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ABSTRACT

This paper is motivated by the desire to integrate and expand two recent literature streams, one that models effects of prior 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 joint predictions of continuance intention, prior IT use, and habit strength within our research model are superior to subsets of the model across the range of frequency we studied. However, subsets of the model are able to provide reasonable predictions where all measures are not available.

Keywords

IT Acceptance, Behavior Model, Survey Research, Behavior Frequency

INTRODUCTION

Three recent studies utilize measures of prior IT use and habit strength to predict IT continuance, i.e., continuing use of IT following an introductory period. The major 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) study students' use of an online learning system. They find continuance intention does not predict continued IT use, habit strength predicts continued IT use through both moderating and direct effects, and prior IT use directly influences continued IT use. Wilson, Mao, and Lankton (2010) studied student use of specific features for which use is characteristically infrequent, i.e., *sporadic,* within an online university information system. They find continuance intention has no effect on continued IT use, and prior IT use and habit strength have independent direct effects on continued IT use.

Considered jointly, the three studies present researchers with two key implications: Prior IT use is a potent direct predictor of continued IT use, and habit strength is a potent predictor both through direct effects on continued IT use and as a moderator of the relationship between continuance intention and continued IT use. However, other aspects of the research are less clear. These include two issues that motivate the design of the present study:

- Continuance intention is a significant predictor of continued IT use only in the Limayem et al. (2007) study where direct effects of prior IT use were not assessed. While the relationship between prior IT use on continued IT use appears to subordinate the effects of continuance intention, further study is necessary to ascertain this interpretation.
- Limayem et al. (2007) and Limayem and Cheung (2008) studied types of IT that are typically used on a frequent basis, but Wilson et al. (2010) studied IT system features that are used only sporadically, which they define as less than 12 times per year on average. Although researchers have called for expanded study of such *sporadic-use* IT (Kim and Malhotra, 2005; Wilson and Lankton, 2009), only a few studies have been reported to date (Lankton et al., 2010; Wilson et al., 2010). Thus, further study is necessary to learn whether findings of frequent-use and sporadic-use IT are generalizable.

In the following sections, we develop a research model and hypotheses to investigate the issues outlined above, followed by analysis and discussion of the finds.

