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Role of time in self-prediction of behavior

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Abstract

This paper examines three specific manifestations of time—anticipation (proximal vs. distal), prior experience with the behavior, and frequency (episodic vs. repeat)—as key contingencies affecting the predictive validity of behavioral intention, perceived behavioral control, and behavioral expectation in predicting behavior. These three temporal contingencies are examined in two longitudinal field studies: (1) study 1—a 6-month study of personal computer (PC) purchase behavior among 861 households and (2) study 2—a 12-month study among 321 employees in the context of a new technology implementation in an organization. In study 1, where the episodic behavior of PC purchase was examined, we found that increasing anticipation (i.e., more distal) weakened the relationship between behavioral intention and behavior and strengthened the relationship between behavioral expectation and behavior. In contrast, increasing experience strengthened the relationship between behavioral intention and behavior and weakened the relationship between behavioral expectation and behavior. In study 2, where the repeat behavior of technology use was examined, we found two significant 3-way interactions: (1) the relationship between behavioral intention and behavior was strongest when anticipation was low (i.e., proximal) and experience was high and (2) the relationship between behavioral expectation and behavior was strongest when anticipation was high (i.e., distal) and experience was low.

For decades, the behavioral intention construct has been employed in organization behavior, marketing, psychology, and other fields of research to predict behavior. Behavioral intention has been used to predict many behaviors in organizations, including whistle-blowing (Somers & Casal, 1994), being absent (Johns, 1994), transferring (Brett & Reilly, 1988), mentoring (Ragins & Scandura, 1994), seeking feedback (Levy, Albright, Cawley, & Williams, 1995), and voluntary turnover (for meta analyses, see Hom et al., 1992; Tett & Meyer, 1993). Similarly, in household contexts, behavioral intention has been used to predict purchase and consumption behavior (Armstrong & Overton, 1970; Kalawani & Silk, 1982; Kaynama & Smith, 1994; Morrison, 1979; Venkatesh & Brown, 2001). Behavioral intention is often studied in conjunction with perceived behavioral control (see Ajzen, 1991; Albarracin, Johnson, Fishbein, & Muellerleile, 2001). Behavioral intention has known limitations, such as the inability to account for the influence of non-volitional factors on behavior, that are remedied by perceived behavioral control (Ajzen, 1991). However, perceived behavioral control also has some known limitations, such as inaccuracy in the face of uncertainty regarding behavior (Sheeran, Trafimow, & Armitage, 2003). Therefore, finding constructs and contingencies that would help further our ability to predict individual behavior can have far-reaching scientific and practical implications.

Drawing on prior research (e.g., Davis & Warshaw, 1992; Warshaw & Davis, 1985a), we present behavioral expectation as a predictor of behavior that can remedy limitations of behavioral intention and perceived behavioral control. Little research has examined when and why behavioral expectation will be better than behavioral

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intention and perceived behavioral control in predicting behavior. To address this issue, we examine *time* as an important element that influences the predictive validity of these constructs. There have been several calls for the integration of time into theory and theory building (e.g., Bluedorn & Denhardt, 1988; George & Jones, 2000). The few studies that have explicitly incorporated time into the theorizing provide support for the critical role of temporality in understanding organizational phenomena (e.g., Ancona, Goodman, Lawrence, & Tushman, 2001; Harrison, Price, & Bell, 1998; Labianca, Moon, & Watt, 2005; Poole & Van de Ven, 1989). In particular, temporal considerations can significantly add to our understanding of behaviors distributed over time. Thus, in this research, we adopt a temporal lens to better understand the underlying differences between behavioral intention and perceived behavioral control, and behavioral expectation in their ability to predict behavior. In addition, adopting a temporal lens will give us a better understanding of the behavioral expectation construct which, compared to behavioral intention and perceived behavioral control, has received much less attention in the literature. Through a review of the extant literature, we explain *why* and *under what temporal conditions* behavioral expectation will be better than behavioral intention and perceived behavioral control in predicting behavior. The specific temporal conditions expected to influence the relative predictive validity of these constructs are: (a) the anticipation, or distal vs. proximal nature, of the target behavior; (b) the amount of experience with the target behavior; (c) the frequency with which the behavior is performed.

Background

Behavioral intention and perceived behavioral control

Behavioral intention (BI) represents an individual's consciously formulated plan to perform a specific behavior, e.g., BI to exercise (Ajzen, 1991). The concept of BI is rooted in research on motivation that states most human behavior is initiated by an intention or a goal (Ryan, 1958). As Boden (1973) points out, BI draws heavily upon the individual's general belief system that represents the internalized structure of his or her external world. The internal deliberations serve as the driving force behind the formation of BI (Boden, 1973). However, while BI is necessary, it is not a sufficient condition for the execution of behavior (Ajzen, 1985; Ryan, 1958). BI is limited in its ability to predict behaviors that are not completely volitional. To address this limitation, perceived behavioral control has been incorporated in the widely employed theory of planned behavior (Ajzen, 1991) as a construct that incorporates the influence of non-volitional factors and predicts behavior.

Perceived behavioral control (PBC) is defined as "people's perception of the ease or difficulty of performing the behavior of interest" (Ajzen, 1991, p. 183; see also Ajzen, 1985). PBC is somewhat aligned with Bandura's (1977) self-efficacy. However, self-efficacy is reflective only of an individual's assessment of his or her own ability to perform a behavior and does not account for situations when a behavior is not under an actor's complete volitional control; PBC does account for such situations (Ajzen, 2002). PBC serves as a proxy for actual control and is thus limited by the extent to which an individual's perception of control accurately reflects reality. As Ajzen notes, "when the behavior/situation affords a person's complete control over behavioral performance, intentions alone should be sufficient to predict behavior, as specified in the theory of reasoned action" (1991, p. 185). When the requisite conditions of volitional control are absent or low, BI, by itself, becomes less predictive of behavior and PBC becomes an important predictor of behavior. Although BI and PBC are strong predictors of behavior, they are limited by the potential for BI to change over time, particularly in situations where BI is formed well in advance of the time at which the target behavior would need to be performed. Behavioral expectation has been proposed as a construct that accounts for such considerations (Warshaw & Davis, 1984).

Behavioral expectation

Behavioral expectation (BE) 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 & Davis, 1984, p. 111). The behavioral determinants that comprise BE are: BI, beliefs, abilities, PBC, habits, and lack of volition (Warshaw & Davis, 1984). Volitional behavioral determinants, such as BI, provide the motivational drivers on which BE builds its prediction. Non-volitional behavioral determinants, such as the availability of facilitating conditions, add to the estimation of the probability of performing the behavior. The cognitive appraisal on which BE is based involves an evaluation of the motivational drivers and environmental facilitators/inhibitors of behavior and how they will influence the probability of behavioral performance. Thus, the formation of BE is based not only on the cognitive appraisal of volitional and non-volitional behavioral determinants, but also on the anticipated changes in these determinants (Warshaw & Davis, 1984, 1985a; Warshaw, Sheppard, & Hartwick, 1983).

BE's incorporation of factors external to BI, including limitations due to environmental constraints, may suggest close ties to PBC. However, we underscore that

BE is a broader construct, as evidenced in a meta-analysis of the BI–behavior relationship (Sheppard, Hartwick, & Warshaw, 1988). Sheppard et al. (1988) found that measures of BI and BE shared similar predictive power for proximal volitional behaviors, but BE was significantly more powerful for predicting goals, which are distal behaviors. In sum, while BI represents conscious behavioral commitment (Fishbein & Ajzen, 1975), BE includes an individual's estimation of the probability that he or she will perform the behavior (Warshaw & Davis, 1985a).

Theory development

Time has been identified as an important element in understanding organizational behavior (e.g., Ancona, Okhuysen, & Perlow, 2001; Bluedorn & Denhardt, 1988; George & Jones, 2000; Harrison et al., 1998; Poole & Van de Ven, 1989). As noted earlier, the current research focuses on three aspects of time: anticipation of, experience with, and frequency of performing a behavior. Anticipation refers to the temporal distance—proximal vs. distal—between the present time and the time of performance of a target behavior. Experience refers to the extent to which a behavior has been performed in the past. Frequency refers to the repetitive nature, or rhythm, with which a behavior has been and/or will be performed. These various manifestations of time are expected to have implications for the relative predictive validity of behavioral intention, perceived behavioral control, and behavioral expectation. We now develop the theoretical rationale for these relationships.

