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PREDICTING DIFFERENT CONCEPTUALIZATIONS OF SYSTEM USE: THE COMPETING ROLES OF BEHAVIORAL INTENTION, FACILITATING CONDITIONS, AND BEHAVIORAL EXPECTATION[1]

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Abstract

Employees' underutilization of new information systems undermines organizations' efforts to gain benefits from such systems. The two main predictors of individual-level system use in prior research—behavioral intention and facilitating conditions—have limitations that we discuss. We introduce behavioral expectation as a predictor that addresses some of the key limitations and provides a better understanding of system use. System use is examined in terms of three key conceptualizations: duration, frequency, and intensity. We develop a model that employs behavioral intention, facilitating conditions, and behavioral expectation as predictors of the three conceptualizations of system use. We argue that each of these three determinants play different roles in predicting each of the three conceptualizations of system use. We test the proposed model in the context of a longitudinal field study of 321 users of a new information system. The model explains 65 percent, 60 percent, and 60 percent of the variance in duration, frequency, and intensity of system use respectively. We offer theoretical and practical implications for our findings.

Keywords: Technology adoption, user acceptance, system use, behavioral expectation, behavioral intention, facilitating conditions, duration of use, frequency of use, intensity of use

Introduction

Information systems continue to play a vital role in organizational life. Investment in, and implementation of, enterprise-level systems, such as enterprise resource planning (ERP) systems, supply chain management systems, customer relationship management (CRM) systems, and business intelligence systems, have become the hallmark of organizational strategies for survival and competitive advantage (Melville et al. 2004). Evidence in the trade press as well as academic journals suggests that employees' underutilization of such newly implemented systems results in the failure to garner the expected benefits of such implementations and threatens the long-term viability of such systems (Jasperson et al. 2005; Mabert et al. 2001).

Against this backdrop, the system use construct has played a critical role in the information systems literature. It is the ultimate dependent variable in technology adoption models (Davis et al. 1989; Venkatesh et al. 2003) and a key variable in IS success models (DeLone and McLean 1992, 2003). System use has been identified as the most important surrogate measure for IS success (for a recent review, see Sabherwal et al. 2006). The importance of the system use construct is further underscored by its inclusion as a core property of the IT artifact's nomological network (Benbasat and Zmud 2003). Benbasat and Zmud suggest that researchers should focus on the "managerial, methodological, and operational practices for directing and facilitating IT artifact ***usage***" (2003, p. 186). Nevertheless, there is a dearth of research in the IS literature that richly theorizes about system use, relationships between different measures of system use, and their causal determinants and outcomes (Burton-Jones and Straub 2006; Jasperson et al. 2005).

In addition to theoretical limitations, there are limitations related to the clarity and purpose of the measurement of system use. System use has indeed been measured in many different ways. IS researchers have used both objective (e.g., system logs) and subjective (e.g., user assessments of duration, frequency, or intensity of use) measures (e.g., Davis et al. 1989; Straub et al. 1995; Venkatesh et al. 2003). Recently, Jasperson et al. (2005) and Burton-Jones and Straub (2006) reviewed prior research on system use and provided theoretical and operational insights into how this research has dealt with system use. Jasperson et al. found that much prior research has treated system use as a black box and there are only a few studies that have incorporated system features in the operationalization of system use. Consistent with this observation, Burton-Jones and Straub found that prior research has primarily used "lean" measures of system use and has not provided any theoretical justification for selecting measures of system use. Their proposed two-stage approach to conceptualizing system use couples theory with operationalization. Therefore, it is critical that conceptualizations of system use be theoretically tied to proposed predictors (Burton-Jones and Straub 2006).

Behavioral intention (BI)—defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw and Davis 1985b, p. 214)—has been used extensively as a predictor of system use (for a review, see Venkatesh et al. 2003). Duration, frequency, and intensity of use are three commonly employed conceptualizations of system use (Davis et al. 1989; Venkatesh et al. 2003). While Venkatesh et al. (2003) suggest that we may have reached the practical limits of our understanding of adoption and use, we suggest that their conclusion is true only within an ***intentionality*** framework, where external factors are taken into account via facilitating conditions (FC), defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al. 2003, p. 453). The intentionality framework—which includes facilitating conditions—has limitations (which we discuss in detail later) that can reduce our ability to accurately predict system use (Sheeran 2002; Sheppard et al. 1988; Warshaw and Davis 1985b). Further, prior research has failed to theoretically justify the relationships between behavioral intention, facilitating conditions, and specific conceptualizations of system use, instead treating them as being interchangeable (Burton-Jones and Straub 2006). The measurement has followed fairly directly from these conceptualizations and has typically been driven by practical considerations. Consequently, little consideration has been given to the potential differences in the underlying predictors that drive the different conceptualizations of system use—for example, an unanswered question is: Are the drivers of frequency of system use different from the drivers of duration of system use? While practical constraints are common considerations and limitations of research efforts, we argue that an important next step is indeed to address this limitation by understanding the differences in the predictors that drive these different conceptualizations of system use. Thus, it is not only important to go beyond the intentionality framework, but important also to expand our understanding of the drivers of various conceptualizations of system use.

Behavioral expectation (BE) has been proposed to overcome the limitations of behavioral intention and facilitating conditions (Warshaw and Davis 1984). Behavioral expectation is "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). A particular strength of behavioral expectation is its ability to capture and account for uncertainty in the prediction of behavior (Venkatesh et al. 2006; Warshaw and Davis 1984, 1985a). The strengths of behavioral expectation are expected to apply to the prediction of system use as well. However, as prior research suggests, the concept of system use is varied and complex (Burton-Jones and Straub 2006; Jasperson et al. 2005; Straub et al. 1995). This paper complements our recent work that examined the role of behavioral intention and behavioral expectation in predicting behavior (see Venkatesh et al. 2006). This research also seeks to explicate the mechanisms by which behavioral expectation influences different conceptualizations of use, which we will argue and demonstrate differ from how and why behavioral intention drives system use (see Warshaw and Davis 1985a). In sum, the objectives of this paper are to

1. discuss the limitations of behavioral intention and facilitating conditions, and discuss how behavioral expectation addresses those limitations

2. refine our understanding of the psychological mechanisms underlying the prediction of various conceptualizations of system use

3. empirically test the proposed model in a longitudinal field study

Theory

In this section, we first discuss the roles of the two main predictors of system use from individual-level technology adoption literature (i.e., behavioral intention and facilitating conditions) and discuss their limitations. We follow this with a description of behavioral expectation and how it addresses some of the shortcomings of behavioral intention and facilitating conditions as predictors of system use. Finally, we present a model that employs behavioral intention, facilitating conditions, and behavioral expectation as predictors of the three different conceptualizations of system use.

Behavioral Intention and Facilitating Conditions: Roles and Limitations

According to well-established theories in IS and social psychology, behavioral intention is an important causal predictor of behavior that mediates the influence of various beliefs and external variables (e.g., individual characteristics, system characteristics, etc.) on behavior (Davis et al. 1989; Sheeran 2002). While behavioral intention has been empirically demonstrated to be an important determinant of many behaviors (Albarracin et al. 2001; Sheeran 2002; Sheppard et al. 1988), including system use (see Venkatesh et al. 2003), it has at least three known limitations.

