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Predicting Continuing Acceptance of IT in Conditions of Sporadic Use

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ABSTRACT

This paper tests a new predictive model of IT acceptance in conditions where use is characteristically sporadic. The model utilizes cognitive constructs from the well-known technology acceptance model (TAM) [8] in combination with habit and a new construct measuring perceived regularity of use. Initial tests indicate that the model explains several important effects of regularity and predicts substantially more of the variance in continuing acceptance than alternative models.

Keywords

Regularity, frequency, continuance, habit, Triandis.

INTRODUCTION

Models of IT acceptance (i.e., the intention to use IT and actual use of IT) typically assume that IT will be evaluated in conditions where there is a regular call for its functions, e.g., as part of a daily or weekly routine. For example, the technology acceptance model (TAM) was initially used to analyze MBA students' acceptance of word processing software, a choice based in large part on the recognition that "students would face opportunities to use a word processor throughout the MBA program for memos, letters, reports, resumes, and the like" ([9] p. 989). Correspondingly, a great deal has been learned about initial and continuing IT acceptance in the context of applications that tend to be used regularly, including payroll [23], day-to-day scheduling [24], email [13], and online banking [2].

Historically, costs associated with manufacturing and distributing IT applications have been substantial. Thus, IT applications through the 1990s were developed predominantly to meet regular organizational needs that could justify high costs of use, including communication, transaction, documentation/reporting, and storage/retrieval functions. However, new business models associated with the WWW have made it cost-effective to implement IT applications for which use is sporadic rather than regular. Some commercial examples include:

- E-health (e.g., *WebMD.com*): Use is associated with onset of illness, injury, or medical condition.
- Online employment (e.g., *Monster.com*): Use is associated with changes in job situation or geographic location.
- Online auto sales (e.g., *Autobytel.com*): Use is associated with mechanical breakdowns, transportation needs, or personal finances.

We have not found any research that directly studies effects of sporadic use (i.e., use that is irregular, intermittent, or inconsistent) on continuing acceptance of IT. However, several factors suggest that existing IT acceptance models will not perform well in these conditions. The normative relationship between behavioral intention and action [17] is necessarily confounded where need is sporadic. Consider a woman who intends to use Monster.com for future job searches. Despite this intention, her action of posting a résumé on the site probably will occur only if her job situation changes, e.g., she receives notice of a pending layoff. Further, it is unlikely that habit and beliefs formed by users toward IT through sporadic use will be as strong as those formed through regular use.

Our study tests several hypothesized effects of sporadic use on continuing acceptance of IT among users of a university intranet application (UIA). The UIA is particularly appropriate for this type of research because it supports a variety of student activities that occur sporadically due to academic schedules (e.g., looking for open class sections) and personal circumstances (e.g., changing university contact information). As part of this testing, we present a new model of continuing acceptance of IT and contrast its predictions to alternative models.

RESEARCH MODEL AND HYPOTHESES

The research model we are testing in this study is based in significant part on work by Gefen [12], who extends TAM with a habit construct, defined as a behavioral preference in the present that is distinct from intended future behaviors. Gefen hypothesizes that IT acceptance under continuing use is largely determined by habit. His model posits direct effects of habit on intention as well as indirect effects mediated by beliefs regarding usefulness and ease of use. The habit of current use is anticipated to influence intention through development of positive feelings toward the action [20] [21] and through practice effects that automate the decision process [16]. Empirical testing of the Gefen model finds habit alone accounts for 40% of the variance in intention among experienced online shoppers to return to a favored website.

Our study does not focus on habit, *per se*. However, the Gefen model offers several benefits to our research objective of predicting continuing acceptance in sporadic use. It is one of only a small number of relevant models incorporating a habit construct, which we believe to be necessary in order to understand several effects of sporadic use. Unlike alternative models, the Gefen model is parsimonious[1]. Remaining constructs in the model are drawn from TAM and have been validated by numerous empirical studies. Although the Gefen model has received only limited testing, it has shown good model fit characteristics. These benefits drove our decision to extend the Gefen model in preference to alternative models.

Our research model is presented in Figure 1. The Gefen model comprises habit, belief, and intention constructs. To this framework, we add measures of regularity[2] and continuing use.