Time as the future: Anticipation of behavior

BI is highly predictive of behavior when the action is taken shortly after the BI has been formed (for meta-analyses, see Albarracin et al., 2001; Armitage & Conner, 2001; Godin & Kok, 1996; Randall & Wolff, 1994; Sheppard et al., 1988). However, as individuals project their performance of behavior farther into the future, i.e., more distal, the predictive validity of BI is expected to decrease. Two reasons underlie this argument. First, as the time between BI formation and behavior increases, there is greater potential for BI to change and thus be less predictive of behavior (Ajzen & Fishbein, 1974; Sutton, 1998).[1] For instance, Ajzen and Fishbein (1974) suggest that new information may change an individual's beliefs, thereby influencing BI and consequently, whether or not the individual performs the behavior. Therefore, Ajzen and Fishbein (1980) specifically restrict BI as a predictor of behavior stating that ''the longer the time interval, the less accurate the prediction of behavior from intention'' (p. 47). Second, the farther into the future that individuals project their performance of a behavior, the less information they have about the potential environmental and motivational states needed for the behavior. Recognition of this lack of information can trigger individuals to make their BI provisional. Provisional BI reflects uncertainty about the future (Sheeran & Orbell, 1998; Sutton, 1998). Bassili (1993) found that certainty about one's BI contributed significantly to the accuracy of predicting voting behavior. In the context of Bassili's (1993) study, certainty was an indication of whether or not respondents' BI toward voting was final. In other words, certainty represented the strength of BI. Voters with greater certainty were found to follow through with their BI (Bassili, 1993). Greater certainty is, therefore, associated with less provisionality. Thus, temporally, the *closer* individuals are to the target behavior—i.e., behavior performance is proximal—the *less* likely they are to provide a provisional BI (Sutton, 1998). These arguments suggest that BI may have limited ability to predict distal behaviors because individuals are more likely to express a provisional BI.

In contrast to BI, the predictive validity of BE is expected to increase as behavior becomes temporally distal. Our earlier definition of BE emphasized the fact that it involves the subjective estimation of the probability of performing a behavior (Warshaw & Davis, 1985a). Implicit in this self-prediction is a consideration of information (or lack thereof) pertaining to the behavior. As we noted earlier, the farther into the future that individuals project their behavior, the less information they have about the circumstances surrounding the behavior and the greater the uncertainty. This lack of information and increased uncertainty trigger an individual to consider a greater variety of potential impediments to performing a behavior than would otherwise be the case. Arguably, individuals with more information and greater certainty about a behavior are likely to focus on using that information in their formation of BE and will place less emphasis on considering potential impediments to behavior. Consumers' use of brand information to make summary judgments about product quality supports this notion (Wright, 1975; Zeithaml, 1988). Consequently, the incorporation of more potential impediments to behavior performance increases the accuracy of BE. These arguments suggest that the predictive validity of BE is best when behavior is temporally distal.

To illustrate, Warshaw and Davis (1985b) asked participants (students) about their BI and BE to finish all their unfinished schoolwork during the weekend. The following week, the same students responded to a

[1] Sutton (1998) identifies additional factors that contribute to the poor prediction of intention. However, these other factors are of a methodological nature, e.g., violation of the principle of compatibility, violation of scale correspondence, and restriction of range in intention or behavior.

questionnaire asking if they had performed the behavior over the weekend. The results indicated a non-significant correlation between BI and actual behavior ($r = .17$) while BE was significantly correlated with actual behavior ($r = .36$, $p < .05$). Arguably, students' BEs regarding finishing school work during the weekend would have included the probability that interruptions, such as the desire to watch a movie or having friends visit, would occur. According to Warshaw and Davis (1985a), BE takes such estimated probabilities into account. Based on the arguments above, BE could be more comprehensive in reflecting constraints and thus a better and more accurate proxy for the true impediments to behavior.

Hypothesis 1a. Anticipation (proximal/distal) will moderate the relationship between BI and behavior such that the relationship will become weaker as behavior becomes distal.

Hypothesis 1b. Anticipation (proximal/distal) will moderate the relationship between BE and behavior such that the relationship will become stronger as behavior becomes distal.

Time as the past: Experience with behavior

Our review of the literature suggests that there is little research examining the influence of experience on the predictive validity of BE relative to BI and PBC. Experience refers to whether the target behavior is being performed for the first time or if it has been performed before. When a behavior has not been performed before, individuals have little information about the environmental states needed for the behavior. This lack of information can reduce the predictive validity of BI and PBC for reasons similar to those previously discussed (Sheeran & Orbell, 1998).

Experience with a target behavior improves the predictive validity of BI and PBC in several ways. First, the actual experience of performing the behavior provides much of the information necessary to reduce uncertainty (Sheeran & Orbell, 1998). Each cumulative behavior performance episode can reveal new information about the necessary environmental and motivational states for performing the behavior. Second, as George and Jones (2000) point out, the past, present, and future are tightly intertwined. Thus, the past and present are connected insofar as current behavior is based on prior experience performing it. Similarly, the future is connected to the past and the present, to the extent that the motivation (BI) to perform a future behavior is reflective of prior experience with performing the behavior (George & Jones, 2000). By similar logic, the extent to which PBC is reflective of actual control will increase as an individual gains experience with performing a behavior. Thus, with increasing experience, an individual's present BI and PBC are reflective of all prior knowledge accumulated from performing the behavior over time and consequently, will have greater predictive validity.

Earlier, we suggested that a key strength of BE is that it does a better job of capturing uncertainty and incorporating it into the prediction of behavior. Like assumption-based reasoning (Cohen, 1989; Lipshitz & Ben Shaul, 1997), the formation of BE might entail the construction of a mental model of a behavior performance situation based on assumptions/beliefs that go beyond what is firmly known about the behavior. Increasing experience provides an individual with more information about a target behavior. The accumulated information reduces uncertainty about the behavior (Sheeran & Orbell, 1998) and negates the need for going beyond what is currently known. Therefore, as an individual gains experience with performing the behavior, they are more likely to base their self-predictions on what is *known* about the behavior and less likely to fixate on the potential *unknowns* that can impede behavior performance. Thus, the predictive validity of BE is expected to decrease as experience with performing a behavior increases.

Hypothesis 2a. Experience will moderate the relationship between BI and behavior such that the relationship will become stronger as experience increases.

Hypothesis 2b. Experience will moderate the relationship between PBC and behavior such that the relationship will become stronger as experience increases.

Hypothesis 2c. Experience will moderate the relationship between BE and behavior such that the relationship will become weaker as experience increases.

Time as rhythm: Episodic and repeat behaviors

Behaviors can be episodic or repeat. Episodic behavior differs from repeat behavior in that the former tends to be performed infrequently during one or a few isolated occasions, usually at irregular intervals, whereas the latter is performed frequently, at regular intervals (Brudney, 1990; Harrison, 1995). For instance, the purchase of a personal computer once every couple of years is considered as an episodic behavior even though it is repeated. Repeat behaviors are frequently performed and tend to become routinized and part of an individual's repertoire of activities. Conceptually, the lines that distinguish these two types of behaviors may be blurred for behaviors that are performed with some degree of frequency. For example, although the purchase of groceries is a behavior that is typically repeated on at least a monthly basis, it is considered to be an episodic behavior. Harrison (1995) suggests that even behaviors that are performed 1–2 times per week could be considered to be episodic due to the long intervals between episodes. In contrast, repeat behaviors are those that are performed over and over again with very short time intervals between behavioral occurrences, such as driving to and from work.

Our definition of episodic behaviors suggests that by nature they are performed relatively irregularly (Harrison, 1995). Hence, uncertainty about the future and the possibility of impediments to performing behavior are likely to persist over time. In other words, information gathered through experience with the behavior is unlikely to carry over into the prediction of subsequent behavior due to the irregular temporal rhythm with which it is performed. This suggests that, because of the infrequency of episodic behaviors, BI and PBC may continue to be plagued by limitations caused by uncertainty. Thus, even with increasing experience with the behavior, we would expect anticipation to have a moderating influence on the relationship between BI, PBC, and BE, and episodic behavior.