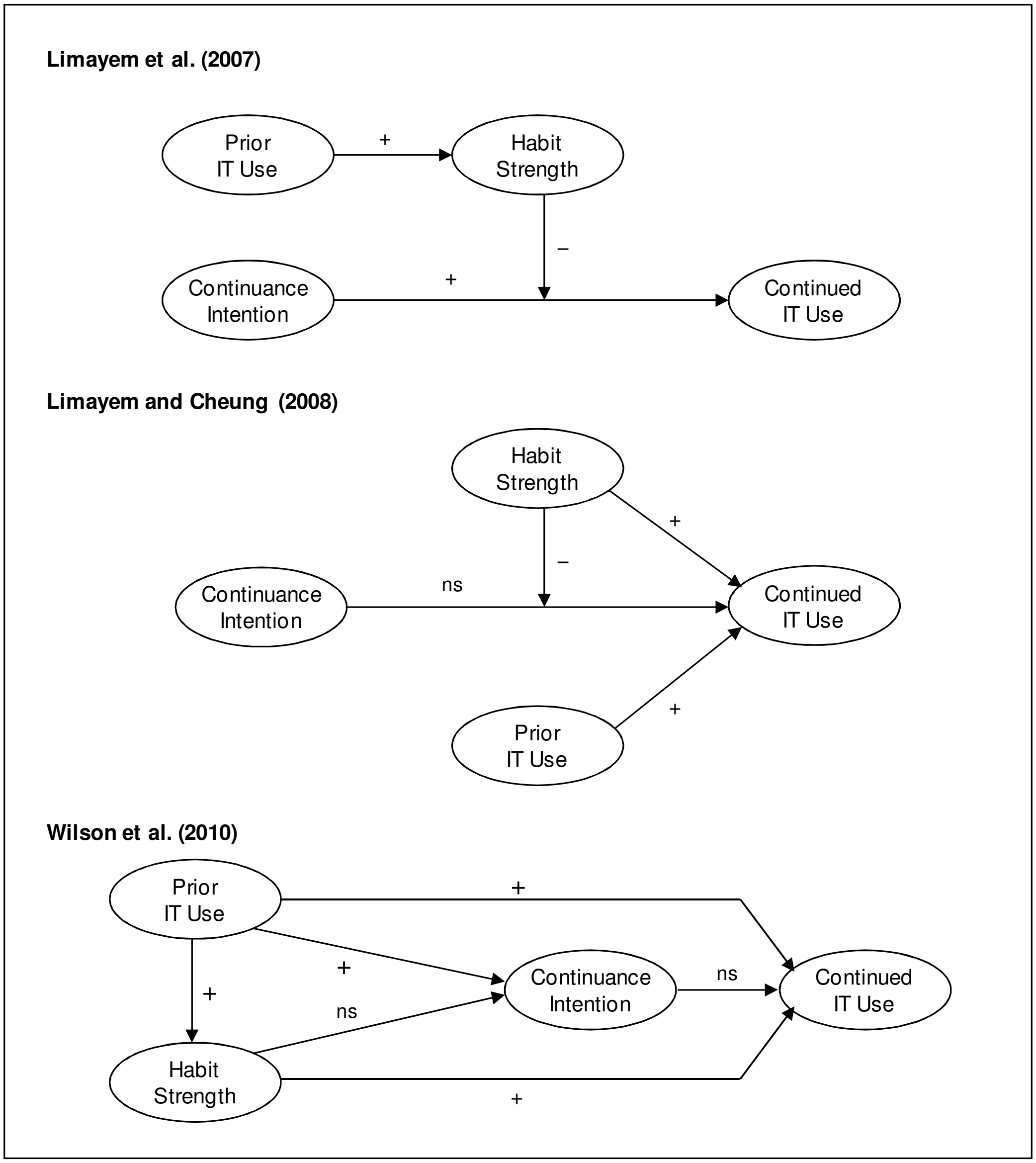

Figure 1. IT continuance studies that measure prior IT use, continuance intention, and habit strength.

BACKGROUND AND HYPOTHESES

As the study of information technology (IT) adoption has matured, information systems (IS) researchers have begun to extend this line of research toward predicting and explaining individuals' long-term IT use, also known as *IT continuance.* Initial studies in this area (e.g., Bhattacherjee, 2001; Bhattacherjee and Premkumar, 2004; Karahanna, Straub, and Chervany, 1999) 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.

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). Specifically, 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).

Our first objective in the present paper is to test the joint effects of continuance intention, prior IT use, and habit strength on continued IT use within the research model shown in Figure 2. Although these elements have been studied separately (Limayem et al., 2007; Limayem and Cheung, 2008; Wilson et al. 2010), no prior study we are aware of has incorporated the full range of direct and moderating effects we assess herein. Our second objective is to apply this model across conditions in which IT use is characteristically sporadic vs. frequent. Although Wilson et al. (2010) present an initial assessment of sporadic-use IT continuance, their research did not address frequent-use IT. Incorporating a full range of use frequency contexts will help identify differences, if any, that exist in modeling IT continuance and in generalizing findings between contexts.

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

A substantial literature reports that past behavior and/or 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 and Venkatesh et al. (2000), Kim and Malhotra (2005), Lankton et al. (2010), Limayem and Hirt (2003), and Wilson et al (2010) report direct effects. Based on IS research and the general literature, we anticipate both prior IT use and habit strength will influence continuance. In order to capture the multiple paths in which this influence may be enacted, we hypothesize both moderating and direct effects for each factor will occur in contexts of sporadic and frequent IT use.

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

H2: Habit strength moderates the relationship between continuance intention and continued IT use across sporadic and frequent usage contexts.

H3: Prior IT use frequency increases continued IT use across sporadic and frequent usage contexts.

H4: Habit strength increases continued IT use across sporadic and frequent usage contexts.