First, behavioral intention is a reflection of an individual's ***internal*** schema of beliefs. It does not represent the ***external*** factors that can influence the performance of a behavior (see Boden 1973). Therefore, the role of external factors that can potentially facilitate or impede the performance of a behavior is not fully captured by behavioral intention. Facilitating conditions was proposed as a construct that would address the role of external factors but, as we will soon discuss, it does not fully consider all possible external factors that can influence behavioral performance. Second, behavioral intention has limited predictive and explanatory ability to deal with uncertainty and unforeseen events between the time the intention is formed and the behavior is performed. An individual's beliefs, and consequently their behavioral intention, can change in the face of new information (Ajzen and Fishbein 1974). In such cases, behavioral intention may be provisional (see Sutton 1998) and because of various internal and external stimuli, such a provisional intention may change drastically over time (Sheeran and Orbell 1998; Sutton 1998), rendering behavioral intention unstable, inaccurate, and less predictive of behavior. Finally, behavioral intention is limited in its ability to predict behaviors that are not completely within an individual's volitional control (Ajzen 1985).

Facilitating conditions—which considers nonvolitional factors for which behavioral intention is unable to account—also has known limitations in dealing with such factors. Facilitating conditions is a construct that reflects an individual's perceptions about his or her control over a behavior.[2] Taylor and Todd (1995b) underscored the overlap between facilitating conditions and perceived behavioral control. Facilitating conditions, in general, refers to individual perceptions of the availability of technological and/or organizational resources (i.e., knowledge, resources, and opportunities) that can remove barriers to using a system (Venkatesh et al. 2003). Facilitating conditions has limitations that constrain its overall scope in capturing the effect of external factors. In particular, a key limitation of facilitating conditions is its inability to account for incomplete information (Sheeran et al. 2003). In order for facilitating conditions to predict behavior, individuals' perceptions about these conditions should accurately and realistically reflect their actual control over a behavior (Ajzen and Madden 1986). Therefore, in the presence of incomplete information and/or uncertainty regarding a behavior, facilitating conditions may not be a good predictor of the behavior (Ajzen 1991; Sheeran et al. 2003).

[2]Venkatesh et al. (2003) conceptualized and operationalized facilitating conditions by integrating constructs from prior theories—that is, perceived behavioral control from the theory of planned behavior (Ajzen 1991; Mathieson 1991) and facilitating conditions from the model of personal computer utilization (Thompson et al. 1991, 1994).

Behavioral Expectation: Addressing Limitations

Recall that behavioral intention is limited in its ability to fully account for external factors that can influence the performance of a behavior. Behavioral expectation addresses this limitation because anticipated changes in behavioral determinants are incorporated into the formation of behavioral expectation. Behavioral determinants that may change over time include behavioral intention, limitations in ability, and environmental inhibitors or facilitators (Warshaw and Davis 1985b). Behavioral expectation captures many such factors external to behavioral intention (Warshaw and Davis 1985b). Another limitation of behavioral intention and facilitating conditions is their inability to account for uncertainty and lack of information. Behavioral expectation may be a more robust predictor of behavior in such situations (see Sheppard et al. 1988; Warshaw and Davis 1985b). There are many situations in which the ability to perform an intended behavior, given total effort, is uncertain. Such uncertainty may arise when a behavioral intention is formed well in advance of the intended behavior such that unforeseen events and impediments may change the initial behavioral intention (Venkatesh et al. 2006). Behavioral expectation takes such impediments into consideration and, thus, addresses this limitation.

Behavioral expectation is also able to address the limitation of facilitating conditions that is tied to an individual's need to have accurate and realistic perceptions of their actual control over the behavior by incorporating an individual's tacit sense of control over behavioral enactment in the face of uncertainty. There are two possible underlying mechanisms (i.e., *mental simulation* and *extrapolation tactics*) that explain how and why behavioral expectation can be a better predictor of behavior in situations when behavioral intention and facilitating conditions have limited predictive ability. *Mental simulation* is an uncertainty reduction tactic that involves imagining possible future events unfolding in a script-like manner (Klein and Crandall 1995; Lipshitz and Strauss 1997; Schoemaker 1995) and takes into account events that might prevent behavioral performance. *Extrapolation tactics*—such as *assumption-based reasoning* and *statistical estimation*—are also used by individuals when faced with uncertainty due to a lack of information (Allaire and Firsirotu 1989; Wildavsky 1988). *Assumption-based reasoning* entails constructing a mental model of a situation based on assumptions/beliefs that go beyond, yet are constrained by, what is firmly known and can be retracted in the face of conflicting new evidence (Cohen 1989; Lipshitz and Ben Shaul 1997). *Statistical estimation* involves the prediction of future events using past or present information (Allaire and Firsirotu 1989; Lipshitz and Strauss 1997). The self-estimated probability of performing the target behavior may thus be based on high probability outcomes in mental simulations. For example, individuals with incomplete or inaccurate information about a behavior could use mental simulations in estimating their probability of performing the behavior. In such situations, behavioral expectation would be more accurate than behavioral intention and facilitating conditions in predicting behavior because of its ability to account for possible outcomes (Warshaw and Davis 1985b).

Hypothesis Development

In this section, we develop the theoretical rationale for our research model shown in Figure 1. We first present the hypotheses related to behavioral intention and behavioral expectation, followed by the hypotheses related to facilitating conditions.

Relationships among Behavioral Intention, Behavioral Expectation, and System Use

In relating behavioral intention to behavioral expectation, we highlight the temporal sequencing of events leading up to the execution of a target behavior. The motivational drive to perform a target behavior stems from an individual's internal evaluation of the behavior. This internal evaluation results in the formation of a behavioral intention (Ajzen and Fishbein 1980; Boden 1973; Ryan 1958). Following such an internal determination to perform a behavior, the individual forms an appraisal of the likelihood that he or she will not be constrained by external factors when attempting to perform the behavior (Warshaw and Davis 1985b). Harrison (1995) points out that the probability of performing a behavior (i.e., behavioral expectation) is a function of the strength of the associated behavioral intention given a choice among a set of competing behaviors. Behavioral expectation, therefore, reflects the strength of the focal behavioral intention over other (competing) behavioral intentions. Thus, in terms of temporal sequencing, behavioral intention necessarily precedes the formation of behavioral expectation.

> *H1: Behavioral intention will positively influence behavioral expectation.*

As noted earlier, system use has been conceptualized in different ways in the literature, with the three most common conceptualizations of use being duration, frequency, and intensity

