2010

The Distinct Roles of Prior IT Use and Habit Strength in Predicting Continued Sporadic Use of IT

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Communications of the Association for Information Systems

CAIS

The Distinct Roles of Prior IT Use and Habit Strength in Predicting Continued Sporadic Use of IT

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Abstract:

This article studies prediction of continued IT use in conditions where individuals use the technology sporadically. Our study augments the unified theory of acceptance and use of technology (UTAUT) model [Venkatesh et al., 2003] with measures of prior IT use frequency and habit strength. We find these two factors provide distinct predictions which explain most of the effects that occur within the model under sporadic use conditions.

Keywords: frequency of IT use, stability of IT use, prior behavior, habit, rational models, models of behavior

Volume 27, Article 12, pp. 185-206, August 2010

The manuscript was received 11/4/2009 and was with the authors 1 month for 2 revisions.

I. INTRODUCTION

Among the many changes brought about by the Internet is a growing number of information technologies (IT) designed primarily for sporadic use, i.e., use that occurs only now and then. These *sporadic use IT* (referenced hereafter as *SU-IT*) provide services in a wide range of domains, including healthcare, employment, home sales, and even online matchmaking (see Table 1). Traditionally, most IT were developed to meet user needs that are frequent and recurring, such as payroll, transaction processing, and communication. In contrast, SU-IT support needs that occur infrequently in the user's life, such as access to e-health initiated by a child's earache or use of an online employment service prompted by news of a pending layoff.

Table 1: Examples of Sporadic-Use IT (SU-IT)

IT Focus	SU-IT Example	Sporadic Use Is Associated With:
E-health	WebMD.com	Onset of illness, injury, or medical condition
Government	IRS.gov	Quarterly and annual tax deadlines
Employment search	Monster.com	Changes in job situation or geographic location
Employee benefits	http://hrweb.mit.edu/benefits	Entering employment, retirement, or personal/family changes
Education	Fafsa.ed.gov	Student financial aid needs
Insurance	Geico.com	Renewal notice or change in insurance needs
Auto sales	AutoTrader.com	Mechanical breakdowns, transportation needs, or personal finances
Home sales	Realtor.com	Job relocation, personal finances, or family changes
Personal loans	Bankrate.com	Personal financial needs
Matchmaking	eHarmony.com	Status of romantic relationship(s)

As is the case with frequently-used IT, the ability to predict long-term use of SU-IT could help organizations to manage risks and improve allocation of resources. Yet, as described later in the article, the predictive ability of prominent IT use models diminishes under conditions of sporadic use due to obstruction of the normative relationship between individuals' intentions and behaviors [Ajzen, 2002].

In an attempt to provide better predictions, we conducted a study in which the unified theory of acceptance and use of technology (UTAUT) [Venkatesh et al., 2003] was augmented with measures of prior IT use frequency and habit strength. This article presents an empirical test of the resulting model among student users of a university intranet application (UIA). The UIA is particularly appropriate for this type of research because it supports a variety of needs that arise infrequently due to academic schedules and personal circumstances, and it is voluntary for students to use the UIA for the activities we assessed.

The overarching contribution of this research is to enhance prediction of individuals' continued use of SU-IT beyond the ability of UTAUT and related models. We add to the existing literature by studying distinct effects of prior IT use frequency and habit strength as predictors of UTAUT constructs and by conducting our research within the emerging area of SU-IT. In the following sections we present the theoretical background supporting our research model and hypothesize several effects within the model relating to the SU-IT context.

II. THEORETICAL BACKGROUND

UTAUT is based upon a theoretical tradition—including the theory of reasoned action (TRA) [Ajzen and Fishbein, 1980], the theory of planned behavior (TPB) [Ajzen, 1991], social cognitive theory (SCT) [Bandura, 1986], and the technology acceptance model (TAM) [Davis, 1989]—in which behavior is conceptualized as resulting from rational decisions rather than from "self-repetitive" origins [Kim and Malhotra, 2005a, p. 742]. Following this tradition, core indicators in UTAUT represent salient factors within individuals' belief structures. Three belief factors in the model jointly predict intention toward IT use (see Figure 1a). *Performance expectancy* is the degree to which an individual believes that using the IT will help attain gains in job performance. This factor encompasses extrinsic motivation, job fit, relative advantage, and outcome expectations, as well as the perceived usefulness factor drawn from TAM. *Effort expectancy* is the degree of ease associated with use of the IT, encompassing the perceived ease of use factor from TAM, as well as perceived complexity. *Social influence* is the degree to which an individual believes that other important individuals want him or her to use the IT. It encompasses social factors (e.g., relating to group culture and interpersonal arrangements), image, and the subjective norm factor posited by TRA but dropped during development of TAM. In UTAUT, IT use is jointly predicted by *intention,* measured as in TAM, and by *perceived facilitating conditions,* the degree to which an individual believes that personal, organizational, and technical capabilities exist to support use of the IT. We refer to this construct as perceived facilitating conditions to denote that it is a personal, subjective measure. The facilitating conditions construct originally proposed by Triandis [1977, 1980] and applied to IT acceptance modeling by prior researchers [e.g., Thompson et al., 1991] is external to the individual and is measured using objective criteria. Perceived facilitating conditions encompass perceived behavioral control over the IT and perceived compatibility of the IT with an individual's work preferences. In addition, UTAUT posits that a number of moderating relationships can exist with core constructs, including effects of *gender, age, experience,* and *perceived voluntariness of use.* Venkatesh and his associates extensively tested and validated the new theory under conditions of initial and continued use. They present UTAUT as *"a definitive model that synthesizes what is known and provides a foundation to guide future research in this area"* [Venkatesh et al., 2003, p. 467] (italics added).

Initial Acceptance vs. Continued Use

IT acceptance models were first developed to predict and explain individual decisions to initially adopt a technology. Over the years, researchers began to apply the models to study IT use following initial adoption. Several models, including TAM and UTAUT, have proved successful in predicting continued use of IT as well as initial adoption [Karahanna and Straub, 1999; Venkatesh and Davis, 2000; Venkatesh et al., 2003]. However, a number of researchers have criticized modeling of long-term behaviors through purely rational approaches that ignore effects of prior behaviors [Bentler and Speckart, 1981; Conner and Armitage, 1998; Ouellette and Wood, 1998].

Several studies undertaken to address these criticisms in the context of continued IT use report that models are improved by incorporating a measure of prior IT use frequency. Venkatesh et al. [2000] show that initial use of an organizational data retrieval system explains most of the variance in subsequent continued use, eliminating the need to re-assess beliefs in a longitudinal model. Cheung and Limayen [2005] find prior IT use frequency significantly predicts continued use of an online system for student communication and downloading homework. As students gained experience with the system in their study, this relationship became stronger and the intention-behavior link became weaker. Kim and Malhotra [2005a] augment TAM with a measure of prior IT use frequency in their study of a student website portal (see Figure 1b). They report that prior IT use predicts continued IT use frequency better than TAM alone, as measured by model fit indices and explained variance (R^2).

Because the present research focuses on continued IT use, it is important to reconcile criticisms before applying UTAUT. Some guidance in this direction is provided by Kim and Malhotra [2005a], who theorize that continued use of IT is predicated on mechanisms, including feedback and behavioral repetition, in which prior behavior plays a more prominent role than rational decision processes. The research findings of Kim and Malhotra are not directly generalizable to UTAUT, which includes measures of social influence and perceived facilitating conditions, in addition to the TAM constructs their study assessed. Nonetheless, the theoretical propositions and findings Kim and Malhotra present recommend incorporating a measure of prior IT use frequency when UTAUT is applied to predict continued IT use rather than initial adoption of IT.

Frequent Need vs. Sporadic Need

IT is designed to fulfill the needs of humans, independently or within organizational contexts. Use of a given IT is predicated to a large degree upon human perceptions that there is a need for the particular set of functions that the IT offers. Thus, we expect an individual's intentions toward using an online banking website will be acted on to fulfill needs for banking services, for example, but not for less-salient needs, such as communicating with friends or writing a proposal. In cases where need is frequent, individuals will have numerous opportunities to act on their intentions toward use of the related IT, as predicted by rational models such as UTAUT, and to repetitively practice the action of IT use. Where need is sporadic, however, opportunities for action and practice are diminished. As a result, the role of intention in determining IT use is limited and formation of habit toward IT use is retarded. Further consequences of these distinctions between frequent and sporadic need are elaborated later in the article.

