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Effects of Prior Use, Intention, and Habit on IT Continuance Across Sporadic Use and Frequent Use Conditions

E. Vance Wilson

Worcester Polytechnic Institute

vancewilson@gmail.com

Nancy K. Lankton

Marshall University

Abstract:

This article is motivated by the desire to integrate and expand two literature streams, one that models effects of prior information technology (IT) use and habit strength on continued IT use and another that studies how to apply such models to IT that are used in a characteristically sporadic manner. We find that joint predictions of continuance intention, prior IT use, and habit strength within our research model are superior to subsets of the model across the extended range of usage frequency we studied. However, subsets of the model can also provide reasonable predictions where all measures are not available.

Keywords: prior IT use; habit strength; continuance intention; continuance model; post-adoption behavior; technology adoption

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I. INTRODUCTION

As the study of IT adoption has matured, information systems (IS) researchers have begun to extend this line of research toward predicting and explaining individuals' long-term use of information technology (IT), also known as *IT continuance*. While initial IT adoption is known to be an important first step toward IT success, researchers have argued that IT continuance is vital for long-term success [Bhattacherjee, 2001]. Further, promoting IT continuance requires understanding the factors that drive it [Limayem, Hirt and Cheung, 2007].

Initial studies of IT continuance applied rational models of behavior, in which use is theorized to result from intentions that individuals form through rational decision processes based on their beliefs toward the IT [Bhattacherjee, 2001; Bhattacherjee and Premkumar, 2004; Karahanna, Straub and Chervany, 1999]. However, behaviors also can be motivated through non-rational processes [Wood and Quinn, 2005]. Where behaviors are performed repeatedly there is a tendency to form *habits*, which are defined 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]. Habits are enacted through automated responses to stimulus cues [Aarts, Verplanken and van Knippenberg, 1998; Ouellette and Wood, 1998; Ronis, Yates and Kirscht, 1989] or automated activation of attitudes and intentions [Ajzen, 2002] rather than through rational processes immediately preceding the behavior. Thus, habitual behaviors tend to be performed quickly, with minimal attention or awareness, and in parallel with other activities [Aarts and Dijksterhuis, 2000; Bargh, 1996; Ouellette and Wood, 1998].

Past behavior and habit are closely linked in that repeated behaviors often become habitual. Indeed, the majority of habit research conducted since Triandis [1977, 1980] introduced his model of interpersonal behavior has assessed habit strength through measurement of behavioral frequency [Ouellette and Wood, 1998]. However, past behavior and habit strength are not identical. As Mittal observes, "Repeated occurrence is necessary for the formation of habit, but it is not habit itself" [1988, p. 997]. Instead, habits tend to be formed where behaviors are repeated in stable contexts [Ouellette and Wood, 1998; Wood, Quinn and Kashy, 2002]. This recognition has prompted researchers in IT continuance and other domains to develop independent measures of habit strength and prior behavior [Limayem, Hirt and Cheung, 2007; Verplanken and Orbell, 2003] and to include subjective habit measures in models of IT adoption [Pahnila, Siponen and Zheng, 2011; Polites and Karahanna, 2012; Venkatesh, Thong and Xu, 2012].

This study contributes to the IT continuance literature in two ways. First, it clarifies the related but distinct roles intentions, habit, and prior use have in explaining IT continuance. It does so by integrating earlier findings and examining both direct and moderating effects of habit strength. This can help future researchers incorporate these factors into the often-used rational models of IT continuance. Second, this study investigates these factors' influences across different frequency levels of continued usage. This is important because many successful IT products and services are not used on a daily or even weekly basis. Understanding the roles of intentions, habit, and prior use in driving continued use of these IT products and services cannot only expand academic research, but can also help vendors more effectively meet customers' needs.

II. BACKGROUND

Three studies apply measures of prior IT use, habit strength, and continuance intention to predict IT continuance. Selected relationships identified by these studies are presented in Figure 1. Limayem, Hirt, and Cheung [2007] studied general Web use by students, finding that continuance intention is an important direct predictor of continued IT use and that habit strength both moderates the relationship between continuance intention and continued IT use and mediates effects of prior IT use on continued IT use. Limayem and Cheung [2008] studied students' use of an online learning system. They found habit strength predicted continued IT use through both moderating and direct effects, prior IT use directly influenced continued IT use, and continuance intention did not predict continued IT use.

A related research stream was prompted by the observation by Ouellette and Wood [1998] that the roles of intention and prior behavior in predicting behaviors that are performed daily or weekly differ in characteristic ways from behaviors that are performed only once or twice a year. This distinction led Wilson, Mao, and Lankton [2010] to conceptualize a class of *sporadic-use* IT, which the typical user accesses at rates of less than twelve times per year based on infrequent need for services provided by the IT. Sporadic use IT are becoming ubiquitous, with examples