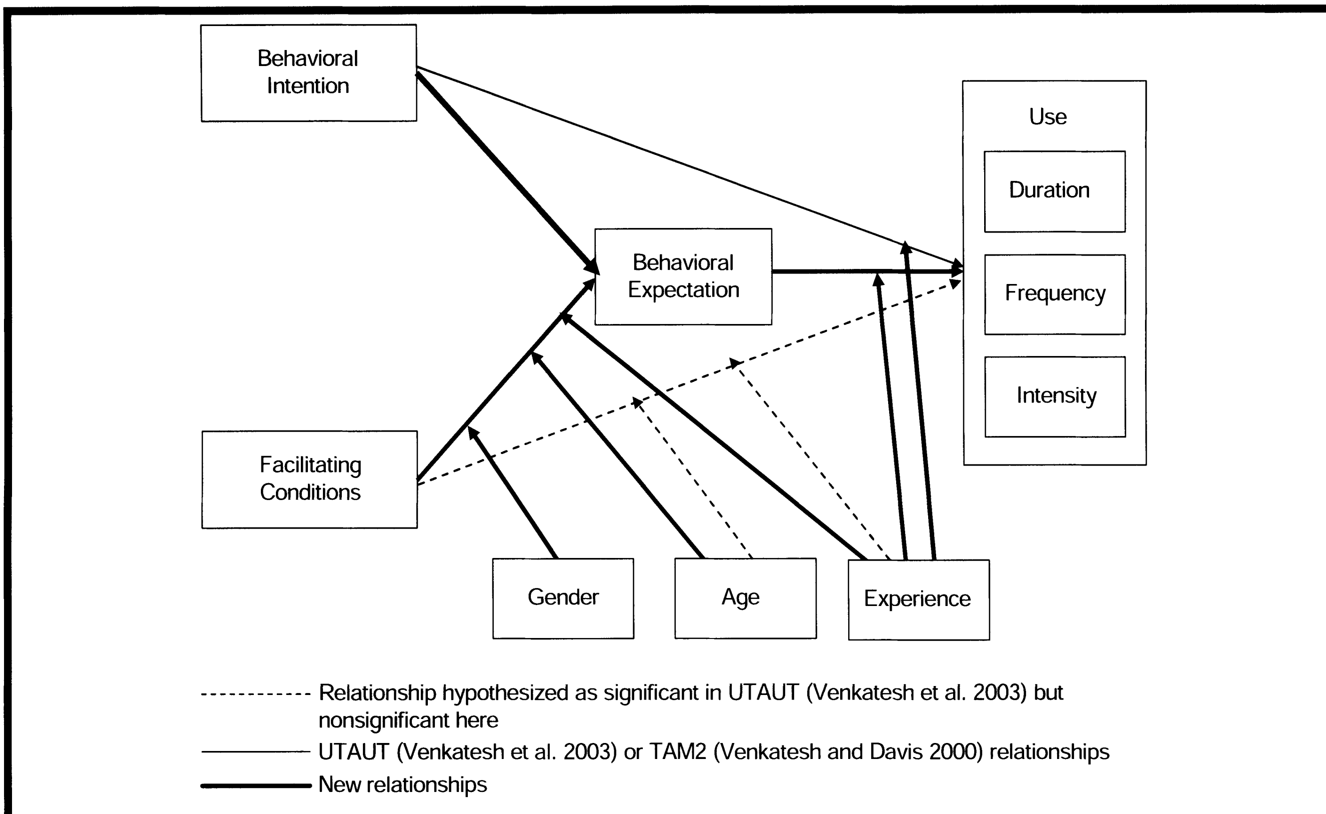

Figure 1. Research Model

(or extent) of use (e.g., Davis et al. 1989; Straub et al. 1995; Taylor and Todd 1995b; Venkatesh and Morris 2000). Although behavioral intention and behavioral expectation are both expected to predict system use, we argue that they do so through different mechanisms. Here, we discuss how these constructs relate to the three conceptualizations of system use: duration, frequency, and intensity. Behavioral intention is expected to be better than behavioral expectation in predicting duration of system use. Duration of use represents the amount of clock time spent using a system. Ancona et al. (2001) characterize clock time as being a linear continuum that is divisible into objective quantifiable units. Duration of use is the accumulation of these quantifiable units. Research suggests that the amount of time spent on an activity is predicted best by internal motivations (e.g., Csikszentmihalyi and LeFevre 1989). Specifically, individuals tend to spend more time on activities that they are internally motivated to perform (Csikszentmihalyi 1975; Csikszentmihalyi and LeFevre 1989; Webster et al. 1993). Empirical evidence suggests that behavioral intention is driven by and reflects various internal motivations (e.g., Agarwal and Karahanna 2000; Venkatesh 2000; Venkatesh et al. 2002). This suggests a positive linear relationship between behavioral intention and duration of use. External factors can also drive duration and such factors are taken into account by behavioral expectation, which will play a role in predicting duration, but to a lesser extent than behavioral intention. For example, duration of use can be influenced by the nature of work-related tasks—a factor reflected in behavioral expectation. This line of reasoning is supported by the direct effect of facilitating conditions, which accounts for external factors, on behavior over and above the effect of behavioral intention. While we anticipate that behavioral expectation will predict duration, we believe it will do so to a lesser extent than that predicted by behavioral intention due to the internally motivated nature of duration.

> *H2a: Behavioral intention will be better than behavioral expectation in predicting duration of system use.*

Behavioral expectation is expected to be better than behavioral intention in predicting both frequency and intensity of use. Employee jobs are characterized by a series of activities designed to achieve specific work-related goals. Ancona et al. (2001) suggest that these activities can be scheduled along a defined temporal continuum, and their frequency can vary depending on the nature of one's work. Thus, the frequency with which a system is used tends to be structured around many of the activities that make up an employee's job. Such work activities are not typically driven by internal motivations, but instead are determined by external needs that relate to the job. Hence, frequency of use is tied to external factors rather than internal factors. An individual's understanding of the nature of the work environment and the likelihood that it necessitates repeated episodes of system use are incorporated into the formation of behavioral expectation. Similarly, intensity of system use is tied to the nature of the activities that make up an employee's job and its demands. For example, highly complex work activities may require greater intensity of use than simple/routine work activities do. Such job-related considerations are better captured by behavioral expectation as it accounts for external factors, including those related to the work environment. Consistent with prior research (e.g., Davis et al. 1989), we expect behavioral intention to predict the frequency and intensity, but to a lesser extent than predicted by behavioral expectation.

> *H2b: Behavioral expectation will be better than behavioral intention in predicting frequency of system use.*

> *H2c: Behavioral expectation will be better than behavioral intention in predicting intensity of system use.*

We expect experience will moderate the effects of behavioral intention and behavioral expectation on system use. As discussed earlier, behavioral expectation is a better predictor of a behavior when (1) the uncertainty associated with the behavior is high and individuals have incomplete information pertinent to the behavior and (2) individuals perceive that they do not have adequate control over the behavior, suggesting the absence of favorable or high facilitating conditions. Increasing experience with a target system reduces uncertainty associated with the system and enhances individuals' sense of control over the system (Venkatesh et al. 2003; Venkatesh et al. 2006). In such a situation, individuals are able to reevaluate their initial behavioral intention and form a more accurate behavioral intention. Thus, behavioral intention will improve as a predictor of behavior as individuals gain experience with the target behavior. In contrast, the influence of behavioral expectation on behavior will decrease with increasing experience. Increasing familiarity with external factors (e.g., environment) related to the behavior means that behavioral intention becomes more comprehensive and reflects one's experiences, thus making behavioral intention more stable and nonprovisional. Behavioral expectation, in such a situation, will only add marginal predictive power above and beyond a well-formed, stable behavioral intention.

> *H3a: The effect of behavioral intention on system use (duration, frequency, and intensity) will be moderated by experience such that with increasing experience with the target system, the effect will become stronger.*

> *H3b: The effect of behavioral expectation on system use (duration, frequency, and intensity) will be moderated by experience such that with increasing experience with the target system, the effect will become weaker.*

Facilitating Conditions

Research in IS (e.g., Taylor and Todd 1995b) and social psychology (e.g., Armitage and Conner 1999) have conceptualized and operationalized facilitating conditions using two or more constructs to represent the internal and external facets separately (see also Sparks et al. 1997; Terry and O'Leary 1995). Internal facets of facilitating conditions operate through the effort expectancy construct, which has a direct influence on behavioral intention (Venkatesh 2000; Venkatesh et al. 2003). Given that the conceptualization and operationalization of facilitating conditions in the unified theory of acceptance and use of technology (UTAUT) emphasizes external facets (e.g., resources), consistent with Venkatesh et al. (2003), we do not hypothesize a direct relationship between facilitating conditions and behavioral intention. Beyond what is specified in UTAUT, we expect the relationship between facilitating conditions and system use to be fully mediated by behavioral expectation.