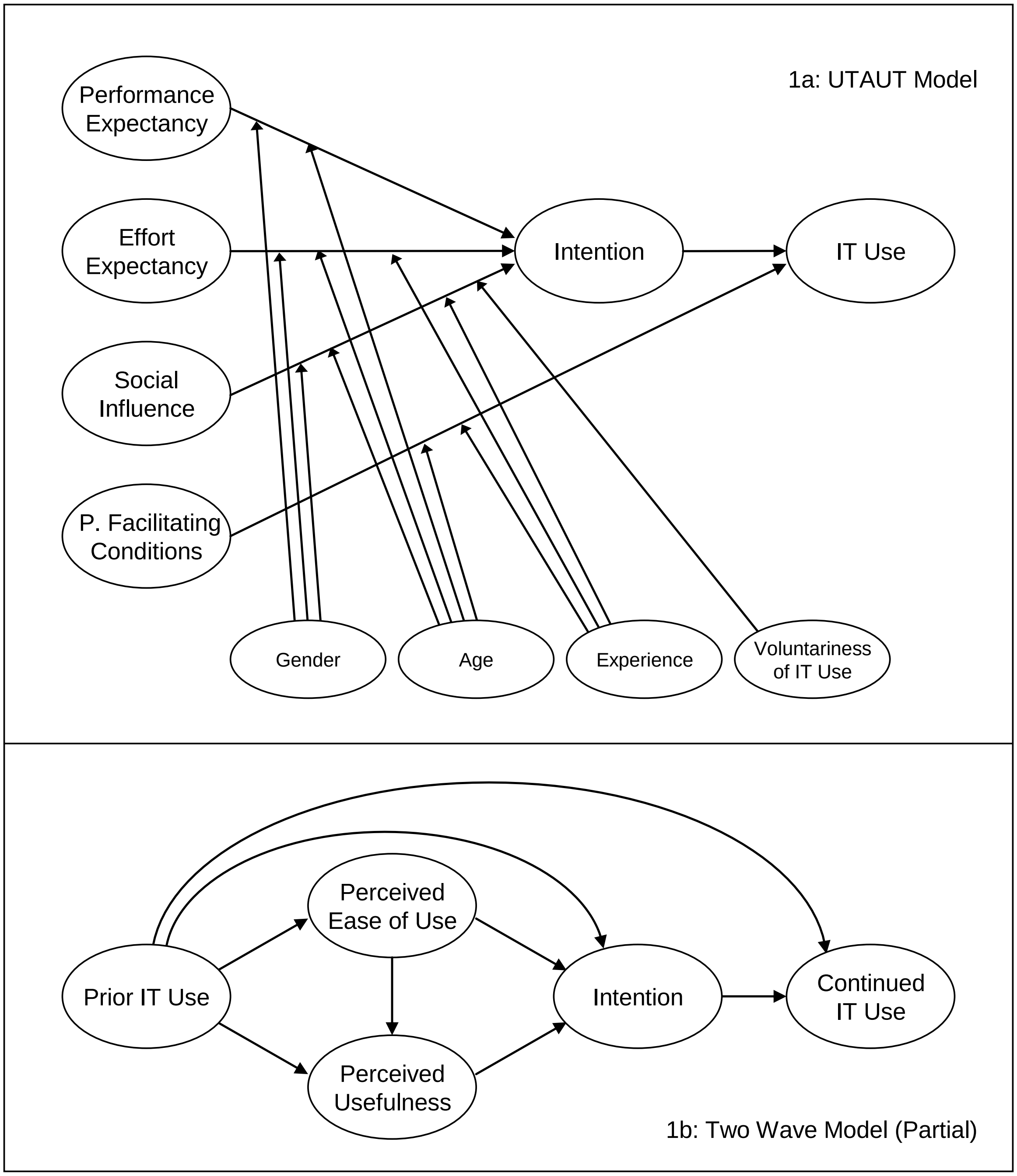

Figure 1. Two Models of IT Use

UTAUT and related models were developed and tested primarily using IT designed to support frequent needs, often as part of a daily or weekly routine. The major categories of IT used in 101 TAM studies investigated by Lee, Kozar, and Larsen [2003] overwhelmingly support frequent needs, such as e-mail communication and word processing. However, researchers are beginning to recognize the limitations of this approach. As Kim and Malhotra observe in their study of a frequently-visited website, “the results may not generalize to ... other websites (e.g., ‘online auto retailing’) which are not necessarily used on a routine basis” [2005a, p. 753].

In this study, we consider SU-IT as having been used at a rate of less than twelve times per year during the prior period, specifically excluding IT that are used monthly or more frequently, on average. This choice of frequency range is based on research which shows that the roles of intention and prior behavior in predicting behaviors performed daily or weekly differ characteristically from situations where behaviors are performed once or twice a year [Ouellette and Wood, 1998]. Our definition is necessarily arbitrary due to the absence of empirical research which studies behavior frequencies that are intermediate to these extremes (i.e., occurring between two and fifty-two times per year). We also note that our use of the descriptor *sporadic* is not synonymous to *episodic*, which denotes a lack of regularity [Venkatesh et al., 2006] rather than frequency *per se*. SU-IT are used to support infrequent needs that are repetitive (e.g., annual tax filings), as well as actions that are episodic (e.g., dating).

Sporadic Need and the Intention–Behavior Relationship

Sporadic need can give rise to effects that obstruct the normative relationship between intention and may not be accounted for by models that assume frequent need, such as UTAUT. Reviews of the general behavior literature find that a normative, positive association exists between intention and behavior [Armitage and Conner, 2001; Ouellette and Wood, 1998; Sheppard et al., 1988]. A similar association is reported in the IT literature between intention and IT use [Lee et al., 2003]. However, SU-IT are designed for "now and then" need that typically is motivated by some event that is outside the users' normal routine, such as access to e-health motivated by a child's earache. These external events constitute facilitating conditions, as originally conceptualized by Triandis [1977, 1980].

> Facilitating conditions are objective factors, "out there" in the environment, that several judges or observers can agree make an act easy to do. The person's conceptions that the act is easy are "internal" factors... [Triandis, 1980, p. 205].

To the extent that behavior is significantly dependent on facilitating conditions, the normative relationship between intention and behavior will be obstructed; even strong intentions will not be acted on until motivated by external events. UTAUT includes a measure of perceived facilitating conditions; however, the items that form this measure principally assess personal resources, knowledge, and feelings of control. These items correspond to the internal factors described by Triandis [1980] rather than providing an objective assessment of facilitating conditions.

Events that motivate sporadic behaviors are frequently outside individuals' personal control and can be difficult to predict. Thus, it is unlikely that effects of these events will be modeled well by the perceived facilitating conditions construct of UTAUT. Indeed, one obvious way to improve the predictiveness of UTAUT for SU-IT is to incorporate measurements of the events that motivate each instance of use. Unfortunately, such events are both numerous and situational. For example, use of a job search SU-IT may be motivated by a multitude of factors related to one's financial needs, family obligations, geographic mobility, and current employment status. Yet these factors would be only marginally relevant to the use of an e-health SU-IT, which will typically be motivated by advent of illness, injury, or medical condition [Wilson and Lankton, 2009]. It must be recognized that a fundamental strength of UTAUT is the model's parsimony. Although it might be possible to improve predictions of use by identifying and measuring facilitating conditions specific to each SU-IT, it would be cumbersome to apply such measures and difficult to generalize findings among diverse SU-IT.

As an alternative approach, we propose to apply two measures of IT use occurring during a prior period. One such measure we have already discussed is prior IT use frequency. In the context of SU-IT, this measure assesses the number of times a behavior (IT use) has been performed during the prior period. A second measure is habit strength, conceptualized as a mental construct with certain characteristics that are distinct from prior behaviors [Verplanken and Orbell, 2003; Verplanken, 2006]. Key among these characteristics is the important role contextual stability plays in assisting the formation of habits, a relationship which is described in detail in the following sections.

The approach of applying prior IT use frequency and habit strength is clearly more parsimonious than attempting to identify and assess a wide variety of situational factors, and it avoids being overly dependent on the specific activity that is being addressed. We previously discussed the theoretical basis for augmenting UTAUT with a measure of prior IT use frequency. Now we present the rationale for incorporating a measure of habit strength.

Sporadic Need and Habit Formation

Despite the emphasis that IT use researchers have placed on rational decision processes, most human actions are linked to habits and involve little if any rational decision making [Aarts and Dijksterhuis, 2000]. We adopt the definition of habits as "learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals" [Verplanken and Aarts, 1999, p. 104]. In common usage, however, habits are considered to be the customary way an individual acts [Ouellette and Wood, 1998]. Indeed, frequency of prior behaviors often has been applied as a surrogate measure for habit strength [e.g., Triandis, 1977, 1980]. But this approach is problematic. As Mittal observes, repetition of prior behaviors "is necessary for the formation of habit, but is not habit itself" [1988, p. 1001], and conflating the two constructs leads to circular arguments when habits are modeled in causal relationships among observed actions [Ajzen, 1987].

Over the past decade, social psychology researchers have revisited the role of habit in predicting behaviors, and advances have been made in elaborating the conceptual distinction between prior behaviors and habits. A key finding is that habit formation is highest where behaviors are repeated in stable contexts [Ouellette and Wood, 1998] [Wood et al., 2002]. Ouellette and Wood [1998] investigated this issue in a meta-analysis of sixty-four studies which measure effects of prior behavior frequency on subsequent factors. They find prior behaviors to be important predictors of beliefs, intention, and future actions, but note that the relationship between prior behaviors and habit is lessened "[w]hen supporting contexts shift or when behavior is difficult or not performed on a daily or weekly basis" [Ouellette and Wood, 1998, p. 69]. This conclusion is reinforced by Verplanken et al. [1994], who measure habit strength using a a set of choice scenarios in which subjects are told about an imaginary journey and then asked to choose from transportation options of bus, bicycle, cab, car, train, or walking. They find habit strength exerts distinct effects beyond those associated with prior behavior, including mediation of relationships between antecedent factors (decisional involvement and choice availability) and behavior. The overall findings support an emerging *cognitive-motivational* view of habits [Sheeran et al., 2005], in which habits are conceptualized as mentally-represented states that are distinct from associated actions, including both actions which prompt the formation of habit and actions which habit serves to motivate [Aarts and Dijksterhuis, 2000; Aarts et al., 1998].

Specifically, these findings suggest that habit strength can provide a unique assessment of the stability of the context in which prior behaviors occur [Wood et al., 2002; Verplanken, 2006]. This attribute is especially relevant to the present study, as it suggests habit strength will reflect stability of IT use. Habit strength may be expected to increase where behaviors are stable across time, controlling for behavior frequency, and thereby provide an alternative measure of behavior that is distinct from simple frequency.

Progress also has been made toward developing perceptual measures of habit strength that are more generally applicable and easier to administer than the choice scenario measure developed by Verplanken et al. [1994]. One approach is based upon a theoretical definition by Bargh [1994, 1996] of *automaticity* as a process that is characterized by four independent features: unintentionality, uncontrollability, lack of awareness, and efficiency. Verplanken and Orbell draw from this definition to develop a self-report index of habit strength, conceptualized as a construct "that is intentional in its origin, is controllable to a limited extend, is executed without awareness, and is efficient" [2003, p. 1317]. Empirical testing indicates the instrument provides reliable and valid measurement of habit strength that is conceptually distinct from prior behavior frequency [Verplanken and Orbell, 2003; Verplanken, 2006]. Other perceptual measures of habit strength have been successfully tested in separate studies [Bamberg and Schmidt, 2003; Boots and Treloar, 2000; Cheung and Limayem, 2005; Gefen, 2003; Limayem et al., 2003, 2007; Limayem and Hirt, 2003].

Refinements in habit research during the past decade clarify conceptual differences between prior behaviors and habits and provide guidance for assessing habit strength as a construct that is distinct from prior behavior frequency. In addition, the sensitivity of habit to contextual stability can provide predictions that are distinct from prior behavior frequency and are especially relevant to SU-IT. These observations suggest it will be important to augment UTAUT with a measure of habit strength in addition to the measure of prior IT use frequency that we discussed previously.