The first time a potential repeat behavior is performed, whether or not it will be repeated in the future, the relative predictive validity of BI, PBC, and BE is expected to be identical to the context of episodic behavior. However, we expect the pattern of relationships to differ with increasing experience. In contrast to later episodes of episodic behaviors, frequently repeated behaviors provide the experience necessary for the behavior to become sufficiently rehearsed and routinized (Bargh & Barndollar, 1996). As a behavior becomes more rehearsed, BI and PBC will likely improve as predictors of behavior because they would be based on concrete information and experiences. Increasing experience with the behavior enables individuals to reformulate their BI and PBC to be more accurate. With regard to BI, experience with the behavior provides the information necessary to reduce uncertainty (Sheeran & Orbell, 1998; Sutton, 1998). Consequently, increased certainty about the future reduces the likelihood that BI will be provisional, thus improving the stability of BI over time (Bassili, 1993; Sheeran, Orbell, & Trafimow, 1999). With increasing experience with a behavior, individuals are able to reassess their perceptions of control to be more reflective of actual control. Hence, with increasing experience, proximal and distal repeat behaviors are predicted well by BI and PBC.

In contrast to BI and PBC, the prediction of distal behaviors by BE will decrease with increasing experience as the uncertainty associated with temporal distance is reduced. In sum, unlike episodic behaviors, temporal distance in the anticipation of repeat behaviors is expected to be irrelevant with significant behavioral experience because of the reduced uncertainty with respect to distal behaviors.

Hypothesis 3a. In the context of repeat behaviors, there will be a 3-way interaction between BI, anticipation, and experience such that the relationship between BI and behavior will be strongest when anticipation is low and experience is high.

Hypothesis 3b. In the context of repeat behaviors, there will be a 3-way interaction between BE, anticipation, and experience such that the relationship between BE and behavior will be strongest when anticipation is high and experience is low.

Method

We conducted two longitudinal studies modeled to reflect the two types of behavior. Study 1 spanned 6 months and examined an episodic behavior: the first, second, and third PC purchase decisions in American households. Study 2 spanned 1 year and was conducted in a context where initial behavior and repeat behavior decisions had to be made: initial and continued use of an information system (software) in the workplace. We captured data regarding BI, PBC, BE, and behavior. The study of the context of technology adoption is particularly interesting from a management perspective given the widespread diffusion of technology in both work and home environments.

Study 1

Setting, participants, and measurement

We worked closely with a market research firm to identify 5400 households to participate in the study. The households were randomly selected from the market research firm's list of residential names and addresses. A direct mailing was used, including an incentive to increase response rate: a $5 AMEX® gift certificate for all respondents completing the survey. All respondents were entered in a lottery for a $500 AMEX® gift certificate. Both gift certificates could be used like cash in many business establishments. In order to receive their gift certificates, respondents provided their address on an information blank that was separate from the questionnaire.

Over an 8-week period, 1247 usable responses were received. This resulted in a response rate of just over 24household responses, 501 already owned one or more PCs. Specifically, 300 of the households owned one PC and 201 owned two. Of the 300 households that owned one PC, 198 responded to the follow-up survey 6 months after the initial survey. Of the 201 households that owned two PCs, 140 responded to the follow-up survey 6 months after the initial survey. Of the 1247 households, 746 households did not possess a PC. Of these 746 households, 523 responded to the follow-up survey 6 months after the initial survey. The resulting sample size of households that responded to both waves of the survey was 861 (i.e., $198 + 140 + 523$). Thus, the response rate for the follow-up survey was about 70%. We compared the demographic characteristics of respondents vs. non-respondents and found no significant differences.

BI, PBC, and BE were measured on a 7-point Likert scale, where 1 = "strongly disagree" and 7 = "strongly agree." BI and PBC measures were adapted to fit the context of household PC adoption. A sample item from the 3-item BI scale was: "It is my intention to buy a computer for use at home in the next month." A 4-item scale was used to measure PBC. A sample item from the 4-item PBC scale was: "I have control over the purchase of a computer for my home." These scales have been used extensively in information system adoption contexts in prior research (e.g., Mathieson, 1991; Taylor & Todd, 1995). BE was operationalized based on the guidelines of Warshaw and Davis (1985a) and Sheppard et al. (1988), and adapted from other behavioral domains. A sample item from the 4-item BE scale was: "I expect to adopt a computer at home in the next month." Respondents were asked to indicate their BI and BE to perform the behavior in the next month, 3 months, and 6 months. Thus, all items for the BI and BE scales were repeated for each time frame resulting in nine total items for BI and 12 total items for BE. Anticipation of behavior was coded as an ordinal variable with each time frame coded as follows: 0 = 1 month; 1 = 3 months; and 2 = 6 months. Experience with behavior was measured as the number of prior PC purchases. As noted earlier, the sample consisted of households that had made 0, 1, and 2 prior PC purchases. Finally, PC purchase behavior in the follow-up was measured by asking respondents if they had actually purchased a PC and when it was purchased. The outcome variable was coded 1 if a PC had actually been purchased and 0 otherwise.

The Cronbach alpha for each scale was greater than 0.70, suggesting adequate reliability of the measures. We used factor analysis with oblique rotation to examine the convergent and discriminant validity of the scales (Fabrigar, Wegener, MacCallum, & Strahan, 1999). We conducted one analysis per time frame. All loadings were greater than 0.70 and cross-loadings were mostly less than 0.30 (there were two exceptions where the cross-loadings were 0.36 and 0.37). We do not report the detailed results of this analysis in the interest of space and, particularly, because of the consistency of the findings with that of prior research (e.g., see Mathieson, 1991; Taylor & Todd, 1995).

Procedure

A cover letter from the sponsoring retail electronics store, detailing the goals of the study and assuring respondent confidentiality, was included in each of the 5400 questionnaires mailed. The cover letter stated that the goal of the study was to gather information from households about technologies for homes. Pre-paid return envelopes were provided to further increase the response rate. Reminder postcards were sent to all addresses at 2-week intervals. Four weeks after the 8-week data collection window concluded, 13 responses were received. These late responses were excluded from the study. Random checks were conducted on the data set to ensure accuracy.

The brief follow-up survey of the participants in the initial survey was conducted via phone 6 months after the initial survey. Up to 20 callbacks were attempted in some cases. In cases where a phone number was not available, mail and email follow-ups were attempted. The respondent for the follow-up survey was either the primary decision-maker in the household or the respondent to the initial survey, who responded primarily to questions about their PC purchase behavior. The households that did not provide data in the follow-up were those that did not include any contact information, were not available at the contact information provided (e.g., moved with no forwarding information), or refused to participate (e.g., refused on the phone, did not respond to mail/email survey).

Analysis and results

Table 1 presents the descriptive statistics and correlation matrix for respondents who had 0, 1, and 2 prior PC purchase experiences. The hypotheses were tested using logistic regression, given the binary nature of the dependent variable. We mean-centered the variables in the model before computing the interaction terms to reduce multicollinearity (Aiken & West, 1991). BI, PBC, BE, anticipation, and experience were entered into the regression equation in the first step and the interaction terms were entered in the second step. The estimated β coefficients were exponentiated so that they could be interpreted as odds ratios (Harrison, 2002). Positive β coefficients produce odds ratios greater than 1 and negative coefficients yield odds ratio values between 0 and 1. Thus, in the context of this study, when the odds ratios are greater than 1, the likelihood of adoption increases.

The results of the logistic regression are presented in Table 2. As the results of the main effects model (model 1) indicate, BI, PBC, and BE each had a positive influence on behavior (odds ratios of 1.93, $p < .01$; 1.47, $p < .01$; and 2.55, $p < .001$, respectively). Specifically, the odds of actual PC purchase behavior would increase due to one unit increases in each of the predictors. The main effects model explained 34% of the variance in PC purchase behavior. The full model with interaction terms (model 2) explained 66% of the variance in PC purchase behavior ($\Delta R^2 = 0.32$). The odds ratio for BI $\times$ anticipation was 0.72 ($p < .001$), suggesting that BI becomes less

Table 1
Study 1: Descriptive statistics and correlation matrix[a]