Recognition of the presence of favorable facilitating conditions (or lack thereof) alone is not expected to directly influence system use. Rather, system use is contingent on the consideration of whether, and to what extent, an individual perceives that facilitating conditions will enable system use in light of other potential behavioral impediments. As discussed earlier, such considerations are incorporated into the formation of behavioral expectation (Warshaw and Davis 1985a). Behavioral expectation is a function of the evaluation of facilitating conditions, captured by the external impediments aspect of facilitating conditions (Warshaw and Davis 1985a). Facilitating conditions can have an influence on behavioral expectation without affecting behavioral intention. For example, no matter how competent (e.g., self-efficacy, knowledge) an individual is in using a system, if the organization does not have adequate resources (e.g., technology infrastructure) to support system use, the individual's behavioral expectation to use that system will be lowered. Although the individual may still have a behavioral intention to use the system, he or she may not have a high behavioral expectation to do so given the lack of necessary resources. Moreover, when employees resist the implementation of a new system, they might be offered new resources (e.g., upgrading their computers). Such an action is likely to have a positive impact on employees' behavioral expectation regarding use of the new system, but may not increase their behavioral intention to use the system. Further, as we discussed earlier, compared to facilitating conditions, behavioral expectation incorporates more comprehensive mechanisms in predicting a target behavior. Therefore, we expect that behavioral expectation will fully mediate the influence of facilitating conditions on system use.

> *H4: The effect of facilitating conditions on use will be fully mediated by behavioral expectation.*

Facilitating conditions are expected to be more important for women than they are for men. Venkatesh et al. (2000) argued that women are more process-oriented. Facilitating conditions, such as availability of external help, support, training, etc., will help women to learn about the process of using the system. Hence, they will place more importance on facilitating conditions in shaping their behavioral expectation regarding system use. Access to resources and assistance are also important facilitating conditions for older users because of the difficulty they experience in performing various work-related tasks (see Morris and Venkatesh 2000). Older individuals place a greater emphasis on the external aspects of perceived behavioral control, a construct similar to facilitating conditions (Morris and Venkatesh 2000). We also expect that with increasing experience, the effect of facilitating conditions on behavioral expectation will be stronger because with increasing experience, individuals become more familiar with the external resources and discover various ways to find support to facilitate their use of the system, thus placing more importance on external factors. We expect the moderating effects of gender, age, and experience to work in tandem as a four-way interaction.

> *H5: The effect of facilitating conditions on behavioral expectation will be moderated by gender, age, and experience, such that the effect will be strongest for women, particularly older women in later stages of experience.*

Method

Our study was conducted in one organization implementing a new system. We collected data at multiple points so as to capture both initial and continued use. The study spanned one year and included data collection every 3 months. In this section, we describe the setting, participants, measurement, and data collection procedure.

Setting and Participants

The participants in the study were employees of a telecommunications firm that was introducing a major new system—a web-based front-end for informational and transactional systems. The system was being introduced in three different business units within the organization. Although the new system was significantly different from the old system, the functionality of the system itself remained closely aligned with the jobs of the employees involved. Employees were allowed to use either the old front-end or the new web front-end. Thus, use of the new system was voluntary. Of the 918 total employees in the organization, 720 participated in the study, with 321 providing usable responses at all 5 points of measurement. Given that the study duration was 1 year and had 5 points of measurement, it was not feasible to have all employees participate throughout the study, although it certainly would have been ideal. However, the response rate was quite high (about 45 percent) despite the duration of the study. Of the 321 participants, 110 were women (34 percent). Average age of the participants was 37.2, with a standard deviation of 9.5. The final sample for the study included employees spanning all levels of the organizational hierarchy. We compared the participants who responded at all measurement points to nonrespondents on the demographic variables used here—namely, gender and age—and found no significant differences.[3]

Measurement

Behavioral intention and facilitating conditions were measured using validated items from UTAUT (Venkatesh et al. 2003). The constructs were measured on a seven-point Likert scale. The measures for behavioral expectation were operationalized following the guidelines of Warshaw and Davis (1985a, 1985b) and Sheppard et al. (1988), and were adapted to fit the technology adoption context. Behavioral expectation was also measured on a seven-point Likert scale.

[3]Among nonrespondents, 35% were women and average age was 39.6 (standard deviation of 10.1).

Table 1. Items Used and Loadings from PLS (N = 321 at Each Time Period)

	Items		T1	T2	T3	T4
Facilitating Conditions (FC)	FC1	I have the resources necessary to use the system.	.70	.72	.74	.73
	FC2	I have the knowledge necessary to use the system.	.68	.75	.73	.80
	FC3	The system is not compatible with other systems I use.	.73	.71	.73	.75
	FC4	A specific person (or group) is available for assistance with system difficulties.	.76	.72	.79	.78
Behavioral Intention (BI)	BI1	I intend to use the system in the next <n> months.	.82	.84	.85	.85
	BI2	I predict I would use the system in the next <n> months.	.85	.85	.88	.88
	BI3	I plan to use the system in the next <n> months.	.90	.91	.89	.82
Behavioral Expectation (BE)	BE1	I expect to use the system in the next <n> months.	.91	.92	.92	.90
	BE2	I will use the system in the next <n> months.	.88	.87	.94	.85
	BE3	I am likely to use the system in the next <n> months.	.87	.82	.81	.84
	BE4	I am going to use the system in the next <n> months.	.84	.84	.86	.83
Use	Duration	On average, how many hours do you use the system each week?	NA			
	Frequency	How often do you use the system?				
	Intensity	How do you consider the extent of your current system use?				
Gender	Circle one: Male Female					
Age	What is your age in years? _____					
Experience	Not directly measured; coded based on point of measurement		1 to 4			

Notes:
1. Each indicator of use is treated separately; all other latent variables are modeled with reflective indicators. Frequency has a 7-point scale ranging from "Don't use at all" to "Use several times each day." Intensity also has a 7-point scale ranging from "Non use" to "Heavy use."
2. The loadings at T1, T2, T3, and T4 respectively are from *separate* measurement model tests.
3. All cross-loadings were below .35.

We measured duration, frequency, and intensity of system use by drawing from measures used in prior research (e.g., Adams et al. 1992; Davis 1989; Davis et al. 1989; Straub et al. 1995; Taylor and Todd, 1995b). Experience was operationalized based on the point of measurement using an ordinal scale. The items are shown in Table 1.

Procedure

The data were collected during and after the implementation of the new system. Training programs were conducted by the organization to educate the employees about the new system. A training company was contracted to work closely with the designers and developers of the new system to develop appropriate training materials for different job types. Immediately post-training, employees rated their behavioral intention and behavioral expectation as it related to use of the new system. Given that we wanted to track responses over time, unique bar codes were printed on each survey to allow responses from different time periods to be matched. Every 3 months for the next 9 months, employees responded to a survey that included questions about (1) duration, frequency, and intensity of system use in the past 3 months, and (2) facilitating conditions, and behavioral intention and behavioral expectation as it related to the next 3 months. A final survey was administered a year after the initial survey to measure behavior in the previous 3 months. Figure 2 presents the study design.

