 1991). Ease of use, from Innovation Diffusion Theory, measures "the degree to which an innovation is perceived as being difficult to use" (Moore et al. 1991). All of these constructs measure how difficult a system is to use, and have been found to be important predictors of technology acceptance. Since all measure system complexity, they are combined into the new construct, effort expectancy. The hypothesis relating to the UTUAT construct of effort expectancy is:

H6: There will be a significant positive relationship between effort expectancy and behavioral intentions to use a new information technology.

Social Influence (SOC)

The next construct of interest is social influence, and aspects of social influence can be found in TRA, TPB, C-TAM-TPB, Innovation Diffusion Theory and the PC Utilization Model. Social influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003). The construct called subjective norms, from the Theory of Reasoned Action, is the first component of social influence. Defined as the "person's perception that most people who are important to him think he should or should not perform the behavior in question" social norms were found to positively influence behavioral intentions (Fishbein et al. 1975). Image, a similar construct from the Innovation Diffusion Theory model, is the "degree to which use of an innovation is perceived to enhance one's image or status within a social system" (Moore et al. 1991). Finally, social factors influencing PC use, a component of the PC Utilization Model, is another similar component used to create the new construct of social influence in the UTAUT model. The hypothesis relating to the UTAUT construct of social influence is as follows:

H7: There will be a significant positive relationship between social influence and behavioral intentions to use a new information technology.

Facilitating Conditions (FC)

Not all organizations support their technology equally. Facilitating conditions are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al. 2003). Past models that include similar constructs include TPB, Combined TAM-TPB, Innovation Diffusion Theory and the PC Utilization Model. Perceived behavioral control, a similar construct from TPB refers to "people's perceptions of the ease or difficulty of performing the behavior of interest" (Ajzen 1991). Facilitating conditions, from the PC Utilization Model, refers to the support available to assist individuals with the hardware and software selected for the job (Thompson et al. 1991). Compatibility, from the Innovation Diffusion Theory model, refers "to the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters" (Moore et al. 1991). Past research indicates that when both performance and effort expectancy constructs are present, the role that facilitating conditions play in predicting behavioral intentions to use technology is minimized. Without the presence of these constructs, however, facilitating conditions becomes an important predictor of intentions to use technology. Empirical studies have shown, however, that facilitating conditions are a direct predictor of actual usage, above what is already being predicted by behavioral intentions (Venkatesh et al. 2003). The findings from previous research show that facilitating conditions are non-significant predictors of intentions in the presence of performance and effort expectancy, and that facilitating conditions are a significant predictor of actual use, leading to the following hypothesis:

H8: There will be a significant positive relationship between facilitating conditions and actual use of a new information technology.

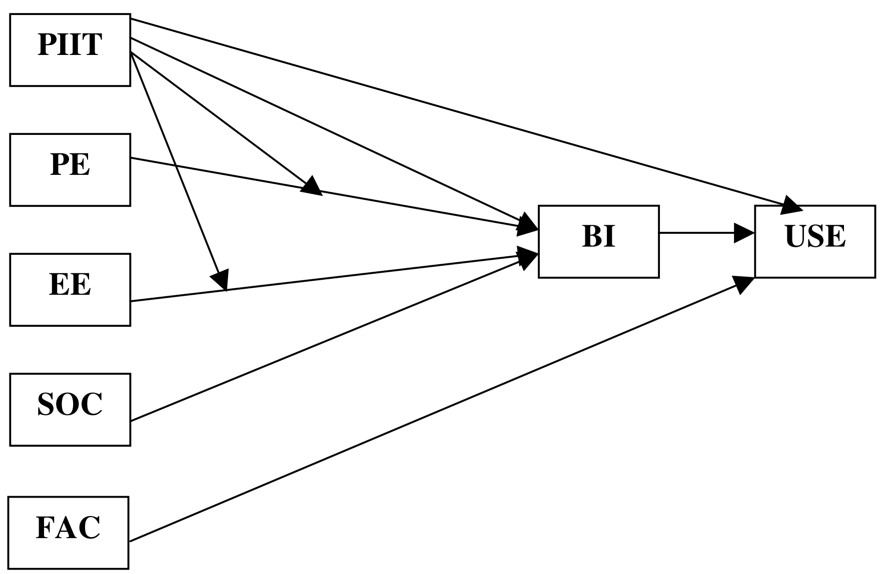
Behavioral Intentions (BI)

All of the models tested in the UTAUT study have behavioral intention to use a technology, or actual use of technology as a dependent variable. Behavioral intentions are "indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior" (Ajzen 1991). This construct appears in the Theory of Reasoned Action, Theory of Planned Behavior, Technology Acceptance Model, Combined TAM-TPB, and the Motivation Model. Based on a large body of research in the technology acceptance literature, the following hypothesis can be generated:

H9: Behavioral intentions will have a significant positive influence on actual usage of a new information technology.

In summary, the nine hypotheses comprise the basis for this study. Innovativeness, in the form of PIIT, will be examined in hypotheses 1-4 in an attempt to show where it best fits in the technology acceptance process. Hypotheses 5-9 attempt to validate the findings of Venkatesh et al (2003) and show which variables influence behavioral intentions to use, and actual use of technology. The complete picture of hypotheses 1-9 can be shown in Figure 2, which is the research model for this study.

Figure 2 – Research Model



CHAPTER III

METHODOLOGY

Subjects

This study was conducted in two phases during the 2004-2005 academic year. First, a pilot was conducted which exposed some of the flaws of the research design. The main study was done in the second phase and corrected these design flaws. Information about the pilot study can be found in Appendix 1.

In order to test the hypotheses outlined in the preceding section, survey data was from a group of undergraduate students enrolled in MSIS 3223 – Production and Operations Management (POM) at Oklahoma State University Tulsa. All of the participants were enrolled in the William S. Spears School of Business Administration and are either in their junior or senior year of study. Approximately 120 participants were available to the researcher, but due to attrition and absenteeism, the final number of participants was less than this. Participants represented all of the major disciplines in the School of Business, including accounting, economics, finance, general business, international business, management, management information systems, and marketing.

An initial questionnaire (see Appendix 2 – Background Survey) was given to each participant during the second week of the Spring 2005 semester. The questionnaire contained nine questions: name, birth date, gender, major, years and months of general computer experience, and the 4-item PIIT scale. Birth date, gender, major and length of time of general computer experience were captured to be used as possible control variables in future studies, but will not be used presently. The PIIT scale was administered during this first questionnaire and in each one following, as it was theorized to be a stable personality trait that does not change over time. Mean scores showed that PIIT was fairly constant over the six time periods in which it was measured, supporting the claim that it is a stable personality trait that does not change over time. The results from the initial questionnaire also showed that there were 52 females (43%) and 68 males (57%), with an average age of just above 26 years old.

Study Context

Over the course of the semester, students in the POM class were required to complete five homework assignments. While assignments have traditionally been completed by hand, students were allowed to use a software program called DS for Windows 2.0 to complete the same work during the study period (Weiss 2000). The software automates problem solving in the areas of linear programming, inventory control, statistical process control, project management, forecasting, transportation, and line balancing, (among others) that are faced by production and operations managers. The software was designed to be easy to use, with an interface that is similar to Microsoft Excel. The software was made available free of charge in the main OSU-Tulsa computer lab, as well as on-line for download to a home computer if desired. The software could also be purchased as an optional textbook for the course, which was sold in the campus bookstore. All five homework assignments could be completed either by hand or with the software.

Participants were introduced to the DS for Windows 2.0 software package during a hands-on tutorial during the third week of class. The tutorial started with the students watching a 15-minute Power Point tutorial prepared by the author of the software (see http://wps.prenhall.com/wps/media/objects/89/91661/pom/intro/pom.html), which demonstrated the basic features of the program. The students were then required to solve two problems found in their textbook and asked to submit the associated files. In this way the tutorial was standardized across the two sections of the course, and the instructor played a minimal part in the demonstration. This was done to limit any instructor bias effects. In the pilot study, students were given a demonstration of the software instead of a hands-on tutorial. It was discovered that the tutorial was too quick and not effective for many of the participants. So this hands-on tutorial represented a change from the pilot study and an improvement to the research design of the main study.

Following the demonstration, and seven days preceding the due date of the first homework assignment, the first survey was administered (see Appendix 3 – Survey Instrument). The instructor used Blackboard Learning System, an on-line course management system as a place for lecture notes and homework assignments (see http://www.blackboard.com/). Because the students were already familiar with Blackboard, the survey instrument was placed on the Blackboard website. Participants in the study downloaded the surveys, completed them, and then uploaded them back to the Blackboard. This method was used for all five surveys and worked as an excellent method for transmission of the instruments to and from the participants. An additional reason for posting the surveys online was due to the necessary timing of the completion of the surveys. Since the behavioral intention construct asked if the participants planned to use the software to complete the homework assignment, the survey must have been completed before the homework. Some students completed the homework assignment early and some completed the homework at the last minute. By placing the survey online a week in advance of the homework due date, the researcher captured responses from those who started their homework early as well as those who waited until the last minute to complete the assignment.

The survey instrument was almost the same for all five data collections. It contained questions on the following constructs: PIIT, effort expectancy, performance expectancy, social influence, facilitating conditions, computer anxiety, computer self-efficacy, attitude toward the software, and behavioral intentions to use the software. A qualitative question asked the participants to list three reasons for either use or non-use of the software. To determine whether the software was used for the completion of the assignment, students who used the program were required to submit the printouts and the computer files generated by DS for Windows 2.0 for homework credit.