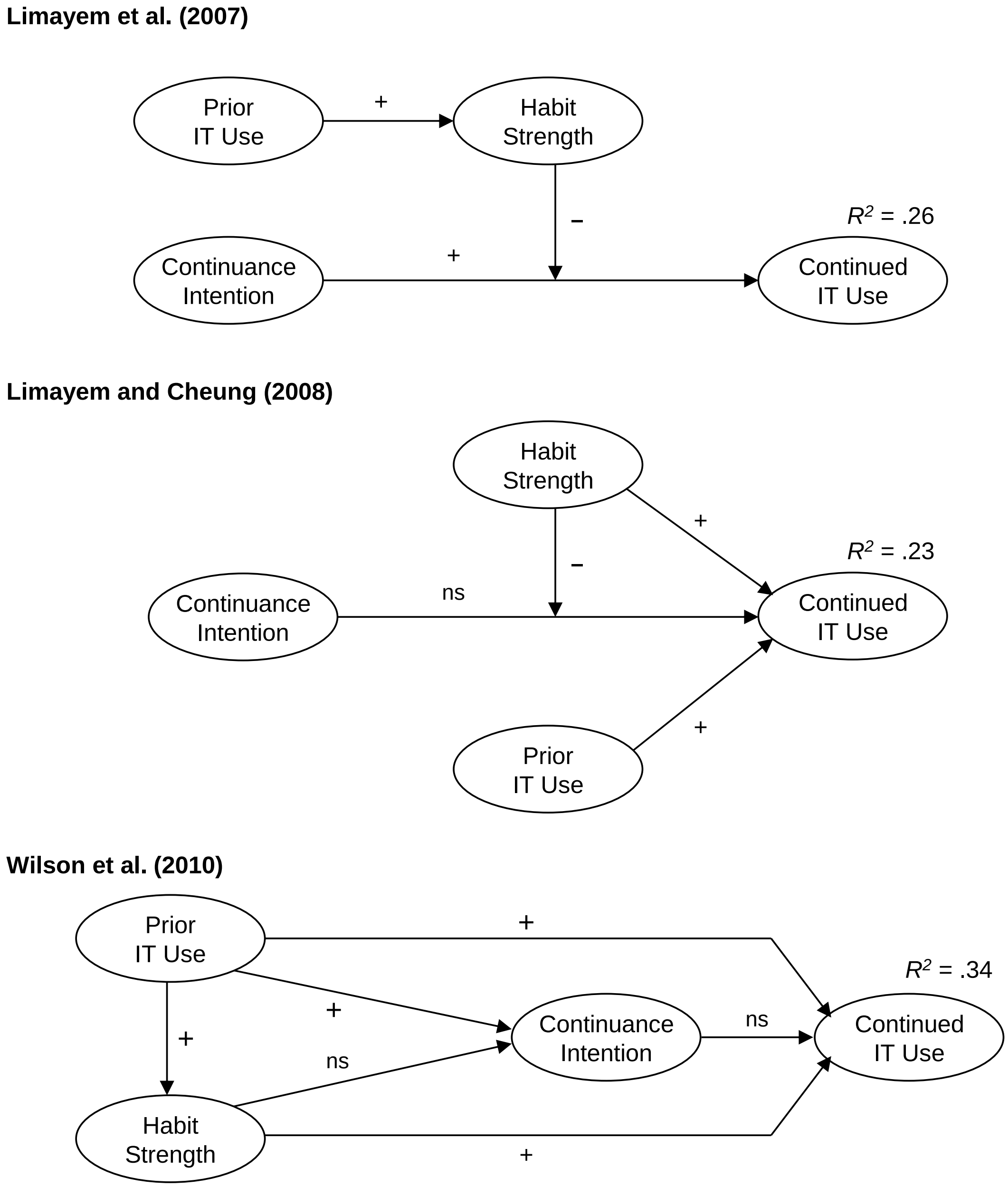

Figure 1. IT Continuance Studies that Measure Prior IT Use, Intention, and Habit

including e-health (WebMD.com), employment search (Monster.com), auto sales (AutoTrader.com), and online matchmaking (eHarmony.com). In contrast, Wilson et al. [2010] conceptualize *frequent-use* IT as a class for which need is frequent and regular, such as email or word processing.

Although researchers have called for expanded study of IT that is used infrequently [Kim and Malhotra, 2005; Wilson and Lankton, 2009], only a few studies in this area have been reported to date [Lankton, Wilson and Mao, 2010; Wilson et al., 2010]. Wilson et al. [2010] take the approach of studying students' use of features within an online university information system for which use is characteristically sporadic. They find prior IT use and habit strength have independent direct effects on continued IT use but find no effect of continuance intention on continued IT use.

Considered jointly, these studies imply that prior IT use, continuance intention, and habit strength are important predictors of continued IT use. However, they do not address three key issues that motivate the present study. These issues are described in the following sections.

Integration of Findings Across Frequent- and Sporadic-Use Conditions

Limayem et al. [2007] and Limayem and Cheung [2008] studied IT that typically are used on a frequent basis, and Wilson et al. [2010] studied IT functions that are used only sporadically. Whereas Limayem et al. [2007] demonstrate that habit limits the predictive power of continuance intention for IT that are used frequently, Wilson et al. [2010] find that effects of habit decrease substantially as frequency of prior IT use declines to minimal levels. However, no prior study has assessed the effects of habit strength and continuance across a range of sporadic *and* frequent IT use. We propose that such assessment is necessary to integrate the existing research findings.

Joint Effects of Prior IT Use and Attention

The literature is inconsistent in jointly testing effects of prior IT use and intention. It is important to note that continuance intention was found to significantly predict continued IT use in the Limayem et al. [2007] study in which direct effects of prior IT use were not assessed, but this is not the case in Limayem and Cheung [2008] or Wilson et al. [2010] in which prior IT use was assessed. Wilson et al. [2010] argue that the relationship between prior IT use and continued IT use subordinates the effects of continuance intention, but conditions that lead to this effect are unclear. We propose that further study incorporating direct effects of prior IT use can clarify this issue.