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10
First PC purchase[a]												
1. BI (1 month)	3.8	1.19	.82									
2. BI (3 months)	3.9	1.15	.41***	.85								
3. BI (6 months)	4.1	1.17	.33***	.31***	.88							
4. PBC	3.1	1.02	.33***	.30***	.28**	.78						
5. BE (1 month)	3.1	.88	.61**	.38***	.25**	.55***	.83					
6. BE (3 months)	3.4	.91	.18*	.51***	.31**	.40***	.55***	.81				
7. BE (6 months)	4.2	1.06	.20*	.25**	.44***	.31**	.50***	.52***	.79			
8. Adopt (1 month)	N/A	N/A	.70***	.51***	.43***	.31**	.72***	.35***	.36***			
9. Adopt (3 months)	N/A	N/A	.47***	.58***	.45***	.29**	.53***	.72***	.46***	.39***		
10. Adopt (6 months)	N/A	N/A	.35***	.49***	.57***	.28**	.45***	.48***	.77***	.44***	.43***	
Second PC purchase[b]												
1. BI (1 month)	3.7	1.13	.84									
2. BI (3 months)	3.8	1.08	.43***	.80								
3. BI (6 months)	4.2	1.06	.30**	.27**	.77							
4. PBC	3.1	1.05	.32***	.29***	.31**	.84						
5. BE (1 month)	3.2	1.03	.62**	.42***	.33***	.52***	.75					
6. BE (3 months)	3.6	1.10	.25**	.48***	.27**	.41***	.51***	.72				
7. BE (6 months)	4.0	1.15	.28**	.28**	.40***	.35***	.44***	.49***	.79			
8. Adopt (1 month)	N/A	N/A	.68***	.47***	.34***	.33***	.70***	.42***	.39***			
9. Adopt (3 months)	N/A	N/A	.42***	.57***	.42***	.27**	.51***	.71***	.44***	.37***		
10. Adopt (6 months)	N/A	N/A	.34***	.45***	.55***	.27**	.42***	.44***	.75***	.41***	.48***	
Third PC purchase[c]												
1. BI (1 month)	3.5	1.01	.80									
2. BI (3 months)	3.7	1.20	.41***	.90								
3. BI (6 months)	4.0	1.21	.28**	.27**	.84							
4. PBC	3.4	1.10	.30**	.31**	.34***	.74						
5. BE (1 month)	3.1	.98	.60**	.39***	.34***	.53***	.80					
6. BE (3 months)	3.5	.99	.27**	.45***	.29**	.44***	.48***	.83				
7. BE (6 months)	3.7	1.05	.33***	.29**	.45***	.36***	.45***	.53***	.79			
8. Adopt (1 month)	N/A	N/A	.65***	.45***	.31**	.31***	.72***	.39***	.35***			
9. Adopt (3 months)	N/A	N/A	.40***	.56***	.38***	.28**	.49***	.73***	.41***	.40***		
10. Adopt (6 months)	N/A	N/A	.32***	.40***	.50***	.30**	.38***	.40***	.73***	.32**	.51***	

Notes. BI, behavioral intention; PBC, perceived behavioral control; BE, behavioral expectation; Adopt, actual PC purchase. Cronbach α are on the diagonal. Blank diagonal elements indicate single-item scales.

[a] $n = 523$.

[b] $n = 198$.

[c] $n = 140$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

predictive of behavior with increasing anticipation (i.e., as behavior is projected farther into the future). This provides support for Hypothesis 1a. The odds ratio for BE × anticipation was 2.34 ($p < .001$), suggesting that BE becomes a stronger predictor of behavior with increasing anticipation. Thus, Hypothesis 1b is supported. Hypothesis 2a posited that BI would become more predictive of behavior with increasing experience. The odds ratio for BE × experience was 2.17 ($p < .001$), thus providing support for Hypothesis 2a. Similarly, Hypothesis 2b predicted that PBC would become a stronger predictor of behavior as experience increased. This hypothesis is supported (odds ratio = 1.25, $p < .001$). Finally, Hypothesis 2c predicted that BE would become less predictive of behavior as experience increased. Consistent with this hypothesis, the odds ratio for the BE × experience interaction was 0.76 ($p < .001$).

Study 2

Setting, participants, and measurement

Participants were employees of a telecommunications firm, the site of a major new information system introduction. Specifically, the system introduced was a web-based front-end for informational and transactional systems in three different organizational units. Although the functionality of the information system continued to relate to the jobs of the various employees, the new information system was significantly different from the old system. The employees could use either the old

Table 2
Study 1: Results of logistic regression predicting PC purchase behavior[a]

Variables	Model 1	Model 2
Dependent variable: PC purchase behavior		
Step I: Main effects		
BI	1.93**	.16*
PBC	1.47**	.08
BE	2.55***	.21**
Anticipation	.08	.05
Experience	.10	.02
Step II: Interaction terms		
BI × anticipation		.72***
BE × anticipation		2.34***
BI × experience		2.17***
PBC × experience		1.25***
BE × experience		.76***
Pseudo-R^2	.34	.66
ΔR^2		.32

Notes. BI, behavioral intention; PBC, perceived behavioral control; BE, behavioral expectation. Reported coefficients are odds ratios.
[a] ($n = 861$).
* $p < .05$.
** $p < .01$.
*** $p < .001$.

front-end or the new web front-end, thus rendering the behavior volitional and within the scope of the intention and expectation theories. This study focused on the new web-based system. Of the nearly 918 total employees, 720 participated in the study and 321 provided usable responses at all five points of measurement for an effective response rate of about 45%. While ideally we would have wanted all employees to participate in the entire study, this was not feasible given that the study duration was 1 year and had five points of measurement—yet the response rate was quite high. Of the 321 participants, 110 were women (34%). The average age of the participants was 37.2 with a standard deviation of 9.5. All levels of the organizational hierarchy were adequately represented in the sample. We compared the participants who responded at all measurement points to non-respondents on variables such as age, gender, income, and organizational position. No significant differences were detected.

BI, PBC, and BE were measured on a 7-point Likert scale, where 1 = "strongly disagree" and 7 = "strongly agree." We adapted the measurement items for BI and PBC to fit the context of our study. Our measurement of these constructs was consistent with prior studies (Mathieson, 1991; Taylor & Todd, 1995). A sample item from the 3-item scale for BI included was: "I intend to use the system in the next month." A sample item from the 4-item scale used to measure PBC was: "I have the resources necessary to use the system." The measures for BE were operationalized following the guidelines outlined by Warshaw and Davis (1985a) and Sheppard et al. (1988), and were adapted to fit the technology adoption context. A sample item from the 4-item BE scale was: "I expect to use the system in the next month." Respondents provided ratings of their BI and BE to perform the behavior in the next month, 2 months, and 3 months. Thus, all items for the BI and BE scales were repeated for each time frame resulting in nine total items for BI and 12 total items for BE. Anticipation of behavior was coded as an ordinal variable with each time frame coded as follows: 0 = 1 month; 1 = 2 months; and 2 = 3 months. Experience with behavior was measured as the number of months of prior system use (i.e., 0, 3, 6, and 9 months). Consistent with prior literature (e.g., Davis, Bagozzi, & Warshaw, 1989; Taylor & Todd, 1995; Venkatesh & Morris, 2000), we measured behavior as the extent, intensity, and average duration of use.[2] These measures of behavior were summed to create an overall measure of behavior.

All of the scales in our analyses had Cronbach α greater than 0.70 at all points of measurement. We used factor analysis with oblique rotation to assess validity. We conducted one analysis per time frame at each point of measurement. Given that the study involved repeated measures in a stable environment, it could be reasonably expected that measures of the same construct at different points in time could be highly correlated and may not necessarily discriminate. These analyses yielded loadings greater than 0.70 and cross-loadings less than 0.35 in all cases. Thus, there is assurance of convergent and discriminant validity. We do not report the detailed results of these analyses here in the interest of space, especially given the consistency with prior research (e.g., Mathieson, 1991; Taylor & Todd, 1995).

Procedure

The data were collected in naturally occurring conditions during and after the organization's major new information system implementation. The organization conducted training programs to educate the employees about the new information system. Specifically, a training company was contracted to work with the information system designers and developers to prepare training material appropriate for different job types. Immediately after the training, employees filled out a questionnaire related to the new information system that included items to measure: (a) PBC and (b) BI and BE for the next 1, 2, or 3 months. Given that it was important to track specific respondents over time, unique bar codes were printed on each survey to allow specific responses to be tracked over time. Every 3 months for the next 9 months, employees responded to a survey that included questions about (a) their PBC and (b) their BI and BE for the next 1, 2, or 3 months. The extent, intensity,

[2] Average duration of use was measured as the average duration of use per week for a specific time frame.