During the pilot study, subjects were only allowed to use the software for one of the five homework assignments. Because of this, many students indicated that they were unwilling to learn how to use the software for just one assignment. The pilot study suffered from an omitted variable problem, as a factor outside of the model was determining software use. To correct this problem, the design of the main study was altered to allow participants to use the software for all five of the homework assignments.

Seven days preceding the due date of each of the five homework assignments, the same instrument was administered. The only difference between the survey instruments was the wording of the tense of the words, reflecting a future tense the first time the survey is administered and present tense for the remaining instruments. With the exception of the tense, all questions will be identical during the administration of surveys 1-5.

Analysis Method

As there are two dependent variables, behavioral intentions and use, analysis was run separately for each. First, hierarchical regression was utilized with the dependent variable of BI. This technique examines significance change with the addition of new variables. At each model stage, more terms are added, and changes in variance explained (R-squared) examined. If significant then the model with additional terms is then used instead of the model from the previous stage. For this study, a three-stage analysis was conducted with the initial main effect variables (PE, EE and SOC) used in stage 1, the addition of PIIT to the main effect variables in stage 2, and with PIIT used to moderate the PE-BI and EE-BI relationship in stage 3. Second, logistic regression was used to analyze the relationship of BI, PIIT, and FAC to actual system use.

The appropriate analyses were conducted for each of the five time periods of data collection (immediately preceding each homework assignment). Results for each of the five time periods, and similarities and differences over time will be discussed next.

CHAPTER IV

RESULTS

Surveys were given to approximately 120 students who were enrolled in MSIS 3223 – Production & Operations Management at the OSU-Tulsa campus during the Spring 2005 semester. The surveys were given at five time periods over the course of the semester, one week before each of the five homework assignments were due. Only those students who both completed a homework assignment and submitted a survey were used for analysis. From the original pool of 120 participants, the following number of usable responses were returned: N=97 at time 1, N=85 at time 2, N=83 at time 3, N=89 at time 4, and N=85 at time 5.

Reliability

Since the scales developed by Venkatesh et al (2003) for performance expectancy (PE), effort expectancy (EE), social influence (SOC), and facilitating conditions (FAC) were relatively new, it was necessary to check construct reliability. Internal consistency reliability (ICR), as measured by Cronbach's Alpha is reported. A Cronbach's Alpha of 0.70 or above is generally deemed acceptable in the social sciences literature (Fornell et al. 1981).

In retrospect the method used by Venkatesh et al. (2003) to generate these scales may not be methodologically sound. The previous study combined elements from each of the eight previous models of technology acceptance, and selected the four items that best loaded on each factor. For example, the four highest loading items for the performance expectancy factor include one item from the perceived ease of use construct in TAM, two items from the relative advantage construct of the Innovation Diffusion Theory model, and one item from the PC Utilization model. Before the Venkatesh et al (2003) study, these items had never been combined into one construct, so verifying the internal consistency reliabilities of all of the constructs is an important step.

Each of the constructs had four items in its scale (with the exception of behavioral intention which was measured by a three-item scale). The reliabilities for each scale (PIIT, PE, EE, SOC, FAC, and BI) are shown in Table 2 with Cronbach's Alpha values reported.

Table 2 – Reliability – Cronbach's Alpha Values

Construct	Time 1	Time 2	Time 3	Time 4	Time 5
PIIT	0.840	0.851	0.858	0.864	0.868
PE	0.916	0.898	0.904	0.922	0.918
EE	0.947	0.965	0.968	0.981	0.975
SOC	0.852	0.842	0.851	0.897	0.853
FAC	0.680	0.599	0.710	0.689	0.671
BI	0.961	0.961	0.990	0.990	0.991

Only one construct, facilitating conditions, had a Cronbach's Alpha of less than 0.70 at any point in time. Since the values for the facilitating conditions construct were very near the 0.70 level, all constructs were deemed to be acceptable for use in this study.

Means

Survey questions were measured on a Likert-type 1-7 scale, with 1 representing total disagreement with the question and 7 representing total agreement with the question. As this was a longitudinal study, examining how the subjects' perceptions changed over time is of great interest. The mean scores for the scales over the five time periods are shown below in Table 3. Some variables were relatively consistent over the course of the semester, while others changed significantly.

Table 3 – Mean Scores

Construct	Time 1	Time 2	Time 3	Time 4	Time 5
PIIT	4.85	4.77	4.79	4.69	4.79
PE	5.72	5.36	4.71	4.65	4.71
EE	5.38	5.30	4.80	4.94	5.06
SOC	4.54	4.17	3.96	3.88	4.11
FAC	5.50	5.71	5.49	5.62	5.49
BI	5.45	4.95	3.76	3.80	3.67
USE	53.61%	24.71%	27.71%	29.21%	29.41%

As an example, PIIT has been theorized to be a stable personality trait that does not change over time. The mean scores of PIIT ranged from 4.69 to 4.85, supporting the idea that innovativeness does not change over time, with the time frame being four months. The mean scores for other constructs varied widely over the course of the study. For example, the mean score of the PE (usefulness) construct varied from 5.72 during the first measurement to 4.65 during the fourth measurement. Thus, participants of this study perceived the DS for Windows software as less useful over time. A similar pattern was found for both behavioral intentions to use the software and actual use of the software. On the first survey, the mean score for behavioral intentions was 5.45, indicating that many subjects intended to use the software. On the last survey the mean score for intentions to use the software dropped to 3.67, indicating that many fewer people intended to use the software at that time. Actual use of the software followed closely along with intentions. During the first time period nearly 54% of the subjects actually used the software. Use of the software fell dramatically during the second time period to about 25%, and remained around the 28% level for the rest of the study.

Participants were generally satisfied with the level of support given for the software as measured by facilitating conditions (means ranged from 5.49 to 5.71). They also perceived the software as relatively easy to use (means ranged from 4.80 to 5.38). Subjects generally did not deem their peers to be important influencers on their decision to use / not use the software, as measured by the social influence construct (means ranged from 3.88 to 4.54). Many of the students did not know each other very well, and also only saw each other in class once a week. The educational setting used for this study is different from a business organization, where employees typically need to work closely together in order to succeed.

To summarize, the most important finding in viewing results longitudinally was that the software was deemed very useful at first, but less so during the course of the experiment. Intentions to use the software went down correspondingly as well. This would indicate a strong link between performance expectancy and behavioral intentions, which will be further explored in the next section.

Another important observation is that the model does not perfectly explain the process. For instance, in the evaluation portion of the survey, 41 participants indicated on the last survey that they did not use the software because it was not available during the exam. While one could argue that this appeared as a decline in performance expectancy, it could be equally argued that this was an omitted variable problem that appeared due to the context of the study; an educational setting where the software could not be used on exams.

Correlations

A standard diagnostic approach before performing regression is to analyze variable correlation to help determine any possible complication of the analysis. Table 4 shows for each of the 5 time periods two sets of independent variables are highly correlated: performance expectancy and effort expectancy as well as facilitating conditions and effort expectancy. As facilitating conditions is theoretically not a predictor of behavioral intentions, this high correlation has no impact on the analysis. The performance expectancy to effort expectancy relationship, however, is of note and cannot be ignored. Since the correlation averages around 0.65 during the five time periods, this indicates that these two variables have much shared variance in the explanation of behavioral intentions.

Table 4 – Pearson Correlations

Correlations - Time Period One

		ptavg	peavg	eeavg	socavg	facavg	biavg	useavg
ptavg	Pearson Correlation	1	.207*	.335**	.175	.356**	.169	.037
	Sig. (2-tailed)		.041	.001	.087	.000	.097	.718
	N	97	97	97	97	97	97	97
peavg	Pearson Correlation	.207*	1	.627**	.536**	.378**	.703**	.231*
	Sig. (2-tailed)	.041		.000	.000	.000	.000	.023
	N	97	97	97	97	97	97	97
eeavg	Pearson Correlation	.335**	.627**	1	.441**	.592**	.598**	.174
	Sig. (2-tailed)	.001	.000		.000	.000	.000	.087
	N	97	97	97	97	97	97	97
socavg	Pearson Correlation	.175	.536**	.441**	1	.272**	.376**	.086
	Sig. (2-tailed)	.087	.000	.000		.007	.000	.405
	N	97	97	97	97	97	97	97
facavg	Pearson Correlation	.356**	.378**	.592**	.272**	1	.473**	.216*
	Sig. (2-tailed)	.000	.000	.000	.007		.000	.034
	N	97	97	97	97	97	97	97
biavg	Pearson Correlation	.169	.703**	.598**	.376**	.473**	1	.338**
	Sig. (2-tailed)	.097	.000	.000	.000	.000		.001
	N	97	97	97	97	97	97	97
useavg	Pearson Correlation	.037	.231*	.174	.086	.216*	.338**	1
	Sig. (2-tailed)	.718	.023	.087	.405	.034	.001	
	N	97	97	97	97	97	97	97