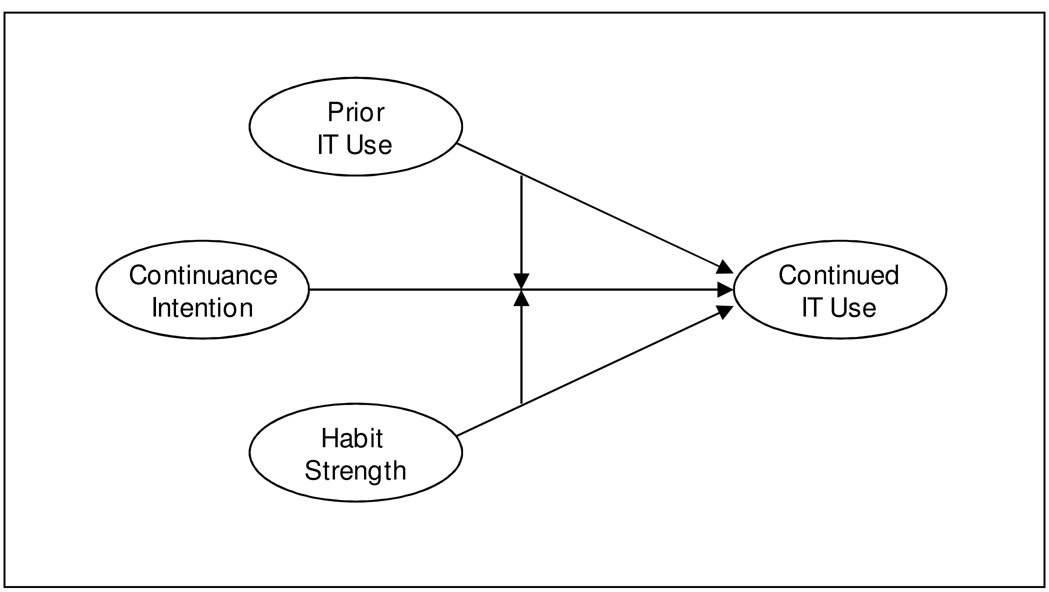

Figure 2. Research model.

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 research model in the present study will predict significantly more variance in continued IT use than model subsets across sporadic and frequent usage contexts.*

Trade-Off Between Effects of Continuance Intention and Habit Strength

In addition to our primary research emphasis—studying joint effects of prior IT use, habit strength, and continuance intention across a bread frequency range of continued IT use—our research design provides the opportunity to assess a reported tradeoff 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 paper 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 daily or weekly routine. This finding has been confirmed by IT continuance researchers (Cheung and Limayem, 2005; Kim and Malhotra, 2005; Kim et al., 2005; Lankton et al. 2010). 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.*

RESEARCH METHOD

A longitudinal study measured habit strength, continuance intentions, and use of a university Internet application (UIA) at a large urban U.S. university. Students can use the UIA for a variety of interactions with the university, including activities that are supported only during certain portions of the semester, e.g., dropping classes and looking for open course sections, or are available continuously during the student's enrollment, e.g., changing university contact information. Our focus in the present study is on activities which are continuously available for student access.

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 successfully 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. Average age of subjects used in the final analysis is 20 years, and gender split is 49% males, 51% females.

Treatment Conditions

We implemented a multi-treatment approach in the following way. Subjects were first queried as to whether they had ever used the UIA for performing three activities: paying tuition and fees, changing university contact information, and/or viewing personal federal financial aid information. Each of these activities could be performed alternatively by visiting the campus registrar office, thus, use of the UIA was considered to be voluntary. Subjects were then randomly assigned to one of the activity treatment conditions which they had previously performed. The three activities selected as treatment conditions were identified in pilot testing as representing average usage frequencies ranging between one and 16 times per year. In addition these activities are continuously supported by the UIA, excluding activities such as dropping a class for which support is disabled after a certain deadline each semester. The assumption that it is valid to assess these three treatment conditions as a single sample population is evaluated empirically in the Results section later in the paper.

Measures

The questionnaire administered at Time 1 includes the following measures. Prior IT use is measured through two items assessing the number of times subjects recall using UIA to perform the specified activity during the 12 months immediately prior to Time 1. Other constructs tested at Time 1 were measured using validated scales. These include 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. Questionnaire items are shown in Table 1. 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.

Construct	Item	Item Content*
Prior IT Use	PITU1	To the best of your recall, how many times during the past 12 months did you use UIA to [perform activity]? *(Numeric entry)*
	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	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	CI1	I intend to use UIA to [perform activity] during the Fall 2006 semester
	CI2	I predict I would use UIA to [perform activity] during the Fall 2006 semester.
	CI3	I plan to use UIA to [perform activity] during the Fall 2006 semester.
Continued IT Use	CITU1	To the best of your recall, how many times during the Fall 2006 semester did you use UIA to [perform activity]? *(Numeric entry)*
	CITU2	To the best of your recall, which category best describes the total number of times during the Fall 2006 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 1. Questionnaire Items

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 for 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.