Direct and Moderating Effects of Habit Strength

The literature also is inconsistent in testing direct and moderating effects of habit strength and has not previously tested moderating effects of prior IT use. Although Limayem and Cheung [2008] test direct effects of habit strength on continued IT use as well as moderating effects on the relationship between continuance intention and continued IT use, Limayem et al. [2007] test only moderating effects, and Wilson et al. [2010] test only direct effects. We propose that simultaneous testing of direct and moderating effects of both habit strength and prior IT use will further integrate and clarify the findings of this literature stream.

In the following sections, we develop a research model and hypotheses to investigate these issues, followed by a presentation of our research method, analysis and results, and discussion of the findings.

III. RESEARCH MODEL AND HYPOTHESES

Prior research in this area drew from two theoretical models of IT continuance. Limayem et al. [2007] and Limayem and Cheung [2008] based their studies in the expectation-confirmation model presented by Bhattacherjee [2001]. Wilson et al. [2010] grounded their study on the unified theory of adoption and use of technology (UTAUT) developed by Venkatesh, Morris, Davis, and Davis [2003] and later augmented to include habit and other constructs [Venkatesh et al., 2012]. Both theory streams emphasize the relationship between continuance intention and continued IT use, and we carry on the approach applied by prior researchers in this area of augmenting this central relationship with relationships of habit strength and prior IT use (see Figure 2).

Our research model extends prior research by simultaneously addressing direct effects of continuance intention, habit strength, and prior IT use on continued IT use as well as moderating effects of habit strength and prior IT use on the relationship between continuance intention and continued IT use. The model is proposed as a mechanism for predicting IT continuance across a range of sporadic- and frequent-use conditions.

In the following sections we present and justify our hypotheses regarding the joint effects of continuance intention, prior IT use, and habit strength on continued IT use as illustrated by the research model. We further hypothesize trade-offs that may be anticipated to occur between continuance intention and habit strength under conditions in which IT use is characteristically sporadic vs. frequent.

Moderating and Direct Effects of Prior IT Use and Habit Strength on Continuance

Substantial literature streams report that past behavior and habit strength contribute significantly to future behaviors [Ouellette and Wood, 1998]. However, these findings are split between studies that model these contributions as moderating effects on the intention-behavior relationship and others that model direct effects. This dichotomy is reflected in IT continuance research, where Limayem et al. [2007] and Limayem and Cheung [2008] report moderating effects whereas Venkatesh, Morris, and Ackerman [2000], Limayem and Hirt [2003], Kim and Malhotra [2005], Lankton et al. [2010], Wilson et al. [2010], Pahnila et al. [2011], and Venkatesh et al. [2012] report direct effects. The argument for direct effects is that both habits and routines (as indicated by prior actions) independently augment rational decisions in determining subsequent actions [Betsch, Haberstroh and Höhle, 2002]. The argument for moderating effects is that the role of rational decision-making is subordinated by habits and routines only when these become well-developed. We anticipate both prior IT use and habit strength will influence continuance through some combination of augmentation and/or subordination of continuance intention. In order to capture the multiple

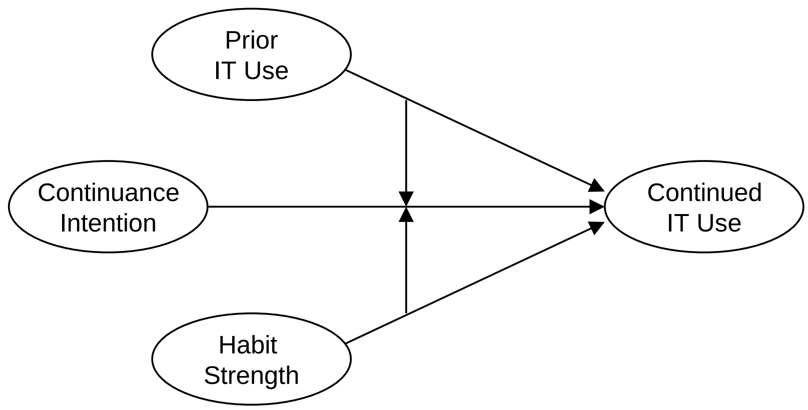

Figure 2. Research Model

paths in which this influence may be enacted, we hypothesize both moderating and direct effects will be found for each factor.

> *H1: Prior IT usage frequency moderates the relationship between continuance intention and continued IT use across sporadic and frequent use conditions.*

> *H2: Habit strength moderates the relationship between continuance intention and continued IT use across sporadic and frequent use conditions.*

> *H3: Prior IT usage frequency increases continued IT use across sporadic and frequent use conditions.*

> *H4: Habit strength increases continued IT use across sporadic and frequent use conditions.*

A further hypothesis extends the findings of Limayem and Cheung [2008] and Wilson et al. [2010] that prior IT use and habit strength provide independent predictions of continued IT use.

