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ABSTRACT

This paper investigates the dynamics of users' beliefs and intention to adopt a new technology during the course of its training. It also identifies the relationships among the dynamic elements over a time continuum. As a research method, we introduce latent growth curve modeling to better analyze the dynamics over a longitudinal time horizon. We provide an outline of the method for a research in progress. In addition, we demonstrate the application of latent growth curve modeling to a secondary data set obtained from Venkatesh et al. (2006). The results indicate that those with a higher level of initial behavioral intention to use are likely to have a higher level of initial use of a technology. In addition, those who have a steeper rate of increase in behavioral intention during the implementation are likely to have a steeper increase in their use of the technology.

Keywords

Technology Acceptance Model, Latent Growth Curve Modeling, Dynamics of User Beliefs and Intention.

INTRODUCTION

Firms have invested substantial capital and efforts in implementing new information systems technologies to streamline their businesses and operations. Since the benefits of such IT investments can be realized only when users utilize the technology to meet strategic and organizational goals (Agarwal and Karahanna, 2000), the acceptance of IT in the organizational contexts has been a prevalent research topic in the IS area for over many decades. In this stream of research, Technology Acceptance Model (TAM) was initially developed by Davis (1989) based on the theory of reasoned action and the theory of planned behavior (Ajzen, 1985). Since then, numerous studies have improved the model with regard primarily to the antecedents of technology acceptance (See Venkatesh et al. (2003) and Jeyaraj et al. (2006) for a detailed review). These studies fundamentally posit that individuals' behavioral beliefs in IT (e.g., ease of use and usefulness) along with other contingent variables (e.g., social factors, person-job fit, and self-efficacy) influence intention to adopt (use), which in turn affects actual use or usage (Davis, 1989; Venkatesh et al., 2003).

However, this explanation may lead researchers to the following question: If users form their beliefs such as usefulness or ease of use based on their initial use and/or experience with an IT, would their beliefs hold over time, i.e., are there dynamics at play in fashioning their beliefs as they gain experience with the IT? We believe that this issue may be a pointer to a possible theoretical lacuna in understanding the time-dimension in extant adoption studies. Other scholars have also observed that extant IS studies lack sufficient theoretical underpinnings to suggest temporal dynamics in belief constructs, and their relationships with intention to use (Venkatesh and Morris, 2000). Especially so, as most IS studies were mainly conducted in a cross-sectional setting after individuals' acceptance/rejection decision was already made (Venkatesh et al., 2003).

To address this limitation, we propose to incorporate the time dimension into TAM (Davies, 1989) in order to identify the dynamics in users' beliefs as they adopt IT. This approach is in line with prior studies which emphasized the role of time in theory and theory building (e.g., Bluedorn and Denhardt, 1988; George and Jones, 2000). Additionally, we introduce latent growth curve modeling, as a statistical method to capture the dynamics of user beliefs and intention during the adoption of a technology.

The rest of this paper is organized as follows: First, we provide a logical framework that identifies the dynamics of user beliefs and intention during their adoption of IT. Then, we introduce latent growth curve modeling to assess the dynamics, and demonstrate an example based on the secondary data obtained from Venkatesh et al. (2006). We believe that this approach will provide an expanded view of adoption with regard to the time dimension.

CONSIDERATION OF TIME IN PRIOR TAM-RELATED STUDIES

Several scholars have conceptually discussed the issues related to time in their adoption decision studies. For example, Karahanna et al. (1999), based on the cognitive dissonance theory, asserted that as individuals use and experience IT, they may change their perceptions of and attitudes toward the technologies, which would lead to different belief structures in post-adoption compared to those before adoption. Jasperson et al. (2005) asserted that IT use history as a manifestation of the time dimension would direct post-adoptive behavior. Venkatesh et al. (2006) categorized the concept of time into three aspects: anticipation of performing a behavior, experience with performing a behavior, and frequency of performing a behavior[1]. The authors then argued that 'time' is a critical variable which influences the predictive validity of users' adoption intention and expectation[2].