III. RESEARCH MODEL AND HYPOTHESES

The research model we are testing in this study augments UTAUT [Venkatesh et al., 2003] with constructs representing prior IT use frequency and habit strength (see Figure 2). Specific relationships proposed within the research model are described and justified as part of hypothesis development in subsequent sections of the article.

Extending rational models of behavior with measures of prior behavior or habit is not novel to our research. Bentler and Speckart [1979] successfully extended a TRA model using a measure of prior behavior, and other authors have tested a range of extended models (see review by Ouellette and Wood [1998]). Chaiken and Eagly write:

> The addition of past behavior to the model is eminently sensible from behaviorist perspectives which postulate that behavior is influenced by habit, or more generally, by various types of conditioned releasers or learned predispositions to respond that are not readily encompassed by the concepts of attitude and intention. Thus, the relation between past behavior and subsequent behavior may not be completely explicable through past behavior's impact on attitudes and intentions [Chaiken and Eagly, 1993, p. 179].

From this perspective, augmenting a rational model such as UTAUT with effects of prior behavior and habit is justified theoretically, and empirical testing shows that including these factors can lead to improved predictions [Ouellette and Wood, 1998].

Our research design adds to the existing literature at three levels. First, we approach frequency of prior behavior and habit strength as two distinct constructs which we hypothesize will exert a range of unique effects on elements within

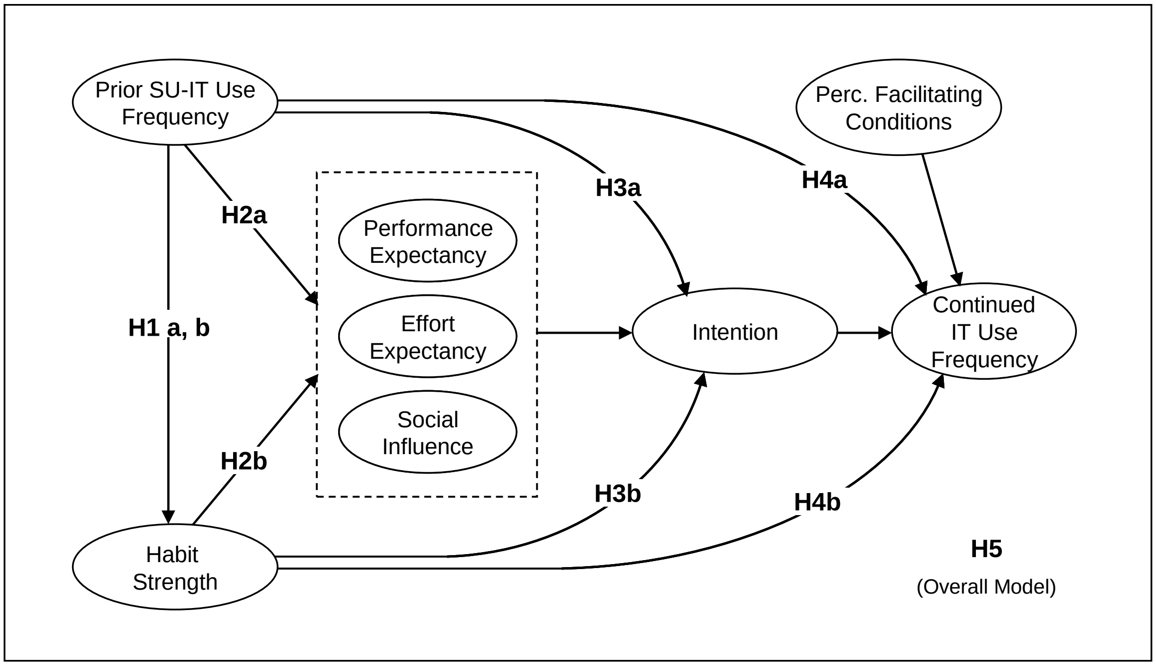

Figure 2. Research Model

UTAUT (i.e., beliefs, intention, and continued IT use) based upon their representation of distinct aspects of IT use during the prior time period. This approach may illuminate the process of habit formation and identify effects that are specific to these constructs, e.g., relating to various aspects of automaticity [Bargh, 1994, 1996]. Second, our study addresses IT use, an important subdomain within general models of behavior. Prediction of IT use has been enhanced substantially by specialized development and testing of constructs and relationships beyond those of TRA and other general models [Venkatesh et al., 2003], and we anticipate that our focus on prior IT use frequency and habit strength toward IT use will produce findings that enhance understanding of IT use in general. Third, our interest in sporadic use expands an area of study that has seen only limited prior research. In their review, Ouellette and Wood [1998] include several examples of low-frequency behaviors, however, these are primarily behaviors that are scheduled at annual or biannual intervals. Although SU-IT are characterized by infrequent use, such uses often are unscheduled and may be more frequent than once or twice a year, e.g., accessing e-health multiple times during the winter cold and flu season but not at all during other seasons. Our study design offers the opportunity to assess frequency levels that are representative of actual SU-IT use.

Distinguishing Prior SU-IT Use Frequency from Habit Strength

Verplanken argues: "Overall, there is good reason not to consider habit as mere behavioural frequency, but as a mental construct that consists of a number of facets; that is, lack of awareness, difficulty to control and mental efficiency, in addition to the experience of repetition" [2006, pp. 640–641]. To support this proposition, he conducted three studies to assess the relationship between subjects' self-reports of prior behavioral frequency and a survey measure of habit strength. Although these measures share substantial variance, Verplanken reports that each makes an independent contribution to criterion factors and that it is possible to experimentally manipulate habit strength independently of prior behavior frequency. The distinction between prior behavioral frequency and habit strength has not been assessed previously in the context of SU-IT, leading to Hypothesis 1a.

H1a: Prior SU-IT use frequency and habit strength toward use will form distinct factors in predicting continued use of SU-IT.

A second important consideration in assessing effects of prior IT use and habit within the context of SU-IT is the assumption that habits begin to be formed where behaviors are repeated very infrequently. This assumption may appear to contradict standard conceptions of habit. For example, Ronis et al. [1989] propose that a behavior must be performed at least twice a month and repeated at least ten times to be considered a fully-formed habit. However, Ajzen [2002] notes that habit formation has been observed following behaviors of very low frequency, including extra-relational affairs [Drake and McCabe, 2000], employment searches [Van Ryn and Vinokur, 1992], and health checkups [Norman and Conner, 1996]. Hypothesis 1b tests the assumption that habits can begin to form even where IT use is very infrequent.

H1b: Habit strength toward SU-IT use will form at levels of use frequency associated with SU-IT, i.e., less than 12 times per year.

Hypothesized Effects of Prior SU-IT Use Frequency and Habit Strength

We envision three key mechanisms through which prior IT use frequency and habit strength may influence continued use of IT under conditions where use is sporadic. These effects relate to beliefs regarding the IT, intention toward IT use, and continued IT use frequency. Note that we do not include hypotheses that reconstruct relationships identified in development of UTAUT, however, these relationships are assumed to exist within our research model.

Effects of Prior SU-IT Use Frequency and Habit Strength on Beliefs

Direct effects of prior IT use frequency on formation of beliefs regarding the IT are implied by the availability heuristic, which describes the human tendency to use the first information that comes to mind, i.e., the information that is easiest to recall [Tversky and Kahneman, 1973]. Ease of recall is reported to directly influence development of a variety of beliefs, including personal assertiveness [Schwartz et al., 1991], social evaluations among men and women [Rothman and Hardin, 1997], and perceived risks of heart disease [Rothman and Schwarz, 1996]. Further, it is typical for frequent prior behaviors to be associated with favorable attitudes, positive perceptions of normative pressure, and feelings of control over the behavior [Ouellette and Wood, 1998]. These findings suggest that higher prior use frequency will increase development of beliefs regarding SU-IT applications.

H2a: Prior SU-IT use frequency will directly influence strength of beliefs developed toward SU-IT.

Habits also have been shown to influence beliefs, including perceived usefulness, perceived ease of use, and affect [Bamberg and Schmidt, 2003; Gefen 2003; Limayem and Hirt 2003]. These findings suggest the following hypothesis.

H2b: Habit strength toward SU-IT use will directly influence strength of beliefs developed toward SU-IT.

Effects of Prior SU-IT Use Frequency and Habit Strength on Intention

The tendency of individuals to develop intentions toward future behaviors in close correspondence with frequently-repeated prior behaviors is well documented [e.g., Bamberg et al., 2003; Ouellette and Wood, 1998; Verplanken et al., 1998]. Matching one's intentions to reflect prior behaviors fulfills intrinsic need for cognitive consistency [Festinger, 1957] and promotes positive self perception [Bem, 1972]. Thus we anticipate that prior IT use will have significant effects on usage intention.

H3a: Prior SU-IT use frequency will directly influence intention to continue to use SU-IT.

We further propose that habit strength will significantly determine usage intention as has been previously reported by Gefen [2003].

H3b: Habit strength toward SU-IT use will directly influence intention to continue to use SU-IT.

Effects of Prior SU-IT Use Frequency and Habit Strength on Continued SU-IT Use Frequency

Rational models of behavior assume that human social behaviors result from decision processes. In the TPB, for example, actions are considered to arise from cognitive sources, i.e., intentions developed from individuals' beliefs regarding such factors as consequences of behavior, expectations of others, and control capabilities [Ajzen, 1991, 2002]. Within such a model, it would be expected that effects of prior behaviors on future behaviors would be fully mediated by cognitive factors. However, a substantial literature finds frequency in prior behaviors to be directly predictive of behaviors in the future [Ouellette and Wood, 1998].

Some controversy exists regarding the processes by which effects of prior behavior occur outside mediation by intention. Bargh and associates propose a nonconscious goal pursuit mechanism which provides flexible responses to ongoing events [Bargh, 2002; Bargh et al., 2001], while Ajzen and Fishbein [2000] argue that well-established attitudes and intentions could function as intermediaries. We have argued earlier in the present article that prior behavior can predict future behaviors where behaviors are characteristically sporadic, and it is likely this effect extends to more frequent behaviors as well. Despite a lack of theoretical consensus in this area, empirical evidence demonstrates that rational models of behavior often can be improved by incorporating a direct relationship between prior behavior and future behavior [Ouellette and Wood, 1998]. Further support for this relationship has been found in IT studies [Cheung and Limayem, 2005; Kim and Malhotra, 2000a, 2000b; Venkatesh et al., 2000]. Thus, we anticipate finding direct effects of prior IT use on continued use in our research setting based upon the empirical record.