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations - Time Period Two

		ptavg	peavg	eeavg	socavg	facavg	biavg	useavg
ptavg	Pearson Correlation	1	.195	.289**	.172	.231*	.362**	.300**
	Sig. (2-tailed)		.073	.007	.115	.034	.001	.005
	N	85	85	85	85	84	85	85
peavg	Pearson Correlation	.195	1	.590**	.413**	.427**	.667**	.327**
	Sig. (2-tailed)	.073		.000	.000	.000	.000	.002
	N	85	85	85	85	84	85	85
eeavg	Pearson Correlation	.289**	.590**	1	.360**	.586**	.449**	.093
	Sig. (2-tailed)	.007	.000		.001	.000	.000	.397
	N	85	85	85	85	84	85	85
socavg	Pearson Correlation	.172	.413**	.360**	1	.364**	.368**	.195
	Sig. (2-tailed)	.115	.000	.001		.001	.001	.074
	N	85	85	85	85	84	85	85
facavg	Pearson Correlation	.231*	.427**	.586**	.364**	1	.389**	.198
	Sig. (2-tailed)	.034	.000	.000	.001		.000	.071
	N	84	84	84	84	84	84	84
biavg	Pearson Correlation	.362**	.667**	.449**	.368**	.389**	1	.344**
	Sig. (2-tailed)	.001	.000	.000	.001	.000		.001
	N	85	85	85	85	84	85	85
useavg	Pearson Correlation	.300**	.327**	.093	.195	.198	.344**	1
	Sig. (2-tailed)	.005	.002	.397	.074	.071	.001	
	N	85	85	85	85	84	85	85

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations - Time Period Three

		ptavg	peavg	eeavg	socavg	facavg	biavg	useavg
ptavg	Pearson Correlation	1	.336**	.480**	.251*	.351**	.370**	.219*
	Sig. (2-tailed)		.002	.000	.022	.001	.001	.047
	N	83	83	83	83	83	83	83
peavg	Pearson Correlation	.336**	1	.663**	.454**	.436**	.658**	.518**
	Sig. (2-tailed)	.002		.000	.000	.000	.000	.000
	N	83	83	83	83	83	83	83
eeavg	Pearson Correlation	.480**	.663**	1	.540**	.464**	.409**	.303**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.005
	N	83	83	83	83	83	83	83
socavg	Pearson Correlation	.251*	.454**	.540**	1	.211	.330**	.153
	Sig. (2-tailed)	.022	.000	.000		.055	.002	.167
	N	83	83	83	83	83	83	83
facavg	Pearson Correlation	.351**	.436**	.464**	.211	1	.218*	.239*
	Sig. (2-tailed)	.001	.000	.000	.055		.048	.029
	N	83	83	83	83	83	83	83
biavg	Pearson Correlation	.370**	.658**	.409**	.330**	.218*	1	.569**
	Sig. (2-tailed)	.001	.000	.000	.002	.048		.000
	N	83	83	83	83	83	83	83
useavg	Pearson Correlation	.219*	.518**	.303**	.153	.239*	.569**	1
	Sig. (2-tailed)	.047	.000	.005	.167	.029	.000	
	N	83	83	83	83	83	83	83

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations - Time Period Four

		ptavg	peavg	eeavg	socavg	facavg	biavg	useavg
ptavg	Pearson Correlation	1	.342**	.374**	.377**	.367**	.294**	.078
	Sig. (2-tailed)		.001	.000	.000	.000	.005	.468
	N	89	89	89	89	89	89	89
peavg	Pearson Correlation	.342**	1	.737**	.474**	.535**	.749**	.429**
	Sig. (2-tailed)	.001		.000	.000	.000	.000	.000
	N	89	89	89	89	89	89	89
eeavg	Pearson Correlation	.374**	.737**	1	.521**	.570**	.471**	.208
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.051
	N	89	89	89	89	89	89	89
socavg	Pearson Correlation	.377**	.474**	.521**	1	.212*	.398**	.172
	Sig. (2-tailed)	.000	.000	.000		.046	.000	.107
	N	89	89	89	89	89	89	89
facavg	Pearson Correlation	.367**	.535**	.570**	.212*	1	.311**	.205
	Sig. (2-tailed)	.000	.000	.000	.046		.003	.054
	N	89	89	89	89	89	89	89
biavg	Pearson Correlation	.294**	.749**	.471**	.398**	.311**	1	.518**
	Sig. (2-tailed)	.005	.000	.000	.000	.003		.000
	N	89	89	89	89	89	89	89
useavg	Pearson Correlation	.078	.429**	.208	.172	.205	.518**	1
	Sig. (2-tailed)	.468	.000	.051	.107	.054	.000	
	N	89	89	89	89	89	89	89

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations - Time Period Five

		ptavg	peavg	eeavg	socavg	facavg	biavg	useavg
ptavg	Pearson Correlation	1	.366**	.516**	.198	.293**	.387**	.172
	Sig. (2-tailed)		.001	.000	.069	.006	.000	.116
	N	85	85	85	85	85	84	85
peavg	Pearson Correlation	.366**	1	.702**	.464**	.431**	.615**	.453**
	Sig. (2-tailed)	.001		.000	.000	.000	.000	.000
	N	85	85	85	85	85	84	85
eeavg	Pearson Correlation	.516**	.702**	1	.423**	.539**	.369**	.255*
	Sig. (2-tailed)	.000	.000		.000	.000	.001	.019
	N	85	85	85	85	85	84	85
socavg	Pearson Correlation	.198	.464**	.423**	1	.263*	.364**	.181
	Sig. (2-tailed)	.069	.000	.000		.015	.001	.098
	N	85	85	85	85	85	84	85
facavg	Pearson Correlation	.293**	.431**	.539**	.263*	1	.217*	.313**
	Sig. (2-tailed)	.006	.000	.000	.015		.048	.004
	N	85	85	85	85	85	84	85
biavg	Pearson Correlation	.387**	.615**	.369**	.364**	.217*	1	.483**
	Sig. (2-tailed)	.000	.000	.001	.001	.048		.000
	N	84	84	84	84	84	84	84
useavg	Pearson Correlation	.172	.453**	.255*	.181	.313**	.483**	1
	Sig. (2-tailed)	.116	.000	.019	.098	.004	.000	
	N	85	85	85	85	85	84	85

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

From the earliest technology acceptance models, there has been a link between ease of use and usefulness of technology. In TAM, for example, perceived ease of use is a direct predictor of perceived usefulness. Therefore, it is not surprising that these two variables are highly correlated. Since most TAM studies have shown that the perceived usefulness construct is the best predictor of behavioral intentions, this high correlation may minimize the effects of effort expectancy on behavioral intentions.

Factor Analysis

Exploratory factor analysis is needed to examine whether survey items measure intended constructs. The exploratory factor analysis undertaken showed that, for the most part, the scales of PIIT, PE, EE, SOC and FAC loaded properly with other scales items, and that each scale comprised its own factor. A small problem occurred between effort expectancy and one item in the facilitating conditions scale, but in general the factor loadings were as expected. Pattern matrices using Promax rotation are reported below in Table 5. This type of rotation is recommended when independent variables are correlated with each other (Hair et al. 1998).

Table 5 – Exploratory Factor Analysis

Pattern Matrix – Time One

	Component				
	1	2	3	4	5
PIIT1				.890	
PIIT2				.823	
RPIIT3				.686	
PIIT4				.887	
PE1		.841			
PE2		.882			
PE3		.892			
PE4		.802			
EE1	.789				
EE2	.833				
EE3	.899				
EE4	.887				
SOC1			.977		
SOC2			.940		
SOC3			.612		
SOC4			.682		
FAC1					.618
FAC2	.785				
RFAC3					.782
FAC4					.592

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Values less than 0.50 suppressed

Pattern Matrix – Time Two

	Component				
	1	2	3	4	5
PIIT1				.905	
PIIT2				.906	
RPIIT3				.569	
PIIT4				.895	
PE1		.818			
PE2		.808			
PE3		.876			
PE4		.770			
EE1	.805				
EE2	.875				
EE3	.901				
EE4	.909				
SOC1			.821		
SOC2			.894		
SOC3			.671		
SOC4			.748		
FAC1					.539
FAC2	.872				
RFAC3					.854
FAC4					

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Values less than 0.50 suppressed

Pattern Matrix – Time Three

	Component				
	1	2	3	4	5
PIIT1				.935	
PIIT2				.847	
RPIIT3				.548	
PIIT4				.859	
PE1		.730			
PE2		.827			
PE3		.945			
PE4		.732			
EE1	.790				
EE2	.960				
EE3	.920				
EE4	.908				
SOC1			.749		
SOC2			.803		
SOC3			.789		
SOC4			.864		
FAC1					.797
FAC2	.570				
RFAC3					.888
FAC4					

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Values less than 0.50 suppressed

Pattern Matrix – Time Four

	Component				
	1	2	3	4	5
PIIT1			.840		
PIIT2			.882		
RPIIT3			.662		
PIIT4			.900		
PE1	.666				
PE2	.585				
PE3					.582
PE4					
EE1	1.002				
EE2	.976				
EE3	1.029				
EE4	1.004				
SOC1		.654			
SOC2		.704			
SOC3		1.006			
SOC4		.967			
FAC1				.810	
FAC2	.727				
RFAC3				.927	
FAC4					.743

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Values less than 0.50 suppressed

Pattern Matrix – Time Five

	Component				
	1	2	3	4	5
PIIT1				.927	
PIIT2				.910	
RPIIT3				.533	
PIIT4				.912	
PE1		.675			
PE2		.737			
PE3		.779			
PE4		.843			
EE1	.898				
EE2	.945				
EE3	.876				
EE4	.972				
SOC1			.818		
SOC2			.858		
SOC3			.655		
SOC4			.873		
FAC1					.811
FAC2	.709				
RFAC3					.815
FAC4			.513		

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Values less than 0.50 suppressed

Regression

As previously mentioned, during each of the five time periods where surveys where administered, two regression models were generated. One model used the main effect (PIIT, PE, EE, SOC) and interaction variables (EE*PIIT and PE*PIIT) predicting behavioral intentions to use technology, and the other model used PIIT, FAC and BI to predict the actual use of technology. For the model that predicted behavioral intentions, the analysis was run in three stages. The first stage contained the UTAUT main effect variables PE, EE and SOC. The second stage contained the UTAUT variables plus PIIT.