Regularity is a measure of *usage variance* over time (e.g., variance in uses per week). This contrasts with frequency, which measures *usage count* over time (e.g., average number of uses per week). Consider two individuals who use an IT over a three-month period. The first uses the IT once per week and the second uses the IT 13 times during the first week. Identical frequency would be measured for both individuals over the period. However, regularity from week to week varies markedly between them. We propose that measures of regularity can be useful in explaining IT acceptance patterns in conditions of sporadic use. Research shows that objective frequency of prior use is an important determinant of subsequent IT acceptance [26]. We anticipate that objective measures of regularity also may be predictive. However, we have chosen in this study to focus on internalized effects of regularity, measured through individuals' subjective perceptions of their prior use patterns. IT theorists find usage behavior often is predicted better by perceptual measures than the associated objective measures, due the mediating effect of perceptions on objective reality [15]. We propose that perceived regularity of use (hereafter *regularity*) influences habit, beliefs, and continuing use. Specific relationships are discussed as part of hypothesis development later in the paper.

Gefen [12] did not measure effects of habit on continuing use. However, Limayem and Hirt [14] find habit predicts use as well as intention in their study of a frequently-used IT (approximately two uses per week). Wood, Quinn, and Kashy advise that "past behavior is the primary predictor of future behavior when habits have developed through past repetition in stable contexts, whereas intentions are the primary predictor when behaviors are relatively novel or performed in unstable contexts" ([27] p.1282). We anticipate that sporadic use is indicative of an unstable context in which habit may not be predictive of continuing use, however, this relationship has not been tested previously. To resolve the issue of habit's effects, we include direct effects of habit on continuing use in our model.

We propose that sporadic use of IT can affect continuing acceptance both directly and through distinct mechanisms related to habit and beliefs. We further anticipate that modeling of continuing acceptance can be improved in conditions of sporadic use by incorporating a measure of regularity, as in our research model. Our hypotheses concerning these effects are developed in the following sections.

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[1] One alternative model we considered is the theory of interpersonal behavior (TIB) [20] [21]. Parts of TIB have been applied successfully in prior IT acceptance studies, however, researchers find TIB to be both non-parsimonious and cumbersome to apply in whole [11].

[2] Although our research centers on conditions of sporadic use rather than regular use, we phrase our measure in terms of *regularity* rather than *irregularity*. Our objective in this choice is to avoid confusion that can occur where a measure's numeric value and conceptual value are oppositely directed.

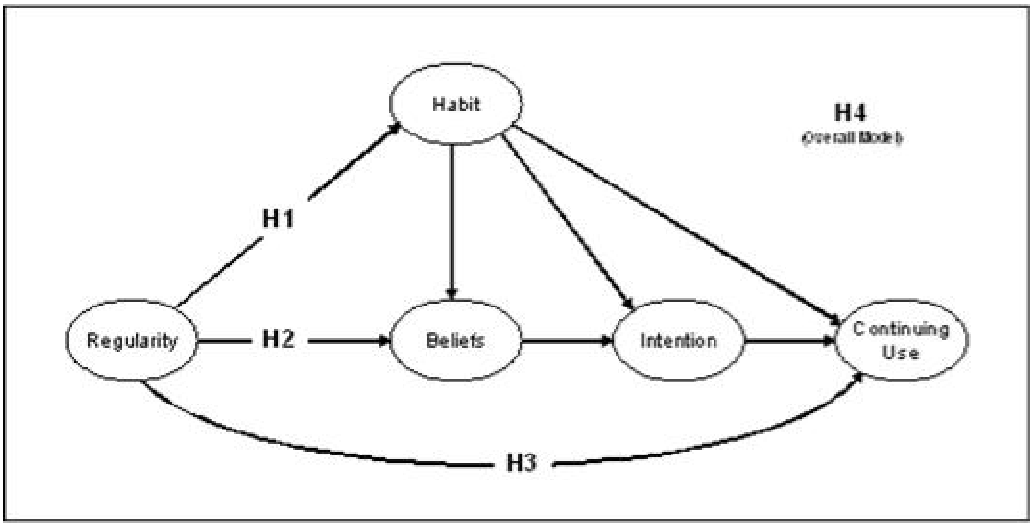

Figure 1. Research Model.

Effects of Sporadic Use on the Formation of Habit

Habits are behavioral preferences formed through experience with an action [12]. Researchers find habit formation is promoted by both frequency and regularity of prior experience [3] [20] [21] [27]. Thus, we anticipate sporadic use will inhibit development of habit toward IT use as a function of reduced regularity of prior experience.

H1: Sporadic use will reduce the level of habit formed toward use of an IT.