The temporality of users' perceptions of (or attitudes toward) IT and the differences in the relevant behavioral models based on time have been noted in a few prior studies, though time was implicitly nested in their models. For example, intention to use a word-processor measured right after an introductory session was found to be correlated with use behavior 14 weeks later (Davis et al., 1989). The behavioral models to explain intention to use for users and potential adopters were found to be distinct (Karahanna et al., 1999). For example, ease of use, perceived usefulness, viability, result demonstrability, and triability were the determinants of intention to adopt for potential adopters, whereas images and perceived usefulness were the determinants of intention to use for users (Karahanna et al., 1999). Perceived behavioral control was found to influence the use of technology over intention to use with increasing experiences with an IT, beginning from a post-training session, to 1 month, and 3 months after the implementation of the IT (Venkatesh et al., 2003). The effect of performance expectancy on intention to use and the effect of intention to use on usage behavior were found to decline with increasing experience with IT (Venkatesh et al., 2003).

In addition, a few other studies (e.g., Venkatesh and Davis, 2000; Venkatesh et al. 2006; 2008) explicitly considered time in their adoption models. For example, Venkatesh and Davis (2000) found that attitude toward technology, social norm, and perceived behavioral control have salient effects on intension to adopt in the short term, whereas the effect of social norm was insignificant in the long term. The authors (p. 393) interpreted that "three months was long enough for internalization to take place, rendering subjective norm non-significant for both groups at that point." Venkatesh et al. (2006, 2008) identified that as time passed by, experience (behavioral expectation) was found to strengthen (weaken) the relationship between behavioral intention and system use. More specifically, the relationship between behavioral intention and system use was found to be strongest when experience was high and anticipation was low, whereas the relationship between behavioral expectation and system use was found to be strongest when anticipation is high and experience is low (Venkatesh et al., 2006, 2008). Table 1 summarizes the results related to the time effect in prior IT adoption studies.

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[1] According to the authors, anticipation of performing a behavior is defined as the temporal distance between the present time and the time of performing a target behavior, while experience with performing a behavior refers to the extent to which a target behavior has been conducted in the past. In addition, the authors defined frequency of performing a behavior as the repetition with which a target behavior has been performed.

[2] Venkatesh et al. (2006, 2008) differentiated behavioral intention ("the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw and Davis 1985, p. 214)) from behavioral expectation ("an individual's self-reported subjective probability of his or her performing a specified behavior, based on his or her cognitive appraisal of volitional and non-volitional behavioral determinants") (Warshaw and Davis 1984, p. 111).

*** Studies that explicitly considered time in their research model.**

Researchers	Time Consideration	Results Related to Time
Davis et al. (1989)	After Introduction of IT and 14 weeks later	- Intention to use the word-processor measured right after one-hour introductory session was found to be correlated with behavior 14 weeks later. - Usefulness and ease of use were determinants of intention to use right after the introductory session, while usefulness was the only factor influencing intention to use 14 weeks later.
Karahanna et al. (1999)	Potential Adopters of Windows (Adoption Model) and Users of Windows (Post Adoption Model)	- For potential adopters, ease of use, perceived usefulness, viability, result demonstrability, and triability influence attitudes, which in turn affect behavioral intention to adopt. - For users, images and perceived usefulness influence attitude, which in turn influences behavioral intention to continue using.
Morris and Venkatesh (2000)	After Initial Training, Three Months after Implementation (Short Term), and Five Months after Implementation (Long Term)	- Attitude toward technology, social norm and perceived behavioral control have a significant effect on usage in the short term, whereas social norm becomes insignificant in the long term. - The interaction effect between age and social norm on short term usage is significant whereas that on long term usage becomes insignificant.
Venkatesh and Davis (2000)*	After Initial Training, One Month after Implementation, Three Months after Implementation, and Five Month after Implementation (Only for Usage Behavior)	- Cross-temporal correlations of perceived usefulness (0.56~0.79), subjective norm (0.51~0.65), and intention to use (0.12~0.37) were stable for the three-month time-window whereas those of ease of use were found to be unstable overtime.
Venkatesh et al. (2003)	Post-Training, 1 Month after Implementation, 3 Months after Implementation	- Perceived behavioral control was found to influence use of the technology over intention to use with increasing experience (from time 1 to time 3). - The effect of performance expectancy on intention to use was found to be lower with increasing experience from time 1 to time 3. - The effect of intention to use on usage behavior was found to be lower with increasing experience from time 1 to time 3.
Venkatesh et al. (2006)*	Study 1 (1 Month, 3 Months, and 6 Months)	- The relationship of behavioral intention (behavioral expectation) with behavior was found to become weaker (stronger) as behavior becomes distal. - The relationships of behavioral intention and perceived behavior control (behavioral expectation) with behavior were found to become stronger (weaker) as experience increases.
	Study 2 (Every Quarters of a Year)	- Same as the two results noted above. - The relationship between behavioral intention and behavior was found to be strongest when experience was high and anticipation was low. - The relationship between behavioral expectation and behavior was found to be strongest when anticipation is high and experience is low.
Venkatesh et al. (2008)*	Immediately Post-Training, 3 Months, 6 Months, 9 Months and 12 Months of System Use.	- Experience (Expectation) was found to strengthen (weaken) the relationship between behavioral intention and system use, as time passed by.