The final stage contained all variables in stage two plus the interaction variables (PE*PIIT and EE*PIIT). This three-stage model will test the impact of the UTAUT variables on intentions, and then the impact of PIIT, and finally the potential effect of PIIT as a moderator variable.

As mentioned previously, hierarchical regression was the technique used to test the impact of the variables being used to predict behavioral intentions, and logistic regression was used to test the impact BI, FAC and PIIT had on actual use.

Using the three-stage model building process described earlier the best model from each time period is presented in Table 6. If no significant change in F-value occurs in the second stage of the model, results of the first stage model are shown. If a significant change in the F-value did occur at the second stage, but not at the third stage of the model, then the second stage is shown. Obviously, if a significant change in the F-value at the second and third stage occurred, the third stage model is shown. Interestingly, during the all time periods studied, the interaction variables (EE*PIIT and PE*PIIT) were found not significant, so none of the third stage models are shown in Table 6.

Prior to the regression, all variables were centered. For each individual, the four questions relating to each construct were added together and the average was found. The mean scores ranged from a possible score of 1 to 7 with 1 representing total disagreement with all four questions, and 7 representing total agreement with all four questions. The mean of those averages were found for all subjects. Centering was then accomplished by subtracting each individual's average from the subject population.

Table 6 – Regression Results

Time 1 – Dependent Variable = Behavioral Intentions

Model Summary

Model	R	R Square	Adjusted R Square	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
1	.732[a]	.536	.521	.536	35.785	3	93	.000
2	.733[b]	.537	.517	.001	.183	1	92	.669

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1		144.558	3	48.186	35.785	.000[a]
	Residual	125.229	93	1.347		
	Total	269.787	96			
2		144.807	4	36.202	26.649	.000[b]
	Residual	124.980	92	1.358		
	Total	269.787	96			

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

d. Dependent Variable: bic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.965E-05	.118		.000	1.000
	socc	-.059	.127	-.040	-.470	.639
	pec	.707	.124	.557	5.704	.000
	eec	.364	.126	.266	2.898	.005
2	(Constant)	3.820E-05	.118		.000	1.000
	socc	-.058	.127	-.039	-.452	.652
	pec	.706	.124	.556	5.670	.000
	eec	.379	.131	.277	2.897	.005
	ptc	-.045	.105	-.032	-.428	.669

a. Dependent Variable: bic

Overall Model Significance

		Chi-square	df	Sig.
Step 1	Step	12.052	2	.002
	Block	12.052	2	.002
	Model	12.052	2	.002

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	121.913	.117	.156

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	facc	.162	.241	.448	1	.503	1.175
	bic	.405	.158	6.599	1	.010	1.499
	Constant	-.137	.217	.395	1	.530	.872

a. Variable(s) entered on step 1: facc, bic.

Time 2 - Dependent Variable = Behavioral Intentions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.676[a]	.457	.437	1.39382	.457	22.764	3	81	.000
2	.712[b]	.506	.482	1.33768	.049	7.940	1	80	.006

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1		132.673	3	44.224	22.764	.000[a]
	Residual	157.361	81	1.943		
	Total	290.034	84			
2		146.882	4	36.720	20.521	.000[b]
	Residual	143.152	80	1.789		
	Total	290.034	84			

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

d. Dependent Variable: bic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3.243E-05	.151		.000	1.000
	socc	.176	.157	.102	1.123	.265
	pec	.762	.137	.584	5.556	.000
	eec	.089	.136	.067	.656	.513
2	(Constant)	-3.201E-05	.145		.000	1.000
	socc	.146	.151	.085	.968	.336
	pec	.758	.132	.581	5.755	.000
	eec	.011	.133	.009	.085	.933
	ptc	.308	.109	.232	2.818	.006

a. Dependent Variable: bic

Time 2 - Dependent Variable = Use

Overall Model Significance

		Chi-square	df	Sig.
Step 1	Step	5.310	1	.021
	Block	5.310	1	.021
	Model	18.655	3	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	73.556[a]	.199	.299

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	facc	.037	.347	.011	1	.916	1.037
	bic	.561	.251	5.012	1	.025	1.753
	ptc	.555	.260	4.557	1	.033	1.741
	Constant	1.693	.394	18.473	1	.000	5.434

a. Variable(s) entered on step 1: facc, bic, ptc.

Time 3 - Dependent Variable = Behavioral Intentions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.661[a]	.437	.416	1.71839	.437	20.459	3	79	.000
2	.687[b]	.471	.444	1.67614	.034	5.033	1	78	.028

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	181.238	3	60.413	20.459	.000[a]
	Residual	233.276	79	2.953		
	Total	414.514	82			
2	Regression	195.377	4	48.844	17.386	.000[b]
	Residual	219.137	78	2.809		
	Total	414.514	82			

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

d. Dependent Variable: bic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.85E-06	.189		.000	1.000
	socc	.121	.199	.062	.607	.546
	pec	.992	.166	.680	5.960	.000
	eec	-.115	.186	-.075	-.619	.538
2	(Constant)	1.409E-05	.184		.000	1.000
	socc	.128	.194	.065	.657	.513
	pec	.981	.162	.673	6.044	.000
	eec	-.266	.194	-.173	-1.377	.173
	ptc	.377	.168	.211	2.243	.028

a. Dependent Variable: bic

Time 3 - Dependent Variable = Use

Overall Model Summary

		Chi-square	df	Sig.
Step 1	Step	31.480	2	.000
	Block	31.480	2	.000
	Model	31.480	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	66.494[a]	.316	.456

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	facc	.262	.310	.716	1	.398	1.300
	bic	.725	.182	15.890	1	.000	2.065
	Constant	1.521	.384	15.701	1	.000	4.577

a. Variable(s) entered on step 1: facc, bic.

Time 4 - Dependent Variable = Behavioral Intentions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.763[a]	.582	.567	1.44575	.582	39.487	3	85	.000
2	.764[b]	.584	.565	1.45064	.002	.428	1	84	.515

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	247.605	3	82.535	39.487	.000[a]
	Residual	177.666	85	2.090		
	Total	425.271	88			
2	Regression	248.505	4	62.126	29.523	.000[b]
	Residual	176.765	84	2.104		
	Total	425.271	88			

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

d. Dependent Variable: bic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.5E-05	.153		.000	1.000
	socc	.191	.153	.103	1.243	.217
	pec	1.170	.143	.858	8.173	.000
	eec	-.310	.157	-.214	-1.980	.051
2	(Constant)	-1.6E-05	.154		.000	1.000
	socc	.168	.158	.091	1.067	.289
	pec	1.163	.144	.853	8.075	.000
	eec	-.323	.158	-.223	-2.040	.044
	ptc	.081	.124	.051	.654	.515

a. Dependent Variable: bic

Time 4 - Dependent Variable = Use

Overall Model Significance

		Chi-square	df	Sig.
Step 1	Step	26.468	2	.000
	Block	26.468	2	.000
	Model	26.468	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	81.054[a]	.257	.367

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	facc	.067	.288	.054	1	.816	1.070
	bic	.640	.163	15.440	1	.000	1.896
	Constant	1.273	.324	15.408	1	.000	3.573

a. Variable(s) entered on step 1: facc, bic.

Time 5 - Dependent Variable = Behavioral Intentions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.629[a]	.396	.374	1.84958	.396	17.495	3	80	.000
2	.669[b]	.447	.419	1.78129	.051	7.251	1	79	.009

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	179.547	3	59.849	17.495	.000[a]
	Residual	273.674	80	3.421		
	Total	453.221	83			
2	Regression	202.553	4	50.638	15.959	.000[b]
	Residual	250.668	79	3.173		
	Total	453.221	83			

a. Predictors: (Constant), eec, socc, pec

b. Predictors: (Constant), eec, socc, pec, ptc

d. Dependent Variable: bic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.025	.202		-.122	.903
	socc	.239	.195	.121	1.226	.224
	pec	.998	.191	.653	5.228	.000
	eec	-.218	.197	-.135	-1.107	.272
2	(Constant)	-.021	.194		-.106	.916
	socc	.254	.188	.129	1.349	.181
	pec	.988	.184	.647	5.377	.000
	eec	-.437	.207	-.271	-2.117	.037
	ptc	.456	.169	.264	2.693	.009

a. Dependent Variable: bic

Time 5 - Dependent Variable = Use

Overall Model Significance

		Chi-square	df	Sig.
Step 1	Step	25.946	2	.000
	Block	25.946	2	.000
	Model	25.946	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	74.563[a]	.266	.381

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	facc	.690	.316	4.781	1	.029	1.994
	bic	.467	.128	13.242	1	.000	1.595
	Constant	1.297	.329	15.546	1	.000	3.660

a. Variable(s) entered on step 1: facc, bic.

Time Period 1

As this period measures initial acceptance of the software, it provides an interesting starting point for the study. The overall model was found to be significant ($F_{3,93}$=35.785, R^2=.536, p<.001), and included the variables PE, EE and SOC. The significant independent variables were PE (t=5.704, p<.001) and EE (t=2.898, p<.01), while SOC was not found to be significant at the alpha=.05 level. This leads to the conclusion that there is support for hypotheses 5 and 6 (PE→BI and EE→BI), and no support for hypothesis 7 (SOC→BI).