> *H5: The full research model will predict significantly more variance in continued IT use than model subsets across sporadic and frequent use conditions.*

Trade-Off Between Continuance Intention and Habit Strength[1]

In addition to our primary research emphasis—studying joint effects of prior IT use, habit strength, and continuance intention across an extended frequency range of continued IT use—our research design provides the opportunity to assess a reported trade-off between intention and habits as predictors of subsequent behaviors. A review study by Ouellette and Wood [1998] implies the existence of two modes of behavior, a high-frequency mode that supports development of habits and a low-frequency mode that does not. They report that intention is the primary predictor of future behaviors for actions performed twice or fewer times per year, a frequency rate which we will operationalize in the present article as *sporadic-use conditions*. Based on these review findings, we propose that intention will be more important than habit strength in predicting IT continuance where use is sporadic.

> *H6: Under sporadic-use conditions, continuance intention will predominate habit strength as a predictor of continued IT use.*

Ouellette and Wood [1998] also find that habit strength is a more important predictor of future behavior than intentions where actions are sufficiently frequent to form habitual behaviors (e.g., as part of a regular routine). This finding has been confirmed by IT continuance researchers [Cheung and Limayem, 2005; Kim and Malhotra, 2005; Kim, Malhotra and Narasimhan, 2005; Lankton et al., 2010; Pahnila et al., 2011. We propose similar findings will emerge in the present study.

> *H7: Under frequent-use conditions, habit strength will predominate continuance intention as a predictor of continued IT use.*

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[1] Hypotheses 6 and 7 explore moderating relationships of usage frequency that involve only the habit strength and continuance intention components of the overall research model. These hypotheses should be considered as exploratory extensions to the research model rather than tests of the model as presented herein.

IV. RESEARCH METHOD

A longitudinal study measured evaluations, intentions, and students' use of a university Internet application (UIA) at a large urban U.S. university. The UIA is available for students to use for a variety of interactions with the university.

Subjects

Subjects were undergraduate students attending a semester-long, second-year business course conducted in a classroom setting. They were offered extra credit for participating in this study or for performing an alternative activity requiring a similar time commitment. Early in the semester, 314 subjects responded to an online questionnaire (Time 1) that collected demographic information and frequency of UIA use during the prior academic year, habit strength toward UIA use, and intention to use UIA during the current semester to perform a specific activity. At the end of the semester, 269 of the original 314 subjects (86 percent) completed a second online questionnaire (Time 2) to report their use of UIA for the same activity during the intervening period. Data were not analyzed for subjects who did not complete both questionnaires. No significant differences were found on Time 1 measures between subjects who completed both questionnaires and those who completed only the Time 1 questionnaire. The average age of subjects used in the final analysis was twenty years, and the gender split was 49 percent males, 51 percent females.

Procedure

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

In order to study a range of usage frequencies, we implemented a multiple-condition approach. Upon entry to the Web application, subjects were initially queried as to whether they had ever used the UIA to perform three activities: changing university contact information, paying fees and bills, and/or viewing personal federal financial aid information. Each of these activities could be performed in an alternative manner by visiting the campus registrar office.

Subsequently, subjects were randomly assigned to one of the activity conditions that they had performed at least once previously. The three activities selected as conditions were identified in pilot testing as representing average usage frequencies ranging between one and sixteen times per year. In addition, these activities are continuously supported by the UIA, excluding activities such as dropping a class, an action for which support is disabled after a certain deadline date in each semester. The assumption that it is valid to assess these three conditions as a single sample population is evaluated empirically in the Results section (Section V) later in the article.

The Web application presented four items at a time and stored responses to these items prior to advancing to the next items. The order of item administration was randomized separately for each subject. Any items that subjects did not respond to were presented again on the following page. If subjects were disconnected during the questionnaire, the Web application would return them on re-entry to the point in the questionnaire that they had previously completed.

Measures

The questionnaire administered at Time 1 included the following measures. Prior IT use was measured through two items assessing the frequency of times subjects recalled using UIA to perform the specified activity during the twelve months immediately prior to Time 1. The first of these items asked for open-ended input of frequency from the subject, as previously assessed by Limayem et al. [2007]. The second item asked subjects to choose among a set of frequency categories, as previously assessed by Venkatesh et al. [2012]. Other constructs tested at Time 1 used validated scale items. These included habit strength [Limayem and Hirt, 2003; Verplanken and Orbell, 2003] and continuance intention [Venkatesh et al., 2003]. Scale items used modified language where appropriate to the research context. The questionnaire administered at Time 2 measured continued IT use with two items assessing the number of times subjects recall using UIA to perform the specified activity during the just-completed academic semester. These items took the same form as those used to assess prior IT use. As discussed by Venkatesh et al. [2012], we argue that potential for common method variance arising from repeated questions is mitigated by the longitudinal design of this study, in which approximately 13 weeks passed between measurements. Questionnaire items are shown in Table 1, and correlations among items are reported in Table 2. Computer logging of student actions was prohibited by university privacy policies, so self-report measures of prior IT use and continued IT use were conducted using both an open-ended scale and a closed-category scale.