Results

The data were analyzed using the various predictors gathered at a particular point in time predicting use gathered 3 months later. Partial least squares (PLS) was used to analyze the data;

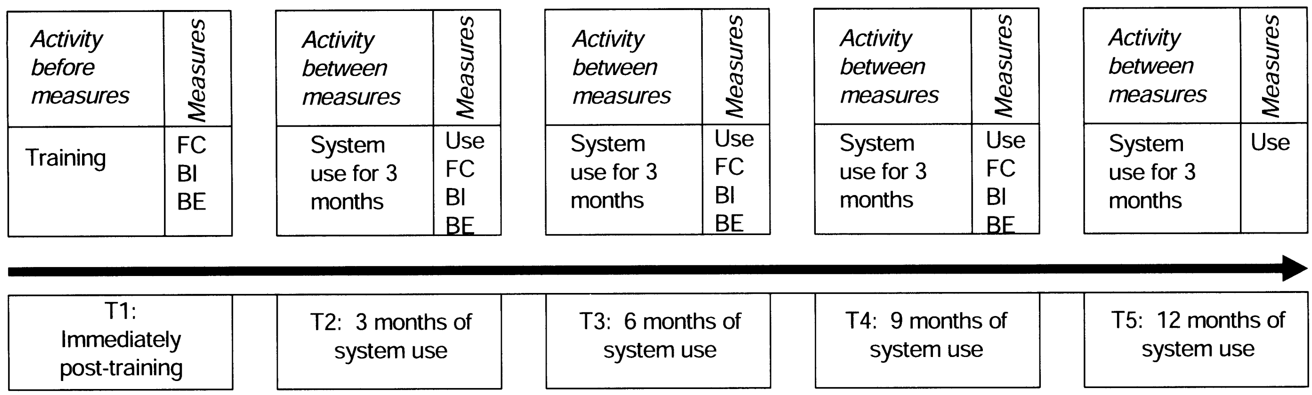

Figure 2. Summary of Study Design with Points of Measurement

the specific software package used was PLS-Graph, version 3, build 1126. We followed the guidelines specified in Chin (1998) and other exemplars in IS research (e.g., Compeau and Higgins 1995a, 1995b). With the exception of system use, all constructs were modeled using reflective indicators. Gender was coded using a dichotomous dummy variable, age was coded as a continuous variable, and experience was coded as an ordinal variable. In order to reduce the potential for multicollinearity, we mean-centered the variables at the indicator level prior to creating the interaction terms (Aiken and West 1991; Chin et al. 2003). We employed a bootstrapping method (500 iterations) that used randomly selected subsamples to test the various PLS models. An examination of the variance inflation factors (VIFs) suggested that multicollinearity was not a major problem in the analyses, with all VIFs being less than 5. While the VIFs of some interaction terms were higher than 1, this is to be expected given the inherent overlap between the main effect terms and interaction terms. Further, mean-centering largely remedies these problems (Aiken and West 1991).

As Table 2 shows, internal consistency reliabilities (ICRs) were greater than .70 for all constructs at all time periods. The square roots of the shared variance between the constructs and their measures were higher than the correlations across constructs, supporting convergent and discriminant validity (Fornell and Larcker 1981). Table 1 shows that with the exception of item FC2 at time 1, all item-loadings were greater than .70, the level that is generally considered acceptable (Fornell and Larcker 1981). Given that the scale for behavioral expectation is new, it is important to demonstrate its empirical distinction from behavioral intention. The inter-item correlation matrix for behavioral intention and behavioral expectation is shown in Table 3. The intra-construct item correlations were significantly higher than the inter-construct item correlations. Inter-item correlation matrices with all variables also (details not shown here due to space constraints) confirmed this pattern related to intra- versus intra-construct item correlations.

Tables 4(a), 4(b), and 4(c) show the detailed model test results at each time period for the dependent variable of system use. Table 5 provides model results at each time period for the dependent variable of behavioral expectation. Also, each table shows the direct effects only model and a model with interactions for each time period. As Tables 4(a), 4(b), and 4(c) show, our research model explained between 32 percent and 65 percent of the variance in the three different measures of system use across the four time periods.

We predicted that behavioral intention would directly influence behavioral expectation. As Table 5 indicates, the coefficient for behavioral intention was significant at all time periods, thus supporting H1. H2a predicted that behavioral intention would be better than behavioral expectation in predicting duration of use. The results of the pooled model with direct effects predicting duration of use, shown in Table 4(a), indicated a positive and significant coefficient for both behavioral intention and behavioral expectation. A Chow's test showed no significant differences between the coefficients at T1 and T2 but the behavioral intention coefficient was stronger than the behavioral expectation coefficient at T3 and T4, thus partially supporting H2a. As the results of the pooled direct effect models in Tables 4(b) and 4(c) show, the coefficients for behavioral intention and behavioral expectation were both positive and significant, with the latter being statistically significantly stronger in predicting both frequency and intensity, thus supporting H2b and H2c.

Table 2. Measurement Model Estimation at Four Time Periods (N = 321 at each time period)

	ICR	Mean	SD	FC	BI	BE	Dur.	Freq.	Int.
FC	.75	3.1	1.21	.71					
BI	.92	4.0	1.07	.23**	.70				
BE	.88	4.3	1.01	.40***	.45***	.75			
Duration	1	11.4	3.75	.34***	.58***	.62***	NA		
Frequency	1	4.1	1.17	.28***	.27***	.61***	.32***	NA	
Intensity	1	4.4	1.19	.20**	.19**	.67***	.34***	.21**	NA
FC	.76	3.7	1.04	.80					
BI	.90	4.4	1.00	.28***	.72				
BE	.92	4.8	1.16	.43***	.40***	.77			
Duration	1	12.7	3.21	.29***	.64***	.67***	NA		
Frequency	1	4.3	.98	.21**	.31***	.64***	.28***	NA	
Intensity	1	4.5	1.17	.20**	.24**	.69***	.35***	.29***	NA
FC	.71	3.9	1.01	.81					
BI	.91	4.4	0.87	.30***	.84				
BE	.93	4.8	1.02	.40***	.41***	.79			
Duration	1	13.8	3.07	.38***	.66***	.69***	NA		
Frequency	1	4.5	1.00	.30***	.30***	.68***	.30***	NA	
Intensity	1	4.6	1.01	.25***	.30***	.69***	.34***	.24**	NA
FC	.74	4.2	0.84	.75					
BI	.87	4.5	0.80	.20**	.79				
BE	.82	4.9	1.00	.24**	.41***	.82			
Duration	1	15.1	2.98	.27***	.62***	.55***	NA		
Frequency	1	4.6	1.01	.19**	.48***	.58***	.33***	NA	
Intensity	1	4.7	1.04	.18**	.59***	.55***	.37***	.32***	NA

Notes:
1. ICR: Internal consistency reliability; Diagonal elements are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs.
2. BI: Behavioral intention; BE: Behavioral expectation; System use in any time period is the use measured at the end of the 3 months after the measurement of the various perceptions.
3. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 3. Inter-item Correlations for Behavioral Intention and Behavioral Expectation

Items	BI1	BI2	BI3	BE1	BE2	BE3
BI1						
BI2	.88***					
BI3	.87***	.90***				
BE1	.40***	.32***	.32***			
BE2	.38***	.31***	.30***	.84***		
BE3	.35***	.34***	.30***	.80***	.84***	
BE4	.32***	.32***	.31***	.80***	.82***	.84***

Notes:
1. Pooled correlations (N = 1284).
2. BI = Behavioral intention; BE = Behavioral expectation.
3. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 4. Structural Model Results

(a) Dependent Variable: Duration of Use

	T1 (N = 321)		T2 (N = 321)		T3 (N = 321)		T4 (N = 321)		Pooled (N = 1,284)	
	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I
R^2 (PLS)	.45	.47	.49	.49	.43	.46	.40	.40	.46	.65
Behavioral intention (BI)	.39***	.37***	.48***	.40***	.44***	.43***	.50***	.47***	.40***	.19**
Facilitating conditions (FC)	.04	.02	.07	.04	.02	.00	.02	.02	.05	.08
Behavioral expectation (BE)	.45***	.44***	.48***	.47***	.30***	.30***	.21**	.20**	.39***	.02
Age (AGE)		.01		.02		.05		.08		.05
Experience (EXP)										.02
FC × AGE		.04		.02		.02		.02		.04
FC × EXP										.02
AGE × EXP										.01
FC × AGE × EXP										.00
BI × EXP										.33***
BE × EXP										-.37***