Both PE and EE were highly correlated with the dependent variable BI, a desirable thing, but also were highly correlated with each other. PE alone could account for nearly 50% of the variation in behavioral intentions (R^2= .494), and due to its the high correlation with EE, the R^2 value only increased by 4% with EE's inclusion. This is similar to past TAM findings where perceived usefulness was the dominant factor predicting user intentions. Also similar to previous results, EE (perceived usefulness) was a significant predictor of user intentions, but far less important than usefulness.

SOC was not found to be a significant predictor of behavioral intentions. This could be attributed to the context of the study. Most previous studies involving a social influence construct were done in business settings, where participants interacted with others in their daily job. This was not the case in this study, and as there was no reliance on others, other subject opinions did not significantly influence their intentions to either use or not use the DS for Windows software package.

The models that included PIIT, and PIIT plus the interaction terms, were not reported, as there was not a significant F-value change in stage 2 and 3. Thus, hypotheses 1, 2 (the PIIT moderation hypotheses) and 3 (PIIT→BI) were not supported in this time period.

The final three hypotheses regarding system use were tested using logistic regression. The overall regression model was significant (Chi-Square=12.052, -2Log Likelihood=121.913, Nagelkerke R^2=.156, p<.01), and the independent variable behavioral intentions was significant (p<.05). PIIT as a predictor of actual use did not significantly impact the model. Thus, this lends support to hypothesis 9, but does not support hypotheses 4 and 8.

FAC was found to not positively influence actual use. One explanation could be that participants in the study found the FAC construct confusing. One item was reverse worded and another item was found to load better on the EE construct (see previous factor analysis).

Behavioral intentions have been shown in many studies to be a strong predictor of actual use of technology. In this study, however, behavioral intentions had far less impact. Just slightly over 11% of actual use was explained by intentions to use technology, a much lower figure than expected. Again, the context of the study might help explain this finding. Many of the study participants completed their work at the last minute. Thus, with a deadline looming, many students in completing the assignment did not do what they indicated on the survey. For example, a student might have decided to not use the software and then, when under time constraints, used the software because it took less time to complete the assignment. Similarly, a student might have indicated that they would use the software, but found themselves unable to devote the time necessary to learn how to use the program given the impending deadline. These reasons may explain why behavioral intentions were a poorer predictor of actual use than in almost every other prior study.

Time Period 2

As stated earlier, fewer participants used the DS for Windows software during the second time period (24.7%) than the first (53.6%). Possible reasons for this may include factors both within and outside the research model. Some participants may have felt that the software was not useful, not easy to use, or that there was a lack of support. Other possible reasons could include a lack of computer training on the module required to do the 2nd assignment, poor homework scores using the software on the 1st assignment, general disinterest in the software, or poor access to computers. Whatever the cause, there was a huge decline in the number of users between the first and second time periods.

The regression results are slightly different from time period 1, as PIIT replaced EE as a significant predictor of behavioral intentions, and in addition to BI, PIIT is also a significant predictor of actual use. A t-test of the innovativeness of users and non-users of the software in time period 1 showed little difference. During the 2nd time period, however, there was nearly a full point difference between users and non-users (on a seven point scale), with users being much more innovative than non-users (5.50 vs. 4.53).

During the 2nd time period, with BI as the dependent variable, the overall model was found to be significant ($F_{4,80}$=20.521, R^2=.506, p<.001), and included the variables PE, EE, SOC, and PIIT. The significant independent variables were PE (t=5.775, p<.001) and PIIT (t=2.818, p<.01), while SOC and EE were not found to be significant at the alpha=.05 level. When the dependent variable was actual use, the overall regression model was significant (Chi-Square=18.655, -2Log Likelihood=73.556, Nagelkerke R^2=.299, p<.01), and both BI and PIIT were found to be significant (p<.05).

There are two potential reasons why effort expectancy was not significant during the 2nd time period. Some longitudinal TAM studies have found that the importance of ease of use diminishes after the first use (Venkatesh et al. 2000). Also, due to the high correlation between EE, PE, and PIIT, it is possible that PIIT added more to the model than EE did after PE was included.

Supported hypotheses during this time period were H3 (PIIT→BI), H4 (PIIT→USE), H5 (PE→BI), and H9 (BI→USE). Non-supported hypotheses included those which involved PIIT moderating the relationships between perceptions and intentions (H1 and H2), H6 (EE→BI), H7 (SOC→BI), and H8 (FAC→USE).

Time Period 3

The results of this time period are similar to the previous period. Only about a quarter of the participants used the software and little switching occurred between users and non-users. Those who used the software in the second period were likely to use it in the third, and those who did not use the software continued not to use the product. As before, users of the software were more innovative than non-users with means of 5.23 and 4.62 respectively for the two different groups.

During the 3rd time period, with BI as the dependent variable, the overall model was found to be significant ($F_{4,78}$=20.459, R^2=.471, p<.001), and included the variables PE, EE, SOC, and PIIT. The significant independent variables were PE (t=6.044, p<.001) and PIIT (t=2.243, p<.05), while SOC and EE were not found to be significant at the alpha=.05 level.

When the dependent variable was actual use, the overall regression model was significant (Chi-Square=31.480, -2Log Likelihood=66.494, Nagelkerke R^2=.456, p<.01), and only BI was found to be significant (p<.001). The differences between the 2nd and 3rd time periods, therefore, was that the model had only one significant independent variable, and the model explained far more of the variance in actual use than the previous two time periods (45.6% vs. 29.9% & 15.6%).

Supported hypotheses during this time period were H3 (PIIT→BI), H5 (PE→BI), and H9 (BI→USE). Non-supported hypotheses included the ones where PIIT moderated the relationships between perceptions and intentions (H1 and H2), H4 (PIIT→USE), H6 (EE→BI), H7 (SOC→BI), and H8 (FAC→USE).

Time Period 4

When analyzing the model with intentions as the dependent variable, the significant variables are similar to previous time periods. The overall model was found to be significant ($F_{3,85}$=39.487, R^2=.582, p<.001), and included the variables PE, EE, SOC. No improvement was found in the model that contained PIIT, or the model that contained PIIT and the interaction terms, so the first stage model was appropriate. The significant variables were PE (t=8.173, p<.001) and EE (t=-2.040, p=.05). While EE is positively correlated with BI, its Beta and t values turn negative in the presence of PE. This is because the two variables are correlated at r=.737, which is very high for two independent variables. When EE is introduced first and then PE is added in a second stage, EE is both positively correlated with BI and a very good predictor of intentions.

A possible explanation for EE significance in this time period might be due to the nature of the homework assignments. The homework assignments are independent of each other, and knowledge of how to accomplish one assignment with the software does not provide insight into how the software might be used for another assignment. Those who used the software for homework #4 rated it significantly easier to use than those who did not use the software for this assignment (mean scores of 5.43 and 4.74 respectively).

When the dependent variable was actual use, the overall regression model was significant (Chi-Square=26.468, -2Log Likelihood=81.054, Nagelkerke R^2=.367, $p<.001$), and only BI was found to be significant ($p<.001$). This time period is similar to time period #3 in that only BI was found to be significant.

Supported hypotheses during this time period were H5 (PE→BI), H6 (EE→BI), and H9 (BI→USE). Non-supported hypotheses included PIIT and intentions (H1-H3), H4 (PIIT→USE), H7 (SOC→BI), and H8 (FAC→USE).

Time Period 5

The final time period was the only period in which PE, EE and PIIT were all found to be significant predictors of intentions to use the software. The overall model was found to be significant ($F_{4,79}$=15.959, R^2=.447, $p<.001$), and included the variables PE, EE, SOC, and PIIT. The significant variables were PE (t=5.377, $p<.001$), EE (t=-2.117, $p<.05$), and PIIT (t=2.693, $p<.01$). The explanation for the negative Beta and t-values for EE is the same as in time period 4.

The model explaining actual use of technology included two significant independent variables, BI and FAC. This is a shift from the other four periods, where FAC was not a significant predictor of USE. The overall regression model was significant (Chi-Square=15.959, -2Log Likelihood=74.563, Nagelkerke R^2=.381, $p<.001$), and as mentioned, both BI ($p<.001$) and FAC ($p<.05$). For this period, the level of support given to the use of the software was influential in predicting use.

Supported hypotheses during this time period were H3 (PIIT→BI), H5 (PE→BI), H6 (EE→BI), H8(FAC→USE), and H9 (BI→USE). Non-supported hypotheses included the ones with PIIT as a moderator (H1 & H2), H4 (PIIT→USE), and H7 (SOC→BI).

Overall Findings

Table 7 shows the results of the nine hypotheses across the 5 time periods in the study. Performance expectancy, similar to perceived usefulness, is a very good predictor of behavioral intentions to use technology. Behavioral intentions were found to be a significant predictor of actual use of technology, a hypothesis supported in all five periods.

Personal innovativeness, the variable of interest in this study, was found to generally be a significant predictor of behavioral intentions to use technology. After the initial time period, where over half of the participants used the technology, PIIT was found to be significant in 3 of the last 4 time periods. The class as a whole seemed curious about using the technology in the initial period, but those who were more innovative tended to indicate that they would continue to use the software as time went on.

PIIT was not found to be a good predictor of actual use of technology, nor did it ever play a significant moderation role between perceptions (PE and EE), and intentions (BI). Therefore, this study lends support to the idea that PIIT should be used as a main effect variable to help predict user intentions within the UTAUT framework. This contradicts the Agarwal and Prasad (1998) study, and represents a significant contribution to the literature.