Table 1: Questionnaire Items		
Construct	Item	Item content*
Prior IT Use [Limayem et al., 2007; Venkatesh et al., 2012]	PITU1	To the best of your recall, how many times during the past 12 months did you use UIA to [perform activity]? (Numeric entry, converted to rank order)
	PITU2	To the best of your recall, which category best describes the total number of times during the past 12 months you used UIA to [perform activity]? (1 = None, 2 = Once, 3 = Twice, 4 = 3 to 5 times, 5 = 6 to 11 times, 6 = 12 to 20 times, 7 = More than 20 times)
Habit Strength [Limayem and Hirt, 2003; Verplanken and Orbell, 2003]	HS1	The use of UIA for [performing activity] has become a habit to me.
	HS2	I don't even think twice before using UIA for [performing activity].
	HS3	Using UIA for [performing activity] has become natural to me.
	HS4	Using UIA to [perform activity] is something I do automatically.
Continuance Intention [Venkatesh et al., 2003]	CI1	I intend to use UIA to [perform activity] during the [current] semester.
	CI2	I predict I would use UIA to [perform activity] during the [current] semester.
	CI3	I plan to use UIA to [perform activity] during the [current] semester.
Continued IT Use [Limayem et al., 2007; Venkatesh et al., 2012]	CITU1	To the best of your recall, how many times during the [current] semester did you use UIA to [perform activity]? (Numeric entry, converted to rank order)
	CITU2	To the best of your recall, which category best describes the total number of times during the [current] semester you used UIA to [perform activity]? (1 = None, 2 = Once, 3 = Twice, 4 = 3 times, 5 = 4 to 5 times, 6 = 6 to 10 times, 7 = More than 10 times)
*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 brackets, this was replaced for the specific activity being surveyed (e.g., "change your university contact information").		

Table 2: Item Correlation Matrix										
	PITU1	PITU2	HS1	HS2	HS3	HS4	CI1	CI2	CI3	CITU1
PITU2	0.823									
HS1	0.302	0.322								
HS2	0.251	0.267	0.513							
HS3	0.303	0.331	0.607	0.602						
HS4	0.244	0.259	0.605	0.615	0.652					
CI1	0.338	0.374	0.518	0.373	0.480	0.432				
CI2	0.361	0.377	0.498	0.366	0.420	0.377	0.795			
CI3	0.379	0.388	0.440	0.347	0.403	0.358	0.825	0.812		
CITU1	0.506	0.526	0.393	0.208	0.313	0.249	0.365	0.345	0.365	
CITU2	0.463	0.448	0.335	0.203	0.299	0.281	0.312	0.314	0.299	0.782

V. RESULTS

Prior to evaluating our research model and performing hypothesis tests, we conducted a series of analyses designed to ensure data integrity and confirm key assumptions of our research design. Some subjects entered very high values for prior IT use and/or continued IT use open-ended frequency responses. As a conservative alternative to removing these records as outliers, we applied a ranking transformation to these prior IT use and continued IT use data items following the recommendations of Conover and Iman [1981]. The ranking transformation replaces the raw number entry in analysis with its rank among the data across all subjects (or average rank in case of ties).

Subjects were randomly assigned to one of three conditions. In order to assess whether subjects were homogeneous, one-way ANOVA was conducted among the conditions for age, gender, and number of completed semesters at the university. No significant differences between subject groups were found across conditions.

Measurement Model

We assessed measurement and structural models using AMOS structural equation modeling (SEM) software [Arbuckle and Wothke, 1999]. All measurement items were entered as reflective measures. The measurement model for our data was assessed through a confirmatory factor analysis (CFA) accompanied by additional analyses to ensure convergent validity, discriminant validity, and model fit. In our initial CFA, twenty-eight parameters were estimated; thus, our sample size of 269 provides a ratio well beyond the minimum criterion of five cases per estimated parameter [Bagozzi and Yi, 1988]. To assess convergent validity, we examined item loadings and calculated the composite reliability (CR), Cronbach's alpha, and the average variance extracted (AVE) for each latent factor. All items load on their respective factor at .73 or above, the CR and Cronbach's alphas for each construct are .86 or higher, and the square root of AVE for each construct is at least .75 (see Table 3). These figures substantially exceed recommended minimum values for assessing convergence [Bagozzi and Yi 1988; Fornell and Larcker, 1981]. Discriminant validity was confirmed by assessing that the square root of the AVE for each construct is higher than the construct's correlation with the other constructs [Chin, 1998], as reported in Table 2.

Goodness of fit statistics for the measurement model are within recommended levels. The χ^2/df is 1.17 (χ^2 = 44.52, df = 38) and is nonsignificant (p = .22). The GFI (goodness of fit index), NFI (normed fit index), CFI (comparative fit index), and RMSEA (root mean square error of approximation) values are .97, .98, .99, and .03, respectively, easily meeting minimum criterion recommendations [Hu and Bentler 1999]. These findings demonstrate that the measurement model provides a good level of fit with the data.

Table 3: Measurement Scale Characteristics*

	Mean	SD	CR	Alpha	PITU	HS	CI	CITU
Prior IT Use (PITU)	7.84	20.32	0.90	0.90	**0.91**			
Habit Strength (HS)	4.52	1.53	0.86	0.86	0.41	**0.78**		
Continuance Intention (CI)	4.96	1.87	0.93	0.93	0.45	0.59	**0.90**	
Continued IT Use (CITU)	3.73	6.78	0.88	0.88	0.61	0.39	0.42	**0.89**

*Means and standard deviations (SD) are calculated from the raw data or, in the case of scale measures, from the average value of raw data comprising the measure; CR = composite reliability; Alpha = Cronbach's alpha; correlations are calculated among latent factors; the square root of average variance extracted (AVE) for each latent factor is shown as a bolded entry in the diagonal.