Table 1. Results Related to the Time Effect in Prior IT Adoption Studies

RESEARCH MODEL

Prior technology acceptance models (e.g., TAM, TAM2, and UTAUT) have contributed to understanding individuals' adoption of technology. Some of these models seem to be primarily focused on the introduction of additional variables such as belief, contingency, and environment factors (Wixom and Todd, 2005). Though a few studies discussed in the prior section suggested the effect of time, most of them implicitly considered time in their model. In other words, time was not a primary focus of these studies. Notable exceptions would be Venkatesh and Davis (2000) and Venkatesh et al. (2006, 2008), which delved into time in their adoption study. However, the temporal dynamics of the users' beliefs in and attitudes toward technologies were not particularly identified even in these three studies.

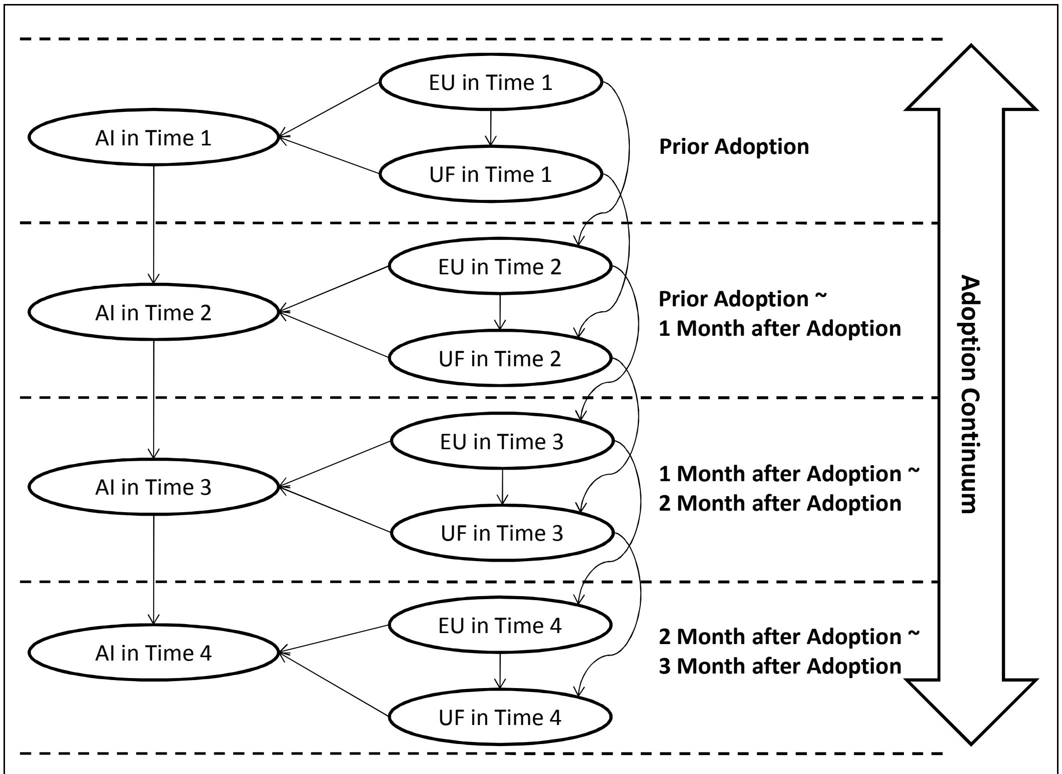

Figure 1. Conceptual Model

Unlike prior studies, this paper focuses on identifying the dynamics of users' beliefs in IT and intention to adopt IT based on the time dimension, which is incorporated into TAM (Davis, 1989), as shown in Figure 1. Additionally, it considers adoption as a continuum, rather than a static single acceptance decision. In other words, we argue that *users' beliefs (i.e., ease of use and usefulness) in IT and intention to adopt IT may be dynamic while the users are experiencing the technology during their adoption, and such dynamics of beliefs may influence the dynamics of their adoption decision.* For example, when a user learns a new technology, he or she forms initial beliefs such as ease of use and usefulness, which may be determinants of an initial adoption of the new technology. During his/her initial usage, if he or she finds that the technology does (or not) meet his or her needs and/or expectations, he or she may confirm (or adjust) the prior adoption intention. While he or she is continuing to use the technology, he or she may also change beliefs and adoption intention since he or she may find new features of the technology and have more familiarity with the technology. With regard to the relationships of behavioral beliefs (i.e. ease of use and usefulness) between the stages, once a user forms higher levels of ease of use and usefulness, he or she may be committed to his or her beliefs in the next stage, unless he or she finds negative aspects related to ease of use and usefulness.

This concept of dynamics of beliefs and intensions during technology adoption is supported by Rogers's (2005) theory '*the diffusion of innovation*'. In his theory, his innovation-decision model is composed of five stages: knowledge, persuasion, decision, implementation, and confirmation. Rogers argued that users may reject a technology after having previously adopted it (a.k.a. active rejection[3]) in the decision stage. In addition, the author (p. 189) stated that "a decision to adopt or reject a new idea is often not the terminal stage … the individual seeks reinforcement for the decision already made and may reverse this decision if exposed to conflicting messages about the innovation." The author attributed this reinforcement mechanism to users' experience with dissonance (a state of internal disequilibrium), which would lead to human