The fact that relationships between SOC→BI and FAC→USE were not supported could be related to the study context. The students did not find the opinions of their peers important in the acceptance process, likely because they saw each other only once a week. Also students did not place much importance on how much support was provided to them about the software. Typically, they used the software if they felt it would improve their performance, and vice versa.

The relationship between effort expectancy and intentions was found to be significant in three of the five time periods and seemed to help predict a small portion of user intentions. With the inclusion of performance expectancy, though, the effect of effort expectancy was minimized. This was due in large part to the high correlation between PE and EE. When PE was not present in the research model, EE became the most important predictor of intentions.

Overall, the modified version of the new UTAUT model was found to be quite good, predicting between 45-58% of the variance in user intentions over the five time periods. The model also did well in predicting actual use of the software, ranging from 30-46% of variance explained, with the exception of the first period when only 15% of the variance was explained. The poor result from the first period was attributed more to the context of the study, using a student sample and asking about homework intentions. Since the assignments were often completed at the very last minute, students actually performed behavior that was contrary to what they indicated they might perform during this first period. As the semester went on, however, students got in the habit of doing the assignments earlier and their intentions were strong predictions of their actual behavior.

Table 7 – Tested Hypotheses

Hypothesis	Time 1	Time 2	Time 3	Time 4	Time 5
EE→BI PIIT	Not supported	Not supported	Not supported	Not supported	Not supported
PE→BI PIIT	Not supported	Not supported	Not supported	Not supported	Not supported
PIIT→BI	Not supported	Supported	Supported	Not supported	Supported
PIIT→USE	Not supported	Supported	Not supported	Not supported	Not supported
PE→BI	Supported	Supported	Supported	Supported	Supported
EE→BI	Supported	Not supported	Not supported	Supported	Supported
SOC→BI	Not supported	Not supported	Not supported	Not supported	Not supported
FAC→USE	Not supported	Not supported	Not supported	Not supported	Supported
BI→USE	Supported	Supported	Supported	Supported	Supported

CHAPTER V

DISCUSSION

Contribution to the Literature

Surprisingly few studies have been conducted in the MIS literature which included the personal innovativeness in the domain of information technology construct. Defined as "the willingness of an individual to try out any new information technology," PIIT would seem to be a natural fit when examining the technology acceptance process. PIIT had been tested as a moderator between end-user perceptions of technology and their intentions to use the technology (Agarwal and Prasad 1998). It had also been tested as an antecedent to a variety of different perceptions, perceived ease of use, perceived usefulness, computer anxiety, and computer self-efficacy.

A more natural fit might be to use PIIT as a main effect variable, along with usefulness and ease of use constructs, to help predict user intentions. In this study, PIIT was found to be a significant predictor of behavioral intentions, above the effects of usefulness and ease of use. Hierarchical regression was used to determine PIIT's added impact in the research model, after performance expectancy and effort expectancy had been included in the first stage of the analysis.

The Marketing literature indicated that domain specific innovativeness, the predecessor of PIIT, was a significant predictor of purchase behavior, implying a direct link from innovativeness to behavior. This led to the hypothesis that PIIT should be a significant predictor of actual use of technology. However, in the context of this study, the PIIT→USE link was not supported.

In summary, one main contribution of the study is PIIT's significance as a main effect variable, predicting user intentions, after the UTUAT variables (PE, EE and SOC) had been included in the model. No support was found that PIIT should be used as a moderator of the perceptions-intentions relationship, and also PIIT was not found to be a good predictor of technology use.

The second contribution of the study is the empirical validation of the "new" UTAUT model. Reliability of the new constructs was strong (performance expectancy, effort expectancy, social influence, and facilitating conditions), and an exploratory factor analysis revealed few problems with the factor loadings of the construct items. The model accounted for 45-58% of the variance in behavioral intentions to use software, and between 30-46% of the variance in actual use of the software. When compared to previous models, like TAM, which typically explained between 17-42% of the variance in user intentions, the modified UTAUT model appears vastly superior. Both results support the use of UTAUT as a predictor of intentions and use of new technology.

Practical Significance

As mentioned in the introduction, the cost of project implementation failure can be high. One cause of such failures is lack of end user acceptance. More projects would succeed if end user acceptance was higher, which would lead to improved productivity, reduced costs, and higher profitability for these successful organizations. With a simple survey that includes the 4-item PIIT scale, organizations can identify those people who are more innovative than others. Identifying those individuals who are more likely to use the new technology could help organizations find champions for the project and individuals who should be included in the first stage of implementation.

Venkatesh et al (2003) found that social influence was a significant predictor of user intentions. If the project champion and initial users of the technology supported the use of the technology, they would likely tell others in the organization, giving the technology good word of mouth. Those that follow then would be more likely to accept the technology, and the organization would be more likely to have a successful implementation. Thus, through investing time in identify innovative users of technology, organizations are likely to improve their technology project implementations.

Limitations

There are a number of limitations of this study. First, the context of the study was a university setting using junior and senior business students who enrolled in Production and Operations Management at OSU-Tulsa. The concept being tested was whether students would use software to complete homework assignments. Because many students complete their assignment at the very last minute, matching their intentions with actual behavior can be difficult.

The next concern is about accuracy of the surveys. Students were given extra credit for completing the surveys, so there is a risk that they quickly answered the questions to receive credit, without putting much thought into their responses. Given the context and the nature of the participants, generalizing these findings to organizations should be done with a degree of caution.

Sample size was another limitation of this study. Of the original 120 students, between 83 and 97 participated in the study at any given time period. As is typical in most courses, about 10% of the sample was lost due to student attrition. Other students did not participate because they either did not need the extra credit or were not interested in completing the survey instruments. If this study was to be repeated in the future, a recommendation would be to increase the available sample size. By increasing the sample size one could test the moderation hypotheses that were done in the original UTAUT study.

Future Research Directions

The logical follow-up is to conduct similar work in an organizational context. It is possible the variables that did not play a big role in this study could play a larger role in an organizational setting. In addition, with a larger sample the moderators in the original UTUAT model (gender, age, voluntariness, and experience) could be tested.

From an educational perspective, it would be insightful to assess if using the software to complete homework assignments enhanced or detracted from the learning process. One argument might be that using the software makes assignments too easy, and therefore, no learning occurs. A counter argument to this would be that the software allows for experimentation and what-if analysis, enhancing learning. An experiment that studies the effect of software use might be valuable for those in the classroom.

Finally, the PIIT construct needs to be tested and examined more completely. Is it a good measure of innovativeness? Some argue that one cannot be innovative unless you perform innovative behaviors. Others would argue that even domain specific innovativeness is too broad. For example, PIIT measures how innovative a person is within the domain of information technology. Does this equally apply to, for instance, computer games and business software? One could argue that someone who is innovative in a specific area of computer games may not be innovative when it comes to business software, even though they are both in the domain of information technology.

Conclusion

The aim of this study was to examine the effect of personal innovativeness in the domain of information technology in a technology acceptance framework. It was shown that PIIT was statistically significant in predicting user intentions, and that it could be practically significant as well. PIIT was found to be best as a main effect variable in the PIIT→BI relationship, and that it did not fit as a moderator, or a predictor of actual use. The secondary goal of validating the UTAUT model was also achieved, with the model explaining between 45-58% of the variance in behavioral intentions to use software, and between 30-46% of the variance in actual use of the software. Limitations of the study were pointed out, including the context, a potential omitted variable problem, and small sample size. Future research directions were suggested, with applications in both the business and education fields.

REFERENCES

Agarwal, R., and Prasad, J. "A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology," *Information Systems Research* (9:2) 1998, pp 204-215.

Agarwal, R., Sambamurthy, V., and Stair, R.M. "Research Report: The Evolving Relationship Between General and Specific Computer Self-Efficacy - An Empirical Assessment," *Information Systems Research* (11:4), Dec 2000, pp 418-430.

Ajzen, I. "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes* (50) 1991, pp 179-211.

Al-Gahtani, S.S. "Computer Technology Acceptance Success Factors in Saudi Arabia: An Exploratory Study," *Journal of Global Information Technology Management* (7:1) 2004, pp 5-29.

Anonymous "IT Projects Can Lose Serious Money," *Country Monitor* (11:9) 2003, p 1. Citrin, A.V., Sprott, D.E., Silverman, S.N., and Sterm Jr., D.E. "Adoption of Internet Shopping: The Role of Consumer Innovativeness," *Industrial Management & Data Systems* (100:7) 2000, pp 294-300.

Compeau, D.R., and Higgins, C.A. "Application of Social Cognitive Theory to Training for Computer Skills," *Information Systems Research* (6:2) 1995, pp 118-143.

Compeau, D.R., Higgins, C.A., and Huff, S. "Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study," *MIS Quarterly* (23:2) 1999, pp 145-158.

Davis, F.D. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3) 1989, pp 319-340.

Davis, F.D., Bagozzi, R.P., and Warshaw, P.R. "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science* (35:8) 1989, pp 982-1003.

DeLone, W.H., and McLean, E.R. "Information System Success: The Quest for the Dependent Variable," *Information Systems Research* (3:1) 1992.

Eastlick, M.A., and Lotz, S. "Profiling Potential Adopters and Non-Adopters of an Interactive Electronic Shopping Medium," *International Journal of Retail & Distribution Management* (27:6) 1999, pp 209-223.

Ewusi-Mensah, K., and Przasnyski, Z.H. "On Information Systems Project Adandonment: An Exploratory Study of Organizational Practices," *MIS Quarterly* (15:1) 1991, pp 67-85.

Fishbein, M., and Ajzen, I. *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research* Addison-Wesley, Reading, MA, 1975.