H4a: Prior SU-IT use frequency will directly influence continued use of SU-IT.

Based upon research findings that habit formation is highest where behaviors are repeated in stable contexts [Ouellette and Wood, 1998; Wood, Quinn, and Kashy, 2002], we anticipate that habit strength will represent stability of IT use. This idea leads to the proposition that habit strength will provide unique prediction of subsequent behaviors beyond the contribution of prior IT use frequency.

H4b: Habit strength toward SU-IT use will directly influence continued use of SU-IT.

Evaluating the Augmented Model

We have identified a number of relationships within the research model that are hypothesized to add predictiveness to UTAUT. In our final hypothesis, we contrast the overall predictiveness of the research model to that of UTAUT and alternative models.

H5: The research model will explain more variance in continued use of SU-IT than UTAUT or other nested models.

IV. RESEARCH METHOD

A two-stage study measured perceptions and use of a university internet application (UIA) at a large urban U.S. university. The UIA is used by students for a variety of interactions with the university. These include several activities we investigate in the present study which occur sporadically due to the limited period during the semester in which they can occur, e.g., dropping classes and looking for open course sections, or occur in response to needs which are inherently infrequent, e.g., changing university contact information. Pilot testing found that students consider use of the UIA to be voluntary for these activities and the majority are able to name at least one alternative means to the UIA for performing the activities.

Subjects

Subjects were undergraduate students attending a second-year business course in the Fall 2004 semester. They were offered extra credit for participating in this study or performing a comparable alternative activity. Early in the semester, 213 subjects responded to an online questionnaire (Stage 1) that collected demographic information and frequency of UIA use during the prior academic year, habit strength toward UIA use, beliefs regarding the UIA's usefulness and ease of use, and intention to use UIA during the current semester to perform a specific activity. At the end of the semester, 201 of the original 213 subjects responded to a second online questionnaire (Stage 2) to report their use of UIA for the same activity during the just-completed semester. Data were not analyzed for twelve subjects (< 6 percent) who participated in Stage 1 but not in Stage 2. Average age of subjects in the final analysis is 20.3 years, and gender split is 44 percent males, 56 percent females.

To ensure that the study addressed a representative range of sporadic use, subjects were randomly assigned to respond to questions addressing one of four activity treatments identified in pilot testing as representing prior use frequencies ranging from approximately one to eight times per year. The activities are: Drop a class (1.15 mean prior uses); change university contact information (1.50 mean prior uses); look for open class sections (6.31 mean prior uses); and check grades (8.19 mean prior uses).

Measures

The questionnaire administered at Stage 1 includes the following measures. Prior SU-IT use frequency is measured as the number of times subjects recall using UIA to perform the specified activity during the academic year immediately prior to Stage 1. In addition, a ranking of this number in relation to other subjects within the treatment condition was calculated using methods recommended by Conover and Iman [1981]. Habit strength uses six items guided by prior studies [Gefen, 2003; Limayem and Hirt, 2003; Verplanken, 2006; Verplanken and Orbell, 2003]. These items focus on individuals' beliefs regarding habit of use, familiarity, regularity of use, and frequency[1] of use in relation to the UIA. Items measuring performance expectancy, effort expectancy, social influence, perceived facilitating conditions, and intention toward continued SU-IT use were applied from the UTAUT model [Venkatesh et al., 2003], using modified language where appropriate. The questionnaire administered at Stage 2 solicits continued SU-IT use, measured as the number of times subjects recall using UIA to perform the specified activity during the current semester period. In addition, continued SU-IT use is assessed as a calculated ranking of this number in relation to other subjects within the treatment condition. Because the semester period offers a natural opportunity for

[1] Although habit strength items regarding frequency and regularity of use may appear to represent prior IT use frequency, Verplanken [2006] finds that these constitute belief measures which correlate with other habit items rather than with subjects' numeric assessments of frequency.

students to perform the full range of activities which we studied, we propose it is appropriate to assess outcomes over this reduced period vs. the one-year period that was assessed at Stage 1.

Responses to all measures other than prior SU-IT use frequency and continued SU-IT use were recorded using seven-position, end-marked scales (see Appendix). Presentation order of scale-response items was re-randomized for each subject. Responses to frequency items were recorded as numeric entries. Demographic and frequency items were placed at the end of the questionnaires.

Procedure

Email was used to send subjects an invitation to participate and instructions for completing both questionnaires, which were implemented as a database-connected web application. Each questionnaire was available for completion during 10 days following the invitation. The first questionnaire was administered during the first weeks of classes during the semester and the second questionnaire during the last weeks of classes. This resulted in questionnaires being completed approximately fourteen weeks apart.

The web application presented four items at a time and stored responses to these items prior to advancing to the next items. Any items that subjects did not respond to were presented again on the following page. As a result, there were no missing data in our study. If subjects were disconnected during the questionnaire, the web application would return them on re-entry to the point in the questionnaire at which they had previously exited.

V. RESULTS

Screening was conducted to prepare the data for subsequent latent factor analysis via PLS-Graph version 03.00.1126. All analyses conducted with PLS-Graph use standardized scale indicators, and calculation of moderation terms followed guidelines presented by Chin et al. [2003]). A one-way ANOVA found no significant differences between activity treatments on demographic data.

Construct Validation

Construct validity for the scales was assessed via confirmatory factor analysis. A measurement model was created in PLS-Graph and internal consistency reliability (ICR) for each construct was computed from PLS-Graph output (see Tables 2 and 3). Convergent and discriminant validity was assessed using criteria developed by Fornell and Larcker [1981]. Convergent validity is established when (1) all indicator loadings are significant and all loadings are above .70, (2) composite construct reliability for each construct is in excess of .80, and (3) average variance extracted (AVE) for each construct is above .50. Most indicator loadings in our data are greater than .70 and are significant at $p < .001$. However, two indicators in the perceived facilitating conditions construct cross-loaded excessively with other factors, and loaded less than .60 with the latent factor (FC3 at .14, FC4 at .57). Thus, we removed these items from subsequent analyses. Three other indicators did not meet the .70 loading criteria (PE1, PE2, and PE4). Because these indicators loaded above .62, did not cross-load with other factors, and are central to the performance expectancy construct of UTAUT, we chose to retain them in the analysis.

Table 2: Construct Reliabilities, AVE*, and Intercorrelations

Construct	ICR	PU	HS	PE	EE	SI	I	FC	CU
Prior SU-IT Use Frequency (PU)	0.865	**0.873**							
Habit Strength (HS)	0.929	0.526	**0.829**						
Performance Expectancy (PE)	0.787	0.253	0.546	**0.717**					
Effort Expectancy (EE)	0.923	0.170	0.564	0.641	**0.865**				
Social Influence (SI)	0.833	0.266	0.563	0.616	0.548	**0.746**			
Intention (I)	0.958	0.418	0.685	0.417	0.313	0.423	**0.940**		
Perceived Facilitating Conditions (FC)	0.860	0.190	0.458	0.586	0.780	0.442	0.298	**0.869**	
Continued SU-IT Use (CU)	0.907	0.550	0.446	0.256	0.226	0.179	0.301	0.182	**0.911**

* The square root of average variance extracted (AVE) is shown for each construct as a bolded figure in the diagonal.

Table 3: Confirmatory Factor Analysis Matrix											
Construct	**Item**	**Mean**	**S.D.**	**PU**	**HS**	**PE**	**EE**	**SI**	**I**	**FC**	**CU**
Prior SU-IT Use Frequency (PU)	PU1	5.39	13.64	**0.820**	0.319	0.146	0.084	0.202	0.199	0.086	0.490
	PU2	101	56.77	**0.923**	0.560	0.274	0.194	0.257	0.483	0.222	0.482
Habit Strength (HS)	HS1	4.30	1.93	0.421	**0.804**	0.436	0.540	0.431	0.600	0.457	0.347
	HS2	4.53	1.80	0.333	**0.756**	0.490	0.653	0.461	0.427	0.522	0.286
	HS3	3.56	1.93	0.485	**0.850**	0.427	0.376	0.503	0.595	0.328	0.397
	HS4	4.13	1.99	0.419	**0.825**	0.486	0.489	0.442	0.551	0.417	0.330
	HS5	3.58	1.97	0.497	**0.866**	0.434	0.377	0.464	0.598	0.267	0.443
	HS6	3.59	1.90	0.452	**0.866**	0.443	0.382	0.496	0.627	0.294	0.410
Performance Expectancy (PE)	PE1	5.57	1.37	0.104	0.385	**0.694**	0.658	0.403	0.194	0.615	0.166
	PE2	5.70	1.37	0.166	0.332	**0.622**	0.541	0.386	0.265	0.552	0.158
	PE3	4.75	1.54	0.220	0.467	**0.819**	0.469	0.509	0.326	0.388	0.187
	PE4	4.32	1.73	0.199	0.320	**0.629**	0.150	0.402	0.364	0.121	0.200
Effort Expectancy (EE)	EE1	5.18	1.53	0.175	0.529	0.551	**0.873**	0.545	0.322	0.666	0.245
	EE2	5.33	1.41	0.111	0.407	0.521	**0.835**	0.429	0.232	0.650	0.113
	EE3	5.38	1.43	0.154	0.507	0.613	**0.888**	0.481	0.305	0.708	0.195
	EE4	5.43	1.52	0.138	0.496	0.530	**0.865**	0.428	0.213	0.678	0.212
Social Influence (SI)	SI1	4.23	1.69	0.213	0.444	0.521	0.380	**0.776**	0.314	0.283	0.127
	SI2	4.38	1.60	0.228	0.373	0.432	0.328	**0.786**	0.347	0.272	0.176
	SI3	4.50	1.61	0.171	0.435	0.382	0.395	**0.705**	0.328	0.308	0.120
	SI4	5.18	1.50	0.181	0.421	0.503	0.534	**0.713**	0.268	0.460	0.113
Intention (I)	I1	5.14	1.93	0.453	0.672	0.415	0.329	0.459	**0.943**	0.295	0.325
	I2	5.32	1.88	0.344	0.626	0.385	0.251	0.358	**0.931**	0.269	0.253
	I3	5.14	1.95	0.375	0.629	0.372	0.299	0.366	**0.943**	0.273	0.266
Perc. Facilitating Conditions (FC)	FC1	5.86	1.35	0.131	0.301	0.483	0.627	0.418	0.228	**0.818**	0.126
	FC2	5.63	1.52	0.190	0.471	0.535	0.724	0.367	0.284	**0.917**	0.183
Continued SU-IT Use (CU)	CU1	4.45	8.22	0.546	0.349	0.202	0.165	0.142	0.220	0.136	**0.916**
	CU2	101	57.28	0.455	0.467	0.267	0.248	0.186	0.332	0.197	**0.906**

Cross-loadings in PLS-Graph can be up to double the size of cross-loadings from a principal components analysis [Gefen et al., 2000], and levels of cross-loading shown in Table 3 are consistent with prior research using PLS-Graph. All composite construct reliabilities are .79 or greater, and all AVE values are above the recommended minimum of .50. To assess discriminant validity, we confirmed that the square root of the AVE for each construct is higher than the construct's correlation with the other constructs [Chin, 1998] and that loadings of all indicators on their hypothesized construct are higher than any of the cross-loadings [Chin, 1998; Yi and Davis, 2003].