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. If subjects were disconnected during the questionnaire, the web application would return them on re-entry to the point in the questionnaire which they had previously completed

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. It was found that 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 (or average rank in case of ties).

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

Measurement Model

We assessed measurement and structural models using AMOS 4 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, 28 parameters were estimated, thus, our sample size of 269 provides a ratio well beyond the minimum criteria of five cases per estimated parameter (Bagozzi and Yi, 1988). To assess convergent validity, we examined item loadings, and calculated the composite reliability (CR) and the average variance extracted (AVE) for each latent factor. All items load on their respective factor at .73 or above, the CR for each construct is .86 or higher, and the AVE for each construct is at least .75 (see Table 2). These figures substantially surpass recommended minimum values for assessing convergence (Bagozzi and Yi 1988; Fornell and Larcker, 1981). Discriminant validity was evaluated 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). This is confirmed, 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, substantially exceeding minimum criterion recommendations (Hu and Bentler 1999). These findings demonstrate that the measurement model provides a good level of fit with the data.

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

* Means and standard deviations (SD) are calculated as averaged summations of the raw data; CR = composite reliability; 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.

Table 2. Measurement Scale Characteristics

Structural Model

In creating the structural model, we added terms representing two hypothesized interactions which moderate 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 modeled between errors of the interaction terms and errors of the constituent 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 treatment conditions focused on use of the UIA for a specific activity. To ensure that these conditions do not vary in ways that systematically influence dependent factors of the study, we assessed the research model with treatment conditions entered as a control factor to habit strength, continuance intention, and continued IT use. Second, we tested for effects of autocorrelation between similar 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 path weight changes, 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.

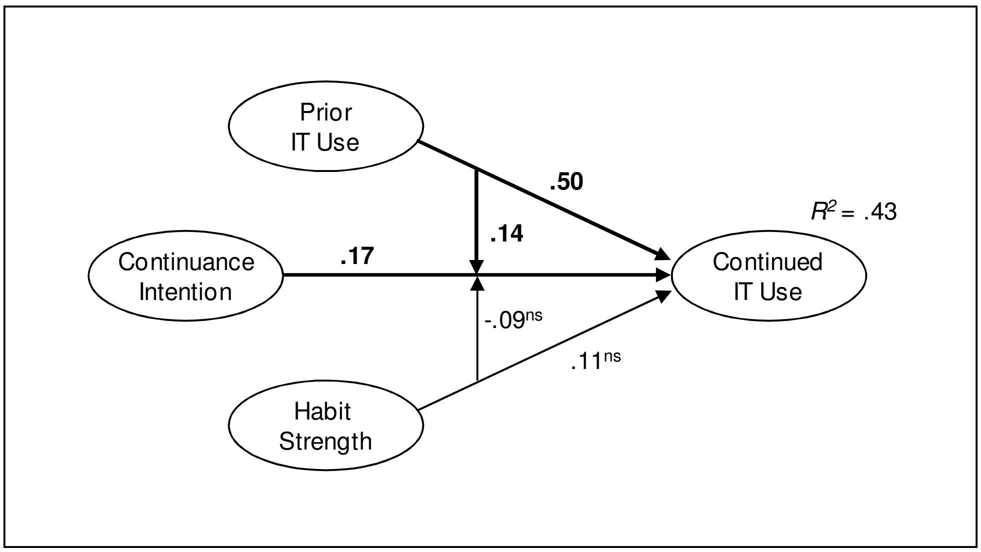

Figure 3. Results of SEM Analysis (Bolded Paths Indicate Significant Relationships)

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 which 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 relative 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). Prior IT use accounts for the greatest increase in prediction of continued IT use through combined direct and moderating effects. However, continuance intention also makes a significant contribution to the overall model, and inclusion 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 differences between usage frequency levels. Based on the prior literature, H6 proposes that continuance intention will predominate predictions of continued IT use under sporadic-use conditions, and H7 proposes that habit strength will predominate under frequent-use conditions.