Effects of Sporadic Use on the Development of Beliefs

Researchers have not previously studied effects of sporadic IT use on development of beliefs toward the IT. However, habit affects a wide range of perceptual factors, including usefulness, ease of use, and affect [1] [12] [14]. These findings suggest sporadic use could influence beliefs indirectly via habit as an extension of the relationship proposed in H1. Direct effects of regularity on beliefs are implied by the availability heuristic [22], which describes the human tendency to use the first information that comes to mind. Regularly-used IT applications are more likely to be recalled and considered, thus generating stronger, more predictive beliefs than IT that is used sporadically. These observations lead us to hypothesize a positive association between regularity and beliefs. However, it is not clear *a priori* whether this relationship will be evidenced through direct effects, indirect effects, or some combination of effects.

H2: Sporadic use will diminish development of beliefs regarding usefulness and ease of use of an IT.

Effects of Sporadic Use on the Relationship Between Intention and Continuing Use

We conceptualize sporadic use as being initiated by some facilitating condition, i.e., an objective factor which influences the ease or difficulty of performing an action [20] [21]. Limayem and Hirt observe, "Even if a person has the intention to perform a particular behavior or habitually performs the behavior, the behavior may not occur when the facilitating conditions do not permit it" ([14] p. 71). We view sporadic use as *symptomatic* of an underlying facilitating condition that inhibits continuing use. Although sporadic use is not the facilitating condition *per se,* we propose it represents a proxy for the condition, leading to Hypothesis 3.

H3: Sporadic use will reduce continuing use of an IT regardless of intention.

We note here that some ambiguity exists regarding the normative relationship between facilitating conditions and actions. At different times, Triandis has explained this relationship as a direct effect of facilitating condition on action [21] and as a moderating effect on the relationships between intention and action and habit and action [20]. Most IT researchers adopt the prior interpretation (e.g., [4] [14] [18] [19]). In order to clarify the form of the hypothesized relationship between sporadic use, intention, and continuing use, we will test for presence of interaction effects as well as direct effects.

Model Evaluation

We anticipate that including a regularity construct within our research model will provide explanatory value beyond that of the underlying TAM and Gefen models. We test this proposition in our final hypotheses.

H4: The research model will explain more variance in intention and continuing use than alternative models.

RESEARCH METHOD

A two-stage study assessed evaluations 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 activities that occur primarily during a certain period in the semester, e.g., dropping classes, checking grades, and looking for open course sections, or at intermittent times during the student's enrollment, e.g., changing university contact information.

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 alternative activities. Early in the semester, 213 subjects responded to an online questionnaire (Stage 1) that surveyed recalled frequency and regularity of use during the prior academic year, habit of 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 subjects responded to a second online questionnaire (Stage 2) to report their use of UIA for the same activity during the intervening period. Data were not analyzed for twelve subjects (6%) who participated in Stage 1 but not in Stage 2. To ensure that the study addressed a range of usage patterns, subjects were randomly assigned to respond to questions addressing one of four activity treatments identified in pilot testing as representing varied usage frequencies. Listed from high to low frequency, the activities are: Look for open class sections; check grades; drop a class; and change university contact information.

Stage 1 measures include the following (see Appendix). Regularity items (developed during pilot testing) center on regularity and consistency in use of UIA to perform the activity during the prior school year. Habit items (developed during pilot testing) focus on habit formation, ease of remembering, and familiarity. Items measuring usefulness, ease of use, and intention toward continued use were drawn from validated scales [8] [25]. Perceptual measures were administered in randomized order (re-randomized for each subject). Demographic and frequency items appeared at the end of questionnaires.

RESULTS

Data screening was conducted to prepare the data for subsequent latent factor analysis via PLS-Graph. No data were missing for any of the measures. A one-way ANOVA found no unanticipated differences between activity treatments on demographic and frequency data (see Table 1). Frequency data did show significant positive skew with outliers. As a conservative alternative to removing the outlying subjects, we applied a ranking transform to frequency data using methods recommended by Conover and Iman [7] in order to mitigate undue effects of outliers.

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 Table 2). All latent constructs for this study have an ICR of .88 or above, indicating they are statistically reliable [10]. Convergent validity was assessed by examining the loadings for each indicator on the respective factors. All indicators in our study show loadings in excess of .70, indicating convergent validity [10].