Hypothesis Tests

PLS-Graph structural models were used to test all hypotheses. For Hypotheses 1-4, these consisted of direct-effects versions of the research model (see Figure 3). In addition, moderated and direct-effects versions of the research model and three nested models (UTAUT, UTAUT plus habit strength, and UTAUT plus prior SU-IT use frequency) were developed to test Hypothesis 5. The moderated models were augmented to include all interactions of model constructs with external factors that were tested in development of UTAUT [Venkatesh et al., 2003]. Preparation of the moderated models followed published guidelines for analysis of interaction using PLS-Graph [Chin et al., 2003].

Distinguishing Prior SU-IT Use Frequency from Habit Strength

Results from the confirmatory factor analysis support the proposition made in Hypothesis 1a that prior SU-IT use frequency and habit strength form distinct factors. Measurement items for these two constructs both load predominantly on their respective factors, as shown in Table 3, and the square roots of the AVE for each construct (.829 and .873) are substantially greater than the intercorrelation between constructs (.525), as shown in Table 2.

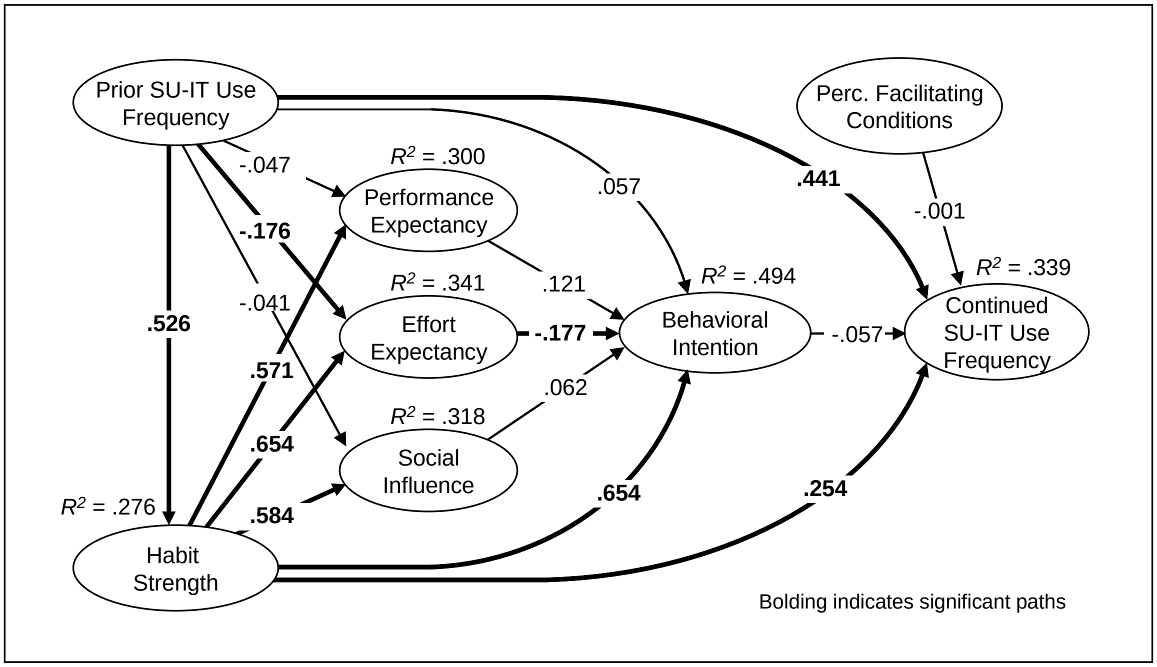

Figure 3. Results of PLS-Graph Analysis for the Research Model

Hypothesis 1b tests the assumption that habits begin to form at the very low frequencies which characterize use of SU-IT. To implement this test, we performed one-way ANOVA and *post hoc* multiple comparisons to compare habit strength across different levels of prior SU-IT use. We find significant increases in habit strength associated with increasing prior SU-IT use ($F_{4, 196} = 23.10$, $p < .001$). Habit strength of subjects who report two or more prior SU-IT uses is significantly higher than for subjects with zero prior uses, and a further significant increase occurs between two or less and six or less prior uses (see Figure 4 and Table 4). These results support Hypothesis 1b by showing that habit strength toward SU-IT use begins to form at very low usage levels and continues to increase across the range of use frequency associated with SU-IT (less than 12 times per year).

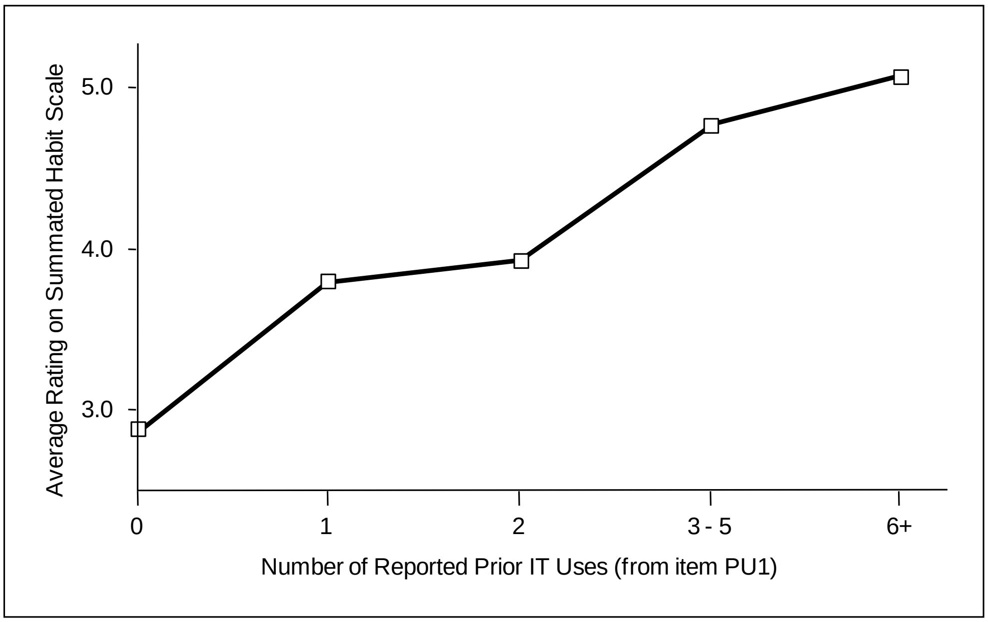

Figure 4. Increase in Habit Strength Ratings at Low Reported Frequencies of Prior SU-IT Use

Table 4: Comparison of Mean Habit Strength Ratings Across Prior SU-IT Use levels						
Number of Prior IT Uses (from item PU1)	**N**	**Mean Habit Strength**	**S.D.**	**Habit Strength Subset***		
				1	**2**	**3**
0	70	2.87	1.40	X		
1	26	3.82	1.43	X	X	
2	25	3.93	1.21		X	
3 – 5	37	4.78	1.41		X	X
6 or more	43	5.08	1.72			X
* Scheffe tests, alpha = .05						

Effects on Beliefs

Prior SU-IT use frequency directly influences effort expectancy within the research model (β = -.177, *t* = 3.00, p = .003), however, the relationship is opposite to the direction hypothesized, indicating that where prior SU-IT use frequency does not lead to habit formation, it is associated with increased effort expectancy. Prior SU-IT use frequency has no direct influence on performance expectancy or social influence. Thus, Hypothesis 2a is not supported. All relationships between habit strength and belief factors are highly significant, supporting Hypothesis 2b.

In addition to the direct effects addressed in testing Hypotheses 2a and 2b, several significant indirect effects on beliefs were found in which prior SU-IT use frequency is mediated by habit strength. Indirect path coefficients were calculated using the Sobel [1982] product of coefficients approach as .305 for performance expectancy (*z* = 7.95, p < .001), .351 for effort expectancy (*z* = 8.43, p < .001), and .313 for social influence (*z* = 7.93, p < .001). These results indicate that principal effects of prior SU-IT use frequency on beliefs are mediated by habit strength.

Effects on Intention

No significant relationship was found between prior SU-IT use frequency and intention toward use, thus Hypothesis 3a is not supported. Habit strength strongly influenced intention (β = .654, *t* = 9.10, p < .001), supporting Hypothesis 3b. To test for effects of prior SU-IT use frequency mediated by habit strength, an indirect path coefficient was calculated (β = .345, *z* = 7.19, p < .001). These results indicate that effects of prior SU-IT use frequency on intention are fully mediated by habit strength.

Effects on Continued SU-IT Use Frequency

Continued SU-IT use frequency was predicted by both prior SU-IT use frequency (β = .441, *t* = 4.29, p < .001) and habit strength (β = .254, *t* = 2.60, p = .005), supporting Hypotheses 4a and 4b. The relationships between intention and continued SU-IT use frequency and between perceived facilitating conditions and continued SU-IT use frequency were not significant.