Structural Model

In creating the structural model, we added terms representing two hypothesized interactions on the relationship between continuance intention and continued IT use. These are habit strength X continuance intention and prior IT use X continuance intention. Interaction terms were calculated using the product of summed indicators, which Ping [1995] recommends as an effective method to minimize undue reduction of model fit while maintaining content validity. Covariance paths were included among the interaction terms and the antecedent constructs.

Structural Model Validation

In developing the structural model, we assessed key research assumptions. The first assumption pertains to our research design of assigning subjects to one of three conditions in which the UIA was used for a specific activity. To ensure that these conditions do not vary in ways that systematically influence outcomes of the study, we assessed the research model with the condition entered as a control factor to habit strength, continuance intention, and continued IT use. Second, we tested for effects of autocorrelation between measures used to assess prior IT use and continued IT use at separate times by temporarily augmenting the research model with covariance paths between each set of measures. In neither test did the additions to the research model result in significant change in path weights, an increase in explained variance for any dependent factor, or improvement in model fit. Finally, we tested for multicollinearity effects in the structural model by reviewing AMOS modification indexes [Byrne, 2001]. None of the modification indexes was excessive (all were under 10 in value), so no additional changes were made. SEM analysis of the resulting structural model is presented in Figure 3.

Goodness of fit statistics for the overall structural model are within accepted levels [Hu and Bentler, 1999]. The χ^2/df is 1.52 (χ^2 = 80.66, df = 53, p = .008). The GFI, NFI, CFI, and RMSEA values are .96, .96, .99, and .04, respectively.

Hypothesis Tests

We hypothesized that prior IT use and habit strength moderate the effects of continuance intention on continued IT use and also exert direct effects, based on prior studies that have reported both types of relationships. We find support for H1, testing interaction between prior IT use and continuance intention (std. coeff. = .14, $p < .05$), and H3, testing the direct effect of prior IT use on continued IT use (std. coeff. = .50, $p < .001$). No support was found for H2 or H4, which respectively test the moderating and direct effects of habit strength on continued IT use.

Hypothesis 5 addresses the contribution of the full research model relative to subsets of the model. The full model explains significantly more variance in continued IT use than any of its nested models (see Table 4). The largest proportion of explained variance in prediction of continued IT use is provided by the direct effects of prior IT use.

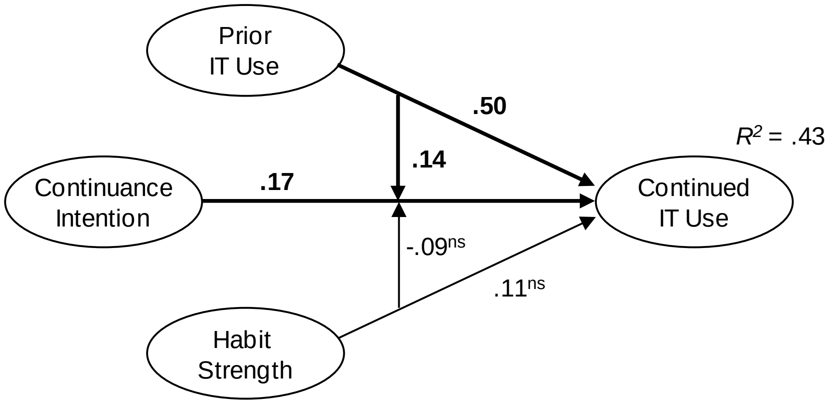

Figure 3. Results of SEM Analysis (Bolded Paths Indicate Significant Relationships)

Table 4: Comparison of Full Research Model and Selected Nested Models

Effect on Continued IT Use	HS	CI	CI + HS + HSxCI	PITU	CI + PITU + HS	CI + PITU + PITUxCI	Full Research Model
Prior IT Use (PITU)				.60***	.50***	.52***	.50***
Habit Strength (HS)	.40***		.22*		.11		.11
Continuance Intention (CI)		.42***	.29***		.13	.19*	.17*
PITU x CI						.02	.14*
HS x CI			-.04				-.09
Model R^2	.16	.18	.21	.36	.40	.40	.43
Effect Size of R^2 Change from Full Model	.33***	.31***	.28***	.11*	.06*	.06*	—
* = p < .05, ** = p < .01, *** = p < .001							

However, continuance intention also makes a significant contribution to the overall model, and inclusion of the direct and moderating effects of habit strength contributes significantly to overall model R^2, although neither of the associated relationships separately achieves significance at the .05 level.

Hypotheses 6 and 7 address characteristic trade-offs in effects of intention and habit strength between usage frequency levels. Based on the prior literature, H6 proposed that continuance intention will predominate predictions of continued IT use under sporadic-use conditions, and H7 proposed that habit strength will predominate under frequent-use conditions.

We split our overall sample into two subgroups based on our conceptualization of sporadic use as subjects reporting prior IT usage frequency of two or less times during the previous twelve months, following Ouellette and Wood [1998]. The sporadic-use subgroup averaged 1.05 prior IT uses (n = 148, SD = .75), and the frequent-use subgroup averaged 16.15 prior IT uses (n = 121, SD = .282). Prior IT usage frequency differs significantly between subgroups (t = 5.89, p < .001). Because these hypotheses did not address prior IT use, the subgroups were separately entered into a reduced version of the research model containing only habit strength, continuance intention, and continued IT use. With twenty-one estimated parameters, sample sizes for both subgroups surpassed the minimum criterion of five cases per estimated parameter [Bagozzi and Yi, 1988]. The results corroborated the findings of Ouellette and Wood [1998] and supported Hypotheses 5 and 6 (see Table 5 and Figure 4).