(b) Dependent Variable: Frequency of Use

	T1 (N = 321)		T2 (N = 321)		T3 (N = 321)		T4 (N = 321)		Pooled (N = 1,284)	
	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I
R^2 (PLS)	.57	.58	.54	.55	.32	.35	.38	.40	.47	.60
Behavioral intention (BI)	.19**	.18**	.20**	.20**	.32***	.33***	.29***	.27***	.30***	.08
Facilitating conditions (FC)	.04	.03	.04	.02	.03	.03	.04	.02	.04	.04
Behavioral expectation (BE)	.65***	.64***	.60***	.57***	.34***	.34***	.39***	.40***	.50***	.17**
Age (AGE)		.01		.02		.02		.02		.04
Experience (EXP)										.02
FC × AGE		.02		.05		.01		.01		.01
FC × EXP										.00
AGE × EXP										.04
FC × AGE × EXP										.05
BI × EXP										.25***
BE × EXP										-.32***

(c) Dependent Variable: Intensity of Use

	T1 (N = 321)		T2 (N = 321)		T3 (N = 321)		T4 (N = 321)		Pooled (N = 1,284)	
	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I
R^2 (PLS)	.59	.60	.52	.54	.32	.35	.40	.41	.46	.60
Behavioral intention (BI)	.19**	.18**	.13*	.12*	.30***	.28***	.33***	.32***	.28***	.09
Facilitating conditions (FC)	.05	.04	.02	.02	.02	.03	.04	.02	.02	.02
Behavioral expectation (BE)	.69***	.65***	.60***	.57***	.38***	.38***	.41***	.37***	.51***	.20**
Age (AGE)		.04		.02		.04		.02		.01
Experience (EXP)										.05
FC × AGE		.04		.00		.08		.01		.02
FC × EXP										.07
AGE × EXP										.02
FC × AGE × EXP										.04
BI × EXP										.20**
BE × EXP										-.33***

Notes: 1. D ONLY: Direct effects only; D + I: Direct and interaction effects.
2. Shaded areas are not applicable for the specific column.
3. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 5. Dependent Variable: Behavioral Expectation

	T1 (N = 321)		T2 (N = 321)		T3 (N = 321)		T4 (N = 321)		Pooled (N = 1,284)	
	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I	D Only	D + I
R^2 (PLS)	.28	.35	.28	.38	.27	.39	.25	.40	.25	.46
Behavioral intention (BI)	.38***	.35***	.39***	.37***	.34***	.30***	.35***	.30***	.30***	.32***
Facilitating conditions (FC)	.34***	.08	.31***	.18**	.35***	.16*	.22**	.15*	.35***	.15*
Gender (GDR)	.04	.07	.02	.05	.02	.02	.04	.04	.01	.04
Age (AGE)	.02	.05	.07	.02	.05	.05	.02	.02	.07	.02
Experience (EXP)										.02
GDR × AGE		.03		.02		.09		.04		.03
FC × GDR		.02		.03		.04		.05		.08
FC × AGE		.02		.02		.02		.02		.09
FC × EXP										.05
GDR × EXP										.03
AGE × EXP										.05
FC × GDR × AGE		.19**		.22**		.32***		.35***		.02
FC × GDR × EXP										.05
FC × AGE × EXP										.02
GDR × AGE × EXP										.01
FC × GDR × AGE × EXP										.32***

Notes: 1. D ONLY: Direct effects only; D + I: Direct and interaction effects.
2. Shaded areas are not applicable for the specific column.
3. *p < 0.05, **p < 0.01, ***p < 0.001.

In H3a, we posited that experience would strengthen the relationship between behavioral intention and all three conceptualizations of system use. As the results of the pooled interaction models indicate, the BI × EXP interaction term was positive and significant in influencing duration, frequency, and intensity. Hence, H3a is supported. H3b posited that experience would weaken the influence of behavioral expectation on all three conceptualizations of system use. Tables 4(a), 4(b), and 4(c) indicate that the BE × EXP interaction term was negative and significant for all three conceptualizations of system use, thus supporting H3b. In order to assess the magnitude of the moderating effects, we calculated Cohen's f^2 for the hypothesized interactions, following Chin et al. (2003).[4] Cohen's f^2 represents the extent to which a phenomenon is present in a given population sample.[5] The f^2-statistic for duration, frequency, and intensity was 0.35 (large effect size), 0.25 (medium/large effect size), and 0.26 (medium/large effect size) respectively, thus indicating that the interaction effects are strong in our analysis.

H4 predicted that the relationship between facilitating conditions and system use would be fully mediated by behavioral expectation. Tables 4(a), 4(b), and 4(c) show that in the presence of behavioral expectation, the relationship between facilitating conditions and use becomes nonsignificant. However, facilitating conditions had a significant direct effect on behavioral expectation (see Table 5) and behavioral expectation had a significant direct effect on use (see Table 4). Therefore, the effect of facilitating conditions on system use was fully mediated by behavioral expectation, supporting H4. Finally, H5 suggested that the effect of facilitating conditions on behavioral expectation would be moderated by gender, age, and experience. Table 5 shows that the four-way interac-

[4]Cohen's f^2 is calculated as:

$$\frac{R^2\text{ (Interaction Model)} - R^2\text{ (Main Effects Model)}}{1 - R^2\text{ (Main Effects Model)}}$$

[5]For Cohen's f^2, values of 0.02, 0.15, and 0.35 are considered to be small, medium, and large effect sizes respectively (Cohen 1988).

tion term was significant. Specifically, the effect was stronger for older women with increasing experience.

Discussion

In this paper, we introduced ***behavioral expectation*** into the nomological network related to system use, thus expanding our understanding of the phenomenon of individual-level technology adoption and use. We discussed how behavioral expectation addresses some known limitations of behavioral intention and facilitating conditions in predicting behavior in general. Further, we provided arguments linking behavioral intention and behavioral expectation to three different conceptualizations of system use: duration, frequency, and intensity. Given differences in the cognitions underlying behavioral intention and behavioral expectation, we theorized and found that behavioral intention related more strongly to duration of use and behavioral expectation related more strongly to frequency and intensity of use. This is one of the first studies in the technology adoption literature that explores the limitations of behavioral intention and facilitating conditions and proposes behavioral expectation as an additional predictor of system use. This study is also one of the first to theorize the mechanisms linking behavioral intention and behavioral expectation to different conceptualizations of system use. The results from our longitudinal study provided strong support for our model explaining 65 percent, 60 percent, and 60 percent of the variance in duration, frequency, and intensity of system use respectively, thus explaining substantially more variance compared to prior research. Table 6 presents a summary of our findings.

Theoretical Contributions

Given the empirical support for our model, this research contributes to the literature in several important ways. First, understanding the three conceptualizations of system use is a step in the direction advocated by Jasperson et al. (2005), who called for richer conceptualizations of system use (see also Burton-Jones and Straub 2006). Further, this work goes beyond simply treating system use as a ***measure*** of the relevant behavior consequent to technology adoption to treating it as a theoretical construct. We not only identified predictors of various conceptualizations of system use, but also identified the mechanisms by which such effects occurred. Further, the clearer and deeper understanding of system use garnered through this research is an important step toward helping us focus on post-adoptive system use and other downstream consequences (see Burton-Jones and Straub 2006; Jasperson et al. 2005; Venkatesh et al. 2003; Venkatesh et al. 2006). Some examples of important directions for future research include studying the relationship between various conceptualizations of system use and important outcomes, such as performance and satisfaction in the contexts of the system, the task, and the job. The further moderation of such relationships (e.g., system use to performance) by contingencies, such as job type, task complexity, and job demands, must be examined.