behavioral change (Festinger, 1957). Prior studies also indirectly support the dynamics. For example, experience with technologies was suggested to influence usage patterns (e.g., Davis et al., 1989; Morris and Venkatesh, 2000; Venkatesh and Davis, 2000). In other words, as users experience technologies and as time passes by, they are likely to be more familiar with them and adopt the technologies at a higher level, unless they experience dissonance. Thompson et al. (2005) also identified that the use of a technology-product structurally changes users' preferences such that users are likely to put more weight on capability and less weight on usability in their judgment of its utility before use, compared to after use. Based on the above discussion, the following two propositions are suggested to identify the dynamics of users' beliefs and intention:

Proposition 1: *An individual's behavioral beliefs in a new technology, such as ease of use and usefulness, will be dynamic during their adoption decision.*

Proposition 2: *An individual's intention to adopt a new technology would be dynamic during their adoption decision.*

Based on the two propositions above and the technology acceptance model (Davis, 1989), the following two propositions can be suggested to capture the relationship of the dynamics:

Proposition 3: *The initial level of behavioral beliefs in a new technology, such as ease of use and usefulness, will affect the initial level of intention to adopt a new technology.*

Proposition 4: *The change in behavioral beliefs in a new technology, such as ease of use and usefulness, will affect the change in intention to adopt a new technology.*

METHOD

1. Research Plan

The data for this study will be collected in business classes at a US Mid-Western University. We will collect data at four points during a semester so as to capture the dynamics of users' beliefs and intention related to the use of *Java Script* and *Excel*. Students will be introduced to the two technologies at the beginning of the semester. The data will be collected upon the completion of the introduction at the beginning of the semester and subsequently each month during the semester. Immediately after the introduction session, students will rate ease of use, usefulness, and intention to use the new technologies. As the training progresses, the same survey will be repeated every month. Users' prior experience with the technologies will be assessed and controlled in the analysis. This data collection strategy is consistent with Venkatesh et al. (2006, 2008). We believe that this research setting would be comparable to organizational settings in that the students have to learn and utilize the technologies to perform the tasks assigned, which seems to support ecological validity.

All the constructs, such as ease of use, usefulness, and intention to use, will be measured using instruments developed and reported in prior studies. For example, ease of use and usefulness will be assessed using Davis's (1989) scales from TAM. These two constructs have six items respectively, rated on a 7-point Likert scale (1=extremely unlikely to 7=extremely likely). Intention to use will be measured using Venkatesh et al.'s (2008) three items, rated on a 7-point Likert scale (1=highly disagree to 7=highly agree).