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							

Table 4. Comparison of Full and Nested Research Models

We split our overall sample into two subgroups based on our conceptualization of sporadic use as subjects reporting a prior IT use frequency of less than three times during the previous 12 months. 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 = .28.2). Prior IT use frequency differs significantly between subgroups (t = 5.89, p < .001). The subgroups were separately entered into a reduced version of the research model containing only habit strength, continuance intention, and continued IT use (see Table 3). With 21 estimated parameters, sample sizes for both subgroups surpass the minimum criteria of five cases per estimated parameter (Bagozzi and Yi, 1988). The results corroborate the findings of Ouellette and Wood (1998) and support Hypotheses 5 and 6.

Predictor of Continued IT Use	Sporadic-Use Subgroup	Frequent-Use Subgroup
Habit Strength Effect	Std. Coeff. = .18 (p = .15)	Std. Coeff. = .31 (p = .01)
Continuance Intention Effect	Std. Coeff. = .24 (p = .04)	Std. Coeff. = .17 (p = .12)
Model R^2	.14	.18
χ^2 / df	33.24 / 24 = 1.39	32.68 / 24 = 1.36
GFI	.96	.94
NFI	.96	.95
CFI	.99	.99
RMSEA	.05	.05

Table 3. Results of Split-Frequency Sample Analysis.

DISCUSSION

Because our research design encompasses a joint focus on continuance intention, prior IT use, and habit strength across a range of use frequency levels, the results are useful in integrating findings of earlier studies that examine separate parts of this domain. Some of our findings are unsurprising. For example, we find prior IT use is much more important than habit strength or continuance intention in predicting continued IT use. This result has previously been reported in several studies of frequently used IT, and the finding is certainly bolstered in the present study by our inclusion of low-frequency usage patterns that effectively obstruct the influence of both habit strength and continuance intention on continued IT use.

However, other findings validate our motivations to study joint effects of prior IT use and habit strength and to study these across usage levels ranging from sporadic to frequent. 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 habit strength is subordinated in our study. Unlike the Limayem and Cheung (2008) study, the design of the present study includes infrequent IT use contexts and, unlike Wilson et al. (2010), it includes moderating as well as direct effects of prior IT use and habit strength. The implication is that when both factors are present (incorporating an extended frequency range and measurement of moderating effects) habit strength is reduced in importance. We address the ramifications involving each factor in the following sections.

The general effects of behavioral frequency have been studied outside IT research, and our findings in testing Hypotheses 6 and 7 corroborate 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). In sporadic-use conditions, rational processes (e.g., continuance intentions) are key predictors of future behavior but automated processes (habits) become predominant 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 in the context of IT use at very infrequent behavior levels, i.e., at approximately three uses per year. This finding supports the contention of Wilson et al. (2010) that the habit of IT use begins to form at very low levels behavioral frequency.

Little research has assessed the moderating effects of prior IT use on the relationship between continuance intention and continued IT use, despite several studies that focus on similar effects of habit strength (e.g., Limayem et al., 2007; Limayem and Hirt, 2003). Although the nominal size of this relationship is small (std. coeff. = .14), researchers should keep in mind that strength of association in correlational designs is typically underestimated for interaction terms due to 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 the PITU x CI interaction term (see Table 4). Explained variance in the model (R^2) dropped from .43 to .39 ($p < .05$), but 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.

Second, several studies have found that prior IT use subordinates the effects of behavioral intention on continued IT use over time (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 action models (Wilson and Lankton, 2009).

Third, there is significant practical value in taking our approach in Hypothesis 5 of studying the nested models as well as the full research model. Although the full model provides 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 noted in Table 4, very good predictions of continued IT use may be achieved by using continuance intention plus prior IT use measures or even prior IT use as a single predictor.

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 common 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 are no longer limited to frequently-used applications such as email and word processing that formed much of the domain for technology acceptance research (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, it is essential that IS researchers expand future research designs to study IT use across sporadic- as well as frequent-use contexts.

LIMITATIONS

There are some limitations to this study. First, we collected data from university students using a university system. While these subjects are the natural users of UIA, our results may not be applicable 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.

CONCLUSION

In summary, our study finds that intention, prior IT use, and habit strength are important joint predictors of continued IT use, although the pattern of prediction varies between sporadic- and frequent-use conditions. Continued use across a range of normative frequencies is important to understand as IT applications come to play larger roles in our day-to-day lives while providing increasingly specialized functions.

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