A second contribution of this study is the introduction of behavioral expectation as a means of addressing the limitations of the intentionality framework within which much prior technology adoption research has been conducted. We found empirical evidence that behavioral expectation mediated the relationship between behavioral intention and use. Further, the introduction of behavioral expectation significantly improved the variance explained in system use relative to models that use behavioral intention and/or facilitating conditions as the only predictors of system use (e.g., TAM, UTAUT). The reliance on behavioral intention as a predictor of behavior underlies much socio-behavioral research, especially studies in which behavior measurement is/was not feasible due to practical constraints. Our work suggests that a more careful investigation of behavioral intention as an appropriate variable for behaviors in general is necessary depending on the conceptualization and measurement of behavior. Although the importance of the role of behavioral expectation in predicting behavior was raised nearly two decades ago in the psychology literature (e.g., Warshaw and Davis 1985a, 1985b), the use of behavioral expectation as a predictor has been limited (see Sheppard et al. 1988). This construct is under-researched to the point that it has not even been included in recent reviews (Albarracin et al. 2001). The current work thus serves as a call to carefully investigate the role of behavioral expectation in IS, organizational behavior, and psychology research. It is important to recognize that there are other important predictors of behavior in general and system use in particular that need to be integrated into the model presented and tested. For example, as behaviors become routinized, it may very well be that habit will play a more influential role rather than either behavioral intention or behavioral expectation. The findings here and in our other recent work (Venkatesh et al. 2006) suggest that volitionality and time are key considerations in individual performance of a behavior. Beyond what we have found in our work, there is emerging evidence supporting the potential role for habit in this context (Kim and Malhotra 2005; Kim et al. 2005; Limayem and Hirt 2003; Limayem et al. 2007; Venkatesh et al. 2000). The interplay among behavioral intention, facilitating conditions, behavioral expectation, and habit is also a topic worthy of future study. Thus, future research should continue to explore contingencies and drivers of system use.

Table 6. Summary of Findings

Hypothesis Number	Dependent Variables	Independent Variables	Moderators	Result	Explanation
H1	Behavioral expectation	Behavioral intention	None	Supported	BI had a positive influence on BE
H2a	Duration of use	Behavioral intention, behavioral expectation	None	Partially supported	BI was a better predictor of duration of use at T3 and T4
H2b	Frequency of use	Behavioral intention, behavioral expectation	None	Supported	BE was a better predictor of frequency of use
H2c	Intensity of use	Behavioral intention, behavioral expectation	None	Supported	BE was a better predictor of intensity of use
H3a	Duration, frequency, and intensity of use	Behavioral intention	Experience	Supported	Effect stronger with increasing experience
H3b	Duration, frequency, and intensity of use	Behavioral expectation	Experience	Supported	Effect weaker with increasing experience
H4	Use	Facilitating conditions, behavioral expectation		Supported	BE fully mediated the effect.
H5	BE	Facilitating conditions	Gender, Age, Experience	Supported	Effect stronger for women, older workers with increasing experience

Third, this work extends prior research that has studied the role of experience (e.g., Taylor and Todd 1995a). The dynamic role of experience as a moderator of key downstream relationships, such as behavioral intention and behavioral expectation to system use, had not been previously studied. By incorporating experience in the model, we have identified the importance of behavioral expectation and the underlying external factors as critical determinants of frequency and intensity of system use, especially in the early stages of experience. In addition to being an important finding, this suggests the need to identify the relevant set of external factors that will influence behavioral expectation, especially given that UTAUT and other adoption models to date have primarily focused on technology-centric drivers of behavior. In this context, the role of social influences, especially in the form of social networks of various forms ranging from friendship to hindrance, should be studied as they may play a critical role in determining behavior directly or by operating through behavioral expectation.

Finally, our model could potentially be a more general model of behavior that incorporates behavioral expectation. Our results suggest that other intention based models of behavior, such as the theory of planned behavior (Ajzen 1991), perhaps the most widely used model of individual behavior, should incorporate behavioral expectation as a predictor of behavior in addition to using behavioral intention and facilitating conditions as predictors. The validity of this is, to some extent, established in prior research—for example, Warshaw and Davis (1985b) studied students' behavioral intention and behavioral expectation to finish their homework over the weekend, and found a nonsignificant correlation between behavioral intention and actual behavior (finishing homework over the weekend) and a significant positive correlation between behavioral expectation and actual behavior. Much like IS research, psychology research has typically used behavior as a criterion variable and used a convenient measure of behavior without much consideration of the underlying conceptualization of the behavior of interest. In many cases, the general focus of the theory of planned behavior leads to the domain of study (e.g., smoking, weight loss, turnover) being just of methodological interest in which some broader theoretical ideas related to human behavior and decision making are investigated. As noted earlier, this leads to the focal behavior being ***merely*** a measurement issue. By demonstrating the importance of conceptualizing richly about behavior in the ***context*** of information systems, we are responding to recent calls to theorize richly about the context (see Johns 2006) and imploring researchers in psychology and organizational behavior to also think deeply about contextual aspects in conceptualizing and measuring behaviors rather than treating them generically.

Implications for Research

Our findings have important implications for future technology adoption research. When the goal of research is to describe the determinants of system use, it is clear that measuring actual objective use is optimal. If, however, the goal of research is to predict system use, then it is imperative to employ the most reliable predictors of behavior. In general, if surrogates for behavior must be used, it is essential to choose the most appropriate surrogate (Dalton et al. 1999). It is important to note, however, that while both behavioral intention and behavioral expectation performed comparably in predicting system use at times 3 and 4, when examined separately, in a combined model, behavioral intention was a stronger predictor at time 4. This indicates that behavioral intention may be more appropriate once a system has become infused in an organization. Thus, examinations of behavioral intention to continue using a system may be appropriate after users have gained significant experience. This is, however, tempered by the conclusions of prior research that suggests behavioral intention is not significant in situations of routinized behavior (Oullette and Wood 1998; Venkatesh et al. 2000). Regardless, our research suggests that behavioral expectation is a significantly better predictor of ***initial*** IS adoption and use.

One potential implication of the findings related to system use is that the weak relationship between behavioral intention and both frequency and intensity combined with the strong relationship between behavioral intention and duration could be a possible explanation for the findings of Straub et al. (1995), who found that while TAM constructs predicted self-reported use, they did not predict actual use. However, being that Straub et al. used measures of system use that most closely related to frequency and intensity, it may very well be that the findings are the result of the conceptualizations of system use employed in their work rather than any potential limitations related to TAM constructs. This further demonstrates the importance of using clear, consistent conceptualizations of system use in IS research, a point that is, in fact, emphasized in Straub's more recent work (i.e., Burton-Jones and Straub 2006).

Behavioral expectation is highly predictive of future system use because it incorporates control beliefs and other factors that ultimately influence behavior (Warshaw and Davis 1985b). Our results show that the presence of behavioral expectation in the model diminished the effect of facilitating conditions on use (see Table 4 and Table 5, Time 1). Prior technology adoption research has supported the significance of control beliefs (i.e., facilitating conditions) in conjunction with intention as determinants of system use (e.g., Taylor and Todd 1995b). The results of this work demonstrate that when behavioral expectation is included, the facilitating conditions construct is no longer a significant determinant of system use. An important direction for future research will be to examine the role of other determinants in predicting behavioral expectation. Given the importance of product experience, we might expect factors such as trialability, visibility, and communicability from innovation diffusion theory (e.g., Moore and Benbasat 1991; Rogers 1995) to be important when behavioral expectation is the object of study, as each of these constructs conveys an experiential aspect of the system in question.