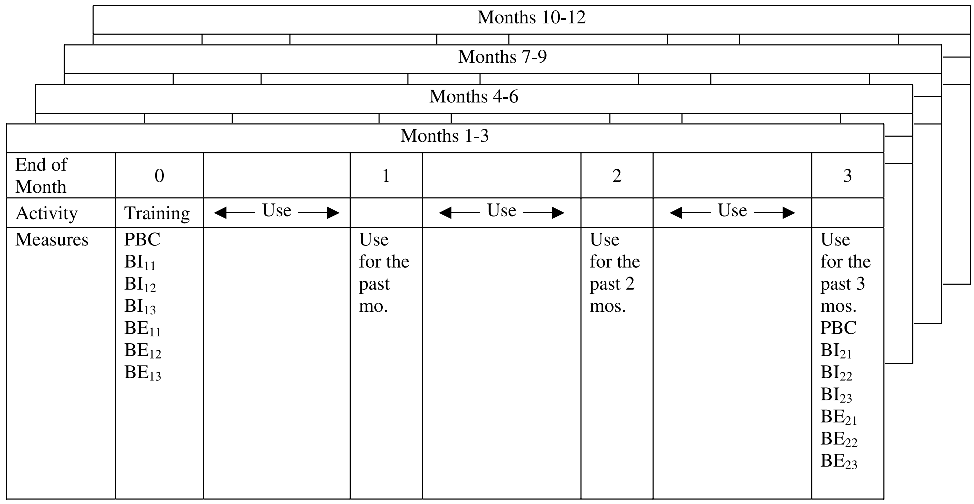

Fig. 1. Summary of study 2 design with points of measurement. The first subscript for B1 and BE indicates when the measure was taken—i.e., T1,T2,T3, etc.— and the second subscript indicates the time frame of the measure—one month, two months, or three months. For example, BI21 would be the intention measure taken at T2 (after 3 months) and would be the intension associated with use for the next month. With the exception of the measurement after training, the measurement points in all subsequent 3-month time periods were the same as the first 3-month period.

and average duration of system use were measured every month. Depending on the month, use was measured with regard to the past 1, 2, or 3 months. A final survey was administered a year after the initial survey to measure behavior in the previous 3 months. Fig. 1 presents an illustration of the study design including all measurement points.

Analysis and results

Table 3 presents the descriptive statistics and correlation matrix. Each construct in the table is marked with a numerical subscript to indicate the point of measurement and the time frame for use as it relates to the figure, e.g., BI_{12} indicates BI measured at T_1 with regard to use in the next 2 months; behavior includes two numbers to indicate the time span for which use was measured, e.g., Use_{46} indicates behavior that occurred between months 4 and 6.

Given the repeated measures design of the study, a generalized estimating equations (GEEs) method was used to test the hypotheses (Zeger & Liang, 1986; Zeger, Liang, & Albert, 1988). GEE is the appropriate analytical technique because it accounts for the correlation of responses within subjects, thus reducing the potential for inefficient and biased regression estimates (Ballinger, 2004). GEEs can be used to test main effects, interactions, and categorical and continuous independent variables (Ballinger, 2004). Although GEE models are robust to misspecification of the correlation structure of the dependent variable, such misspecifications can result in inefficient estimates. Thus, we specified an unstructured correlation model (Fitzmaurice, Laird, & Rotnitzky, 1993) where observations across time are allowed to freely correlate within subjects. Ballinger (2004) suggests that this is the optimal correlation modeling structure because it is the least restrictive in terms of modeling the true within subject correlation structure and because there is no reason to expect within subject correlations to decrease over time when individuals are performing the same behavior in multiple time periods. We mean-centered the variables in the model before computing the interaction terms to reduce multicollinearity (Aiken & West, 1991). BI, PBC, BE, anticipation, and experience were entered into the regression equation in the first step and the 2-way interaction terms were entered in the second step. The 3-way interactions (and the necessary additional 2-way interaction—anticipation × experience) were entered in the third step.

Table 4 presents the results of the GEE model. The main effects model (model 1) explained 28% of the variance in system use. Consistent with prior research, BI, PBC, and BE had positive and significant coefficients ($\beta = 0.27$, $p < .001$; $\beta = 0.18$, $p < .01$; and $\beta = 0.34$, $p < .001$, respectively). Model 2, which included all the 2-way interaction terms, yielded an R^2 value of 0.53 ($\Delta R^2 = 0.25$). The interaction between BI and anticipation was −0.32 ($p < .001$), thus supporting Hypothesis 1a. Hypothesis 1b predicted that anticipation would strengthen the relationship between BE and behavior. The results support this hypothesis ($\beta = 0.45$, $p < .001$).

Hypotheses 2a and 2b predicted that experience would strengthen the predictiveness of BI and PBC. The coefficients for the BI × experience and PBC × experience interaction terms were 0.22 ($p < .001$) and 0.14 ($p < .01$), respectively. Hypotheses 2a and 2b are, therefore, supported. Hypothesis 2c posited that the relationship between BE and behavior would weaken with increasing experience. The interaction between BE and experience was negative and significant ($\beta = -0.15$, $p < .01$). Hence, Hypothesis 2c was supported.

Table 3
Study 2: Descriptive statistics and correlation matrix[a]

	Variable	Mean	*SD*	1 PBC1	2 PBC2	3 PBC3	4 PBC4	5 BI11	6 BI12	7 BI13	8 BI21	9 BI22	10 BI23	11 BI31	12 BI32	13 BI33	14 BI41	15 BI42	16 BI43
1	PBC1	3.1	1.21	.74															
2	PBC2	3.7	1.04	.47***	.70														
3	PBC3	3.9	1.01	.48***	.50***	.71													
4	PBC4	4.2	.84	.50***	.45***	.55***	.73												
5	BI11	3.8	1.12	.28***	.30***	.25**	.28***	.92											
6	BI12	3.8	1.02	.29***	.33***	.27***	.25**	.45***	.90										
7	BI13	4.0	1.07	.23**	.40***	.35***	.30***	.35***	.39***	.80									
8	BI21	4.0	1.10	.30***	.20**	.21**	.18*	.30***	.32***	.28***	.85								
9	BI22	4.1	1.07	.25**	.25**	.24**	.22**	.32***	.31***	.35***	.40***	.86							
10	BI23	4.4	1.00	.25**	.28***	.34***	.25**	.31***	.25**	.29***	.35***	.43***	86						
11	BI31	4.3	1.02	.21**	.27***	.32***	.27***	.30**	.18*	.20**	.34***	.26***	.35***	.89					
12	BI32	4.3	.98	.20**	.25**	.33***	.30***	.28***	.32**	.21**	.21**	.31**	.32***	.33***	.85				
13	BI33	4.4	.87	.25**	.28***	.30***	.28***	.23**	.25**	.32**	.22**	.20**	.38***	.37***	.33***	.82			
14	BI41	4.4	.99	.17*	.20**	.24**	.27***	.29***	.21**	.24**	.34**	.28***	.28***	.36***	.40***	.38***	.72		
15	BI42	4.5	1.01	.23**	.25**	.28***	.25**	.21**	.30*	.28***	.28***	.31**	.25**	.30***	.27***	.30***	.29***	.79	
16	BI43	4.5	.80	.28***	.29***	.29***	.20**	.07	.19*	.33***	.21**	.24**	.32***	.29***	.30***	.42***	.31***	.36***	.75
17	BE11	4.1	1.03	.45***	.29***	.45***	.23**	.40***	.25**	.29***	.31***	.22**	.32***	.21**	.07	.16*	.22**	.19*	.17*
18	BE12	4.2	1.01	.42***	.32***	.43***	.28***	.28***	.37***	.31***	.23**	.19*	.27***	.24**	.22**	.10	.17*	.21**	.25**
19	BE13	4.3	1.01	.40***	.28***	.38***	.31***	.23**	.24**	.45***	.20*	.13	.38***	.09	.20**	.34***	.13	.17*	.35***
20	BE21	4.4	1.04	.38***	.50***	.36***	.32***	.31**	.21**	.10	.35***	.21**	.28***	.33***	.27***	.22**	.25**	.22**	.21**
21	BE22	4.6	1.09	.35***	.47***	.31***	.29***	.20**	.25**	.25**	.30***	.28***	.31***	.28***	.34***	.19*	.21**	.25**	.27***
22	BE23	4.8	1.16	.29***	.43***	.27***	.27***	.24**	.20*	.32***	.24**	.25**	.40***	.27***	.26***	.25**	.18*	.14	.37***
23	BE31	4.8	1.11	.25**	.39***	.44***	.35***	.27***	.11	.22**	.32***	.17*	.13	.32***	.34***	.29***	.35***	.24**	.31***
24	BE32	4.9	1.12	.29***	.35***	.44***	.31***	.21**	.22**	.21**	.28***	.24**	.08	.30***	.41***	.33***	.21**	.33***	.29***
25	BE33	4.9	1.02	.32***	.32***	.40***	.34***	.08	.13	.27***	.19*	.12	.32***	.28***	.31***	.41***	.34***	.30***	.40***
26	BE41	5.0	1.12	.35***	.39***	.48***	.41***	.25**	.20**	.10	.33***	.08	.06	.39***	.19*	.36***	.38***	.31***	.30***
27	BE42	4.9	1.03	.35***	.42***	.41***	.32***	.19*	.25**	.28***	.21**	.20**	.25**	.38***	.38***	.34***	.35***	.39***	.32***
28	BE43	4.9	1.00	.37***	.35***	.36***	.24**	.21**	.09	.35***	.18*	.10	.34***	.31***	.29***	.35***	.27***	.33***	.36***
29	USE11	28.8	7.99	.31***	.28***	.27***	.31***	.69***	.45***	.31***	.28***	.29***	.29***	.33***	.31***	.29***	.21**	.18*	.24**
30	USE12	30.1	7.41	.22**	.23**	.20**	.29***	.44***	.58***	.39***	.19**	.20**	.22**	.28***	.30***	.18*	.27***	.24**	.16*
31	USE13	31.2	7.14	.26***	.24**	.32***	.34***	.44***	.51***	.57***	.28***	.25**	.32***	.29***	.22**	.32***	.22**	.18*	.32***
32	USE21	37.4	8.34	.17*	.20**	.25**	.20**	.24**	.31***	.28***	.60***	.28***	.31***	.33***	.24**	.29***	.31***	.17*	.22**
33	USE22	36.8	7.78	.19*	.25**	.29***	.18*	.29***	.27***	.24**	.41**	.61***	.39***	.21**	.36***	.17*	.28***	.34***	.31***
34	USE23	39.2	8.05	.19**	.29***	.25**	.27***	.30***	.29***	.38***	.44***	.40***	.58***	.25**	.22**	.30***	.13	.20**	.35***
35	USE31	40.1	8.86	.13	.20**	.21**	.30***	.27***	.21**	.18*	.35***	.33***	.25**	.61***	.31***	.33***	.37***	.28***	.35***
36	USE32	39.8	8.12	.22**	.17*	.27***	.29***	.13	.19**	.17*	.28***	.38***	.29***	.24**	.62***	.28***	.31***	.40***	.29***
37	USE33	41.4	7.57	.17*	.25**	.32***	.34***	.22**	.09	.30***	.31***	.22**	.40***	.21**	.34***	.60***	.20**	.33***	.42***
38	USE41	40.6	8.17	.23**	.29***	.31***	.35***	.07	.20**	.18*	.31***	.22**	.21**	.42***	.40***	.37***	.63***	.42***	.45***
39	USE42	42.4	7.44	.28***	.21**	.24**	.33***	.13	.15*	.17*	.29***	.37***	.27***	.37***	.46***	.29***	.42***	.60***	.48***
40	USE43	41.2	7.11	.20**	.24**	.25**	.32***	.16*	.19*	.28***	.36***	.24**	.38***	.39***	.28***	.50***	.38***	.52***	.60***
17	BE11	.77																	
18	BE12	.44***	.73																
19	BE13	.45***	.49***	.79															
20	BE21	.28***	.27***	.21**	.73														