In the model, self-efficacy and job relevance will be employed as control variables since they have been found to influence technology acceptance in prior research (e.g., Venkatesh et al., 2003; Venkatesh and Davis, 2000). Self-efficacy will be measured using Venkatesh et al.'s (2003) four items. Job relevance will be measured using Venkatesh and Davis's (2000) 2 items. Both constructs will be rated on a 7-point Likert scale (1=highly disagree to 7=highly agree).

Appendix 1 provides the scales employed in this study.

ANALYSIS TECHNIQUE: LATENT GROWTH CURVE MODELING

1. Latent Growth Curve Modeling

This paper aims at identifying *1) the temporal dynamics of users' beliefs in IT and intention to use IT* and *2) the relationship of the dynamics during adoption.* In this paper, we introduce latent growth curve modeling to investigate the dynamics.

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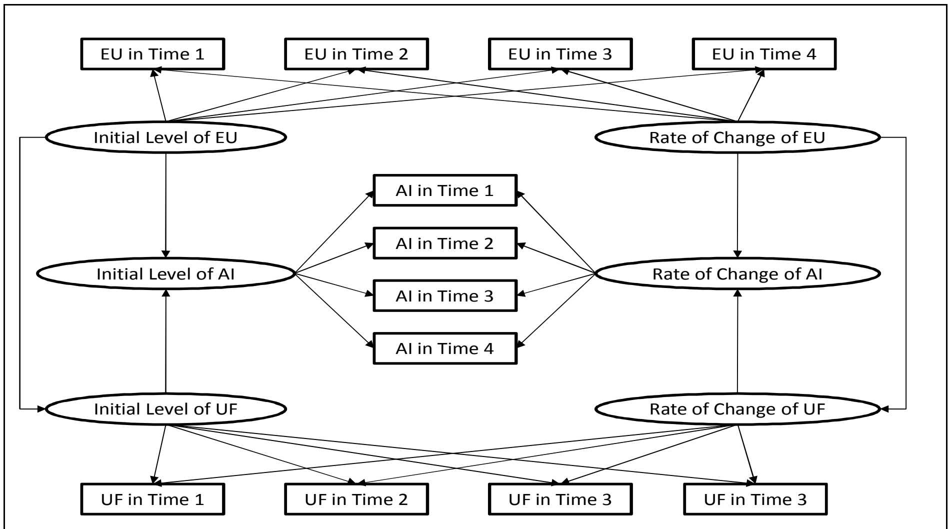
[3] The author (p. 178) differentiated active rejection ("considering adoption of the innovation including its trial but then deciding not to adopt it") from passive rejection ("never really considering the use of the innovation").

Latent growth curve modeling has emerged as a useful tool for studying longitudinal changes (Duncan et al., 1999) while considering individual differences in the repetitive measures. Though traditional statistical techniques such as mean comparisons and regression can present the differences in patterns of perceptions or behaviors, the results from the techniques may mask the individual variations found in longitudinal studies (Walker et al., 1996). Latent growth curve model is known to reduce the threat from the individual variances by considering the variances of a homogeneous group which starts at much the same initial value (intercept) and changes at much the same rate (slope) (Duncan et al., 1999). We believe that the benefits of using this technique are that we can 1) draw some conclusions about changes at the aggregate level, 2) model case-by-case measurement errors, and 3) model the changes in linear and non-linear trajectories. Figure 2 presents the research model based on latent growth curve modeling. The following mathematical formulae present latent growth curve modeling employed based on the model in Figure 2.



- EU [Ease of Use], AI [Intention to Adopt], UF [Usefulness]

Figure 2. Latent Growth Curve Modeling

$\eta = \alpha + \kappa + B\eta + \Gamma\xi + \zeta$ (Structural Equation Model)

$y = \tau_y + \lambda_y\eta + \varepsilon$ (Measurement of Y Variable)

$x = \tau_x + \lambda_x\xi + \delta$ (Measurement of X Variable)

where α and κ are vectors of constant intercept terms

λ_x and λ_y are fixed to the matrix of $\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \end{bmatrix}^T$

x is a matrix of ease of use measured from time 1 to time 4

y is a matrix of usefulness and adoption intention measured from time 1 to time 4