Evaluating the Augmented Model

In order to test Hypothesis 5, which addresses the explanatory power of alternative models, our research model was contrasted with UTAUT and other nested models (see Table 5). None of the moderating effects previously reported for gender, age, experience, or voluntariness [Venkatesh et al., 2003] was found to be significant at the .05 probability level, so only contrasts of the direct effects models are reported here.

Within the UTAUT model, performance expectancy and social influence contribute significantly to intention, and intention contributes to continued SU-IT use frequency. Total effects account for R^2 = .109 in continued SU-IT use frequency. UTAUT plus habit strength accounts for R^2 = .208 in continued SU-IT use frequency and UTAUT plus prior SU-IT use frequency accounts for R^2 = .316 in continued SU-IT use frequency. Within the research model, prediction of continued SU-IT use frequency is driven exclusively by prior SU-IT use frequency and habit strength, with total effects accounting for R^2 = .339. All of the nested models are significantly less predictive of continued SU-IT use than the full research model (*F*-tests indicate p < .01 in comparisons between R^2 of full model and each nested model), thereby supporting Hypothesis 5.

Table 5: Nested Model Comparisons

Relationship	UTAUT Model	UTAUT + Habit Strength	UTAUT + Prior SU-IT Use Freq.	Research Model
Performance Expectancy → Intention	.266**	.125	.215**	.121
Effort Expectancy → Intention	.024	-.192*	.033	-.177*
Social Influence → Intention	.251**	.063	.196*	.062
Perceived Facilitating Conditions → Continued SU-IT Use Frequency	.105	-.029	.064	-.001
Intention → Continued SU-IT Use Frequency	.283***	-.003	.067	-.057
Habit Strength → Performance Expectancy		.547***		.571***
Habit Strength → Effort Expectancy		.567***		.654***
Habit Strength → Social Influence		.563***		.584***
Habit Strength → Intention		.690***		.441***
Habit Strength → Continued SU-IT Use Frequency		.471***		.254**
Prior SU-IT Use Frequency → Habit Strength				.526***
Prior SU-IT Use Frequency → Performance Expectancy			.259***	-.047
Prior SU-IT Use Frequency → Effort Expectancy			.168**	-.176**
Prior SU-IT Use Frequency → Social Influence			.267***	-.041
Prior SU-IT Use Frequency → Intention			.302***	.057
Prior SU-IT Use Frequency → Continued SU-IT Use Frequency			.514***	.441***
Continued SU-IT Use R^2	.109	.208	.316	.339
* p < .05 ** p < .01 ***p < .001				

VI. DISCUSSION

We find several important relationships influence continued use of SU-IT which cannot be accounted for by UTAUT or by prior research designs that are limited to a subset of the measures we used here. Both prior SU-IT use frequency and habit strength proved to be significant, unique predictors within the research model. By including both we were successful in more than tripling the level of predictiveness that is provided by the UTAUT model. Key implications for research and practice are addressed in the following sections.

Effects of Prior SU-IT Use Frequency

As discussed previously, several studies conducted with frequently-used IT have reported that prior use is more important than intention in predicting continued use. Our findings extend this assessment to SU-IT. Only where effects of prior SU-IT use and habit are not considered does the relationship between intention and continued use become significant (see Table 5).

The findings indicate that simple automaticity becomes the predominant theme in continued use of SU-IT. This observation strongly reinforces the view of Kim and Malhotra, who state that "IS researchers have grossly overestimated the impact of behavioral intention on future use because they ignored the impact of past use on future use" [2005a, p. 752]. Further, the results clarify interpretation of prior studies that conflate prior IT use frequency and habit strength, as we find direct effects of automaticity occur *regardless* of whether habits have been formed.

At face value, our findings appear to contradict the proposition that effects of intention on behavior tend to increase where behaviors are performed infrequently [Ouellette and Wood, 1998; Wood et al., 2002]. However, we caution against this interpretation. Because of the now-and-then nature of activities that SU-IT support, it may be anticipated that predictions of continued use will be less accurate overall than is the case for frequently-used IT. Thus, in order to study the range of effects that intention exerts in continued IT use, it will be necessary to contrast the *relative* predictiveness of intention vs. prior IT use frequency under conditions of frequent use vs. sporadic use, which is outside the scope of the present study.

A separate issue is our failure to find any direct, positive effects of prior SU-IT use frequency on beliefs. We hypothesized such a relationship based on the increased cognitive availability of actions that have been repeated over time to influence formation of beliefs. Instead, all positive effects of prior SU-IT use frequency on beliefs were mediated by habit strength, as discussed in the following section. Kim and Malhotra [2005a] suggest that frequent users of IT are likely to be guided by feedback from action to belief and infrequent users by sequential updating from existing belief to subsequent belief. One implication of our findings is that habit strength may be influenced to some degree by prior beliefs, in support of Kim and Malhotra's proposition.

Effects of Habit

Although habit strength plays a subsidiary role to prior SU-IT use frequency in predicting continued use of SU-IT, our findings indicate that effects involving belief constructs in UTAUT are almost completely subordinated by habit strength. Where other relationships occur (i.e., prior SU-IT use frequency influencing effort expectancy and effort expectancy influencing intention), these are opposite to the theorized direction and clearly represent secondary effects.

Prior SU-IT use frequency influences intention in UTAUT entirely through mediation by habit strength, reinforcing the view of habits as cognitive constructs that are "learned" from repetitive behaviors [Verplanken and Aarts, 1999]. Kim and Malhotra [2005a] suggest that correspondence between prior IT use frequency and individuals' belief structures is explained by self-perception theory, which posits that "[i]ndividuals come to 'know' their own attitudes, emotions, and other internal states partially by inferring them from observations of their own overt behavior and/or the circumstances in which this behavior occurs" [Bem, 1972, p. 5]. Our findings show habit plays an essential mediating role in development of self-attributions, at least under conditions of sporadic use. This caveat is important, as when behaviors are performed infrequently there is less certainty that habits will form [Ouellette and Wood, 1998]. Our test of Hypothesis 1a confirms that, statistically, habit strength toward SU-IT use begins to form and increases rapidly during the first few uses of SU-IT. Thus, there is reason to expect that habit strength will vary more across the subject population in the present study than may be the case under conditions where IT use is more frequent.

Habit strength also partially mediates effects of prior SU-IT use frequency on continued use within the research model (Sobel test indirect path coefficient = .126, z = 2.40, p = .008). To quantify this effect, we removed the habit strength construct and continued SU-IT use from the research model and analyzed this reduced model using PLS-Graph (see Table 5). Explained variance of continued SU-IT use in the reduced model was lowered from 33.9 percent to 31.6 percent, a significant decrease (effect size = .033, $F_{6,7}$ = 6.41, p = .007). Our interpretation is that habit strength contributes to predictions of continued SU-IT use frequency by representing the stability of prior SU-IT use. Because habit formation is greatest where the behavioral context is stable [Ouellette and Wood, 1998; Wood et al., 2002], we contend that habit strength provides a predictive measure that is distinct from the contribution of prior SU-IT use frequency.

As discussed previously, prior behavior frequency has been used by many researchers as a surrogate for habit strength [e.g., Triandis, 1977, 1980]. In retrospect, this has been an unfortunate practice. While repetitive behavior is necessary for habit formation, it is not sufficient in itself to produce habits [Mittal, 1988]. This observation is especially important to the context of sporadic IT use, as when behavior is not performed on a daily or weekly basis the relationship between prior behavior frequency and habit may be expected to diminish [Ouellette and Wood, 1998].

Cognitive measures for habit strength have been developed in recent studies; however, only a few directly assess the relationship between prior behavior frequency and habit strength. Verplanken and Orbell [2003] study behaviors that occur in frequency, ranging from twice a day (turning on music at home) to three times per month (watching a popular Dutch soap opera). Correlations between prior behavior frequency and habit strength averaged .65 across treatments compared to our findings of .52 (see Table 2). This difference in strength of association between the studies suggests that the relationship between prior behavior frequency and habit strength may attenuate under conditions of sporadic use. Although this interpretation is necessarily speculative pending further research, the finding reinforces the idea that both measures are needed in order to adequately capture the various roles that automaticity plays in determining behaviors.

Future Research Directions

The findings raise several additional issues which can be resolved only by further study. These relate to the need to better quantify the level of frequency that defines sporadic IT use, to identify characteristics of SU-IT use that may impact formation of use habits, and to reevaluate the role of rational decision models of IT use.

Quantification of Sporadic Use

Recall that we operationalized sporadic use at a level occurring at a rate of less than twelve times per year during the prior period. This criterion was grounded in review findings by Ouellette and Wood [1998], who show prior behavior frequency is relatively less predictive for activities performed once or twice a year vs. activities performed as part of a daily or weekly routine. We find some support for this position in contrasting the relationship between prior SU-IT use and continued use from the present study (β = .44) with findings of Kim and Malhotra [2005a], who report a substantially stronger relationship between these factors in their study (β = .77). The disparity between these findings suggests that effects of automaticity diminish as SU-IT use becomes more sporadic. We do not know whether these effects diminish in a continuous fashion or if there is a precipitous decrease at some point, such as our criterion of monthly regularity. Future research should attempt to quantify this relationship and to identify any extraneous determinants.

Developing Better Measures of IT Use

Our application of reflective, self-report measures of IT use frequency follows precedent in IT research [e.g., Cheung and Limayem, 2005; Kim and Malhotra, 2005a, 2005b], as well as social psychology and other behavioral disciplines [see Ouellette and Wood, 1998]. However, by assessing only the rate of occurrence, such measures are inherently one-sided. Future researchers should augment frequency with additional use characteristics, such as average duration and regularity of use, as well as associated perceptual factors, such as personal involvement. In order to overcome common method biases, it also will be important to test alternative measures to reflective self-report of frequencies, including objective observation [Szajna, 1996], alternative scale designs [Kim and Malhotra, 2005b], and diaries [Wood et al., 2002].

SU-IT Use and Habit Formation

We find habit strength to be an important predictor of continued SU-IT use. This finding may seem counterintuitive to some, given that habit formation is expected to be greatest where prior behaviors are frequent rather than sporadic [Ouellette and Wood, 1998; Wood et al., 2002]. Yet our findings show the greatest rate of increase in habit strength occurs in the range where prior SU-IT use is lowest, increasing almost one scale point between one and three-to-five prior uses. This suggests that habit strength potentially is more valuable as a predictor of behavior where *behaviors are infrequent* than is the case for the frequent, repetitive behaviors that habits are typically associated with.