(*continued on next page*)

Table 3 (*continued*)

	Variable	17 BE11	18 BE12	19 BE13	20 BE21	21 BE22	22 BE23	23 BE31	24 BE32	25 BE33	26 BE41	27 BE42	28 BE43	29 USE 11	30 USE12	31 USE13	32 USE21	33 USE22
21	BE22	$.26^{**}$	$.28^{****}$	$.20^{**}$	$.42^{***}$	.79												
22	BE23	$.21^{**}$	$.23^{**}$	$.35^{***}$	$.47^{***}$	$.51^{***}$	.75											
23	BE31	$.32^{***}$	.11	.07	$.40^{***}$	$.19^{*}$	$.22^{**}$	.80										
24	BE32	$.25^{**}$	$.21^{**}$	$.18^{*}$	$.23^{**}$	$.38^{***}$	$.28^{***}$	$.48^{***}$	.81									
25	BE33	$.21^{**}$	.07	$.28^{***}$	$.28^{***}$	$.29^{***}$	$.39^{***}$	$.45^{***}$	$.51^{***}$	.80								
26	BE41	$.29^{***}$	.10	.12	$.38^{***}$	$.26^{***}$	$.20^{**}$	$.44^{***}$	$.33^{***}$	$.31^{***}$	.71							
27	BE42	$.23^{**}$	$.22^{**}$	.07	$.30^{***}$	$.31^{***}$	$.27^{***}$	$.37^{***}$	$.39^{***}$	$.38^{***}$	$.44^{***}$	.79						
28	BE43	$.16^{*}$	$.17^{*}$	$.30^{***}$	$.21^{**}$	$.27^{***}$	$.35^{***}$	$.28^{***}$	$.25^{**}$	$.45^{***}$	$.41^{***}$	$.54^{***}$	.76					
29	USE11	$.73^{***}$	$.50^{***}$	$.49^{***}$	$.42^{***}$	$.40^{***}$	$.29^{***}$	$.25^{**}$	$.31^{***}$	$.24^{**}$	$.28^{***}$	$.31^{***}$	$.20^{**}$					
30	USE12	$.54^{***}$	$.72^{***}$	$.52^{***}$	$.39^{***}$	$.33^{***}$	$.35^{***}$	$.29^{***}$	$.35^{***}$	$.34^{***}$	$.27^{***}$	$.30^{***}$	$.27^{***}$	$.57^{***}$				
31	USE13	$.50^{***}$	$.49^{***}$	$.74^{***}$	$.32^{***}$	$.34^{***}$	$.28^{***}$	$.33^{***}$	$.40^{***}$	$.38^{***}$	$.21^{**}$	$.31^{***}$	$.35^{***}$	$.61^{***}$	$.54^{***}$			
32	USE21	$.33^{***}$	$.37^{***}$	$.39^{***}$	$.71^{***}$	$.49^{***}$	$.47^{***}$	$.31^{***}$	$.29^{***}$	$.17^{*}$	$.32^{***}$	$.35^{***}$	$.29^{***}$	$.51^{***}$	$.62^{***}$	$.64^{***}$		
33	USE22	$.37^{***}$	$.41^{***}$	$.40^{***}$	$.60^{***}$	$.74^{***}$	$.54^{***}$	$.29^{***}$	$.33^{***}$	$.19^{**}$	$.25^{**}$	$.39^{***}$	$.32^{***}$	$.44^{***}$	$.60^{***}$	$.62^{***}$	$.70^{***}$	
34	USE23	$.41^{***}$	$.38^{***}$	$.52^{***}$	$.50^{***}$	$.61^{***}$	$.70^{***}$	$.24^{**}$	$.20^{**}$	$.28^{***}$	$.29^{***}$	$.37^{***}$	$.40^{***}$	$.40^{***}$	$.48^{***}$	$.75^{***}$	$.62^{***}$	$.63^{***}$
35	USE31	$.32^{***}$	$.35^{***}$	$.29^{***}$	$.41^{***}$	$.42^{***}$	$.24^{**}$	$.63^{***}$	$.61^{***}$	$.52^{***}$	$.37^{***}$	$.32^{***}$	$.41^{***}$	$.47^{***}$	$.51^{***}$	$.55^{***}$	$.56^{***}$	$.57^{***}$
36	USE32	$.29^{***}$	$.41^{***}$	$.40^{***}$	$.47^{***}$	$.31^{***}$	$.41^{***}$	$.47^{***}$	$.65^{***}$	$.56^{***}$	$.32^{***}$	$.41^{***}$	$.33^{***}$	$.42^{***}$	$.47^{***}$	$.52^{***}$	$.49^{***}$	$.62^{***}$
37	USE33	$.33^{***}$	$.38^{***}$	$.45^{***}$	$.39^{***}$	$.30^{***}$	$.52^{***}$	$.44^{***}$	$.43^{***}$	$.64^{***}$	$.28^{***}$	$.34^{***}$	$.45^{***}$	$.49^{***}$	$.42^{***}$	$.60^{***}$	$.42^{***}$	$.44^{***}$
38	USE41	$.31^{***}$	$.23^{**}$	$.31^{***}$	$.41^{***}$	$.36^{***}$	$.37^{***}$	$.42^{***}$	$.39^{***}$	$.32^{***}$	$.60^{***}$	$.51^{***}$	$.52^{***}$	$.51^{***}$	$.40^{***}$	$.57^{***}$	$.40^{***}$	$.41^{***}$
39	USE42	$.34^{***}$	$.34^{***}$	$.27^{***}$	$.32^{***}$	$.30^{***}$	$.38^{***}$	$.35^{***}$	$.47^{***}$	$.40^{***}$	$.49^{***}$	$.55^{***}$	$.48^{***}$	$.43^{***}$	$.34^{***}$	$.52^{***}$	$.42^{***}$	$.45^{***}$
40	USE43	$.29^{***}$	$.21^{**}$	$.40^{***}$	$.33^{***}$	$.29^{***}$	$.48^{***}$	$.41^{***}$	$.40^{***}$	$.54^{***}$	$.42^{***}$	$.44^{***}$	$.55^{***}$	$.41^{***}$	$.33^{***}$	$.58^{***}$	$.37^{***}$	$.35^{***}$