Table 5: Results of Split-Frequency Sample Analysis

Predictor of continued IT use	Sporadic-use subgroup n = 148	Frequent-use subgroup n = 121
Habit strength effect	Std. Coeff. = .18 (p = .150)	Std. Coeff. = .31 (p = .014)
Continuance intention effect	Std. Coeff. = .24 (p = .045)	Std. Coeff. = .17 (p = .116)
Model R^2	.14	.18
χ^2 / df	33.24 / 24 = 1.39	32.68 / 24 = 1.36
GFI	.956	.943
NFI	.959	.950
CFI	.988	.986
RMSEA	.051	.055

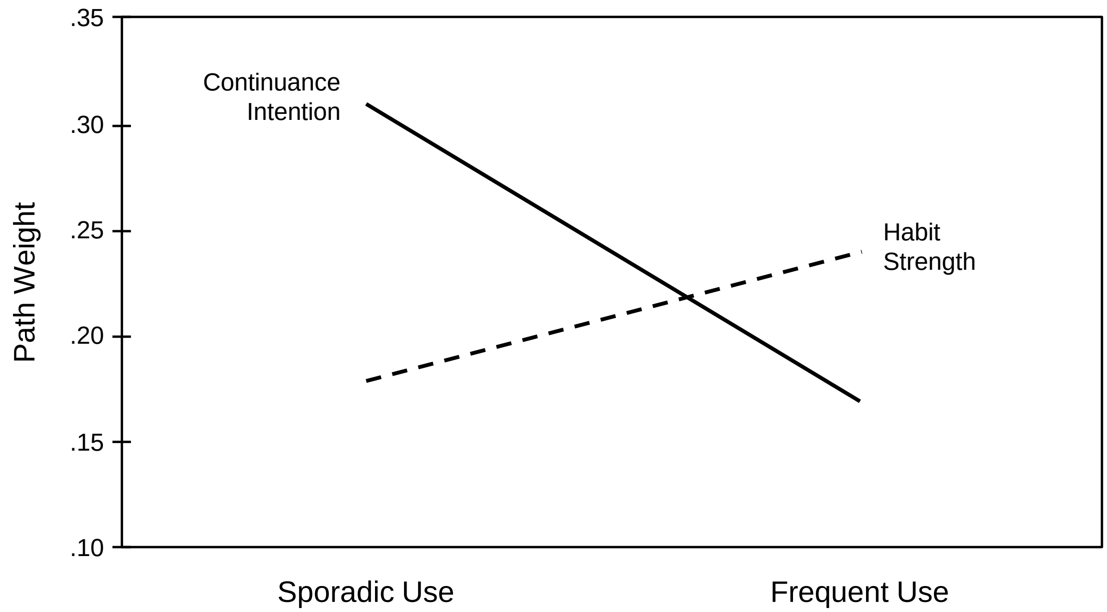

Figure 4. Interaction of Path Coefficients Across Sporadic- and Frequent-Use Conditions

VI. DISCUSSION

Because our research design encompasses a joint focus on prior IT use, habit strength, and continuance intention across a range of usage frequency levels, the results are useful in integrating findings of earlier studies that examine separate parts of this domain. Some of our findings confirm earlier research. For example, we find prior IT use is much more important than habit strength or continuance intention in predicting continued IT use, as previously has been reported. However, several other findings have not previously been reported.

First, although earlier studies show that prior IT use and habit strength measures subordinate the effects of continuance intention [Limayem and Cheung, 2008; Wilson et al., 2010], we find it is habit strength that is subordinated. Unlike Limayem and Cheung [2008], the design of our study includes infrequent IT use contexts, and unlike Wilson et al. [2010], the design includes moderating effects of prior IT use and habit strength in addition to direct effects. The implication is that when other factors are accounted for—by incorporating an extended frequency range and measurement of moderating effects—habit strength is reduced in importance.

Second, our findings in testing Hypotheses 6 and 7 corroborate the existence of a trade-off between the relative predictiveness of intentions and habit strength that occurs when contextual frequency increases, as proposed by Ouellette and Wood [1998] but not previously tested in the context of IT use. In sporadic-use conditions, rational processes (e.g., continuance intentions) are relatively important predictors of future behavior; automated processes (habits) gain importance as behavioral frequency increases. Ouellette and Wood [1998] reviewed studies that constrained them to compare behaviors performed daily or weekly vs. behaviors performed only once or twice a year. This left open to speculation where in the range between those frequencies the trade-off between intention and habit strength takes place. Our research design was able to identify that this trade-off occurs at very infrequent behavior levels of approximately two-to-three uses of the IT during the previous year. This finding supports the contention of Wilson et al. [2010] that the habit of IT use begins to form at very low levels of behavioral frequency.