τ_x is an initial level of ease of use

ξ is a rate of change of ease of use

τ_y is a vector, which represents an initial level of both usefulness and adoption intention

η is a vector, which represents a rate of change of both usefulness and adoption intention

Ease of use, usefulness, and adoption intention are assessed using multiple items as noted earlier. In other words, these variables are aggregations of the measurement items based on each time-window. Thus, the issue of data equivalence (also called measurement invariance) across different time-windows should be considered as a relevant issue of investigation (Salzberger and Sinkovics, 2006; Malhotra et al., 1996), similar to the context of multi-group comparison. Especially, during the factor identification, measurement equivalence issues are commonly encountered (van Herk et al., 2005). One of the dominant approaches for the analysis of multi-group data is multi-group confirmatory analysis approach (MGCFA). Consistently, we will also conduct MGCFA to test the measurement equivalence of the psychological factors employed in this study using LISREL (Jöreskog & Sörbom, 1993) for their applicability across the four time-windows. This process is known to serve as a necessary condition to enable the testing of measurement equivalence of the scales in multi-group populations (Cui et al., 2005). An example of analysis in the next section demonstrates the latent growth curve modeling using secondary data.

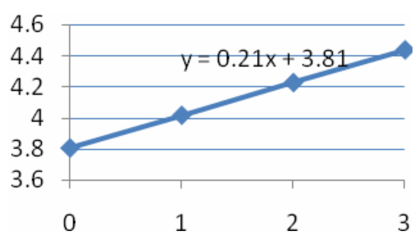
2. Sample Analysis

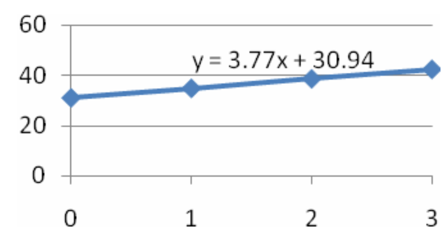
As a research in progress, we used secondary data obtained from Venkatesh et al. (2006) to demonstrate latent growth curve modeling. Venkatesh et al. (2006) reported correlations between two variables (e.g., behavioral intention and use), means and standard deviations of the variables in four different time-windows spread over a year (See Table 2). We assumed a linear combination of the measurements in the four time-windows. Table 2 shows a correlation-matrix among variables and means and standard deviations. We used these correlations, means, and standard deviation provided in Venkatesh et al. (2006) in analyzing latent growth curve model using LISREL (Jöreskog and Sörbom, 1993).

Behavioral Intention 11	1							
Behavioral Intention 21	0.3	1						
Behavioral Intention 31	0.3	0.34	1					
Behavioral Intention 41	0.29	0.34	0.36	1				
USE11	0.69	0.28	0.33	0.21	1			
USE21	0.24	0.6	0.33	0.31	0.51	1		
USE31	0.27	0.35	0.61	0.37	0.47	0.56	1	
USE41	0.07	0.31	0.42	0.63	0.51	0.4	0.6	1
Mean	3.8	4.0	4.3	4.4	28.8	37.4	40.1	40.6
Std	1.12	1.10	1.02	0.99	7.99	8.34	8.86	8.17

Table 2. Correlations, Means and Standard Deviations (n=321)
(Copied from Venkatesh et al. (2006)

Behavioral Intention		**Use**	
Intercept (t-Value)	**Slope (t-Value)**	**Intercept (t-Value)**	**Slope (t-Value)**
3.81 (69.04)	0.21 (9.34)	30.94 (73.08)	3.77 (24.90)
df=5 Chi-Square = 3.69 (p=0.60) SRMR=0.01 GFI=1.00		*df*=5 Chi-Square = 176.83 (p=0.00) SRMR=0.08 GFI=0.91	