	Variable	34 USE23	35 USE31	36 USE32	37 USE33	38 USE41	39 USE42	40 USE43
34	USE23							
35	USE31	$.62^{***}$						
36	USE32	$.57^{***}$	$.66^{***}$					
37	USE33	$.72^{***}$	$.69^{***}$	$.71^{***}$				
38	USE41	$.49^{***}$	$.60^{***}$	$.57^{***}$	$.72^{***}$			
39	USE42	$.51^{***}$	$.57^{***}$	$.54^{***}$	$.60^{***}$	$.64^{***}$		
40	USE43	$.64^{***}$	$.52^{***}$	$.47^{***}$	$.78^{***}$	$.68^{***}$	$.63^{***}$	

Notes. The first subscript for BI, BE, and Use indicates when the measure was taken—i.e., T1, T2, T3, etc.—and the second subscript indicates the time frame of the measure—1, 2, or 3 months. For example, BI21 would be the intention measure taken at T2 (after 3 months) and would be the intention associated with use for the next month.

Cronbach α are on the diagonal. Blank diagonal elements indicate single-item scales.

[a] $n = 321$, data reported broken down by time period.

[*] $p < .05$.

[**] $p < .01$.

[***] $p < .001$.

Table 4
Study 2: Generalized estimating equations (GEEs) regression predicting system use[a]

Variables	β coefficients		
	Model 1	Model 2	Model 3
Dependent variable: System use			
Step I: Main effects			
BI	.27***	.14*	.05
PBC	.18**	.05	.03
BE	.34***	.18**	.00
Anticipation	.03	.02	.00
Experience	.07	.08	.05
Step II: 2-way interaction terms			
BI × anticipation		−.32***	−.10
BE × anticipation		.45***	.17**
BI × experience		.22***	.03
PBC × experience		.14**	.10
BE × experience		−.15**	−.04
Step III: 3-way interaction terms			
Anticipation × experience			.09
BI × anticipation × experience			.28***
BE × anticipation × experience			.35***
R^2	.28	.53	.65
ΔR^2		.25	.12

Notes. BI, behavioral intention; PBC, perceived behavioral control; BE, behavioral expectation. Standardized regression coefficients are reported.
[a] $n = 1284$ (321 × 4).
* $p < .05$.
** $p < .01$.
*** $p < .001$.

The two 3-way interaction terms explained an additional 12% of the variance in behavior (full model $R^2 = 0.65$). Hypothesis 3a predicted a 3-way interaction such that the relationship among anticipation, experience, BI, and behavior would be strongest when experience was high and anticipation was low. As the model 3 results indicate, the 3-way interaction between BI, anticipation, and experience was significant ($\beta = 0.28$, $p < .001$). We followed the guidelines in Aiken and West (1991) to understand the nature of the 3-way interactions. We explored the 3-way interaction of BI × anticipation × experience via a plot of the predicted values of behavior for values of behavioral intention (−1 and +1 standard deviation from the mean of behavioral intention) at low and high values of both anticipation and experience. Fig. 2 shows the plot. All simple slopes were significant, thus confirming that behavioral intention did indeed predict behavior at both levels of experience and anticipation. Further, consistent with our earlier argument, the relationship between behavioral intention and behavior was strongest when anticipation was low and experience was high, as evidenced by the steepest slope. We also explored plots at other levels of BI, as suggested by Aiken and West (1991). Those results were similar to what was shown in Fig. 2 and are not shown here due to space constraints.

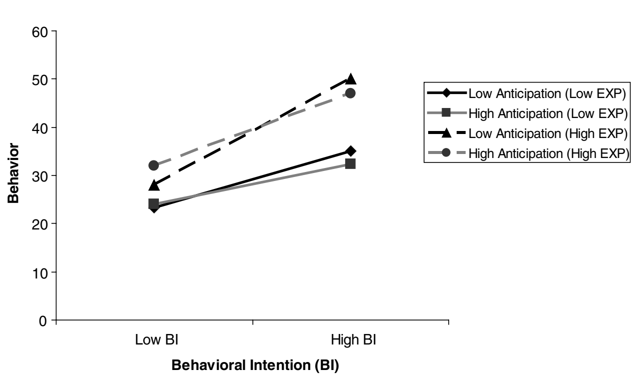

Fig. 2. 3-Way Interaction of BI × anticipation × experience.

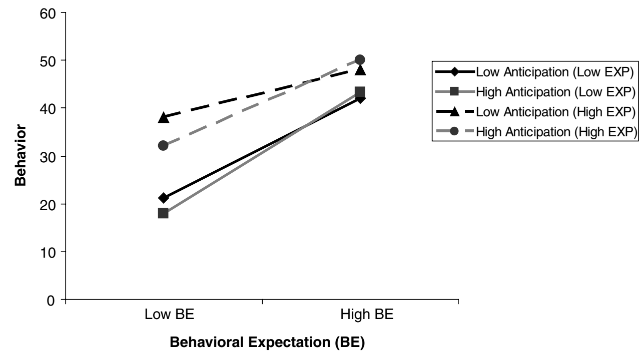

Fig. 3. 3-Way interaction of BE × anticipation × experience.

Hypothesis 3b predicted a 3-way interaction such that the relationship between BE and behavior will be strongest when anticipation is high and experience is low. We explored the second 3-way interaction—i.e., BE × anticipation × experience—that is shown in Fig. 3, with predicted values of behavior plotted against values of behavioral expectation (−1 and +1 standard deviation from the mean of behavioral expectation) at low and high values of both anticipation and experience. All simple slopes were significant, confirming that behavioral expectation influenced behavior at both levels of experience and anticipation. The relationship between BE and behavior was strongest at low levels of experience and particularly stronger when anticipation was high (i.e., distal). The 3-way interaction between BE, anticipation, and experience was significant ($\beta = 0.35$, $p < .001$). We also explored plots at other levels of BE, as suggested by Aiken and West (1991). The pattern of results was similar to what was shown in Fig. 3 and are not shown here due to space constraints. Thus, Hypotheses 3a and 3b were supported.

Discussion

The objective of this research was to expand our understanding of behavior and its predictors in organizational research. Specifically, we examined three time-related constructs—anticipation, experience, and frequency—that were expected to affect the predictiveness of BI, PBC, and BE. We predicted that BI would become less predictive of behavior as behavior becomes increasingly distal and would become more predictive of behavior as experience with the behavior increases. In the context of repeat behaviors, the proximal vs. distal nature of behavior was expected to become less important in BI's prediction of behavior as experience with the behavior increases. As with BI, we expected PBC to become a stronger predictor of behavior as experience with the behavior increased. In contrast to BI, we expected BE to become more predictive of behavior as behavior became more distal and to become less predictive of behavior as experience with behavior increased. Consistent with arguments made for BI, we predicted that, in the context of repeat behaviors, the proximal vs. distal nature of behavior would become less important in BE's prediction of behavior as experience with the behavior increases. The results from two longitudinal field studies of behavior provided support for the hypothesis.

Given the empirical support for our hypotheses, this research makes several contributions to theory. First, the results highlight the important role played by time in the study of behavior. By adopting a temporal lens, we were able to identify the various factors that can either impede or facilitate behavior. Anticipation, experience, and frequency were found to be important temporal moderators in the prediction of behavior. To the authors' knowledge, this is one of the first studies to empirically examine the combined effects of these temporal contingencies. The intentionality framework (which includes BI and PBC) seemed to be appropriate for predicting behaviors that are temporally proximal. However, the intentionality framework was found to be limited in its ability to predict distal behaviors. Experience with performing a behavior appeared to significantly improve the predictiveness of the intentionality framework.