We assessed discriminant validity in three ways. First, we examined the average variance extracted (AVE) for each construct by its indicators (see Table 2). All constructs have an AVE of greater than .50. Second, we confirmed that the square root of the AVE for each construct is higher than the construct's correlation with the other constructs [5], which is true in all cases. Third, we confirmed that loadings of all indicators on their hypothesized construct are higher than any of the cross-loadings [5] [28]. Results indicate discriminant validity among the constructs.

Hypothesis Tests

PLS-Graph structural models were used to test all hypotheses. These consisted of the direct-effects version of the research model presented in Figure 1 and an alternative moderated-effects model developed to test Hypothesis 3. This model was augmented by including moderating effects of regularity on the intention-use and habit-use relationships. Preparation of the alternative model followed published guidelines for studying moderating effects using PLS-Graph [6]. No significant interactions were found in the alternative model, so the reported analysis uses the direct effects model (see Figure 2). Results of hypothesis testing are presented below.

Factor \ Activity Treatment	Drop a class	Change university contact information	Look for open class sections	Check my grades
N	48	57	49	47
Age	20.40 (4.10)	20.02 (4.89)	20.84 (5.94)	20.13 (4.10)
Gender	38% M, 63% F	42% M, 58% F	49% M, 51% F	47%M 53% F
Months since first use of UIA	9.67 (8.98)	7.70 (8.71)	9.10 (9.35)	9.55 (9.30)
Frequency of prior use	1.15 (1.81) [a]	1.50 (2.08) [a]	6.31 (8.60) [a, b]	8.19 (16.51) [b]
Frequency of current use	1.58 (1.81) [a]	1.77 (2.67) [a]	5.06 (5.96) [a]	8.83 (12.97) [b]

[a, b] Indicate homogeneous subsets (*post hoc* Scheffe test, $\alpha = .05$) where one-way ANOVA finds significant difference between conditions.

Table 1. Descriptive and Demographic Data

Construct	ICR	Regularity	Habit	Usefulness	Ease of Use	Behavioral Intention
Regularity	0.923	**0.865**				
Habit	0.908	0.698	**0.844**			
Usefulness	0.880	0.535	0.531	**0.805**		
Ease of Use	0.923	0.530	0.802	0.593	**0.865**	
Behavioral Intention	0.957	0.690	0.486	0.372	0.310	**0.939**

***** Internal consistency reliability (ICR) statistics are reported in the first column; AVE figures are shown in bold on the diagonal.

Table 2. Reliabilities, Average Variance Explained (AVE), and Correlations Among Latent Constructs*

Sporadic use reduces habit formation. Within the research model, regularity predicts habit to a substantial degree (t = 19.037, one-tailed p < .0001). A subset of the research model containing only regularity and habit shows that regularity predicts 48% of the variance in habit. These findings support Hypothesis 1.

Sporadic use diminishes beliefs. Regularity directly predicts usefulness (t = 4.231, one-tailed p < .001) but not ease of use. A subset of the research model containing only regularity, usefulness, and ease of use shows that regularity accounts for 28% of the variance in habit and 28% in ease of use. This indicates that effects of regularity on ease of use are entirely mediated by habit and effects of regularity on usefulness are partially mediated by ease of use. The findings support Hypothesis 2 and provide additional clarification on the mediating role of habit in determining belief structures.

Sporadic use reduces continuing use of an IT. As previously noted, no significant moderating effects of regularity were found, so analysis was conducted using the direct-effects model shown in Figure 2. Although habit, ease of use, and usefulness each contribute to intention in this model, only regularity has significant effects on continuing use (t = 3.589, one-tailed p < .001). A subset of the research model containing only regularity and continuing use shows that regularity predicts 19% of the variance in continuing use. These findings support Hypothesis 3.

The research model explains more variance in both intention and continuing use than alternative models. Subset models were created representing TAM and the Gefen model (extended to include continuing use), and these were contrasted with the research model (see Table 3). Compared to TAM, the research model shows an increase in R^2 of .124 for intention (effect size = .146, p < .01) and .085 for continuing use (effect size = .096, p < .01). Compared to the extended Gefen model, the research model shows no change in R^2 for intention and an increase of .037 for continuing use (effect size = .044, p < .01). These findings support Hypothesis 4.