The Relationships between Behavioral Intention and Use

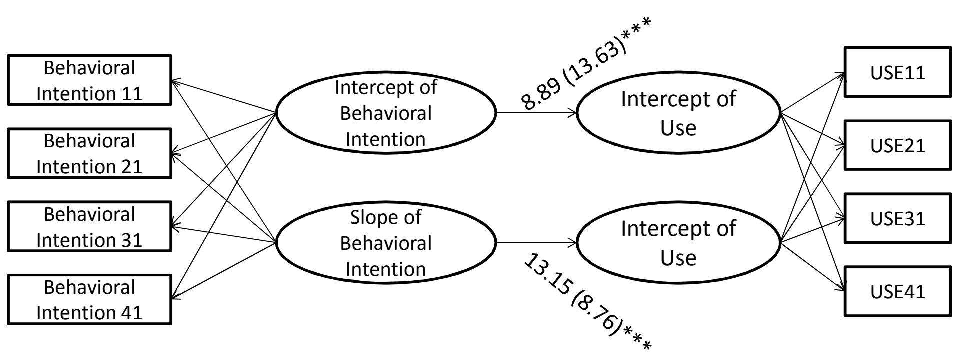


Table 3. Results of Latent Growth Curve Modeling

Table 3 shows results of latent growth curve modeling. The behavioral intention model has SRMR of 0.01 and GFI of 1.00, and the use model has SRMR of 0.08 and GFI of 0.91, though the latter has a high level of chi-square[4]. Thus both models are considered to have reasonable goodness-of-fit indices based on Bentler and Bonnet's (1980) criteria. Behavioral intention is found to have a significant intercept (mean=3.81, t-value=69.04) and slope (0.21, 9.34). Use also has a significant intercept (30.94, 73.08) and slope (3.77, 24.90). Based on these results, users' level of 'behavioral intention' and 'use' are likely to increase, as individuals experience with the technology increases during the adoption. A diagram at the bottom of Table 3 presents that the intercept (an initial level) of behavioral intention positively influences the intercept of use (path coefficient=8.89, t-value=13.63) and that the slope (dynamics) of behavioral intention positively affects the slope of use (13.15, 8.76). Based on these results, those who have a higher level of initial intention to use a technology are likely to have a higher level of initial use of the technology. In addition, those who have a steeper level of slope of behavioral intention are likely to have a steeper increase in their use.

CONCLUDING REMARKS

In this paper, we explore the dynamics of individuals' IT adoption and the relationship of the dynamics. We introduce latent growth curve modeling, and demonstrate its application based on secondary data. Currently, we are conducting a study to identify the dynamics of user beliefs and adoption intention and collecting data for it. We believe the final results would be of interest to IS researchers as well as practitioners for better understanding of the underlying nuances of technology adoption as a continuum.

REFERENCE

1. Agarwal, R. and Karahanna, E. (2000) Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage, *MIS Quarterly*, 24, 4, 665-694.
2. Ajzen, I. (1985) From intentions to actions: A theory of planned behavior," in *Action Control: From Cognition to Behavior*, J. Kuhl and J. Beckmann (eds.) Springer Verlag, New York, 11- 39.
3. Bentler, P. M., and Bonnet, D. G. (1980) Significance tests and goodness of fit in the analysis of covariance structures, *Psychological Bulletin,* 88, 3, 588-606.
4. Bluedorn, A. C., and Denhardt, R. B. (1988) Time and organizations, *Journal of Management,* 14, 299–320.
5. Cui, C. C., Mitchell, V. Schlegelmilch, B. B., and Cornwell, B. (2005) Measuring consumers' ethical position in Austria, Britain, Brunei, Hong Kong, and USA. *Journal of Business Ethics,* 62, 52-71.
6. Davis, F. D. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly,*13, 3, 319-340.
7. Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1989) User acceptance of computer technology: A comparison of two theoretical models, *Management Science*, 35, 4, 982-1002.
8. Duncan, T. E., Duncan, S. C., Stryker, L. A., Li, F., and Alpert, A. (1999) An introduction to latent variable growth curve modeling: concepts, issues, and applications, Lawrence Erlbaum Associates, Mahwah, NJ.
9. Festinger, L. (1957) *A theory of cognitive dissonance,* Stanford University Press, Stanford, CA.
10. George, J. M., and Jones, G. R. (2000) The role of time in theory and theory building. *Journal of Management,* 26, 4, 657–684.
11. Jasperson, J., Carter, P. E., and Zmud, R. W. (2005) A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems, *MIS Quarterly*, 29, 3, 525-557.
12. Jeyaraj, A., Rottman, J. W. and Lacity, M. C. (2006) A review of the predictors, linkages and biases in it innovation adoption research, *Journal of Information Technology,* 21, 4, 1-23.
13. Jöreskog, K., and Sörbom, D. (1993) *Lisrel 8: User's reference guide*, Scientific Software International, Lincolnwood, IL.