Third, our design addressed moderating effects of prior IT use on the relationship between continuance intention and continued IT use, a relationship that has received little prior attention despite several studies that focus on similar effects of habit strength [Limayem et al., 2007; Limayem and Cheung, 2008]. Although the nominal size of the relationship we found is small (std. coeff. = .14), researchers should keep in mind that strength of association in correlational designs is typically underestimated for moderation terms due to the multiplicative effects of measurement error and lack of research controls [McClelland and Judd, 1993]. In order to assess whether the moderating effect we found for prior IT use acts to diminish effects of habit strength, we ran a version of the research model which removed only the PITU x CI interaction term (see Table 4). Explained variance in the model (R^2) dropped from .43 to .39 ($p < .001$, f^2 effect size = .07), and the change did not cause either the direct or moderating effect of habit strength to become significant. These findings indicate that the moderating effect of prior IT use adds a small but unique prediction to the overall model.

Fourth, several studies have found that prior IT use subordinates the effects of continuance intention on subsequent IT use [Kim and Malhotra, 2005; Venkatesh et al., 2000]. This effect has been proposed to arise through mechanisms ranging from spontaneous activation of intention [Ajzen, 2002] to habituation [Kim et al., 2005]. Yet in the present study prior IT use on its own explains the majority of variance in continued IT use (R^2 = .36), far more than habit strength (R^2 = .16) or continuance intention (R^2 = .18). The magnitude of difference in these relationships coupled with the significant direct influence of prior IT use on continued IT use found in the full research model (std. coeff. = .50) imply that effects of prior IT use cannot be explained in entirety by spontaneous activation of intention or habituation. Because prior IT use has proved to be an effective direct predictor of IT continuance, it is not in the interest of our discipline for researchers to discount the contribution of this factor. Thus, our findings suggest that IS researchers should actively investigate alternative explanations, such as exploring the distinctions between habits and routines [Betsch et al., 2002] and revisiting the role of objective facilitating conditions in models of IT acceptance and continuance [Wilson and Lankton, 2009].

Fifth, there is significant practical value in the approach we took in Hypothesis 5 of studying nested models in addition to the full research model. Although the full model provides a significantly better explanation of variance than any subset, it may not always be possible to obtain all the measures we used for our study. As illustrated in Table 5, very good predictions of continued IT use may be achieved by using continuance intention plus prior IT use measures or even by applying prior IT use as a sole predictor. Use of these measures can help IT vendors to effectively meet customers' needs.

Finally, there is additional practical value in studying IT usage across the range of frequency contexts that represent actual use in practice. Sporadic-use IT have quietly become ubiquitous, as illustrated by the examples identified by Wilson et al. [2010], including e-health (WebMD.com), employment search (Monster.com), auto sales (AutoTrader.com), and even matchmaking (eHarmony.com). Modern IT systems are no longer limited to frequently used applications such as email and word processing that typify the domain in which technology acceptance research has been conducted [Lee, Kozar and Larsen, 2003]. We find that certain aspects of prediction are not generalizable across use-frequency contexts, such as the relative predictiveness of continuance intention and habit strength. Thus, we recommend that IS researchers expand future research designs to study IT use across sporadic- as well as frequent-use contexts.

Limitations

There are limitations to this study that suggest caution in generalizing the results. First, we collected data from university students using a university intranet application. While these subjects are the natural users of this system, our results may have limited applicability to other populations that differ in age, experience, and use context. Second, due to university privacy practices we used self-report use measures rather than objective use measures. While this is common practice in IT research, our results might differ from those obtained using objective measures.

VII. CONCLUSION

Understanding factors that promote continued use across a range of normative frequencies is increasingly important as IT applications come to play larger roles in our day-to-day lives while providing increasingly specialized functions. This study presents findings that prior IT use, habit strength, and continuance intention are unique and important joint predictors of continued IT use, although the pattern of prediction varies between sporadic- and frequent-use conditions. This meets our objective of integrating findings across a wide range of usage frequency, as well as testing both moderating and direct effects of prior IT use and habit strength. We argue that our findings herein add incremental value to prior findings reported by Limayem et al. [2007], Limayem and Cheung [2008], and Wilson et al. [2010].

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Editor's Note: The following reference list contains hyperlinks to World Wide Web pages. Readers who have the ability to access the Web directly from their word processor or are reading the article on the Web can gain direct access to these linked references. Readers are warned, however, that:

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ABOUT THE AUTHORS

E. Vance Wilson is an Associate Teaching Professor in the School of Business at Worcester Polytechnic Institute. He received his BA in Psychology from Reed College, MSBA in Information and Decision Systems from San Diego State University, and PhD in Information Systems from the University of Colorado at Boulder. His research focuses on organizational aspects of human-computer interaction with special emphasis on patient-centered e-health, computer-mediated communication, and online persuasion. He is Supervising Editor of the Information Systems and Healthcare Department of *Communications of the Association for Information Systems.*

Nancy K. Lankton is an Associate Professor in the College of Business at Marshall University. She received her BS in Accounting, MBA; MS in Computer Information Systems; and PhD in Business Administration from Arizona State University. Nancy’s main research interests include trust’s impacts on individual and organizational use of information technology, as well as privacy behaviors related to social networking websites. She has published in journals such as *Contemporary Accounting Research, IEEE Transactions on Engineering Management, Journal of Management Information Systems,* and *Journal of the American Medical Informatics Association.* She currently serves as an Associate Editor for *Communications of the Association for Information Systems.*

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