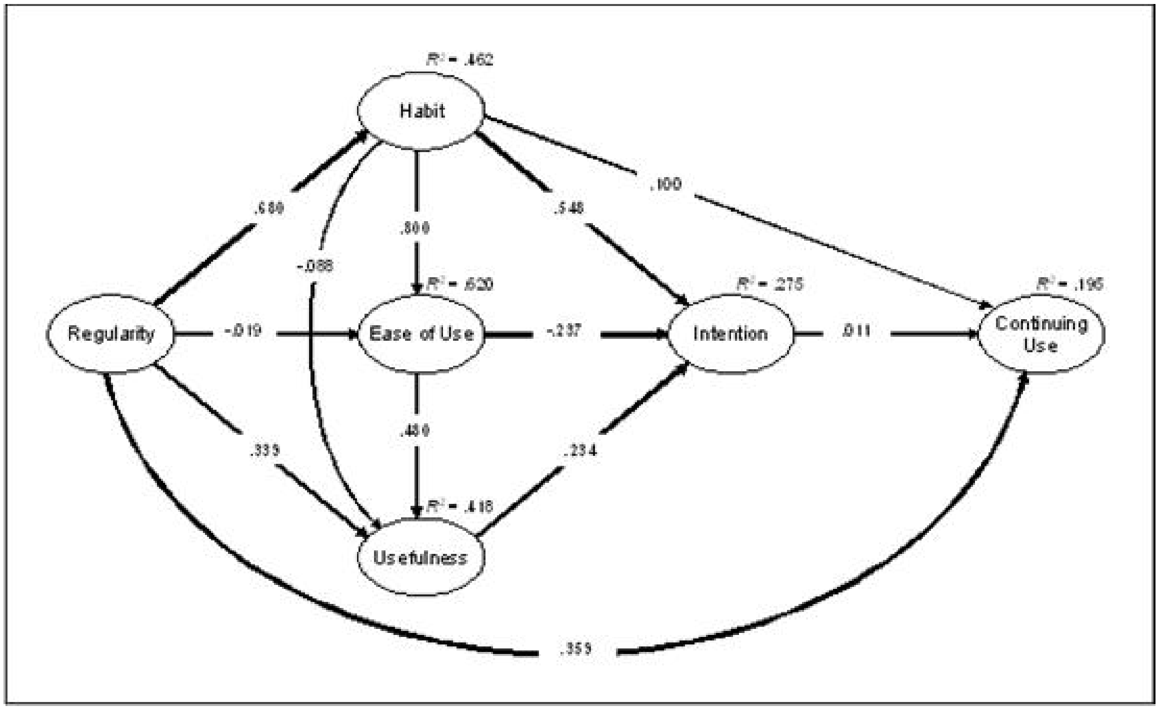

Figure 2. PLS-Graph Path Model of UIA Data

Follow-up Analysis

In order to assess assumptions of the research, two follow-up analyses were conducted:

1. Structural models were created with Stage 1 frequency of use replacing regularity and with Stage 1 frequency added as an antecedent factor in the research model. These models were contrasted to assess whether predictions of regularity are distinct from frequency measures. We find regularity increases R^2 for continuing use by .021 in the combined model beyond effects of frequency alone in the replacement model (effect size = .029, $p < .05$). Prediction of intention is unaffected.
2. The research model was augmented to test the relationship between regularity and intention. This relationship was not incorporated into the original model because it is not predicted by the underlying theory regarding facilitating conditions [20] [21]. In the augmented model, R^2 of intention increases to .473 (effect size = .25, $p < .001$), and the relationships of habit, ease of use, and usefulness to intention become insignificant. Effects on continuing use does not change from the research model.

DISCUSSION

As discussed in the results section, we find support for our hypotheses regarding the pathways by which regularity of use affects intention and continuing use. In addition, model comparisons indicate that incorporating a measure of regularity can substantially improve predictions beyond the underlying TAM and Gefen models. However, the findings also raise several questions that have implications for future research.

At what level of sporadic use does regularity become an important predictor of acceptance? We know that *frequency of prior use* in our research ranges from approximately the same level studied by Gefen [12] to one-seventh of that level. However, prior research does not report measures of regularity, so it is difficult to generalize between studies. In addition, many IT applications are used more frequently than those studied by Gefen or us (e.g., [13] [14] [24]), and it will be necessary to extend the study of regularity to these "non-sporadic" applications to fully identify the range of effects. The findings highlight the need for researchers to report measures of regularity along with frequency in order to advance understanding in this area.