[4] We think that this may be due to a lack of standardization in the measurement of the variable, since the variable 'use' was measured with the number of hours of information systems usage in Venkatesh et al. (2006).

14. Karahanna, E., Straub, D. W. and Chervany, N. L. (1999) Information technology adoption across time: a cross-sectional comparison of pre-adoption and post adoption beliefs, *MIS Quarterly,* 23, 2, 183-213.
15. Malhotra, N. K., Agarwal, J. and Peterson, M. (1996) Methodological issues in cross-cultural marketing research, *International Marketing Review,* 13, 7-43.
16. Morris, M. G. and Venkatesh, V. (2000) Age differences in technology adoption decisions: implications for a changing work force, *Personnel Psychology,* 53, 375-403.
17. Rogers, E. M. (2003) *Diffusions of innovations* 5th Edition, Free Press, New York.
18. Sabherwal, R., Jeyaraj, A. and Chowa, C. (2006) Information system success: Individual and organizational determinants," *Management Science,* 52, 12, 1849-1964.
19. Salzberger, T., and Sinkovics, R. R. (2006) Reconsidering the problem of data equivalence in international marketing research contrasting approaches based on CFA and the RASCH model for measurement, *International Marketing Review*, 23, 390-417.
20. Thompson, D. V., Hamilton, R. W. and Rust, R. (2005) Feature fatigue: when product capabilities become too much of a good thing, *Journal of Marketing Research,* 42, 431-442.
21. van Herk, H., Poortinga, Y. H., and Verhallen, T. M. (2005) Equivalence of survey data: relevance for international marketing, *European Journal of Marketing,* 39, 351-364.
22. Venkatesh, V., and Davis, F. D. (2000) A theoretical extension of the technology acceptance model: four longitudinal field studies, *Management Science,* 46, 2, 186-204.
23. Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. B. (2003) User acceptance of information technology: Toward a unified view, *MIS Quarterly,* 27, 3, 425-478.
24. Venkatesh, V., Maruping, L. M., and Brown, S. A. (2006) Role of time in self-prediction of behavior, *Organizational Behavior and Human Decision Processes*, 100, 160-176.
25. Venkatesh, V., Brown, S. A., Maruping, L. M., and Bala, H. (2008) Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation, *MIS Quarterly,* 32, 3, 483-502.
26. Walker, A. J., Acock, A. C., Bowman, S. R., and Li, F. (1996) Amount of care given and caregiving satisfaction: A latent growth curve analysis," *Journal of Gerontology,* 51, 3, 130-142.
27. Warshaw, P. R., and Davis, F. D. (1984) Self-understanding and the accuracy of behavioral expectations, *Personality and Social Psychology Bulletin,* 10, 1, 111-118.
28. Warshaw, P. R., and Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation, *Journal of Experimental Social Psychology*, 21, 3, 213-228.
29. Wixom, B. H. and Todd, P. A. (2005) A technology integration of user satisfaction and technology acceptance, *Information Systems Research,* 16, 1, 85-102.

Appendix 1. Scales Employed (Based on *Java Script*)

Ease of Use	Using Java Script in my job would enable me to accomplish tasks more quickly
	Using Java Script would improve my job performance
	Using Java Script in my job would increase my productivity
	Using Java Script would enhance my effectiveness on the job
	Using Java Script would make it easier to do my job
	I would find Java Script useful in my job.
Usefulness	Learning to operate Java Script would be easy for me.
	I would find it easy to get Java Script to do what I want it to do.
	My interaction with Java Script would be clear and understandable.
	I would find Java Script to be flexible to interact with.
	It would be easy for me to become skillful at using Java Script.
	I would find Java Script easy to use.
Intention to Adopt	I intend to use Java Script in the next month.
	I predict I would use Java Script in the next month.
	I plan to use Java Script in the next month.
Job Relevance	In my job, the usage of Java Script is important.
	In my job, the usage of Java Script is relevant.
Self Efficacy	I could complete a job or task using the system ~
	If there was no one around to tell what to do as I go.
	If I could call someone for help if I got stuck.
	If I had a lot of time to complete the job for which the software was provided.
	If I had just the built-in help facility for assistance.