To date, few IT studies have investigated effects of habit strength measured distinctly from prior IT use. Thus, it is uncertain which of the factors surrounding IT use are salient to habit formation or whether these factors may differ between conditions of frequent and sporadic use. Exploring antecedents and covariates to prior IT use and habit strength could be a productive area for future research.

Limitations of Rational Decision Models in SU-IT

Our final suggestion for future research addresses the practice of predicting continued IT use with UTAUT and other rational models of behavior. Although we approached the present study by augmenting UTAUT, we find that UTAUT constructs add no significant value to the joint predictions of prior IT use frequency and habit strength in the context of SU-IT. Results from our study add to findings of Kim and Malhotra [2005a]. Further, both studies provide sound bases for choosing alternative explanations for continued IT use beyond the approach of rational decision making. Kim and Malhotra ground their approach of incorporating prior IT use frequency in theories of feedback and repetitive behavior. In the present study, we add habit strength as an additional, distinct measure of prior IT use. Combined results of the two studies provide empirically-validated alternatives to the rational decision models which have dominated studies of continued IT use, and we propose that these alternatives deserve consideration by future researchers.

Implications for Practice

For organizations developing SU-IT, the results highlight the critical *gate-keeping* role that environmental factors play in determining use of these applications. At the same time it must be recognized that positive beliefs and intentions toward use may be important in other types of SU-IT than the UIA which we studied, especially where awareness of the SU-IT is lower than in the present study or where alternatives are more numerous. Students who participated in pilot-testing considered use of the UIA to be voluntary, and most were able to name at least one alternative method to using the UIA to performing the treatment activity. However, there are not a large number of alternatives to using the UIA. It also is clear that students are highly aware of the UIA, which is promoted through university publications, posters, and online notices. Because the UIA bundles a variety of functions, users are further reminded of functions designed for sporadic use each time they use any function. Along with being highly aware of the UIA, students in the present study held overall positive beliefs regarding the UIA and intention using the UIA for the studied activities (see item mean statistics in Table 3).

Although prior SU-IT use frequency and habit strength were the only significant predictors of continued SU-IT use in the UIA activities we studied, we anticipate beliefs and intention toward use could be significant predictors in conditions where awareness of the SU-IT is lower or where alternatives are numerous. Under such conditions, it is logical that once an individual is motivated toward action, his or her beliefs and intention toward use would then become important in selecting the SU-IT over alternative mechanisms.

Limitations of This Research

Several factors may constrain the interpretability and generalizability of our findings. First, this study collected data from student subjects using a university system. We argue that this is an appropriate test, as students constitute the natural population of UIA users and the UIA is important to these students' interactions with the university. Thus, subjects' levels of experience and involvement with the IT are not a critical limitation as might be the case with other research designs that use student subjects in place of a natural population. However, it is possible that the results will not be applicable to other populations that differ in age, experience, or context of use (as discussed in our Implications for Practice section). For example, our failure to find significance in tests of moderation using age and experience factors may be due to the limited range of these characteristics in our subject population. We do not believe that these issues impact the validity of our findings within the research setting we chose, but they do suggest that there is need to broaden this line of research to other populations and other forms of IT.

Second, we followed a tradition in IT use research of applying self-report measures, and it is difficult to know how well our findings will generalize to objective measures of use. Because of university privacy concerns, it was not possible for us to log subjects' use of UIA. This must be seen as a limitation, and we recommend this topic as an important area for future study where researchers can overcome pragmatic constraints.

Third, our study does not address initial acceptance. Based on our findings, however, we propose that a construct focusing on frequency of need may be important in modeling initial acceptance of SU-IT similar to the role of prior SU-IT use frequency in the present study. This issue is speculative pending further research, thus our findings should not be generalized to the context of initial acceptance.

VII. CONCLUSION

Researchers have been highly successful in predicting and explaining IT use in conditions where there is frequent need for the technology. However, numerous SU-IT have emerged in which sporadic use is typical rather than unusual. We find that rational decision models of IT use are not well adapted to study of SU-IT. Our initial testing finds explanatory power of models such as UTAUT can be superseded by modeling with prior IT use frequency and habit strength and that previous models that incorporate only one of these factors may be improved for the SU-IT context by adding the other.

REFERENCES

Aarts, H. and A. Dijksterhuis (2000) "Habits as Knowledge Structures: Automaticity in Goal-Directed Behavior", *Journal of Personality and Social Psychology* (78)1, pp. 53–63.

Aarts, H., B. Verplanken, V. Knippenberg (1998) "Predicting Behavior from Actions in the Past: Repeated Cecision Making or a Matter of Habit?" *Journal of Applied Social Psychology* (28)15, pp. 1355–1374.

Ajzen, I. (1987) "Attitudes, Traits, and Actions: Dispositional Prediction of Behavior in Personality and Social Psychology" in Berkowitz, L. (ed.) *Advances in Experimental Social Psychology,* Vol. 20, San Diego, CA: Academic Press, pp. 1–63.

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

Ajzen, I. (2002) "Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives", *Personality and Social Psychology Review* (6)2, pp. 107–122.

Ajzen, I. and M. Fishbein (2000) "Attitudes and the Attitude–Behavior Relation: Reasoned and Automatic Processes" in Stroebe, W. and M. Hewstone (eds.) *European Review of Social Psychology,* Chichester, UK: Wiley, pp. 1–33.

Armitage, C.J. and M. Conner (2001) "Efficacy of the Theory of Planned Behaviour: A Meta-Analytic Review", *British Journal of Social Psychology* (40), pp. 471–499.

Bajaj, A. and S.R. Nidumolu (1998) "A Feedback Model to Understand Information System Usage", *Information & Management* (33), pp. 213–224.

Bamberg, S., I. Ajzen, P. Schmidt (2003) “Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action”, *Basic and Applied Social Psychology* (25)3, pp. 175–187.

Bamberg, S. and P. Schmidt (2003) “Incentives, Morality, or Habit? Predicting Students’ Car Use for University Routes with the Models of Ajzen, Schwartz, and Triandis”, *Environment and Behavior* (35)2, pp. 264–285.

Bandura, A. (1986) *Social Foundations of Thought and Action: A Social Cognitive Theory,* Englewood Cliffs, NJ: Prentice Hall.

Bargh, J.A. (1994) “The Four Horsemen of Automaticity: Awareness, Intention, Efficiency, and Control in Social Cognition” in Wyer, R.S. and T.K Srull (eds.) *Handbook of Social Cognition,* Vol. 1, Hillsdale, NJ: Lawrence Erlbaum, pp. 1–40.

Bargh, J.A. (1996) “Automaticity in Social Psychology” in Higgins, E.T. and A.W. Kruglanski (eds.) *Social Psychology: Handbook of Basic Principles,* New York: Guilford, pp. 169–183.

Bargh, J.A. (2002) “Losing Consciousness: Automatic Influences on Consumer Judgment, Behavior, and Motivation”, *Journal of Consumer Research* (29)2, pp. 280–285.

Bargh, J.A., et al. (2001) “The Automated Will: Nonconscious Activation and Pursuit of Behavioral Goals”, *Journal of Personality and Social Psychology* (81)6, pp. 1014–1027.

Bem, D.J. (1972) “Self-Perception Theory” in Berkowitz, L. (ed.) *Advances in Experimental Social Psychology,* Vol. 6, San Diego, CA: Academic Press, pp 1–62.

Bentler, P.M. and G. Speckart (1979) “Models of Attitude–Behavior Relations”, *Psychological Review* (86), pp. 452–464.

Boots, R.J. and C. Treloar (2000) “Prediction of Intern Attendance at a Seminar-Based Training Programme: A Behavioural Intention Model”, *Medical Education* (34), pp. 512–518.

Cheung, C.M.K. and M. Limayem (2005) “The Role of Habit in Information Systems Continuance: Examining the Evolving Relationship Between Intention and Usage” in Avison, D., D. Galletta, J. DeGross (eds.) *Proceedings of the 26th International Conference on Information Systems,* Las Vegas, NV, pp. 471–482.

Cheung, W., M.K. Chang, V.S. Lai (2000) “Prediction of Internet and World Wide Web Usage at Work: A Test of an Extended Triandis Model”, *Decision Support Systems* (30), pp. 83–100.

Chin, W. (1998) “The Partial Least Squares Approach to Structural Equation Modeling” in Marcoulides, G.A. (ed.) *Modern Methods for Business Research,* Mahwah, NJ: Lawrence Erlbaum Associates, pp. 295–336.

Chin, W., B.L. Marcolin, P.R. Newsted (2003) “A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-Mail Emotion/Adoption Study”, *Information Systems Research* (14)2, pp. 189–217.

Conner, M. and C.J. Armitage (1998) “Extending the Theory of Planned Behavior: A Review and Avenues for Further Research”, *Journal of Applied Social Psychology* (28), pp. 1429–1464.

Conover, W.J. and R.L. Iman (1981) “Rank Transformation as a Bridge Between Parametric and Nonparametric Statistics”, *American Statistician* (35), pp. 124–133.

Davis, F.D. (1989) “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology”, *MIS Quarterly* (13)3, pp. 319–329.

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

Drake, C.R. and M.P. McCabe (2000) “Extrarelationship Involvements Among Heterosexual Males: An Explanation Based on the Theory of Planned Behavior, Relationship Quality, and Past Behavior”, *Journal of Applied Social Psychology* (30), pp. 1421–1439.

Eagly, A.H. and S. Chaiken (1993) *The Psychology of Attitudes,* Forth Worth, TX: Harcourt Brace Jovanovich.

Festinger, L. (1957) *A Theory of Cognitive Dissonance,* Evanston, IL: Row, Peterson.

Fornell, C. and D.F. Larcker (1981) “Evaluating Structural Equations with Unobservable Variables and Measurement Error”, *Journal of Marketing Research* (18), pp. 39–50.

Gagnon, M.P., et al. (2003) “An Adaptation of the Theory of Interpersonal Behaviour to the Study of Telemedicine Adoption by Physicians”, *International Journal of Medical Informatics* (71), pp. 103–115.