Relationship	TAM	Extended Gefen Model	Research Model
Ease of use → Usefulness	.599***	.472***	.480***
Ease of use → Intention	.139	-.332**	-.237*
Usefulness → Intention	.289**	.236**	.234**
Intention → Continuing Use	.332***	.212**	.011
Habit → Ease of Use		.806***	.800***
Habit → Usefulness		.157	-.068
Habit → Intention		.622***	.548***
Habit → Continuing Use		.249***	.100
Regularity → Habit			.680***
Regularity → Ease of Use			-.019
Regularity → Usefulness			.339***
Regularity → Continuing Use			.359***
Intention R^2	.151	.284	.275
Continuing Use R^2	.110	.158	.195

***** p < .05 ** p < .01 ***p < .001 (one-tailed *t*-tests)

Table 3. Model Comparisons

Why is regularity not mediated by habit? Along with Gefen [12] and Limayem and Hirt [14], we find that habit is an important contributor to intention, if regularity is not considered. However, regularity emerges in our findings as the overwhelming direct determinant of both intention and continuing use. We suspect this relationship occurs primarily in conditions of sporadic use, as suggested by [27], but this issue will require further study to clarify.

Is intention an important measure in highly sporadic use? TAM and other major models of IT acceptance have come to focus on predicting intention, based upon the normative relationship between intention and use [17]. Studies of habit also consider intention to be important, especially in unstable contexts [27]. Yet we find intention is predictive only where the direct effect of regularity on continuing use is not considered. These findings suggest that attention to actual usage is key to modeling IT acceptance effectively in conditions of sporadic use.

Limitations

Several factors could constrain the interpretability and generalizability of our findings. First, this study collected data from student subjects using a university system. The UIA is important to these students' interactions with the university. However, it is possible that the results will not be applicable to other populations that differ in age, experience, or context of use. We do not believe that these issues impact the validity of our findings within the specific research setting we chose, but they do suggest that there is need to broaden this line of research to other populations and research designs.

Second, we followed a tradition in IT acceptance research of using perceptual measures. However, it is difficult to know how well our findings will generalize to objective measures related to use. Because of university privacy concerns, it was not possible for us to log subjects' UIA activity. Thus, we recommend this topic as an interesting area for future study where researchers can overcome pragmatic constraints.

Third, by focusing on regularity of use our study does not address initial acceptance. We anticipate that a related construct focusing on *regularity of need* could be important in augmenting models of initial IT acceptance. However, this issue is speculative pending further research.

Conclusion

Researchers have been very successful in predicting and explaining IT acceptance in conditions that fulfill the assumption of regularity in evaluation and use of the technology. However, numerous IT applications have emerged in which sporadic use is common. We find that existing models of IT acceptance are not well adapted to this new domain. Initial testing indicates explanatory power of models such as TAM can be improved by incorporating a measure of regularity. However, further research will be necessary to clarify several of the issues raised by our study.

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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.

Regularity

1. Using [UIA] to [conduct activity] is: *1 = Not typical for me / 7 = Typical for me*
2. Using [UIA] to [conduct activity] is: *1 = Not one of my ordinary activities / 7 = One of my ordinary activities*
3. My use of [UIA] to [conduct activity] is: *1 = Intermittent / 7 = Ongoing*
4. My use of [UIA] to [conduct activity] is: *1 = Not regular / 7 = Regular*

Habit

1. Using [UIA] to [conduct activity] is: *1 = Not something I know how to do from habit / 7 = Something I know how to do from habit*
2. Using [UIA] to [conduct activity] is: *1 = Hard to remember how to do / 7 = Easy to remember how to do*
3. My use of [UIA] to [conduct activity] is: *1 = Something I have to think about to remember how to do / 7 = Something I've committed to memory*
4. When trying to use [UIA] to [conduct activity] it is: *1 = Difficult to think of the right way to do it / 7 = Easy to think of the right way to do it*

Ease of Use

1. My interaction with [UIA] to [conduct activity] is clear and understandable.
2. It is easy for me to become skillful at using [UIA] to [conduct activity].
3. I find it easy to use [UIA] to [conduct activity].
4. Learning to operate [UIA] to [conduct activity] is easy for me.

Usefulness

1. Using [UIA] to [conduct activity] improves my performance.
2. Using [UIA] to [conduct activity] enhances my effectiveness.
3. Using [UIA] to [conduct activity] increases my productivity.
4. Using [UIA] to [conduct activity] is useful.

Intention

1. I intend to use [UIA] to [conduct activity] during the current school year.
2. I predict I would use [UIA] to [conduct activity] during the current school year.
3. I plan to use [UIA] to [conduct activity] during the current school year.

Continuing Use

1. Approximately how many times since the end of [the last] semester have you used [UIA] to [conduct activity]? *(Numeric entry)*