Fisher, S.L., and Howell, A.W. "Beyond User Acceptance: An Examination of Employee Reactions to Information Technology Systems," *Human Resource Management* (43:2&3), Summer/Fall 2004, pp 243-258.

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

Gatignon, H., and Robertson, T.S. "A Propositional Inventory for New Diffusion Research," *Journal of Consumer Research* (11) 1985, pp 849-867.

Gefen, D., and Keil, M. "The Impact of Developer Responsiveness on Perceptions of Usefulness and Ease of Use: An Extension of the Technology Acceptance Model," *Database for Advances in Information Systems* (29:2) 1998, pp 35-49.

Goldsmith, R.E. "Convergent Validity of Four Innovativeness Scales," *Educational and Psychological Measurement* (46) 1986, pp 81-87.

Goldsmith, R.E. "Using the Domain Specific Innovativeness Scale to Identify Innovative Internet Consumers," *Internet Research: Electronic Networking Applications and Policy* (11:2) 2001, pp 149-158.

Goldsmith, R.E. "Explaining and Predicting Consumer Intention to Purchase Over the Internet: An Exploratory Study," *Journal of Marketing Theory and Practice* (10:2) 2002, pp 22-28.

Goldsmith, R.E., and Hofacker, C.F. "Measuring Consumer Innovativeness," *Journal of the Academy of Marketing Science* (19:3) 1990, pp 209-221.

Goodhue, D.L., and Thompson, R.L. "Task-Technology Fit and Individual Performance," *MIS Quarterly* (19:2) 1995, pp 213-236.

Hair, J.F., Anderson, R.E., Tatham, R.L., and Black, W.C. *Multivariate Data Analysis*, (5th ed.) Prentice-Hall, Upper Saddle River, NJ, 1998.

Hirschheim, R.A. "The Effect of A Priori Views on the Social Implications on Computing: The Case of Office Automation," *Computing Surveys* (18:2) 1986, pp 165-195.

Hirschman, E.C. "Innovativeness, Novelty Seeking, and Consumer Creativity," *Journal of Consumer Research* (7) 1980, pp 283-295.

Hurt, H.T., Joseph, K., and Cook, C.D. "Scales for the Measurement of Innovativeness," *Human Communication Research* (4:1) 1977, pp 58-65.

Jackson, D.N. *Jackson Personality Inventory Manual* Research Psychologists Press, Inc., Goshen, New York, 1976.

Karahanna, E., Ahuja, M., Srite, M., and Galvin, J. "Individual differences and relative advantage: The case of GSS," *Decision Support Systems* (32:4), Mar 2002, pp 327-341.

Kirton, M. "Adaptors and Innovators: A Description and Measure," *Journal of Applied Psychology* (61:5) 1976, pp 622-629.

Kishore, R., Lee, J., and McLean, E.R. "The Role of Personal Innovativeness and Self-Efficacy in Information Technology Acceptance: An Extension of TAM with Notions of Risk," *Unpublished*), 2001.

Klein, K.J., and Sorra, J.S. "The Challenge of Innovation Implementation," *The Academy of Management Review* (21:4) 1996, pp 1055-1080.

Leavitt, C., and Walton, J.R. "Development of a Scale for Innovativeness," in: *Advances in Consumer Research,* M.J. Schlinger (ed.), Association for Consumer Research, Ann Arbor, MI, 1975, pp. 545-554.

Lee, Y., Kozar, K.A., and Larsen, K.R.T. "The Technology Acceptance Model: Past, Present, and Future," *Communications of the Association for Information Systems* (12) 2003, pp 752-780.

Leonard-Barton, D., and Deschamps, I. "Managerial Influence in the Implementation of New Technology," *Management Science* (34:10) 1988, pp 1252-1265.

Lewis, W., Agarwal, R., and Sambamurthy, V. "Sources of influence on beliefs about information technology use: An empirical study of knowledge workers," *MIS Quarterly* (27:4), Dec 2003, pp 657-678.

Limayem, M., Khalifa, M., and Frini, A. "What Makes Consumers Buy From Internet? A Longitudinal Study of Online Shopping," *IEEE Transactions on Systems, Man, and Cybernetics--Part A: Systems and Humans* (30:4) 2000, pp 421-432.

Lu, J., Yu, C.-S., Liu, C., and Yao, J.E. "Technology acceptance model for wireless Internet," *Internet Research* (13:3) 2003, p 206.

McKnight, D.H., Choudhury, V., and Kacmar, C. "Developing and validating trust measures for e-commerce: An integrative typology," *Information Systems Research* (13:3), Sep 2002, pp 334-359.

Midgley, D.F., and Dowling, G.R. "Innovativeness: The Concept and Its Measurement," *Journal of Consumer Research* (4) 1978, pp 229-242.

Moore, G.C., and Benbasat, I. "Developing an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information Systems Research* (2:3) 1991, pp 192-222.

Nah, F.F.-H., Tan, X., and Teh, S.H. "An Empirical Investigation on End-Users' Acceptance of Enterprise Systems," *Information Resources Management Journal* (17:3), July-Sept 2004, pp 32-53.

Pinto, J.K., and Mantel, S.J. "The Causes of Project Failure," *IEEE Transactions on Engineering Management* (37:4) 1990, pp 269-276.

Robertson, T.S., and Myers, J.H. "Personality Correlates of Opinion Leadership and Innovative Buying Behavior," *Journal of Marketing Research* (6) 1969, pp 164-168.

Rogers, E.M. *Diffusion of Innovations*, (5th ed.) Free Press, New York, 2003, p. 551.

Rogers, E.M., and Shoemaker, F.F. *Communication of Innovations: A Cross-Cultural Approach*, (2nd ed.) Free Press, New York, 1971, p. 476.

Thatcher, J.B. "Post-Acceptance Intentions and Behaviors: An Empirical Investigation of Information Technology Use and Innovation," (*Unpublished*) 2004.

Thatcher, J.B., and Perrewe, P.L. "An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy," *MIS Quarterly* (26:4), Dec 2002, pp 381-396.

Thompson, R.L., Higgins, C.A., and Howell, J.M. "Personal Computing: Toward a Conceptual Model of Utilization," *MIS Quarterly* (15:1) 1991, pp 125-143.

Venkatesh, V., and Davis, F.D. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Management Science* (45:2) 2000, pp 186-204.

Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3) 2003, pp 425-478.

Weiss, H.J. *DS for Windows*, (2nd ed.) Prentice Hall, New York, 2000, p. 192.

Woszczynski, A.B., Roth, P.L., and Segars, A.H. "Exploring the theoretical foundations of playfulness in computer interactions," *Computers in Human Behavior* (18:4), Jul 2002, pp 369-388.

APPENDIXES

APPENDIX 1 – Pilot Study

Pilot Study Sample

Approximately 360 students fully participated in the pilot study, which included all participants who attended the DS for Windows demonstration and completed both surveys. There were approximately an even number of women (46.38 %) and men (53.62 %) who participated. The average age of the participants was 23.9 years old, with a minimum of 19.3 years and a maximum of 53.93 years of age. Of the participants, 270 were from the OSU-Stillwater campus, and 90 were from the OSU-Tulsa campus. The average number of years of computer experience was 7.94, with a minimum of zero years, and a maximum of 23 years of computer experience. T-tests were run to determine if subjects from the two campuses were different, and the only difference found was that the OSU-Tulsa participants were older on average than the OSU-Stillwater students. The T-tests allowed the researcher to determine that the students on the two campuses were similar enough to be used as one group for purposes of the study.

The subjects represented all possible majors offered in the CBA, including accounting, economics, finance, general business, international business, management, management information systems, and marketing. This was intentional as the researcher theorized that those in quantitative majors (accounting, economics, finance, and MIS) would be more innovative than those in non-quantitative majors (general business, international business, management, marketing, and undecided). If this was true, including subjects from all majors would give the researcher a lot of variance on the innovativeness measure, something that was desirable. This turned out to be the case as those subjects who were deemed to come from quantitative majors were significantly higher in innovativeness than those from non-quantitative majors.

Pilot Study Results

The collected data was analyzed using SPSS 12.0 for Windows. As one of the first steps, Internal Consistency reliabilities (ICR) were generated for each construct to see if the items in each construct were measuring the same thing. Cronbach's Alpha is used to measure ICR and should be above 0.70 (Nunally 1978). Since most of these scales have been used in prior studies, one would expect to find ICR values even higher than 0.70. One construct, FAC, exhibited poor ICR with a Cronbach's Alpha value of 0.575. The four questions asked in the facilitating conditions construct are as follows:

I have the resources necessary to use DS for Windows
I have the knowledge necessary to use DS for Windows
DS for Windows would not be compatible with other systems I use
The lab monitors would be available for assistance with DS for Windows difficulties

In addition to exhibiting poor reliability, the items on this scale load on multiple constructs. The 2nd and 4th items from this scale load on the same construct as the effort expectancy items, while the 1st and 3rd items from this scale load with the social influence items. It is clear that the questions need to be revised, and perhaps there are problems with the original scale developed by Venkatesh et al. One potential problem area is that the first three items from this scale come from the construct perceived behavioral control, while the final item comes from a facilitating conditions construct. The other problem may be with how the items were revised when used for the pilot study. This area needs to be addressed before the FAC construct is used again in the main study. Similar reliability issues occurred with the constructs of self-efficacy and social influence. While not to the same extent as with facilitating conditions, ICR values were under 0.80, and not all of the items loaded on the construct where they were expected to be found.