In our related work (Venkatesh et al. 2006), we examined the role of behavioral expectation in episodic and repeat behaviors and the role of ***time*** conceptualized in different ways. Together with this paper, a richer understanding of the prediction of behavior has emerged. While these two papers provide empirical support for the need to broaden the predictors of behavior and moderators of relationships, the findings at this point are limited to the IS adoption context. As mentioned earlier, future work should examine the generalizability of these findings through a careful review and empirical examination of research in other behavioral domains, such as organizational behavior and psychology, with particular attention to the context (Johns 2006). Specifically, the temporal patterns and their generalizability to other contexts should be examined in future work.

Researchers should develop models predicting behavioral expectation in various domains. Such research must consider beliefs currently used to predict behavioral intention and employ possible new beliefs unique to the prediction of behavioral expectation. Understanding the underlying belief structure for behavioral expectation (versus behavioral intention) will enable researchers and managers to design interventions that will promote system use. We found behavioral intention and facilitating conditions to be important predictors of behavioral expectation. However, identification of other key predictors is necessary. To date, almost no research has examined the determinants of behavioral expectation. A good potential starting point for IS researchers would be to integrate behavioral expectation into existing models of technology adoption. For example, integrating behavioral expectation into TAM or UTAUT would advance our understanding of the cognitions underlying the construct.

Finally, while this research focused on commonly used conceptualizations of system use—duration, frequency, and intensity—it is necessary for future research to examine the relationship between behavioral expectation, behavioral intention, and other conceptualizations of use, such as cognitive absorption and deep structure use (Burton-Jones and Straub 2006). Understanding the nature of the relationship between behavioral expectation, behavioral intention, and these other conceptualizations of system use will provide theoretical and practical value. For example, an examination of the relationship between behavioral expectation, behavioral intention, and deep structure use would enable researchers to understand why some employees use a broader array of system features than other employees. Important insights could be gained by knowing whether interventions should be designed to target employees' behavioral expectation or behavioral intention, depending on the specific type of use that is desired.

Strengths and Limitations

This study has several strengths that enhance the validity of the results. One strength of this work is that we collected data at multiple points in time in a naturally occurring field setting. This design aided our understanding of how the theorized relationships unfolded over time. Additionally, such a research design minimized the threats of common method bias, which is a significant concern in cross-sectional studies (Podsakoff et al. 2003; Burton-Jones and Straub 2006). The predictors of system use were measured at different times from when the ultimate dependent variable (i.e., system use) was measured. This temporal separation is important to limit confounding and spurious effects. Finally, multiple measures of system use were used that also reduce the threats of common method bias and enhance construct validity. We mentioned that behavioral intention would not accurately predict behavior when there is uncertainty or when unforeseen events occur between behavioral intention formation and behavioral performance. However, our study did not measure uncertainty regarding the use of the system. Finally, in this study, we did not measure actual use of the system. Prior research has suggested some limitations of self-reported use (e.g., Straub et al. 1995). Therefore, another important research direction will be to apply our research model in predicting actual use of a system.

Implications for Practice

Our work has important implications for practitioners as well. One of the challenging tasks that IT managers face today is how to enhance system use. As we noted at the outset, despite huge investments in IT in recent years, there is a concern that the implemented systems are underutilized and that users restrict themselves only to using the basic functionalities of the systems (Jasperson et al. 2005). In this situation, it is important for managers to understand and predict employees' system use behaviors. While much technology adoption research provides a rich understanding of behavioral intention, the current work enhances our ability to understand and predict system use by incorporating behavioral expectation in the nomological network of technology adoption determinants. In addition to providing a more accurate prediction of use relative to prior research, the current work makes a contribution to practice in other important ways by helping managers identify potential design interventions: managers can consider interventions to positively influence individuals' behavioral expectation regarding system use or develop interventions designed to reduce the uncertainty associated with system use and, thus, enhance behavioral expectation. Prior research and practical applications on self-fulfilling prophecies and regulatory self-control could play a relevant role here to help managers further leverage the strong role of behavioral expectation. Often heightened uncertainty and the associated lowering of behavioral expectation have the potential for an individual to believe he or she will not be able to perform the behavior and, consequently, to adjust their effort and self-control in a downward direction. Such adjustments will lead to a self-fulfilling prophecy of lower system use.

Keeping in mind the primary practical objective of the research stream of individual-level technology adoption (i.e., predicting the adoption and use of *new* systems), this work raises potential concerns about behavioral intention being the most appropriate dependent variable. Behavioral expectation is less susceptible than behavioral intention to the uncertainty associated with future behavior and, thus, should serve as a better proxy for system use in technology adoption studies. The greatest organizational benefits of predicting system use come when the determinants of system use are assessed well in advance of the physical introduction of any new system. In the pre-implementation, rather than post-implementation, stages, it is easier and more cost effective for designers to make changes to the system. In fact, designers would like to identify and rectify these issues earlier, rather than later, in the process (Davis 1989). Thus, in technology adoption research, it is important that the antecedents of system use are able to account for the time lag between belief formation and actual system use, reinforcing the importance of behavioral expectation.

One approach to enhancing system use is to reduce the impact of behavioral expectation on system use. One way to do this is to reduce the uncertainty associated with a new system. From a managerial perspective, this could mean increasing the type and amount of training sessions, providing demonstrations of the new system, providing information about the technology, and organizational support and resources related to the system, and allowing employees to have additional hands-on opportunities to use the system prior to implementation. These activities would not only serve to increase experience but also reduce uncertainty. One additional approach to increasing the use of a new system would be to hire people with experience using the system being implemented. Given that experience is an important moderator of the behavioral expectation-use and behavioral intention-use relationships, this could have a positive effect on system use by increasing the overall experience level in the organization and reducing the uncertainty associated with the system. Such experienced users could serve as confederates and/or aid in providing the informal support that in turn can positively influence system use.

Researchers have frequently suggested that maximal system use is important and it is, in fact, an important assumption underlying IS research attempting to help practice (see Agarwal 2000; Venkatesh et al. 2003). Other research has noted that system use is the critical link between IT investments and performance (e.g., Devaraj and Kohli 2003). If the findings in this work were to be related to the findings of other recent work (e.g., Burton-Jones and Straub 2006), it is clear that the drivers of different types alternative predictor are different and not all types of system use lead to performance benefits. Thus, managers should exercise caution in drawing conclusions about productivity based on certain types of system use as high levels of all types of system use will not necessarily be beneficial. Such misconceptions could be underlying conclusions related to the productivity paradox which suggests that greater system use does not lead to greater performance. It is thus important for managers to understand the specific types of system use that are most pertinent in the context of different types of systems and, consequently, relate them to the most meaningful predictors of the type of system use of interest. Although, as noted earlier, much further research is necessary before drawing definitive conclusions related to the ***beliefs → behavioral intention → behavioral expectation → type of system use*** causal chain, there is enough evidence in the current work and other recent research to suggest that behavioral expectation and the type of system use should be taken into account to help better manage system implementations.

Conclusions

We critically examined the validity of behavioral intention and facilitating conditions as predictors of three conceptualizations of system use: duration, frequency, and intensity. A number of concerns were discussed regarding the use of behavioral intention and facilitating conditions as predictors of the three conceptualizations of system use. Behavioral expectation was introduced as an alternative predictor of system use. The mechanisms through which these three predictors influence the three conceptualizations of system use were theorized and one temporal factor—experience—was identified as a contingency affecting the predictive validity of these two determinants of system use. The results provided support for the proposed model and highlight the importance of behavioral expectation as a key construct in individual-level technology adoption and use.

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