Gefen, D. (2003) “TAM or Just Plain Habit: A Look at Experienced Online Shoppers”, *Journal of End User Computing* (15)3, pp. 1–13.

Gefen, D. (2004) “What Makes ERP Implementation Relationship Worthwhile: Linking Trust Mechanisms and ERP Usefulness”, *Journal of MIS* (21)1, pp. 263–288.

Gefen, D. and D.W. Straub (1997) “Gender Difference in the Perception and Use of E-Mail: An Extension to the Technology Acceptance Model”, *MIS Quarterly* (21)4, pp. 386–400.

Gefen, D., D.W. Straub, M. Boudreau (2000) “Structural Equation Modeling and Regression: Guidelines for Research Practice”, *Communications of the Association for Information Systems* (4)7.

Karahanna, E., et al. (1999) “Information Technology Adoption Across Firms: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs”, *MIS Quarterly* (23)2, pp. 183–213.

Kim, S.S. and N.K. Malhotra (2005a) “A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Postadoption Phenomena”, *Management Science* (51)5, pp. 741–755.

Kim, S.S. and N.K. Malhotra (2005b) “Predicting Systems Usage from Intention and Past Use: Scale Issues in the Predictors”, *Decision Sciences* (36)1, pp. 187–196.

Lee, Y., K.A. Kozar, K.R.T. Larsen (2003) “The Technology Acceptance Model: Past, Present, and Future”, *Communications of the Association for Information Systems* (12)50, pp. 752–780.

Limayem, M. and S.G. Hirt (2003) “Force of Habit and Information Systems Usage: Theory and Initial Validation”, *Journal of the Association for Information Systems* (4), pp. 65–97.

Limayem, M., et al. (2003) “Habit in the Context of IS Continuance: Theory Extension and Scale Development” in C.U. Ciborra, et al. (eds.) *Proceedings of the 11th European Conference on Information Systems,* Naples, Italy.

Limayem, M., et al. (2007) “How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance”, *MIS Quarterly* (31)4, pp. 705–737.

Mittal, B. (1988) “Achieving Higher Seat Belt Usage: The Role of Habit in Bridging the Attitude Behavior Gap”, *Journal of Applied Social Psychology* (18), pp. 993–1016.

Norman, P. and M. Conner (1996) “Predicting Health-Check Attendance Among Prior Attenders and Nonattenders: The Role of Prior Behavior in the Theory of Planned Behavior”, *Journal of Applied Social Psychology* (26), pp. 1010–1026.

Ouellette, J.A. and W. Wood (1998) “Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior”, *Psychological Bulletin* (124)1, pp. 54–74.

Ronis, D.L., J.F. Yates, J.B. Kirscht (1989) “Attitudes, Decisions, and Habits as Determinants of Repeated Behavior” in Pratkanis, A.R., S.J. Breckler, A.G. Greenwald (eds.) *Attitude Structure and Function,* Hillsdale, NJ: Lawrence Erlbaum Associates, pp. 219–239.

Rothman, A.J. and C.D. Hardin (1997) “Differential Use of the Availability Heuristic in Social Judgment”, *Personality and Social Psychology Bulletin* (23), pp. 123–138.

Rothman, A.J. and N. Schwartz (1996) “Constructing Perceptions of Vulnerability: Personal Relevance and the Use of Experiential Information in Health Judgments”, *Personality and Social Psychology Bulletin* (24), pp. 1053–1064.

Schwartz, N., et al. (1991) “Ease of Retrieval as Information: Another Look at the Availability Heuristic”, *Journal of Personality and Social Psychology* (61), pp. 195–202.

Sheeran, P., et al. (2005) “The Goal-Dependent Automaticity of Drinking Habits”, *British Journal of Social Psychology* (44), pp. 47–63.

Sheppard, B.H., J. Hartwick, P.R. Warshaw (1988) “The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research”, *Journal of Consumer Research* (15), pp. 325–343.

Szajna, B. (1996) “Empirical Evaluation of the Revised Technology Acceptance Model”, *Management Science* (42)1, pp. 85–92.

Sobel, M.E. (1982) “Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models” in S. Leinhardt (ed.) *Sociological Methodology 1982,* Washington, DC: American Sociological Association, pp. 290–312.

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

Thompson, R.L., C.A. Higgins, J.M. Howell (1994) “Influence of Experience on Personal Computer Utilization: Testing a Conceptual Model”, *Journal of MIS* (11)1, pp. 167–187.

Triandis, H.C. (1977) *Interpersonal Behavior,* Monterey, CA: Brooks/Cole Publishing.

Triandis, H.C. (1980) “Values, Attitudes, and Interpersonal Behavior” in Howe, H.E. and M.M. Page (eds.) *Nebraska Symposium on Motivation 1979,* Lincoln, NE: University of Nebraska Press, pp. 195–259.

Tversky, A. and C. Kahneman (1973) “Availability: A Heuristic for Judging Frequency and Probability”, *Cognitive Psychology* (5), pp. 207–232.

Van Ryn, M. and A.D. Vinokur (1992) “How Did It Work? An Examination of the Mechanisms Through Which an Intervention for the Unemployed Promoted Job-Search Behavior”, *American Journal of Community Psychology* (20), pp. 577–597.

Venkatesh, V. (2000) “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model”, *Information Systems Research* (11)4, pp. 342–365.

Venkatesh, V. and F.D. Davis (2000) “A Theoretical Extension of the Technology Acceptance Model. Four Longitudinal Field Studies”, *Management Science* (46)2, pp. 186–204.

Venkatesh, V., L.M. Maruping, S.A. Brown (2006) “Role of Time in Self-Prediction of Behavior”, *Organizational Behavior and Human Decision Processes* (100), pp. 160–176.

Venkatesh, V., et al. (2003) “User Acceptance of Information Technology: Toward a Unified View”, *MIS Quarterly* (27), pp. 425–478.

Verplanken, B. (2006) “Beyond Frequency: Habit as Mental Construct”, *British Journal of Social Psychology* (45), pp. 639–656.

Verplanken, B. and H. Aarts (1999) “Habit, Attitude, and Planned Behaviour: Is Habit an Empty Construct or an Interesting Case of Automaticity?” *European Journal of Social Psychology* (27), pp. 539–560.

Verplanken, B., et al. (1998) “Habit versus Planned Behaviour: A Field Experiment”, *British Journal of Social Psychology* (37), pp. 111–128.

Verplanken, B., et al. (1994) ”Attitude versus General Habit: Antecedents of Travel Mode Choice”, *Journal of Applied Social Psychology* (24), pp. 285–300.

Verplanken, B. and S. Orbell (2003) “Reflections on Past Behavior: A Self-Report Index of Habit Strength”, *Journal of Applied Social Psychology* (33)6, pp. 1313–1350.

Wilson, E.V. and N.K. Lankton (2009) “Predicting Patients’ Use of Provider-Delivered e-Health: The Role of Facilitating Conditions” in E.V. Wilson (ed.) *Patient-Centered e-Health,* Hershey: PA, IGI Global, pp. 217–229.

Wood, W., J.M. Quinn, D.A. Kashy (2002) “Habits in Everyday Life: Thought, Emotion, and Action”, *Journal of Personality and Social Psychology* (83)6, pp. 1281–1297.

Yi, M.Y. and F.D. Davis (2003) “Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition”, *Information Systems Research* 14(2), pp. 146–169.

APPENDIX—MEASUREMENT ITEMS

Unless otherwise indicated, all items are measured as on seven-point scales anchored on endpoints with 1 = Strongly Disagree / 7 = Strongly Agree (where alternative anchors are used these are indicated following the item). Where the activity is referenced in parentheses, this was replaced for the specific activity being surveyed, e.g., "look for open class sections."

Prior SU-IT Use Frequency

PU1 Approximately how many times during the (prior) school year did you use UIA to (perform activity)? *(Numeric entry)*

PU2 Rank of times during the (prior) school year subject reports using UIA to (perform activity)? *(Calculated rank)*

Habit Strength

HS1 Using UIA to (perform activity) is: 1 = Not something I know how to do from habit / 7 = Something I know how to do from habit

HS2 My use of UIA to (perform activity) is: 1 = Something I have to think about to remember how to do / 7 = Something I've committed to memory

HS3 Using UIA to (perform activity) is: 1 = Not one of my ordinary activities / 7 = One of my ordinary activities

HS4 My use of UIA to (perform activity) is: 1 = Intermittent / 7 = Ongoing

HS5 How often do you use UIA to (perform activity)? 1 = Not often at al / 7 = Very often

HS6 I use UIA to (perform activity) very frequently.

Performance Expectancy

PE1 I find UIA useful to (perform activity).

PE2 Using UIA enables me to (perform activity) more quickly.

PE3 Using UIA to (perform activity) increases my productivity.

PE4 If I use UIA to (perform activity), I will increase my chances of success at the university.

Effort Expectancy

EE1 My interaction with UIA to (perform activity) is clear and understandable.

EE2 It is easy for me to become skillful at using UIA to (perform activity).

EE3 I find it easy to use UIA to (perform activity).

EE4 Learning to operate UIA to (perform activity) is easy for me.

Social Influence

SI1 People who influence my behavior think that I should use UIA for activities like (activity).

SI2. People who are important to me think that I should use UIA for activities like (activity).

SI3 University personnel have been helpful in the use of UIA for activities like (activity).

SI4 In general, the university has supported my use of UIA for activities like (activity).

Intention

I1 I intend to use UIA to (perform activity) during the (current) school year.

I2 I predict I would use UIA to (perform activity) during the (current) school year.

I3 I plan to use UIA to (perform activity) during the (current) school year.

Perceived Facilitating Conditions

PFC1 I have the resources necessary to use UIA to (perform activity).

PFC2 I have the knowledge necessary to use UIA to (perform activity).

PFC3 Using the UIA to (perform activity) is not compatible with other software I use at the university. *(Reverse-coded—Not used in analysis)*

PFC4 People are available to assist me with difficulties in using the UIA to (perform activity). *(Not used in analysis)*

Continued SU-IT Use Frequency

CU1 Approximately how *many times during the (just-completed) semester have you used UIA to (perform activity)? (Numeric entry)*

CU2 Rank of times during the (just-completed) semester subject reports using UIA to (perform activity)? *(Calculated rank)*

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Communications of the Association for Information Systems

ISSN: 1529-3181