The data were analyzed using hierarchical regression. First the main effect and moderator variables were added to the model. Next the two-way interactions were added, followed by the three-way interactions, and then the four-way interactions. None of the interactions variables were significant lending no support for the moderated relationship hypothesized.

Of the twelve hypotheses tested, only two of them turned out as expected. As theorized in hypothesis 12, PIIT was found to positively influence behavioral intention to use DS for Windows. Also, as theorized in hypothesis 4, FAC was found not to exhibit a significant influence on behavioral intention. None of the moderated hypotheses were found to be significant, lending no support for hypotheses 1-3, 5, 10, and 11. Contrary to what was expected, and what Venkatesh et al (2003) found, attitude, self-efficacy, and computer anxiety, were all found to positively influence behavioral intention to use technology, lending no support for hypotheses 6-8. The most surprising finding was that the relationship between behavioral intention and software usage was negative, indicating that those who said they were going to use the software were less likely to actually use the software. This finding goes against over 100 studies, and was probably due to design of the study, and not actually an important result.

Of interest was the fact that all of the main effect variables exhibited a significant effect of the dependent variable behavioral intention to use technology. Computer anxiety exhibited a significant negative effect, while performance expectancy, effort expectancy, social influence, attitude toward using technology, and self-efficacy exhibited a significant positive effect on behavioral intention. The final model that explained the most variance in intention to use technology came from the inclusion of PIIT, PE, EE, SOC, ATT, ANX, and SE, and helped explained 34% of the variance in behavioral intention.

APPENDIX 2 – BACKGROUND SURVEY

OKLAHOMA STATE UNIVERSITY SURVEY

1) First and Last Name: ____

2) Gender: Male _______ Female ___________

3) Date of Birth: _______________

4) Major: ____

5) How long have you used a computer on a consistent basis?
_________ Years & __________ Months

Below are several statements about you with which you may agree or disagree. Using the response scale to the right, indicate your agreement or disagreement with each item below by circling the one number for each question that best matches your opinion.

1 = Strongly disagree
2 = Moderately disagree
3 = Slightly disagree
4 = Neutral
5 = Slightly agree
6 = Moderately agree
7 = Strongly agree

---

6. If I heard about a new information technology, I would look for ways to experiment with it	1	2	3	4	5	6	7
7. Among my peers, I am usually the first to try out new information technologies	1	2	3	4	5	6	7
8. In general, I am hesitant to try out new information technologies.	1	2	3	4	5	6	7
9. I like to experiment with new information technologies.	1	2	3	4	5	6	7

END OF SURVEY

APPENDIX 3 – SURVEY INSTRUMENT

OKLAHOMA STATE UNIVERSITY SURVEY

1) First and Last Name: ____________________________

2) Have you ever used DS for Windows? Yes _______ No _________

3) If yes, how many times have you used DS for Windows? ______________

4) Did you attend the DS for Windows training session? Yes _______No _________

Below are several statements about you with which you may agree or disagree. Using the response scale to the right, indicate your agreement or disagreement with each item below by circling the one number for each question that best matches your opinion.

1 = Strongly disagree
2 = Moderately disagree
3 = Slightly disagree
4 = Neutral
5 = Slightly agree
6 = Moderately agree
7 = Strongly agree

---

5. If I heard about a new information technology, I would look for ways to experiment with it	1	2	3	4	5	6	7
6. Among my peers, I am usually the first to try out new information technologies	1	2	3	4	5	6	7
7. In general, I am hesitant to try out new information technologies.	1	2	3	4	5	6	7
8. I like to experiment with new information technologies.	1	2	3	4	5	6	7

Using your knowledge of DS for Windows, answer the questions below. There are several statements about you with which you may agree or disagree Using the response scale to the right, indicate your agreement or disagreement with each item.

1 = Strongly disagree
2 = Moderately disagree
3 = Slightly disagree
4 = Neutral
5 = Slightly agree
6 = Moderately agree
7 = Strongly agree

---

9. I will find DS for Windows useful for my homework assignments.	1	2	3	4	5	6	7
10. Using DS for Windows will enable me to accomplish homework assignments more quickly.	1	2	3	4	5	6	7
11. Using DS for Windows will increase my homework productivity.	1	2	3	4	5	6	7
12. If I use DS for Windows, I will increase my chances of getting a better grade on my homework assignments.	1	2	3	4	5	6	7

Using your knowledge of DS for Windows, answer the questions below. There are several statements about you with which you may agree or disagree Using the response scale to the right, indicate your agreement or disagreement with each item.	1 = Strongly disagree 2 = Moderately disagree 3 = Slightly disagree 4 = Neutral 5 = Slightly agree 6 = Moderately agree 7 = Strongly agree

---

13. My interaction with DS for Windows will be clear and understandable.	1	2	3	4	5	6	7
14. It will be easy for me to become skillful at using DS for Windows.	1	2	3	4	5	6	7
15. I will find DS for Windows easy to use.	1	2	3	4	5	6	7
16. Learning to operate DS for Windows will be easy for me.	1	2	3	4	5	6	7

---

17. Using DS for Windows will be a good idea.	1	2	3	4	5	6	7
18. DS for Windows will make homework more interesting.	1	2	3	4	5	6	7
19. Working with DS for Windows will be fun.	1	2	3	4	5	6	7
20. I will like working with DS for Windows.	1	2	3	4	5	6	7

---

21. People who influence my behavior will think that I should use DS for Windows.	1	2	3	4	5	6	7
22. People who are important to me will think that I should use DS for Windows.	1	2	3	4	5	6	7
23. The instructor of this class will be helpful in the use of DS for Windows.	1	2	3	4	5	6	7
24. In general, the instructor will support the use of DS for Windows.	1	2	3	4	5	6	7

---

25. I will have the resources necessary to use DS for Windows.	1	2	3	4	5	6	7
26. I will have the knowledge necessary to use DS for Windows.	1	2	3	4	5	6	7
27. DS for Windows will not be compatible with other systems I use.	1	2	3	4	5	6	7
28. The instructor will be available for assistance with DS for Windows difficulties.	1	2	3	4	5	6	7

I will be able to complete my homework using DS for Windows…

29. If there is no one around to tell me what to do as I go.	1	2	3	4	5	6	7
30. If I can contact someone for help if I get stuck.	1	2	3	4	5	6	7
31. If I have a lot of time to complete the homework assignment for which the software was provided.	1	2	3	4	5	6	7
32. If I have just the built-in help facility for assistance.	1	2	3	4	5	6	7

Using your knowledge of DS for Windows, answer the questions below. There are several statements about you with which you may agree or disagree Using the response scale to the right, indicate your agreement or disagreement with each item.	1 = Strongly disagree 2 = Moderately disagree 3 = Slightly disagree 4 = Neutral 5 = Slightly agree 6 = Moderately agree 7 = Strongly agree						
33. I feel apprehensive about using DS for Windows.	1	2	3	4	5	6	7
34. It scares me to think that I could lose a lot of information using DS for Windows by hitting the wrong key.	1	2	3	4	5	6	7
35. I hesitate to use DS for Windows for fear of making mistakes I cannot correct.	1	2	3	4	5	6	7
36. DS for Windows is somewhat intimidating to me.	1	2	3	4	5	6	7
37. I intend to use DS for Windows for the next homework assignment.	1	2	3	4	5	6	7
38. I predict I will use DS for Windows for the next homework assignment.	1	2	3	4	5	6	7
39. I plan to use DS for Windows for the next homework assignment.	1	2	3	4	5	6	7

40. Below list three reasons why you intend to use or three reasons why you intend not to use the DS for Windows software for the next homework assignment.

END OF SURVEY

APPENDIX 4

IRB FORM

Oklahoma State University Institutional Review Board

Date: Wednesday, August 25, 2004

IRB Application No BU054

Proposal Title: The Effect of Personal Innovativeness on Technology Acceptance and Use

Reviewed and
Processed as: Exempt

Approval Status Recommended by Reviewer(s): Approved **Protocol Expires: 8/24/2005**

Principal
Investigator(s):

Peter A Rosen	Rick Wilson
311B CBA	408 Business
Stillwater, OK 74078	Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

[X] The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval.
2. Submit a request for continuation if the study extends beyond the approval period of one calendar year. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of this research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact me in 415 Whitehurst (phone: 405-744-1676, colson@okstate.edu).

Sincerely,

Carol Olson

Carol Olson, Chair
Institutional Review Board

VITA

Peter A. Rosen

Candidate for the Degree of

Doctor of Philosophy

Thesis: THE EFFECT OF PERSONAL INNOVATIVENESS ON TECHNOLOGY ACCEPTANCE AND USE

Major Field: Business Administration

Biographical:

Education: Received Bachelor of Arts degree in Psychology from the University of California, Santa Barbara, California in 1993; Received Master of Business Administration degree with a management emphasis from San Diego State University, California in 1996; Completed the requirements for the Doctor of Philosophy degree with a major in Management Information Systems at Oklahoma State University in July, 2005.

Experience: Served as Project Manager, Aptex Software, Inc., San Diego, CA, 1996; Served as Program Coordinator, Oklahoma State University, Office of Business Extension, Stillwater, OK from 1997 to 1998; Served as Assistant Director, MBA Program, Oklahoma State University from 1998 to 2000; Employed as a Graduate Teaching Associate, Oklahoma State University, Stillwater, OK from 2000-2004; Employed as an Visiting Professor of Management Information Systems at Oklahoma State University, Tulsa, OK, 2004-2005.

Professional Memberships: Association for Information Systems, Decision Sciences Institute, INFORMS