Second, while the work of Warshaw and Davis (1985b) emphasized the superior predictive validity of BE over BI, the current study provided theoretically grounded contingencies that highlight both the strengths and weaknesses of the BE construct. Specifically, the temporal contingencies examined in this research highlight fundamental differences between BI, PBC, and BE and the mechanisms through which they influence behavior. We examined and found empirical support for the predictive superiority of BE when a behavior is distal. However, the results of this research also indicate that the predictive superiority of BE diminishes as experience with a behavior increases, perhaps because the uncertainty diminishes and BI captures all relevant behavioral drivers.

Finally, the two longitudinal field studies made it possible to test the moderating influence of anticipation and experience for behaviors that are performed in different temporal rhythms. Our hypotheses were supported in the context of episodic and repeat behaviors. However, the context of frequently repeated behaviors provided some additional insights on the predictiveness of BI, PBC, and BE. While prior research has found BE to be better than BI in predicting distal behaviors (e.g., Sheppard et al., 1988; Warshaw & Davis, 1985b), we discovered that this is not always the case. In the context of frequently repeated behaviors, we found that as individuals gain experience with performing a behavior, the proximal vs. distal nature of the behavior becomes less important. In other words, with increasing experience the intentionality framework improves in its prediction of distal behavior and the superiority of BE diminishes. As the 3-way interaction plot in Fig. 2 illustrates, the low and high anticipation slopes for BI are steep and almost parallel in the high experience condition, suggesting that—regardless of the level of anticipation—BI is a stronger predictor of behavior when experience is high. In contrast, both the low and high anticipation slopes for BI are flatter when experience is low, with the relationship between BI and behavior being weakest when anticipation is high (i.e., distal) and experience is low. Fig. 3, which presents the 3-way interaction for BE, tells a different story. The slopes for BE, regardless of the level of anticipation, are steep when experience is low, with the relationship between BE and behavior being strongest when anticipation is high (i.e., distal) and experience is low. In contrast, the low and high anticipation slopes for BE are less steep when experience is high, suggesting weaker relationships in those situations.

Strengths, limitations, and future research directions

Our research design has two key strengths that improve the validity of our results. First we tested our hypotheses in two different studies. In study 1, we tested the influence of temporal contingencies on the predictive power of BI, PBC, and BE in the context of household PC adoption—an episodic behavior. In study 2, we tested the effect of the same temporal contingencies on BI, PBC, and BE's prediction of repeat behavior in the context of a newly implemented organizational information system. Second, both of our studies employed a longitudinal research design. A longitudinal research design helps mitigate the threat of common method variance by separating the measurement points for independent and dependent variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Our studies have a few limitations that must be acknowledged. First, both tests of our hypotheses are within the domain of computer technology. To establish the generalizability of the findings, the theoretical arguments need to be applied to other behaviors. For instance, studies of behavior in other organizational contexts, social psychology, and consumer behavior would help examine the generalizability of our model and potentially identify additional contingencies. Another limitation of our research is that while we were theorized about the mechanisms underlying differences in the predictive validity of BI, PBC, and BE, we did not specifically test those mechanisms. For example, we suggested that one reason BI might be limited in predicting distal behavior is because of its provisionality. In the context of our two studies, we were unable to assess the provisionality of BI. It is possible that even provisional BI can translate into actual behavior, depending on the strength of an individual's self-control (Elster, 1979; Rachlin, 2000). Recent research on individual self-control and behavior can shed further light on BI and its prediction of distal behaviors (Benabou & Tirole, 2004). Future research should incorporate variables such as self-confidence and self-control as potential moderators of the relationship between BI and distal behavior.

Also, we suggested that the potential for inaccuracy of PBC as a proxy for actual control could potentially limit the predictive validity of BI. However, we did not assess the accuracy of PBC. Future research should determine how to assess the accuracy of PBC as a proxy for actual control. Recent research has begun to measure provisionality and accuracy of control perceptions (Sheeran et al., 1999, 2003). While consistent with prior research, we did not measure PBC with respect to a specific time frame (i.e., 1, 2, and 3 months). Thus, it is possible that the measurement precision of PBC varied between low and high experience conditions in a way that was not captured in our studies. Future research should include a time-frame-oriented measure of PBC. Finally, prior research suggests that the relationship between BI and behavior might be moderated by control or perceptions of volition. Clearly, organizational behaviors can vary in their degree of volitionality, depending on various work-related factors such as job type or organizational position. Given our focus on temporal moderators, we did not incorporate such factors. Future research should measure perceptions of volition when examining the relationships among BI, PBC, BE, and behavior. While our longitudinal field studies provide evidence for the mechanisms proposed and possess the strength of generalizability, future research is essential to establish internal validity.

Theoretical and practical implications

Our findings have several implications for research. First, our results highlight the importance of considering the temporal characteristics of behavior. Because it is often difficult or infeasible to measure actual or self-reported behavior, theoretical models need to predict behavior as accurately as possible. While proximal behaviors can be accurately predicted by BI and PBC, the performance of distal behavior can be influenced by factors perhaps not accounted for by BI and PBC. It is, therefore, necessary to exercise caution when predicting different types of behavior. Clearly, the amount of experience that respondents have with performing the behavior is an important consideration. BE appears to be well suited for conditions where BI and PBC are limited in their ability to predict behavior. To date, few studies have used BE as a predictor of behavior even when the desired behavior was distal (see Sheppard et al., 1988). In fact, recent reviews (e.g., Albarracin et al., 2001) do not even consider this construct. Given the strengths of the BE construct, future studies should consider the inclusion of this construct when the behavior of interest is distal. Further, future research should be more attentive to the episodic vs. repeat nature of the behavior being studied.

To further our understanding of the relationships among BI, BE, and behavior, potential alternative measurement approaches should be explored in future research. One potential approach might be to ask respondents "Do you intend to do X at time Y?" followed by a second question "How likely is it that your intention to do X will change between now and time Y?" Such an approach would enrich our understanding of how BE affects behavior. Future research would also benefit from a deeper empirical examination of the determinants of BE. The study of the underlying cognitions that lead to the formation of BE would deepen our understanding of its strength as a predictor of distal behavior. Because BE has close ties to probabilistic self-prediction, it possible that the formation of BE includes the use of mental simulation (Klein & Crandall, 1995; Lipshitz & Strauss, 1997; Schoemaker, 1995) or extrapolation (Allaire & Firsirotu, 1989; Wildavsky, 1988) in predicting behavior. Mental simulations and extrapolation might account for BE's ability to predict behavior in conditions of uncertainty. Research techniques such as verbal protocol analysis would be helpful in uncovering the actual mental processes underlying the formation of BE and empirically examining the mechanisms we have proposed. Further, understanding these mechanisms may help to explain why the predictive validity of BE decreases with increasing experience with repeat behavior.

Relevant practical implications are tied to the choice of the appropriate predictor for behavioral performance in different situations. The potential limitations of behavioral intention and a feasible alternative are offered in this research. This is particularly important given that behavioral intention is often used in practice as the predictor of future behavioral performance in organizational and consumer settings. Based on our findings, it is clear that the more distal the behavior, behavioral expectation would be the best form of self-prediction. This is also the case for situations of low experience. While these two key implications hold true in both episodic and repeat behaviors, in the case of repeat behaviors, the predictive ability of behavioral expectation is the strongest when experience is low and the behavior is distal. Further, based on our theorizing, we also believe that environments ridden with greater uncertainty will benefit from the use of behavioral expectation rather than reliance on behavioral intention. In more stable environments, behavioral intention may be more appropriate. Identification of these temporal contingencies provide researchers and practitioners with useful information about what specific construct and scale to use when it comes to behavioral prediction in various circumstances.

Conclusions

We reviewed the literature on predicting behavior and identified temporal conditions that affect the predictive validity of BI, PBC, and BE as predictors of behavior. The key differences between BI and BE were discussed. Two longitudinal field studies were conducted to examine episodic and repeat behaviors in households and organizations, respectively. The results demonstrated that BE becomes a more important predictor of behavior as the behavior becomes increasingly distal. In contrast, BI and PBC become less predictive of behavior as the behavior becomes increasingly distal. This holds true in the context of episodic and repeat behaviors. For repeat behaviors, increasing experience improves the ability of BI and PBC in predicting distal behavior. In such cases, the proximal vs. distal nature of behavior ceases to be a factor influencing the relative predictive validity of BI, PBC, and BE. While the relationship between BI and behavior is strongest when anticipation is low (i.e., proximal) and experience is high, the relationship between BE and behavior is strongest when anticipation is high (i.e., distal) and experience is low.

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